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Food for Fuel: The Effect of the U.S. Biofuel Mandate on Poverty in India

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Abstract

Many countries have adopted energy policies that promote biofuels as a substitute for gasoline in transportation. For instance, more than 40% of U.S. grain is now used for energy and this share is expected to rise under the current Renewable Fuels Mandate. This paper examines the distributional effects of this energy mandate on India using micro-level survey data. First, we use a model with endogenous land use to estimate the effect of the biofuel policy on the world price of selected food commodities - rice, wheat, sugar and meat and dairy, which together provide almost 70% of Indian food calories. Their world prices are predicted to increase between 5% and 11%. Uncertainty in model parameters is incorporated using Monte Carlo techniques that generate standard errors on these price predictions. The effect of these price increases on household welfare is then estimated using data on consumption and wage incomes. We estimate pass-through elasticities from time-series data then compute the negative consumption effects and positive wage impacts under perfect and imperfect pass-through from world to domestic prices. Under perfect pass-through, the mandate leads to a *reduction* in rural poverty by about 39 million people, and an increase in the number of urban poor by 4 million people. Under imperfect price pass-through, both rural and urban poverty increase by a total of 8 million people. Our study suggests that the US biofuel mandate may lead to modest increase in food prices, but have sizable global welfare impacts, which may differ across rural and urban households.

Keywords: Biofuels, Food Prices, Household Welfare, Renewable Fuel Standards, Poverty
JEL Codes: D31, O12, Q24, Q42

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1 Introduction

The United States has been by far 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 biofuel in the world. This share is expected to rise several-fold with the advent of second generation biofuels under the Renewable Fuels Standard (US Congress, 2007).[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.[2]

Given that the US is a large consumer of transport fuels and a major producer of agricultural commodities, the biofuel mandate may have a significant impact on welfare in other nations, especially if food prices rise because of diversion of crops to energy. The effect may be negative through consumption impacts, and positive if wages and income in the agricultural sector of other nations increase. We are not aware of any systematic studies of the global welfare impacts of biofuels policy, especially using micro-data at the household level. In general, 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 sample that is statistically representative at the national level.[3] A recent study (Bento et al., 2009) focuses on the impact of increased gasoline taxes on gasoline consumption and miles traveled in the U.S. as well as the associated distributional effects across households that differ by income, race and other characteristics.

The goal of this paper is to estimate the effect of the U.S. biofuel mandate on household welfare and poverty in India. India is an important country to study because of its high incidence of poverty. A third of the population is below the international poverty line of $1.25 a day, which amounts to over 400 million people - about one-third of the world's poor (Chen and Ravallion, 2010). Nearly 70% of Indians live on less than $2 a day (World Bank, 2014b). 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, 2010a).[4]

There are several methodological challenges in studying the effect of energy policy on poverty in the global economy. We focus on the effect of the US biofuel mandate

[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] See Bourguignon et al. (2008) for a careful discussion of top-down models that use macroeconomic policies to study micro-level impacts. 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.

[4] Most poor people live in villages which are home to 75% of the nation's population. A fifth of the population suffers from malnutrition (FAO, 2010).

on specific crops that are critical to the Indian diet, while aggregating the ones less important.[5] First, we calibrate a partial equilibrium model to trace the effect of the mandate on the world prices of these crops. This 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 uncertainty in the major parameters of the calibration model such as crop yields, production costs and food and fuel price elasticities through Monte Carlo simulations that generate standard errors on the price estimates.

The second part of our paper examines how these predicted commodity price shocks will affect welfare among households in India. We use detailed Indian household data to estimate the effect of the food price shocks on households through the cost of consumption, as well as the positive effects on household wage incomes. The uncertainty in the Monte Carlo analysis is incorporated in this second stage analysis to generate mean and standard errors of the welfare effects for each household. We allow for household heterogeneity in terms of their expenditure shares, factor endowments, income, geographical location and household structure, and identify the groups that are most impacted. Based on the welfare estimations, the net poverty effect is obtained by estimating the change in the poverty rate *ex-post* of the energy policy-induced price shock. We consider both perfect and imperfect price transmission from world to domestic Indian markets, by estimating pass-through elasticities for the selected commodities using available price series data. These pass-through coefficients aim to capture the role of government intervention in agricultural markets, especially relevant for India which has a long tradition of government regulation in the agricultural sector.

We find significant poverty impacts, even with modest world price increases (5-11%) for most food commodities. All households experience a welfare loss through an increase in the the cost of consumption, and this effect is regressive - poorer households are impacted the most. However, households experience a welfare gain through an increase in wage incomes, which is progressive, with the highest gains accruing to the poorest households. The magnitude of the average wage effect is large for poor rural households but small for urban and for rich rural households. As a result, the net welfare effect that accounts for both consumption and wage effects shows a progressive distributional impact for rural populations and a regressive one for urban populations.

These impacts can then be used to estimate the number of poor individuals before and after the price change. The results suggest that the U.S. biofuel mandate leads to a reduction in poverty in rural areas by 4.8% points, and an increase in poverty in urban areas by a little more than 1.0% point. Under imperfect price pass-through of world prices, there is an increase in poverty both in rural and urban households. Using 2011

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

population figures, these results indicate that the US biofuel mandate leads to a 36 million *reduction* in the number of poor individuals under perfect price pass-though, and an 8 million *increase* under imperfect price pass-through. Under perfect pass-through, rural poverty declines while urban poverty increases. There will be 39 million fewer rural poor but about 4 million more poor in urban areas.

Poverty increases among both urban and rural households under imperfect pass-through of prices, mainly due to the low pass-through elasticities of key food commodities such as rice and wheat which contribute to adverse consumption impacts, especially among lower-income households. However, under higher (perfect) pass-through of prices, the positive wage impacts accruing to rural households is large, and this explains the sizable reduction in poverty we find. Even considering smaller wage-price elasticities taken from other studies, the net poverty impacts on rural households remains positive.

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. This enables us to understand how the domestic policy decisions of an economy (the U.S.) that is a major player in world food markets impacts individuals and households in a developing country with a large share of population below the poverty line and employed in agriculture. The surprising implication is that clean energy policies that raise food prices may have significant positive impacts in other nations where a large number of people work in the agricultural sector. In fact, these programs may hurt the urban poor but may benefit the rural poor because of the positive effects on their wages. However, if these wage impacts are muted due to policy intervention and frictions in the economy, the negative consumption impacts may dominate among both rural and urban households.[6]

In section 2, we outline the calibration model used to estimate the biofuel-induced world commodity price shocks and derive the mean and standard error of prices using Monte Carlo techniques. Section 3 develops the theoretical framework underlying the distributional analysis. Section 4 describes the data and related stylized facts. Section 5 presents the estimates of the price pass-through of world to domestic prices. Section 6 shows the estimation results of welfare effects and its components, as well as their distributional impacts and effect on poverty. The variation of welfare effects across different types of households is discussed in section 7. Section 8 concludes the paper. Details of the data used in the estimation are provided in the Appendix.

[6]Although we study the impact of the U.S. biofuel mandate, 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 (e.g, climate change-induced droughts that affect crop yields).

2 Estimating the World Price of Major Food Commodities

In this section we develop a simple, dynamic partial equilibrium model of the world agricultural and transport fuel sector in order to trace the effect of the US biofuel mandate on food prices. This mandate requires the use of biofuels (mainly from corn) in transportation to increase from about 13 billion gallons currently to 21 billion by the year 2022 (EPA, 2010), shown in Figure 1.[7] First we present a simple model which reveals the underlying economic principles behind the calibration model described later in the section.

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.[8] Let $U_j, j = \{e, f\}$, be the utility function for each good assumed to be rising and concave. Transport energy is produced from gasoline or biofuel, which for now are assumed to be perfect substitutes. Food crops and biofuels are produced on land.

Land is assumed to be of uniform quality and may be allocated to energy or food crops. 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 $\sum\limits_{j\in\{e,f\}} L_j(t) = L(t)$. Change in the total land area available under food or energy production equals the new land brought under production for either use, defined by l, i.e., $\dot{L}(t) = l(t)$. 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.

[7] 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).

[8] 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.

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.[9] Total production cost is rising and convex with output q_j and is given by $w_j(q_j)$.

The consumption of transport fuel is given by $k_e L_e + g$ where $k_e L_e$ and g denote consumption of biofuels and gasoline. Let the unit cost of gasoline be c_g.[10] The biofuel mandate 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 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:

$$Max_{\{L_j(t), l(t), g(t)\}} \int_0^\infty e^{-rt}\{[U_e(k_e L_e + g) + U_f(k_f L_f)] - c(L)l - \sum_j w_j(k_j L_j) - c_g g\}dt \tag{1}$$

$$\text{subject to} \qquad k_e L_e \geq k_e \bar{L}_e \tag{2}$$

$$\text{and} \qquad \dot{L}(t) = l. \tag{3}$$

The current value Lagrangian can be written as:

$$L = U_e(k_e L_e + g) + U_f(k_f L_f) - c(L)l - \sum_j w_j(k_j L_j) - c_g g + \lambda l + \theta k_e(L_e - \bar{L}_e), j \in \{f, e\}$$

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:

$$k_f(U_f^{'} - w_f^{'}) - c'(L)l = 0 \tag{4}$$

$$k_e(U_e^{'} + \theta - w_e^{'}) - c'(L)l = 0 \tag{5}$$

$$c(L) = \lambda \tag{6}$$

$$U_e^{'} - c_g = 0 \tag{7}$$

$$\text{and } \dot{\lambda}(t) = r\lambda + c\,'(L)l, \tag{8}$$

along with associated non-negativity constraints, not shown here. Equation (4) states that land is allocated to food production until the price of food ($U_f^{'}$) equals the sum of the marginal cost of production ($w_f^{'}$) and conversion cost $c'(L)l$, adjusted by crop

[9] In the calibration model, we allow for multiple food and energy crops, as explained below.
[10] Production of crude oil and conversion to gasoline is explicitly modeled later in this section.

yield. Condition (5) suggests that the price of energy ($U_e^{'}$) equals the sum of the marginal cost of biofuel production ($w_e^{'}$) and land conversion plus the subsidy θ induced by the mandate. 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 now summarize the main insights from this model. Higher prices for food or energy, for example, from a positive shock to demand will imply increased 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. A larger biofuels mandate will implicitly mean a higher subsidy for biofuel production, increased land under fuel production and lower consumption of the substitute, gasoline.[11]

Calibration

In this section, we modify the simple framework outlined above to calibrate a model that can trace the effect of the US biofuel mandate on the price of selected food commodities in the world market. The empirical model described here follows the same basic optimizing principle we have discussed above, but with some 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 important food commodities which can then be used to examine welfare impacts for India.[12]

The Renewable Fuel Standard (RFS) sets a minimum use of first generation (ethanol from corn) and advanced biofuels (from cellulosic materials) as shown in Figure 1. The consumption of first generation fuel is mandated to increase from 10 billion gallons in 2010 to 15 billion in 2022 (EPA, 2010).[13]

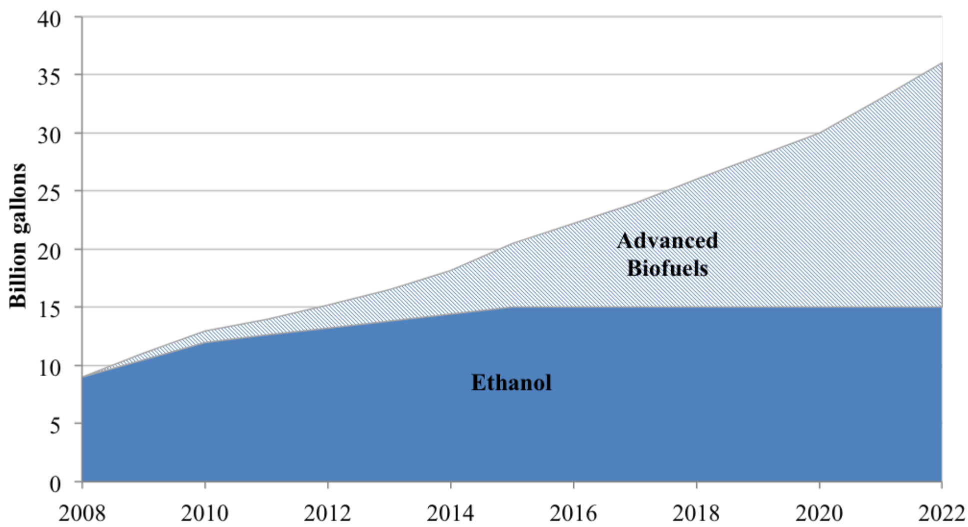
The effect of this mandate is examined by considering three geographical regions - the United States, India, and the Rest of the World (ROW) - the last region aggregates all other nations. We consider five food commodities - rice, wheat, sugar, "other food" which includes all other crops than the three mentioned previously, and "meat and dairy" considered separately. "Meat and dairy" is not directly produced from land but a portion of the "other crops" are used to feed animals which are then transformed into meat and

[11] For further insights on the use of land for food and energy, see Chakravorty et al. (2008).

[12] For a detailed description of the calibration techniques employed, see Chakravorty et al. (2014).

[13] 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.

Figure 1: U.S. Biofuel Mandate



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

dairy products. These specific commodities are chosen because of their importance in the Indian diet and because they use significant land area globally, and therefore may be especially sensitive to the mandate which induces a shift of land away from food to energy production.[14] Rice and wheat are likely to be impacted the most from diversion of land to energy production.[15] The "other food" category includes all grains other than rice and wheat, such as starches and oil crops.[16] 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 (Chakravorty et al., 2014). The model assumes frictionless trading across the three regions in the food commodities, crude oil and biofuels. However, transport fuel which is provided by gasoline and biofuels, is assumed to be consumed domestically in each region and is not traded.

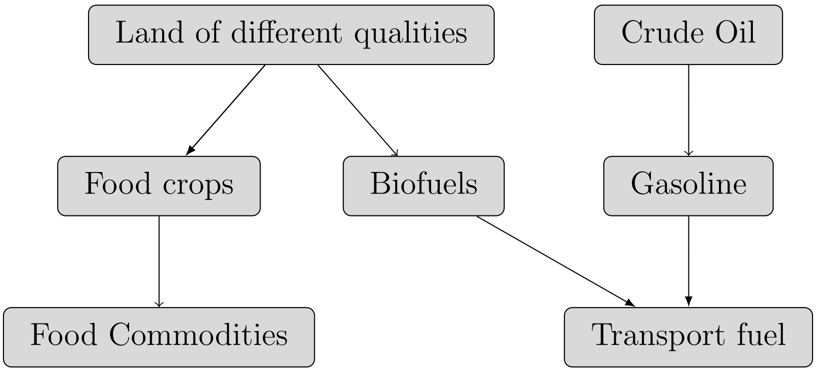
Figure 2 shows a schematic of the calibration model. Land of different qualities is used to grow food crops and biofuels. Gasoline is produced from crude oil. Gasoline and biofuels are substitutes in transport fuel. The five food commodities and transport fuel are characterized by independent demand 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 2010. The discount rate is 2%. All parameters are calibrated to match actual figures for year 2010.

[14] Rice, wheat and sugar together supply 60% of all calories in India.

[15] According to FAO (2014), rice accounts for 10% of world farmland and wheat another 14%.

[16] 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 rice and wheat.

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, sugar and "other crops." These crops are then transformed into food commodities (rice, wheat and sugar). A portion of "other crops" goes into "meat and dairy" production.

Land Use

Crop yields depend on land quality which varies significantly across geographical regions (Eswaran et al., 2003). Yields can be three times higher on high quality land than on low quality land. 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.[17] Total land area in the model includes land cultivated in base year 2010 and fallow land that may be brought into cultivation (See Appendix Table A.1).[18] The cost of conversion of land into farming for each land quality and region is taken from Gouel and Hertel (2006) and 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. The variables ψ_1 and ψ_2 are cost parameters taken from Gouel and Hertel (2006) and reported in Table A.2. These parameters are the same for each land class but different for each region. We thus have three conversion cost functions for each region - one for each land quality. Conversion costs go to infinity as available land gets exhausted.

As shown in Figure 2, land is allocated to produce the four food crops or biofuels

[17] 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 difference is small.

[18] 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).

(first and second generation).[19] We assume linear production, i.e., output is just yield times land area. For each land quality, the FAO/IIASA database has information on the acreage under each crop and its yield.[20] The definition of land quality depends on the level of 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 2010 and choose the level of input 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 A.1). Since the model is dynamic, we allow for exogenous improvements in agricultural productivity specific to region and land quality.[21]

The total cost of crop production in each region is a function of aggregate regional output and assumed to be increasing and convex. The higher the production, the cost of factors such as fertilizers and pesticides increases more than in proportion (Kooten et al., 2004). 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

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

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 is shown in Appendix Table A.3.

The four crops are transformed into five final commodities (rice, wheat, sugar, other foods, and meat/dairy) by applying a constant coefficient of transformation, detailed 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, 94% of US production in 2010 was from corn ethanol (EIA, 2014). In India, sugarcane ethanol is the main source (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.[22] Second generation biofuels are assumed to be available

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

[20] Crop acreage for US and India is readily available from this database. For the ROW region, we subtract the values for US and India from the total world figure. So for wheat, rice 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 and oil crops where the weight used is the share of each crop in total production in the region.

[21] This data is taken from Fischer et al. (2001). To illustrate, for rice, the annual growth rate of yield for the highest land quality is 1.18% and 0.90% for the lowest. See Appendix Table A.1.

[22] Output of biofuel 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

in the US alone since it may be many years before they acquire significant acreage in other regions. We only consider cellulosic ethanol since it has been identified as the most promising second generation fuel (Chen et al., 2014). Since 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 \$3 per gallon (Chen et al., 2014).

Table 1: Data on First Generation Biofuels

	US	India	ROW
	Representative crop and its share in regional production		
	Corn	Sugar	Sugar
	(94%)	(76%)	(80%)
	Energy yield by land quality (gallons/ha)		
High	876	1,200	1,463
Medium	681	912	1,254
Low	487	790	1,115
	Unit production cost (\$/gallon)		
	1.01	1.66	0.74

Notes: Production costs are taken from FAO (2008) and Ravindranath et al. (2011); the numbers in parentheses show the share of first-generation biofuels produced from the representative crop (e.g., corn). The representative crop for ROW is sugarcane - since Brazil is the dominant producer with 75% of ROW production.

Specification of Demand for Food and Energy

Demand for each of the five food commodities and for transport fuel are modeled using generalized Cobb-Douglas functions. They are indexed by $i \in \{$rice, wheat, 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 A.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 (see Appendix).

Transport energy is supplied by gasoline and biofuel, which are imperfect substitutes. Because the substitution between the two fuels may depend on a host of factors such as the future availability of flexible fuel vehicles, we adopt a CES specification as in Ando et al. (2010) given by:

by-products.

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

where q_e is the production of transport fuel in the region and 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 demands for 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), reported in Appendix Table A.5. The parameter λ is a constant which is calibrated to reproduce the base-year production of transport fuel (see Table A.5).

Crude oil supply is modeled as a competitive "bathtub" as in Nordhaus (2009) with a supply elasticity of 0.5. We posit a rising cost of extraction which captures the fact that with increased extraction, the marginal cost of oil rises.[23] Crude oil is then transformed into gasoline (see Appendix).

We run the model for two cases. In the BASE (baseline) model, biofuels are available but there is no mandate. In the REG (regulation) model, the biofuel mandate described earlier is imposed.[24] In this model, we impose three constraints for US biofuels consumption. The first constraint states that the minimum level of consumption of first generation biofuels should increase from 10 billion gallons in 2010 to 15 billion in 2022. This target can be met either by increasing domestic production or by importing from other regions. The two remaining constraints concern the minimum use of advanced biofuels. As we explained earlier, two categories of advanced biofuels are considered. The first one named the low-carbon biofuels must exhibit a 50% reduction in greenhouse gas emissions relative to gasoline. Their consumption should increase from 1 billion gallons in 2010 to 4 billion in 2022. Since only sugarcane ethanol from Brazil can meet this emissions requirement, we impose a minimum level of US imports from ROW. The second one includes the second generation of biofuels. We impose a constraint that second generation biofuels should increase from 0 in 2010 to 16 billion gallons in 2022.[25] 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

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

[24] India has also set a target of minimum use of biofuels of 20% by 2017, however, the share of biofuels in transport fuel is less than 5% in 2013. We do not model this policy in our study since the Indian biofuel policy will not likely impact world food and energy markets significantly - India consumes less than 2% of global transport fuel.

[25] In our model, we assume that second generation are only produced in the US. This target can be met only through domestic production.

have large endowments of low-cost arable land.[26]

Table 2 shows world prices for the year 2022 for the five food commodities with and without the mandate.[27] The effect on commodity prices is modest relative to other studies (Roberts and Schlenker, 2013, Hausman et al., 2012) possibly because of adjustments in land-use built into our model. Wheat prices increase the most followed by "other food" and meat/dairy. There is a shift in acreage away from food to energy production in the U.S. by about 21 million hectares relative to the no mandate in the year 2022. This represents about 12% of U.S. cropland. Since most of this additional land is released from the acreage in "other food," US production of food crops falls by about 7%. Wheat prices show the largest increase because the US is a major wheat producer. Meat prices increase mainly because of the price of feed such as 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.

Table 2: Food Commodity Prices (US dollars/ton) in 2022 with (REG) and without (BASE) the Mandate

	Rice	Wheat	Sugar	Other food	Meat/dairy
BASE	503	481	456	405	2,784
REG	543	556	458	458	3,114
% DIFF	*7.95*	*15.60*	*0.44*	*13.09*	*11.85*

Notes: %DIFF refers to the absolute difference between the BASE and REG prices.

Uncertainty in model parameters

The parameters of the model may be subject to uncertainty from random shocks or extreme events. One way to deal with this issue is to do sensitivity analysis, but that does not generate standard errors on our price predictions. We thus perform Monte-Carlo simulations (Schade and Wiesenthal, 2011). First we do sensitivity analysis to determine which parameter(s) produce price shocks of the largest magnitude in 2022, the year we study. As in Schade and Wiesenthal (2011), we keep this process simple by applying the same percentage change in absolute value for each parameter except for a couple of exceptions detailed below. We shock both models (BASE and REG), and these shocks are identical across the different regions.

[26] Since we have made the model tractable by aggregating countries into three regions, we are unable to say precisely in which country the land conversion takes place. That would require a more disaggregated framework and is of limited interest for our study.

[27] We choose price estimates for the year 2022 because that is the terminal year for the present mandate. We could have chosen an earlier year, but given that the model base year is 2010, we aimed to capture a time period that allowed for supply side adjustments to kick in. Therefore we choose the year 2022. Since the goal of the paper is to show how energy policy-induced price shocks impact poverty, we choose long-run price shocks. Short-run price shocks will be larger, of course.

We consider the following single shocks to model parameters: 1) a 30% decrease in the land conversion cost. This case may represent lax environmental regulation and other government policies or technological change that reduces the cost of converting new land for farming; 2) a 30% decrease in the production cost of first-generation biofuels, again representing technological change and learning in the nascent biofuel industry; 3) a 30% increase in the price elasticity of transport fuel (4) and in the price elasticity of final demand for all the five food commodities. The last two runs account for possible differences in elasticity estimates in the literature because of differences in data or methodology used.[28] We consider an *increase* in the price elasticity because then demand is more sensitive to a change in the commodity price; 5) A 10% decrease in mean crop yield, which may be caused by climatic events such as water shortages or temperature variability over time (see e.g., Ruttan (2002), Auffhammer and Schlenker (2014)). This 10% figure corresponds to the ratio of the standard deviation to mean yield for the five crops during the period 1980-2010 (FAO, 2014), and finally, 6) an average decrease of 4% in regional population. United Nations Population Division (UNDP, 2010b) builds three population scenarios - low, medium and high. Our baseline model adopts the medium case. For the sensitivity analysis, we consider the "low" case for all the three regions. In 2022, world population is projected to be about 8 billion for the medium case and 7.7 billion for low. Given declining fertility in many countries considering the lower number may be more reasonable.[29]

The results for the sensitivity analysis are shown in Table 3. In the top, we repeat the information from Table 2 to facilitate comparison. The panels show the price estimates and the difference between the regulated and unregulated prices for each parameter shock. The figures in parentheses in the last row for each run is the difference in percentage point of the price shock for that run relative to the model with initial parameter values. They tell us which parameter has the largest impact on the price shocks from the mandate. For instance, the price of rice increases with the mandate by 7.95% under the set of initial parameter values (see top panel on left) but with the higher food price elasticity, it increases by 6.37% (second panel). So, the difference is 1.58% points, as noted in the last row. We now try to pick which parameters are most sensitive, and this involves comparison of the vector of price shocks for all five commodities seen in the Table 3 with some subjective judgment. Rice and wheat are the most important crops,

[28] Paul (2011) estimates an Almost Ideal Demand System (AIDS) for different groups of food commodities using data from the National Sample Survey (NSS) over the period 2004-2005. His estimate for the price elasticity for cereals is -0.60 and -1.1 for meat. Mittal (2006) obtains similar elasticities by estimating a Quadratic Almost Ideal Demand System (QUAIDS) also using data from the NSS survey. Hertel et al. (2007) estimate an AIDADS (An Implicit Direct Additive Demand System) model for 10 commodity categories following the procedure of Cranfield et al. (2002). In their study, the price elasticity for cereals and meat are estimated to be -0.10 and -0.20, respectively.

[29] We also shock the model with a 30% decrease in the cost of second generation biofuels to account for rapid technological progress in production and refining technology, but that did not change results significantly, hence is not reported.

Table 3: Food Commodity Prices (US dollars/ton) with (REG) and without the Mandate (BASE) in 2002: Sensitivity to Parameters

	Rice	Wheat	Sugar	Other food	Meat/dairy
			Initial parameter values		
BASE	503	481	456	405	2,784
REG	543	556	458	458	3,114
% DIFF	*7.95*	*15.60*	*0.44*	*13.09*	*11.85*
			High price elasticity of food commodities		
BASE	487	449	456	383	2,644
REG	518	508	457	425	2,905
% DIFF	*6.37*	*13.14*	*0.22*	*10.97*	*9.87*
	(1.58)	(2.36)	(0.22)	(2.12)	(1.98)
			Low crop yields		
BASE	615	693	460	554	3,719
REG	674	804	463	633	4,210
%DIFF	*9.59*	*16.02*	*0.65*	*14.26*	*13.20*
	(1.64)	(0.42)	(0.21)	(1.17)	(1.35)
			Low conversion cost of land		
BASE	479	435	455	372	2,581
REG	513	498	456	417	2,861
%DIFF	*7.09*	*14.50*	*0.22*	*12.10*	*10.85*
	(0.86)	(1.1)	(0.22)	(0.99)	(1.0)
			Low production cost of biofuels		
BASE	506	485	456	408	2,804
REG	545	559	458	460	3,128
%DIFF	*7.71*	*15.26*	*0.44*	*12.75*	*11.55*
	(0.24)	(0.34)	(0)	(0.34)	(0.3)
			Low population		
BASE	472	422	455	363	2,522
REG	507	488	456	411	2,818
% DIFF	*7.42*	*15.64*	*0.22*	*13.22*	*11.74*
	(0.53)	(0.04)	(0.22)	(0.13)	(0.11)
			High price elasticity of fuel		
BASE	504	481	456	405	2,786
REG	544	557	458	458	3,116
% DIFF	*7.94*	*15.80*	*0.44*	*13.09*	*11.84*
	(0.01)	(0.20)	(0)	(0)	(0.01)

Notes: %DIFF refers to the absolute difference in the price increase between the BASE and REG cases. The numbers in parentheses are the absolute difference in the %DIFF figures relative to the initial parameter values shown in the top panel.

from an acreage as well as consumption standpoint, hence price changes in these two crops matter the most.[30] Using this criteria, the bottom three scenarios - low production

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

cost of biofuels, low population and high fuel price elasticity are immediately eliminated. Out of the top three scenarios in the Table 3, we do not have data on land conversion costs although it has a significant effect on prices. Thus we only focus on uncertainty in the top two parameters, price elasticity of food and low crop yields.

Next we assume that the probability density function for these two short-listed parameters is a normal distribution, as in Schade and Wiesenthal (2011). The main source of uncertainty for crop yields comes from climate shocks or extreme events such as droughts and hurricanes.[31] The mean crop yield for each land quality and region is assumed to be the observed yield from the base year (2010), reported in Table 4. The standard deviation of the distribution is computed from yield data for the period 1980-2010 obtained from FAO (2014). This data is readily available for rice, wheat and sugar 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. 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 4. That is, we assume that extreme events affect all land classes equally.

Estimates for the mean and standard deviation for the other parameter, own-price elasticity of food commodities, are obtained from a range of different studies. Figures for the US are from Hertel et al. (2007) and Regmi et al. (2001). Both studies estimate the own-price 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 figure 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 use directly. Data on own-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. [32] We take the mean and standard deviation for these elasticities by region and food commodity, as shown in Table 4.

Next, we introduce the probability density functions for food price elasticities and for crop yields in the calibrated model described previously.[33] The model is iterated $5,000$ times with randomly drawn parameters from the two distributions. For each draw, we run the BASE and REG models. We thus obtain $5,000$ values for the vector of commodity prices. Their mean and the standard error of the mean are shown in Table 5.

[31] For instance, after the 2012 drought, average maize yields in the US declined by 25% from their 2011 levels.

[32] Roberts and Schlenker (2013) estimate world elasticities for one consolidated commodity group that includes maize, wheat, rice and soybeans, which we can use directly for our four commodities.

[33] The value of the other parameters is assumed to be known with certainty.

Table 4: Probability Density Functions for Crop Yields and Price Elasticity of Food Commodities

Crop Yields (tons/hectare)							
		U.S.		India		ROW	
Commodity	Land Class	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
	High	7.1		3.2		4.0	
Rice	Medium	5.1	0.63	2.8	0.22	3.0	0.18
	Low	3.5		3.0		2.0	
	High	6.8		4.0		2.8	
Wheat	Medium	5.0	0.20	1.8	0.20	1.8	0.14
	Low	2.9		1.5		0.8	
	High	86		79		70	
Sugar	Medium	62	4.67	60	5.75	60	2.78
	Low	45		42		50	
	High	4.5		2.0		2.2	
Other food	Medium	3.5	0.50	1.5	0.30	1.8	0.30
	Low	2.5		1.0		0.9	

Food Price Elasticity						
	U.S.		India		ROW	
Commodity	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Rice	-0.10	0.001	-0.50	0.020	-0.15	0.008
Wheat	-0.10	0.001	-0.50	0.037	-0.15	0.008
Sugar	-0.10	0.001	-0.74	0.014	-0.15	0.008
Other food	-0.10	0.001	-0.50	0.020	-0.15	0.008
Meat/dairy	-0.50	0.006	-1.10	0.020	-0.19	0.008

Notes: The probability density function for each parameter is assumed to follow a normal distribution. The mean and the standard deviation for the distribution of crop yield is computed using FAO-IIASA (2002) and FAO (2014) data. The mean and standard deviation of the food price elasticity for each commodity is obtained from various studies (see text).

3 Estimation of Distributional Impacts

In this section, we estimate the distributional impacts of the mandate using micro-level surveys from India. We specifically focus on changes in household welfare caused by the increase in the price of the five food commodities. In our empirical framework, household welfare is composed of the changes in consumption behavior of the household, and in the household wage income due to the price increase. These two components are estimated with (REG) and without the US biofuel mandate (BASE). The welfare impact of the mandate is then defined as the percentage gain or loss to Indian households under the mandate relative to the no mandate policy. 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 absent the mandate.[34]

[34]This method has been used to investigate the impact of price changes arising from trade polices, see e.g., Porto (2006, 2010), Nicita (2009) and Ural Marchand (2012).

Table 5: Mean and Standard Errors for Food Commodity Prices with and without the Mandate

	Rice	Wheat	Sugar	Other food	Meat/dairy
	BASE Model (without biofuel mandate)				
Mean	492	476	455	394	2,839
SE	(0.65)	(1.30)	(0.02)	(1.03)	(6.64)
	REG Model (with biofuel mandate)				
Mean	517	530	457	429	3,090
SE	(0.71)	(1.42)	(0.03)	(1.15)	(7.26)
	Change in commodity prices (%)				
Mean	5.1	11.3	0.5	8.9	8.9
SE	(0.024)	(0.044)	(0.002)	(0.041)	(0.031)

Notes: Mean and standard errors (SE) of commodity prices from 5,000 iterations are reported for the base year 2022.

The welfare impacts through the cost of consumption involve two components. The first order impacts are those which directly affect households through price changes with respect to their initial consumption basket. We allow for second order impacts that incorporate the adjustments in the household consumption basket in response to the differential price changes across goods. After accounting for estimated changes in their wage incomes, we arrive at a net welfare effect for each household. We use the results of the Monte Carlo analysis in section 2 to obtain the standard errors of these welfare effects by household, which arise from the uncertainty in crop yields and crop price elasticity. This micro-level approach lets us differentiate between households based on their characteristics such as expenditure patterns and factor endowments. In addition, the uncertainty in Monte Carlo parameters allows us to obtain a distribution of the welfare effect for each household, and for the overall poverty impact of the biofuel policy.

Consider the following net expenditure function for household h:

$$B_h(p,u) = E_h(p,u) - w_h(p) \tag{13}$$

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 second-order Taylor series expansion of $B_h(p,u)$ around an initial price level p^0 and utility level u^0 yields

$$B_h(p,u) = B_h(p^0,u^0) + \sum_i \left(\frac{\partial e_h}{\partial p_i} - \frac{\partial w_h}{\partial p_i}\right) dp_i + \frac{1}{2}\sum_i\sum_j \left(\frac{\partial^2 e_h}{\partial p_i \partial p_j}\right) dp_i dp_j. \tag{14}$$

By the envelope theorem, $\partial e_h/\partial p_i$ is the Hicksian demand so that $h_i(p_i,u) = x_{ih}$. The compensated price elasticity of good i with respect to good j is then given by $\varepsilon_{i,j} = (\partial^2 e_h/\partial p_i \partial p_j)(p_j/x_i h)$. The term $dB_h(p,u) = B_h(p,u) - B_h(p^0,u^0)$ denotes the compensation the household needs in order 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. The negative compensating variation can be written as a fraction of initial expenditure by multiplying the right hand side of (14) by p_i/p_i and both sides by $1/e_h$ to obtain

$$W_h = -\frac{dB_h(p,u)}{e_h} = -\frac{1}{e_h}\sum_i \left(x_{ih}p_i - \varepsilon_{w_i}w_i\right)\frac{dp_i}{p_i} - \frac{1}{2e_h}\sum_i\sum_j \varepsilon_{i,j}x_{ih}p_i\frac{dp_i}{p_i}\frac{dp_j}{p_j} \tag{15}$$

where W_h is the compensating variation as a fraction of household initial expenditure and ε_{w_i} is the elasticity of wages with respect to the price of good i.

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 $w_{ih} = \sum_m w_{ih}^m$ where $m = 1, ..., M$ represents members of the household. Equation (15) can then be simplified to

$$W_h = -\left(\sum_i \theta_{ih}dlnp_i - \frac{1}{2}\sum_i\sum_j \theta_{ih}\varepsilon_{ij}dlnp_i dlnp_j\right) + \left(\sum_m\sum_i \theta_{w_{ih}}^m \varepsilon_{w_i}dlnp_i\right) \tag{16}$$

where $\theta_{ih} = x_{ih}p_i/e_h$ is the expenditure share of good i and $\theta_{w_{ih}}^m$ is the share of wage income from production of good i in the household budget contributed by member m.

The terms on the right hand side of (16) represent the different components of the compensating variation. The first term gives the direct consumption impact of the price change $dlnp_i$ induced by the biofuel mandate. 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}. Survey data is used to compute this share for each household. The second term in (16) estimates the response of households to the price shock by allowing them to adjust their consumption basket, therefore mitigating the effect of the first-order (direct) impact on their budgets. A positive price shock for good i induces an increase in the consumption of substitute goods and a reduction in the consumption of complement goods. These second order relationships between consumption goods are given by the five by five elasticity matrix, ε_{ij}.[35]

The last component in (16) measures the effect of the price shock on household income, which enters as a positive component in their welfare function. These income changes are measured individually for each member m and then aggregated up to the household. Individuals who are affiliated with industry i experience an increase in their wages by the term $\varepsilon_{w_i}dlnp_i$ where ε_{w_i} is the wage-price elasticity and $dlnp_i$ is the change in price in industry i.[36] The impact on household net expenditure is then proportional

[35] For each good i there are 25 second-order terms that summarize the behavioral response of the household. The set of elasticities used is given in Appendix Table A.6.

[36] 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 items in the household budget, whereas an industry refers to the individual's primary industry affiliation.

to the contribution of member m to the household budget, given by weight $\theta^m_{w_{ih}}$ and computed using the NSS survey data.[37]

The components of household welfare represented in (16) include only the types of income which are likely to be most affected by the price shocks, and therefore are not exhaustive, i.e., they do not represent all possible sources of household income. The estimation approach is also restricted to components for which data are readily available. For example, detailed household-level income data for agricultural profits, remittances, rents and transfers is not available and thus not included in our analysis. The welfare and poverty impacts estimated in this section only incorporate household consumption behavior, both in terms of direct cost and the adjustments in the consumption basket, and direct effect on wage income, without allowing for general equilibrium adjustments across sectors.

The Monte Carlo analysis allows us to estimate the standard errors on the welfare and poverty effects. The uncertainty comes from the distribution of crop yields and crop price elasticity, as presented in Table 4, and produces $5,000$ predictions for the price effects using random iterations. In this section, the estimation of compensating variation is done by resampling from these vectors of price changes. For each random draw, we estimate the welfare outcomes for each household. This delivers a distribution of consumption impacts for each household with mean $\hat{C}_h$ and standard error σ_{C_h}, wage impacts with mean of $\hat{E}_h$ and standard error σ_{E_h}, and total compensating variation with mean $\hat{W}_h$ and standard error σ_{W_h}. The total compensating variation can then be written as

$$\hat{W}_h = \hat{C}_h + \hat{E}_h. \tag{17}$$

This approach obviates the need to make additional distributional assumptions on key parameters of the model. The econometric model therefore does not introduce additional uncertainty, but incorporates the uncertainty introduced previously in the calibration.

4 Description of Data

The analysis relies on two nationally representative surveys from India. The National Sample Survey Organization (NSSO) Consumer Expenditure Survey is used to estimate the consumption component, and the NSSO Employment and Unemployment Survey for the earnings component of household welfare. We use the 66^{th} rounds of both surveys, conducted between 2009 and 2010. This is one of the richest micro-level surveys

[37]Computing second-order wage effects requires data on cross wage-price elasticities which are not available. For this reason, they are not included in the estimation.

for a developing country as approximately 100,000 households and 460,000 individuals are surveyed in each of the 35 states of the country.

The Consumer Expenditure Survey asks each household the value and the quantity consumed for about 500 consumption items. These items are aggregated into the same product groups described in the calibration model (see details in Appendix A.7).[38] The survey separates household consumption into 'purchased from the market' and 'home produced.' In this paper, the analysis focuses only on the purchased amount, as the price impacts are expected to mainly work through the purchased items. The substitution between the quantity produced at home and in the market is therefore not incorporated.[39] In any case, this effect is expected to be small as home production is of the order of 3% of total household consumption.

The Employment and Unemployment Survey is an individual level labor market survey that has information about wages, labor supply, occupation and 5-digit primary industry affiliation codes of each individual reported according to the Indian National Industry Classification (NIC). The matching between the NIC codes and the product categories is provided in Appendix Table A.7. The earnings of individuals who are affiliated with the production of rice, wheat, sugar, meat and 'other food' rise due to the price increase, while the earnings of other individuals are assumed to stay unchanged.[40]

The elasticities in equation (16) are obtained from various sources as shown in Appendix Table A.6. The own-price elasticities (ε_{ij} where $i = j$) are from Mittal (2006) and Paul (2011). Cross-price elasticities (ε_{ij} where $i \neq j$) are assumed symmetric and are adapted from Regmi et al. (2001). Wage-price elasticities, ε_{w_i}, are from Jacoby (2013).[41]

The mean household expenditure shares θ_{ih}, computed from the NSS Consumer Expenditure Survey are shown in Table 6. The distribution of household log per capita expenditure is divided into deciles and the mean shares are shown for each decile for both rural and urban households. In general, the table shows that the budget share for food expenditures is higher for households at the lower end of the distribution. This is consistent with Engel's law, which states that the budget share of food falls with income, even if food expenditure rises. Rural households at the lowest decile spend 9.77% of their budget on rice consumption, decreasing to 3.78% for those at the highest decile. The distribution of budget shares for wheat, sugar and other food follow a similar trend,

[38]The 'other food' category in the calibration model and in the econometric analysis covers the same consumption goods. These goods are starchy foods, other cereal, fruits and vegetables, oil, spices and beverages. The consumption of tobacco and alcohol is not incorporated in either of the analyses. The definitions of other food commodities, namely rice, wheat, sugar and meat, are the same.

[39]This would require estimation of a production function for the household farm, and shadow wages of individuals. Unfortunately, NSS does not report information on household production activities.

[40]This approach does not incorporate general equilibrium impacts that arise from factor reallocations across industries.

[41]As wage responses are an important part of the model, we consider alternative estimates for this parameter later in the paper, using elasticities from Ravallion (1990) for Bangladesh and Datt and Olmsted (2004) for Egypt.

Table 6: Household Mean Expenditure Shares (θ_{ih}) by Commodity (%)

	Rural					Urban				
	Rice	Wheat	Sugar	Meat	Other Food	Rice	Wheat	Sugar	Meat	Other Food
Decile										
1	9.77	5.79	2.12	10.79	32.22	9.31	7.33	2.46	12.20	32.61
2	8.78	4.14	1.98	10.87	31.51	8.88	6.11	2.37	13.52	31.00
3	7.88	3.22	2.03	11.66	31.36	9.24	4.80	2.03	13.36	30.93
4	7.44	2.80	1.94	12.01	30.80	8.15	4.43	1.94	14.16	30.23
5	7.44	2.71	1.84	13.04	29.88	7.69	4.07	1.78	14.30	29.69
6	6.62	2.32	1.77	12.39	29.64	7.25	3.39	1.69	14.37	28.48
7	6.01	2.05	1.65	12.94	28.61	7.06	2.99	1.55	14.27	27.41
8	5.49	1.79	1.53	12.38	27.61	6.34	2.69	1.35	13.92	25.71
9	5.10	1.40	1.39	12.61	24.70	5.76	2.31	1.15	13.11	23.77
10	3.78	1.62	1.15	11.33	20.81	3.59	1.66	0.81	11.04	20.41
All	6.83	2.79	1.74	12.00	28.71	7.33	3.98	1.71	13.43	28.02

Notes: Mean monthly expenditure shares as a fraction of total expenditures (including non-food), computed from the 66^{st} round of the NSS Household Expenditure Survey. Only purchased items are included. Deciles are based on household log per capita expenditures. Sampling weights are used in the estimation.

both for rural and urban households. We observe a relatively uniform distribution of the budget share of meat across deciles, with a slight increase for rural households.

The mean employment shares computed from the NSS Employment and Unemployment Survey are shown in Table 7. It shows the share of all individuals (not households) within each industry as it reflects different industry affiliations of members within each household. The category 'grains' includes all grains including rice and wheat, as the Indian NIC classification of industry affiliations of individuals does not distinguish between production of different types of grains such as rice and wheat (see Appendix Table A.7). As expected, a large share of rural individuals are employed in grain production with a much smaller share for urban residents. At the lowest decile, 52.27% of the individuals report grain production as their primary industry, and this number decreases monotonically to 25.21% among individuals in the highest decile. These shares range between 11.29% and 2.04% among urban individuals. The total share of individuals affiliated with food production is 48.31% in rural and 9.99% in urban areas.

The above variation in expenditure and employment shares plays an important role in the distributional effects of biofuel policy. If the price increase was uniform across commodity groups, then household consumption impact $\hat{C}_h$ would be higher (more negative) at the low end of the distribution due to the relatively high budget share of food expenditures. On the other hand, the wage impact $\hat{E}_h$ would also be higher at the lower end of the distribution, as a relatively higher share of these individuals is affiliated with food production. The net compensating variation therefore depends on the relative size of these two channels. In addition, the consumption impact $\hat{C}_h$ is expected to be similar

Table 7: **Employment Shares for Individuals by Commodity (%)**

	Rural				Urban			
	Grains	Sugar	Meat	Other Food	Grains	Sugar	Meat	Other Food
Decile								
1	52.27	0.45	1.28	3.06	11.29	0.08	0.80	1.18
2	47.24	0.54	1.46	3.12	11.57	0.08	1.12	1.22
3	46.88	0.76	1.88	3.61	11.16	0.18	1.11	1.26
4	45.61	0.80	1.98	4.29	10.24	0.24	1.28	2.72
5	43.45	0.92	2.03	4.16	8.37	0.20	0.95	1.26
6	41.24	1.05	2.38	4.52	7.44	0.06	1.13	1.45
7	39.19	0.88	2.06	5.08	6.05	0.09	0.67	1.16
8	34.95	1.46	2.42	5.47	4.89	0.24	0.98	0.98
9	30.76	1.22	3.24	5.99	3.42	0.16	0.58	1.00
10	25.21	0.68	3.23	6.23	2.04	0.08	0.49	0.68
All	40.68	0.88	2.20	4.55	7.65	0.14	0.91	1.29

Notes: 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 A.7. 'Grains' denotes all grains including rice and wheat: separate NIC codes for rice and wheat are not available. Sampling weights are used in the estimation.

between rural and urban areas due to similar household budget structures, while $\hat{E}_h$ is expected to exhibit large differences from rural to urban, with a much higher effect in rural areas. Finally, note that all households are impacted through the consumption channel, but only a share of households are impacted through wages, leading to a larger magnitude of average effects through the consumption channel.

Table 5 shows that the price effect of the mandate is not uniform across commodities, varying between 0.5% and 11.3%. These differential changes in prices is expected to induce additional distributional impacts across households. Evaluating equation (16) for each household provides a consistent estimate of the net effect through consumption and income channels, taking into account relative price increases, the importance of the commodity in the household budget, as well as the relative share of income from the production of these commodities. These estimates are then used to assess the distributional impact and to obtain a poverty impact for rural and urban households.

5 Pass-through of World Prices to the Domestic Market

One important consideration in our estimation of impacts 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 Kwiecinski and Jones (2010)). This regulatory environment may restrict the transmission of changes in world prices to domestic prices. 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 data prior to 2005 is not available. This period is somewhat unusual because of the spike in commodity prices in 2008 (see Figure 3), and the resulting aggressive short run response by the Indian government.[42] Due to limited data availability, 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 clearly evident from Figure 3), they are distortionary and hence potentially costly in the long run. These costs are not included in our estimates.

The data for estimating domestic prices for rice, wheat, and sugar are obtained from the Indian Ministry of Public Affairs. They reflect averages of the end-of-month prices across different zones of India.[43] 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 come from the World Bank Commodity Price database.[46]

Table 8 shows the summary statistics for price increases and expenditure shares for the major commodities between January 2005 and May 2011. Domestic price increases for rice and meat were somewhat similar to world prices with approximately 6 and 15 percentage point deviations, respectively. However, there was a large difference in the wheat and sugar price series, as can be observed in Figure 3. Movements in world prices are transmitted to the domestic market but only partially. This suggests that the

[42] 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.

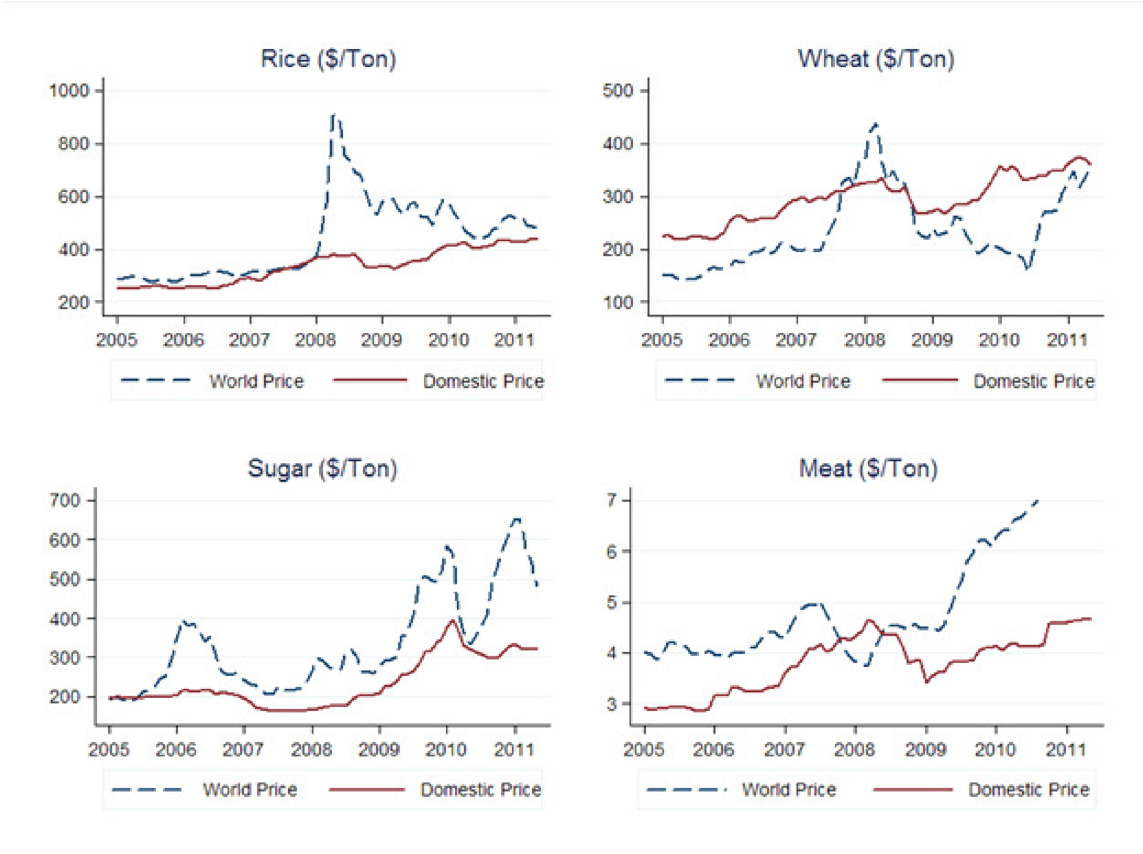
[43] The Ministry of Public Affairs collects information from Northern, Western, Eastern, Northeastern and Southern zones of India. The prices are then averaged to obtain a nationwide price level for each commodity.

[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] We need to estimate pass-through elasticity for grains in order to estimate wage impacts under imperfect pass-though.

[46] For rice prices, the Thai 5 percent variety is used, as it provides the longest series. U.S. Hard Red Winter (HRW) prices are used for wheat. Indian prices by product variety are not available.

Figure 3: Domestic and World Prices for Food Commodities (current US Dollars)



pass-through coefficients are likely to vary across commodities and need to be estimated individually.

Table 8: Increase in World and Domestic Commodity Prices (2005-2011)

	Rice	Wheat	Sugar	Meat	Grains
World	67.74	131.31	151.72	74.33	89.90
Domestic	72.29	61.16	64.11	59.16	67.07

Notes: The price series are first converted to US Dollars by using exchange rates from the Federal Reserve Bank of India. We show the change during the period January 2005-May 2011, as it is the longest period available for all commodities.

Different techniques can be used to estimate the transmission elasticity. De Janvry and Sadoulet (2010) interpret it as the ratio of growth rates in domestic and world prices. Following their approach, we find a 91.3 percent pass-through elasticity for rice. However, this method does not control for factors such as trade policy shocks. Another approach is to estimate a model in levels instead of differences (e.g. Mundlak and Larson (1992)). We find higher and significant elasticities for all commodities using this approach. However, 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.

Given these considerations, we estimate the pass-through elasticities using a single equation framework, as in Campa and Goldberg (2005) and Campa and Gonzalez Minguez (2006). The estimating equation is:

$$\Delta lnp_t^d = \sum_k \beta_k \Delta lnp_{t-k}^w + \gamma \Delta ln(1+\tau_t) + \delta \Delta lne_t + \varepsilon_t \tag{18}$$

where p_t^d is the domestic price vector expressed in domestic 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.[47] Because our study uses projected prices for distributional analysis, it is important to distinguish between long and short term elasticities. Therefore, we include the contemporaneous change in world prices, Δlnp_t^w as well as the quarterly lags in the model, Δlnp_{t-k}^w where k denotes the lag for each quarter.[48] The short term elasticity is thus given by the coefficient on the contemporaneous price level β_0. The long-term elasticity $\sum_{i=0}^{12} \beta_i$ is defined as the sum of the coefficients.

The results are given in Table 9 and show that the transmission of sugar and rice prices is statistically significant, although the magnitude of the pass-through transmission elasticity is small. A 1% increase in the world price of sugar yields a 0.22% increase in the domestic price in the short run and 0.38% in the long run. The rice and grain elasticities are also significant, but smaller in magnitude. The estimates are insignificant for meat and wheat.

The welfare impacts through cost of consumption and wages under imperfect pass-though are estimated by incorporating the pass-through elasticities that are statistically significant. The analysis is based on the long run elasticities as we focus on the long run impacts of the biofuel mandate, consistent with the supply-side adjustments made in the calibration model of section 2. Based on Table 9, world price increases of sugar, rice and grains are transmitted by 38.3%, 18.1% and 18.4% respectively, while the changes in wheat and meat prices are not reflected in the domestic market. The pass-through elasticity for the 'grains' category is estimated as 18.4%. The price effects predicted by the Monte Carlo model are multiplied by these pass-through elasticities prior to the estimation of welfare effects. For the 'other food' category, the pass-through elasticity is taken as unity. The new domestic price can be written as:

[47] 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.

[48] We choose quarterly lags because of the dimensionality problem. Given the length of our data series, it is not possible to consistently estimate the model with all 12 lags.

Table 9: Price Pass-Through Elasticities ($\varepsilon_{i,imp}$)

	Short Run (β_1)	Long Run ($\sum \beta_i$)
	(1)	(2)
Sugar	0.219***	0.383***
	(0.043)	[16.40]
Rice	0.057***	0.181***
	(0.021)	[7.97]
Wheat	0.008	0.006
	(0.035)	[0.01]
Meat	-0.023	0.056
	(0.068)	[0.06]
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. Grain prices are average of rice and wheat prices. 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. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

$$dlnp_{i,imp} = \varepsilon_{i,imp} * dlnp_i \tag{19}$$

where $\varepsilon_{i,imp}$ is the pass-through elasticity. The welfare effects under imperfect pass-through are computed using these price changes. For perfect pass-through, world prices are perfectly transmitted to the domestic market.

6 Household Welfare Effects

Consumption baskets differ across households due to a variety of factors such as cultural attributes, demographic characteristics, availability of different consumption items, preferences and more importantly, their income levels. Relatively poor households with low per capita incomes tend to spend a higher share of their income on food, particularly cheaper calories such as grains. Each household is affected by a price change in good i proportional to the budget share of good i, as well as a price change in good j depending upon the extent of substitution between i and j. The mean consumption impact $\hat{C}_h$ is estimated for each household using the first and second terms of equation (16), taking into account both direct effects and the adjustment of the household budget. We pick random draws from the vector of price increases produced by the Monte Carlo model, then estimate the consumption effect for each household for each draw. Five hundred iterations were run to reach a 10% random sample of Monte Carlo predictions of price changes. This produces a distribution of consumption effects for each household with mean $\hat{C}_h$ and standard error σ_{C_h}.[49]

Table 10 shows the consumption impacts $\hat{C}_h$ and σ_{C_h} for each decile of the per capita expenditure distribution for rural and urban households under perfect and imperfect pass-through. Under the former, households at the lowest decile suffer a welfare loss of about 4.7% of their initial expenditure level through cost of consumption, while this figure is about 3.1% for the highest decile. For urban households, these losses are somewhat higher, respectively 4.9% and 3.2%. The average consumption effects are similar for rural and urban households since their expenditure shares are similar. Under imperfect pass-through, all effects decline in magnitude. Rural households at the lowest end of the distribution experience a 2.7% decline in welfare from consumption and this effect decreases monotonically at higher deciles with the households in the highest decile suffering a 1.75% welfare loss. Recall that only rice and sugar price shocks are transmitted in this case.

Figures 4 and 5 plot the nonparametric local polynomial regression of the household-level consumption impacts on household log per capita expenditure. The positive slopes in these figures indicate that consumption effects are regressive, i.e. poorer households bear a higher welfare loss. Under imperfect pass-through, the effect is regressive but with a smaller magnitude across both rural and urban households.

Table 10: Consumption Effect

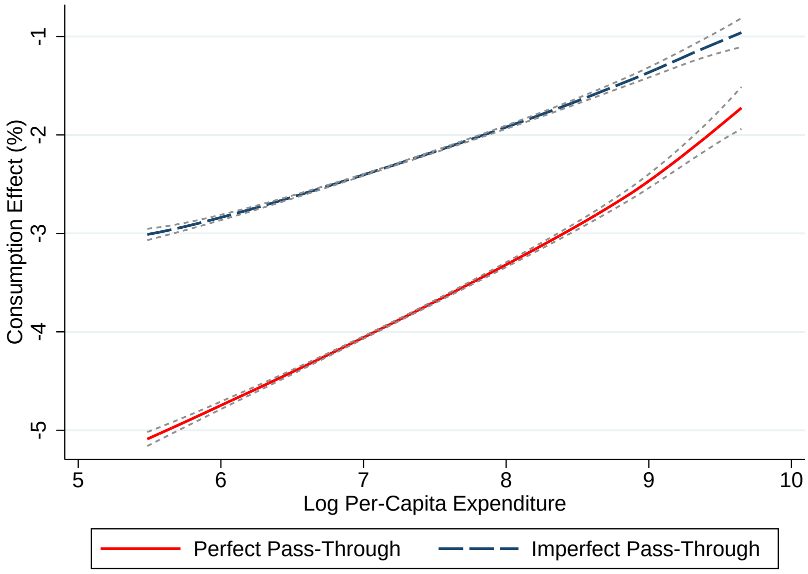
	Perfect Price Pass-through				Imperfect Price Pass-through			
	Rural		Urban		Rural		Urban	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
	$\hat{C}_h$	σ_{C_h}	$\hat{C}_h$	σ_{C_h}	$\hat{C}_h$	σ_{C_h}	$\hat{C}_h$	σ_{C_h}
Decile								
1	-4.672	0.055	-4.901	0.058	-2.724	0.041	-2.762	0.039
2	-4.394	0.052	-4.724	0.056	-2.657	0.040	-2.625	0.037
3	-4.302	0.051	-4.584	0.054	-2.637	0.039	-2.623	0.037
4	-4.216	0.050	-4.497	0.053	-2.587	0.039	-2.555	0.036
5	-4.213	0.049	-4.398	0.052	-2.511	0.038	-2.502	0.035
6	-4.057	0.048	-4.223	0.050	-2.484	0.037	-2.407	0.034
7	-3.957	0.046	-4.063	0.048	-2.394	0.036	-2.309	0.033
8	-3.762	0.044	-3.825	0.045	-2.299	0.034	-2.154	0.030
9	-3.482	0.040	-3.547	0.042	-2.074	0.031	-2.049	0.029
10	-3.140	0.036	-3.170	0.037	-1.750	0.026	-1.835	0.026
All	-4.019	0.047	-4.193	0.049	-2.412	0.036	-2.382	0.034

Notes: The mean and standard error (SE) of the consumption effects are shown by decile according to equation (16). Deciles are determined based on per capita expenditure of the household. The results with imperfect pass-through incorporate price pass-through elasticities.

Wage incomes are affected by price changes in good i according to the number of household members m who participate in its production, as well as the contribution of

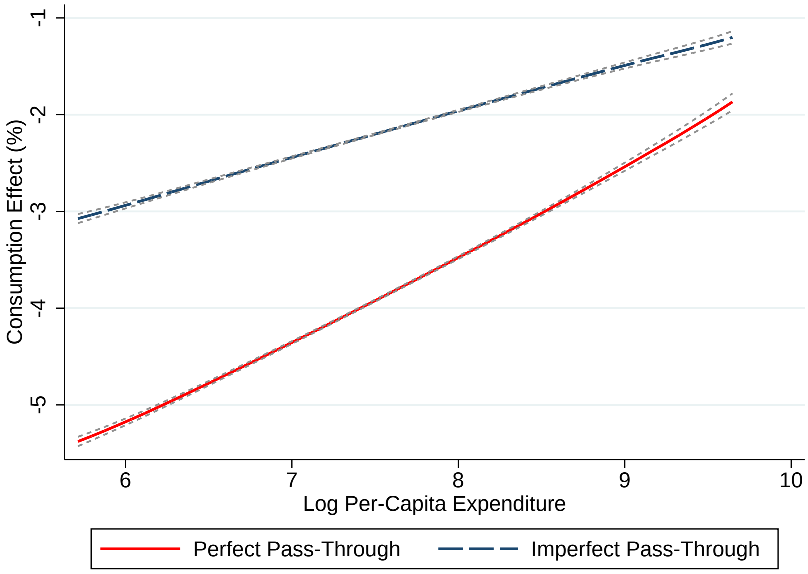
[49] The results are robust to sample sizes of 20% and 50%.

Figure 4: Consumption Effect ($\hat{C}_h$) - Rural Households



Notes: Local polynomial regression of $\hat{C}_h$ on log of household per capita expenditure.

Figure 5: Consumption Effect ($\hat{C}_h$) - Urban Households



Notes: Local polynomial regression of $\hat{C}_h$ on log of household per capita expenditure.

each member to the household budget $\theta^m_{w_{ih}}$. Wage effects are also computed iteratively by resampling from the vector of price increases produced by the Monte Carlo estimation. For each iteration, the individual-level impact is aggregated to the household level by pre-multiplying with the shares $\theta^m_{w_{ih}}$. This produces a distribution of wage impacts for each household with mean $\hat{E}_h$ and a standard error σ_{E_h}.

Table 11 shows the change in household welfare through the wage income channel by deciles of log per capita expenditure. Under perfect pass-through, rural households at the lowest decile experience a sizable welfare gain of roughly 15.5%, mainly due to the large share of households involved in food production. There is less participation in food production by households in the highest decile, hence their welfare gain is only 0.3%. The effect among urban areas is also progressive, but much smaller in magnitude.

Under imperfect pass-though, the impact on wage incomes is still progressive but smaller. Here only grain and sugar prices affect wage incomes. Rural wage incomes in the lowest decile increase by 3.8%, while this estimate is only 0.1% for households at the highest decile. For urban households, the impact is generally lower than 0.3%. Figures 6 and 7 show that the distribution of wage effects has a negative slope for both rural and urban households, although quite muted under imperfect pass-through.

Table 11: Wage Income Effect

	Perfect Price Pass-through				Imperfect Price Pass-through			
	Rural		Urban		Rural		Urban	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
	$\hat{E}_h$	σ_{E_h}	$\hat{E}_h$	σ_{E_h}	$\hat{E}_h$	σ_{E_h}	$\hat{E}_h$	σ_{E_h}
Decile								
1	15.460	0.057	0.596	0.068	3.801	0.017	0.193	0.020
2	10.532	0.057	0.396	0.071	2.363	0.017	0.157	0.026
3	8.106	0.057	0.351	0.074	2.501	0.019	0.203	0.035
4	6.907	0.059	0.195	0.072	2.185	0.021	0.098	0.028
5	5.019	0.059	0.080	0.070	1.430	0.021	0.027	0.025
6	3.354	0.059	0.079	0.068	0.868	0.022	0.020	0.020
7	3.003	0.058	0.055	0.068	0.805	0.025	0.013	0.019
8	1.416	0.061	0.041	0.076	0.277	0.023	0.018	0.035
9	1.109	0.064	0.022	0.079	0.226	0.028	0.002	0.031
10	0.280	0.068	0.007	0.086	0.097	0.039	0.004	0.052
All	5.519	0.060	0.182	0.073	1.455	0.023	0.074	0.029

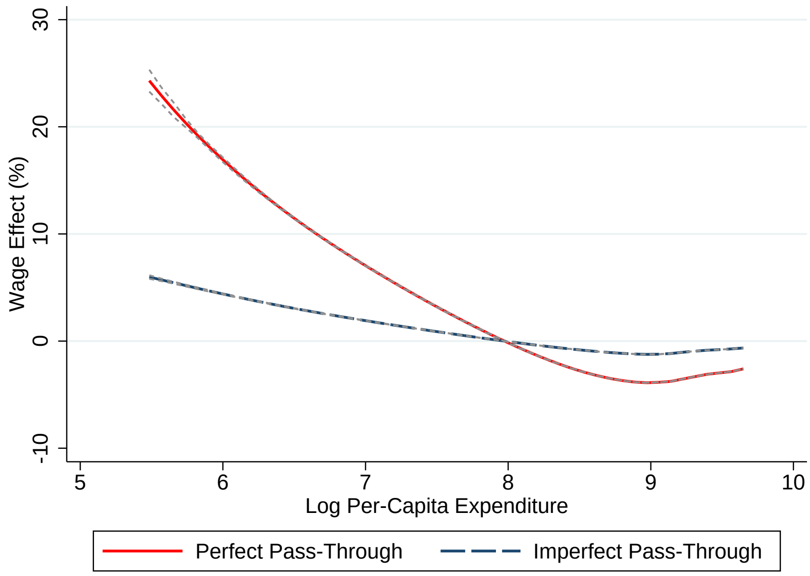
Notes: The mean and standard error of the wage income effect are shown by decile according to equation (16). The results with imperfect pass-through incorporate the price pass-through elasticities.

The consumption and wage income effects are combined in equation (16) to estimate the net welfare effect or negative compensating variation for each household. This aggregation is done for each iteration to arrive at a distribution of welfare effects for each household with mean $\hat{W}_h$ and standard error σ_{W_h}. Table 12 shows that for rural households, the total welfare effect is positive for the lowest five deciles, and negative for the highest five deciles. For the lower half of the distribution, the positive effect through wages dominates the negative effect of the increase in cost of consumption. However, the consumption effect dominates for the richer households, leading to a net welfare loss. For urban households, consumption losses exceed wage gains across the distribution, hence the net effect is negative for all deciles. The local polynomial regressions (Figures 8 and

9) show that the net effect is progressive with a sharp negative slope, due to the large gains experienced by the poorest rural households. Because of the weaker effect on wage incomes, the net welfare effect is regressive for urban households.

Under imperfect pass-through, only the lowest decile among the rural households registers a positive welfare gain. All urban households experience a welfare loss, mainly due to their small wage gains. Similar to the perfect pass-though case, the results suggest a progressive distributional impact for rural households and regressive impacts for urban households since the latter do not benefit from wage increases. Welfare effects in urban areas are driven mainly by consumption, which disproportionately hurts poorer households.

Figure 6: Wage Income Effect ($\hat{E}_h$) - Rural



Notes: Local polynomial regression of $\hat{E}_h$ on log per capita household expenditure.

Impact on Poverty

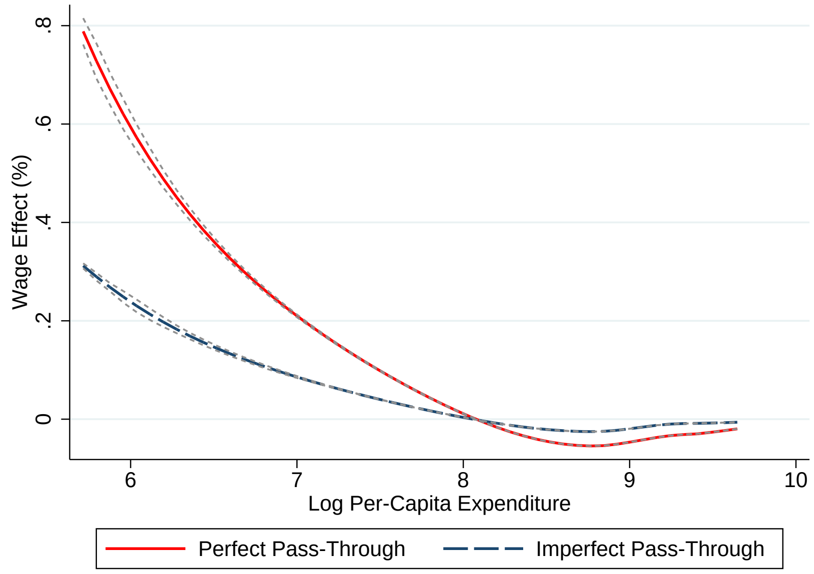
The poverty impact is estimated by computing the number of poor individuals before and after the price change. Let the poverty line be defined by z. Then the poverty rate P is the headcount ratio, i.e., the proportion of population below the poverty line:

$$P = \frac{1}{K}\sum_{i=1}^{K} I(x_i \leq z) \tag{20}$$

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 for whom $x_i \leq z$.

The price increase impacts household expenditures through two channels. First, the higher prices increase wage incomes of individuals who are producers. This will increase

Figure 7: Wage Income Effect ($\hat{E}_h$) - Urban



Notes: Local polynomial regression of $\hat{E}_h$ on log per capita household expenditure.

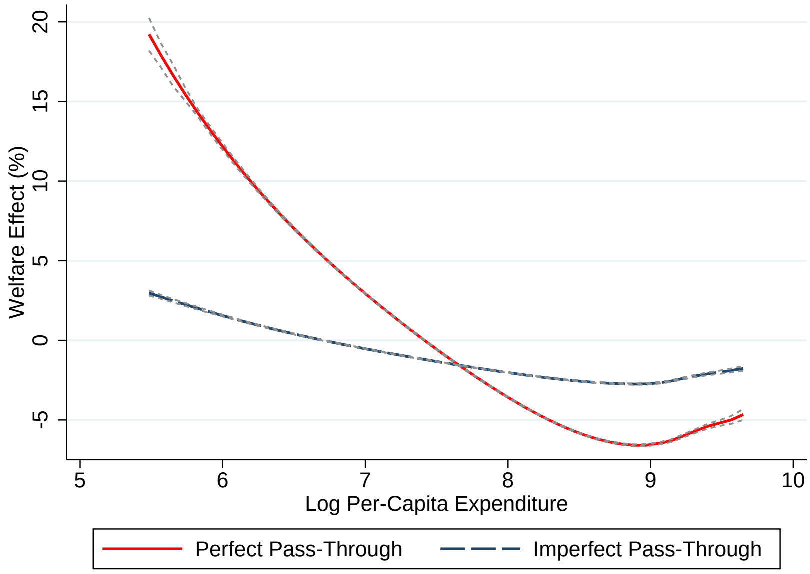
Table 12: Welfare Effect

	Perfect Price Pass-through				Imperfect Price Pass-through			
	Rural		Urban		Rural		Urban	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
	$\hat{W}_h$	σ_{W_h}	$\hat{W}_h$	σ_{W_h}	$\hat{W}_h$	σ_{W_h}	$\hat{W}_h$	σ_{W_h}
Decile								
1	10.788	0.055	-4.304	0.058	1.077	0.041	-2.568	0.039
2	6.139	0.052	-4.327	0.056	-0.294	0.040	-2.468	0.037
3	3.804	0.051	-4.232	0.054	-0.136	0.039	-2.420	0.037
4	2.691	0.050	-4.303	0.053	-0.402	0.039	-2.457	0.036
5	0.806	0.049	-4.318	0.052	-1.081	0.038	-2.475	0.035
6	-0.703	0.048	-4.144	0.050	-1.616	0.037	-2.388	0.034
7	-0.954	0.046	-4.008	0.048	-1.589	0.036	-2.296	0.033
8	-2.346	0.044	-3.785	0.045	-2.022	0.034	-2.136	0.030
9	-2.372	0.040	-3.525	0.042	-1.848	0.031	-2.047	0.029
10	-2.860	0.036	-3.163	0.037	-1.654	0.026	-1.831	0.026
All	1.499	0.047	-4.011	0.049	-0.957	0.036	-2.309	0.034

Notes: The mean and standard error (SE) of the total welfare effect are presented for each decile according to equation (16).

the per capita expenditure of the household proportional to the share of wage income from industry i in the total household budget. This shifts the household expenditure distribution upwards. The second effect is from an increase in the price vector which makes the same basket of good more costly and therefore shifts the poverty line z to the right. From condition (16), this effect is captured by:

Figure 8: Welfare Effect ($\hat{W}_h$) - Rural



$$dz = \sum_i \overline{\theta}_i dlnp_i + \frac{1}{2}\sum_i \sum_j \varepsilon_{ij}\overline{\theta}_i(dlnp_i)(dlnp_j) \tag{21}$$

where $\overline{\theta}_i$ is the average expenditure share of the 'marginal' poor.[50] We use the international poverty line (z) of \$1.25 per day which is equivalent to Rs. 701.25 per month.[51] This poverty line is used to partition poor and non-poor individuals, as well as households who change their poverty status from non-poor to poor or vice versa.

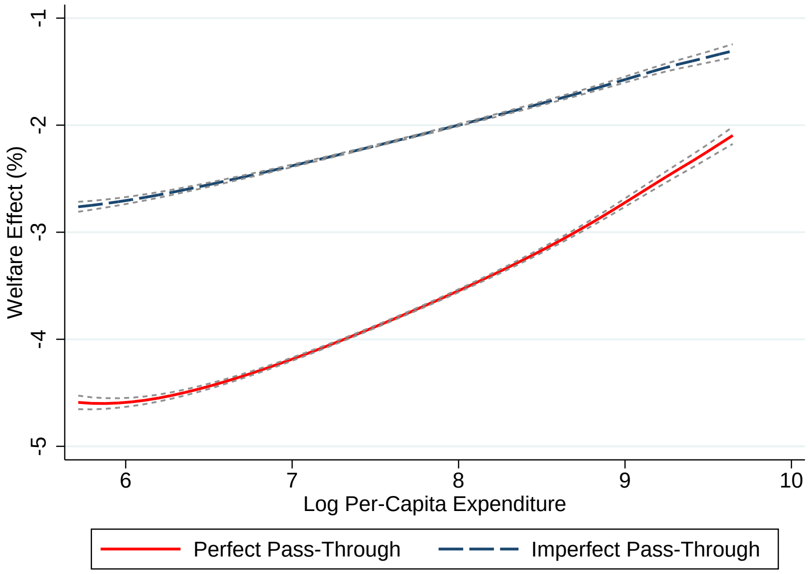
The change in the poverty rate is estimated by adjusting household expenditure with respect to the changes in income $\hat{E}$, while shifting the poverty line upwards using the consumption share of the marginal poor according to equation (21) (De Janvry and Sadoulet (2010), Porto (2010)). Each household is marked according to $I(x_i \leq z)$ as poor and non-poor before and after the policy change. The change in the poverty rate is computed as $\Delta P = P_{pre} - P_{post}$ where P_{pre} and P_{post} represent poverty rates before and after the price increase, respectively. The individuals who were marginally poor prior to the price change may no longer be poor if the income share of household members affiliated with the industries $\sum_m \theta^m_{w_i}$ is relatively high. The marginally non-poor may also become poor if $\sum_m \theta^m_{w_i}$ is low, and as a result the poverty line shifts to a level higher than their per capita expenditure.

As before, we resample from the price changes produced by the Monte Carlo procedure. This yields a distribution of poverty impacts with mean $\Delta\widehat{P}$ and standard error

[50] As in De Janvry and Sadoulet (2010), the 'marginal poor' is defined as households within a 5 percent range of the poverty line.

[51] Conversion is done using 2010 purchasing power parity (PPP) of Rupees 18.7 (World Bank Development Indicators). A month is assumed to be 30 days.

Figure 9: Welfare Effect ($\hat{W}_h$) - Urban



σ_P. For each draw, the mean consumption, wage and total impacts $\hat{C}_h$, $\hat{E}_h$, $\hat{W}_h$ and the change in the poverty rate $\Delta\widehat{P}$ are estimated, so that the results presented in Tables 10, 11, 12 and 13 are all based on the same price changes.

Table 13 summarizes the poverty impact under perfect and imperfect pass-through. It shows that compared to the baseline price change, the poverty rate is 4.8% points lower (negative) under perfect pass-through for rural households. This corresponds to roughly 40 million less poor individuals based on the 2011 population census. Under imperfect pass through, wage gains are largely muted and we estimate an increase in poverty of about 0.66% points. This translates to about 5.5 million newly poor individuals. For urban households, poverty increases under both perfect and imperfect pass through, where the impacts are estimated to be between 0.65 and 1.03% points. This corresponds to about 2.5 and 4 million more poor individuals, respectively.

Table 13: Change in the Mean Poverty Rate

	Rural		Urban	
	Change in poverty rate	New Poor (millions)	Change in poverty rate	New Poor (millions)
Perfect Pass-Through:				
$\Delta\widehat{P}$	-4.794***	-39.942	1.038***	3.913
$\sigma_P * 100$	(0.966)		(0.005)	
Imperfect Pass-Through				
$\Delta\widehat{P}$	0.663***	5.524	0.653***	2.463
$\sigma_P * 100$	(0.649)		(0.062)	

Notes: Mean and standard error of the change in poverty rate ΔP are reported. Standard errors are multiplied by 100. $1.25 poverty line is converted to Rupees using 2010 PPP of 18.7 (WDI, 2013). The number of new poor is computed using 2011 population for rural and urban households.

Alternative Wage-Price Elasticities

An important component of the welfare estimation is the response of wages to price changes. When this elasticity is high, positive wage impacts offset negative consumption impacts, as seen in the previous analysis. It is therefore important to consider alternative estimates of the wage-price elasticity. While the literature on this topic is surprisingly scarce, we consider two papers that are most relevant to a developing country setting such as India. Ravallion (1990) studies the responsiveness of agricultural wages to food prices in Bangladesh, and estimates the long-run (steady-state) elasticity to be 0.47. In a more recent paper, Datt and Olmsted (2004) model agricultural wages in Egypt using a dynamic specification. They find that in the long run agricultural wages are homogeneous with respect to a change in food prices, and nominal wages fully catch up with food prices. This implies a wage-price elasticity equal to unity.

The econometric model is re-estimated under these alternative elasticities, shown in Table 14. Under a lower wage-price response as in Ravallion (1990), poverty still decreases in rural areas, albeit by a lower magnitude (1.2 percentage points or about 10 million individuals). The poverty impacts are smaller under a lower wage-price elasticity since there is a smaller upward shift of the expenditure distribution. The urban poverty rate increases by about one percentage point. With imperfect price transmission, rural and urban poverty increase by 1.37 and 0.64 percentage points, respectively. Estimates for rural households are especially sensitive, because a larger number of rural individuals work in agriculture.

If the price increases are fully reflected in the wages, as suggested by Datt and Olmsted (2004), then the expenditure distribution will shift up proportionately with prices and households will exhibit significant welfare gains. Under perfect pass-through, the estimates suggest that the rural poverty rate decreases by 6.2 percentage points, while the urban poverty rate increases by about one percentage point. Rural poverty declines by about 52 million people under perfect pass-through while urban poverty increases by 4 million. The sign of the rural poverty impact changes to a small positive estimate even under imperfect pass-through. Once again, urban poverty is not substantially affected.

Although the poverty estimates are sensitive to the wage-price elasticity some common trends emerge. First, rural poverty decreases under perfect pass-through and increases under imperfect pass-through in all cases. Second, urban poverty is robust to changes in wage-price elasticity, as it is estimated to increase by about 1 percentage point regardless of the wage response. Finally, the impact on welfare is progressive across rural households and regressive for urban households, with a larger magnitude in the former case.

Table 14: Change in the Mean Poverty Rate - Alternative Wage Responses

	Rural		Urban	
	Change in poverty rate	New Poor (millions)	Change in poverty rate	New Poor (millions)
	Wage -Price Elasticity $\varepsilon_i = 0.47$ (Ravallion 1990, Bangladesh)			
Perfect Pass-Through:				
$\Delta\widehat{P}$	-1.169***	-9.734	1.044***	3.935
σ_P*100	(0.138)		(0.088)	
Imperfect Pass-Through				
$\Delta\widehat{P}$	1.372***	11.433	0.642***	2.422
σ_P*100	(0.311)		(0.109)	
	Wage-Price Elasticity: $\varepsilon_i = 1.00$ (Datt and Olmstead 2004, Egypt)			
Perfect Pass-Through:				
$\Delta\widehat{P}$	-6.215***	-51.799	1.036***	3.908
σ_P*100	(0.000)		(0.056)	
Imperfect Pass-Through				
$\Delta\widehat{P}$	0.320***	2.668	0.642***	0.025
σ_P*100	(0.255)		(0.000)	

Notes: Mean and standard error of the change in poverty rate ΔP are reported. Standard errors are multiplied by 100. The number of new poor is computed using 2011 population for rural and urban households.

7 Variation in Welfare Effects

The analysis so far was based on heterogeneity across households in terms of their consumption baskets and their reliance on different sources of income. These sources of variation, however, are expected to be correlated with other characteristics of the households. It is possible that certain groups are impacted more or less than others due to characteristics such as factor ownership or dietary preferences. In this section, we compare the estimated components of welfare change, $\hat{C}$ and $\hat{E}$, and net welfare effect $\hat{W}$ across different groups of households using a series of mean comparison tests. The estimates are presented under the perfect pass-though assumption and the baseline wage-price elasticity.

The results are shown in Table 15. We first investigate factor ownership across households, particularly land and skilled labor. Column (1) suggests that rural landowners on average see a 3.9% decline in welfare from consumption effects $\hat{C}_h$, while landless households lose 4.1% of their welfare. This is because landless households tend to be poorer and spend a large share of their expenditure on food items. The difference between the two effects is 0.206% points, i.e. landowners see a smaller decline in welfare (by 0.206% points) through the increase in cost of consumption. Column (2) suggests that the wage effect is higher for landowners than for the landless, with a difference of

Table 15: Variation in the Mean Welfare Effect

	Rural			Urban		
	$\hat{C}_h$	$\hat{E}_h$	$\hat{W}_h$	$\hat{C}_h$	$\hat{E}_h$	$\hat{W}_h$
	(1)	(2)	(3)	(4)	(5)	(6)
Land Ownership						
Landowner	-3.922	6.648	1.389	-3.963	0.142	-3.875
	(0.007)	(0.024)	(0.032)	(0.008)	(0.002)	(0.008)
Landless	-4.128	5.364	-0.228	-3.742	0.096	-3.683
	(0.030)	(0.119)	(0.126)	(0.013)	(0.002)	(0.013)
Δ	0.206***	1.124***	1.617***	-0.221***	0.046***	-0.191***
	(0.034)	(0.116)	(0.152)	(0.016)	(0.003)	(0.015)
t-stat	6.067	11.049	10.651	-13.684	15.619	-12.516
Skill						
Unskilled (≤ primary)	-4.102	7.840	2.381	-4.313	0.226	-4.149
	(0.010)	(0.033)	(0.046)	(0.011)	(0.003)	(0.011)
Skilled (> primary)	-3.748	4.887	0.163	-3.701	0.077	-3.661
	(0.010)	(0.031)	(0.038)	(0.008)	(0.001)	(0.008)
Δ	-0.354***	2.953***	2.217***	-0.612***	0.149***	-0.487***
	(0.014)	(0.047)	(0.060)	(0.014)	(0.003)	(0.013)
t-stat	-25.849	62.987	-36.783	-44.047	57.683	-36.501
Gender						
Male	-3.920	6.631	1.392	-3.908	0.128	-3.825
	(0.007)	(0.025)	(0.033)	(0.007)	(0.001)	(0.007)
Female	-4.040	6.259	0.618	-3.928	0.145	-3.857
	(0.023)	(0.073)	(0.096)	(0.021)	(0.004)	(0.020)
Δ	0.120***	0.373***	0.774***	0.020	-0.017***	0.031
	(0.026)	(0.077)	(0.106)	(0.022)	(0.004)	(0.021)
t-stat	5.080	4.811	7.328	0.926	-4.345	1.523
Religion						
Hindu	-3.965	6.836	1.430	-3.834	0.129	-3.761
	(0.008)	(0.028)	(0.036)	(0.008)	(0.002)	(0.008)
Islam and Other	-3.846	5.762	1.036	-4.059	0.134	-3.963
	(0.014)	(0.047)	(0.060)	(0.012)	(0.002)	(0.011)
Δ	-0.120***	1.074***	0.394***	0.225***	-0.005	0.202***
	(0.015)	(0.057)	(0.069)	(0.015)	(0.003)	(0.014)
t-stat	-7.789	18.875	5.734	15.486	-1.626	14.663

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 skilled if the head has more than primary education. t-statistics of the mean comparison tests are reported. Δ denotes the difference in mean impacts.

1.124% points. These differences tell us that it is important to examine both consumption and wage effects. As landowners benefit more through wages, landless individuals are hurt more through cost of consumption. The total welfare effect in column 3 shows that landowners' welfare increases by 1.4% while the landless see a decline of 0.23% - the difference between these estimates is statistically significant.

On the other hand, urban landowners experience a higher welfare loss from consumption relative to landless households. The results in column (4) suggest that welfare effects through consumption, $\hat{C}_h$, are 0.221% points higher (more negative) for urban landowners. This is because landless households in urban areas are mostly engaged in manufacturing and services where the returns to labor are higher. As these households are generally better off compared to their rural counterparts, their expenditure share of food tends to be lower, leading to a smaller consumption effect. The results in column (5) show that the wage effect is higher among landowners relative to the landless, and the overall welfare loss is slightly higher for the former group.

Next, we compare the skill level of the household head, where a skilled individual is defined as someone with more than a primary education. As expected, households with an unskilled head experience greater welfare loss through an increase in cost of consumption in both rural and urban settings. This can again be explained by the fact that unskilled households tend to be poorer with a higher expenditure share of food. However, the increase in wage income is higher for unskilled households - by 2.953% points in rural areas and 0.149% points in urban areas. As agriculture is an unskilled labor intensive industry, the price increase disproportionately benefits unskilled labor by increasing their earnings. This leads to the pro-poor effect through wage incomes presented in the previous section. Relative to skilled households, the total welfare effect for unskilled households is 2.217% points higher for rural and 0.487% points lower for urban residents where the consumption effect dominates.

Gender comparisons among households is shown in the third panel.[52] Households with a male head suffer less through the increase in cost of consumption, by 0.120% points. They also benefit more from an increase in wage incomes - by 0.373% points relative to female heads. As a result, rural households with a male head experience a larger gain in welfare (by 0.774% points). Urban households headed by a female exhibit higher wage impacts, but the overall difference is not significant.

Finally, we check if there are any clear differences in welfare effects among households with different religious affiliations. This is important because dietary habits may be quite different between Hindus and Muslims, the two largest groups, with many Hindus being vegetarians. We observe that rural Hindus suffer larger consumption losses but gain more in wage incomes, with a net positive and significant welfare impact than

[52] There are 6,330 and 5,120 female heads of household among rural and urban residents, corresponding to 12% and 14% of the sample, respectively.

Muslims. The opposite holds for urban households. While the difference in wage effects are insignificant, their overall welfare loss is 0.202% points smaller than for other religious groups.

8 Concluding Remarks

Many countries, including the US, China, India and members of the European Union have adopted policies to promote biofuels and reduce their dependence on imported oil. Most of the literature on the effect of biofuel policies has focused on estimating the effects of diverting crops from food to energy on food prices. In general, these models suggest price increases of 30% or more in the short-run. In this paper, we study how increased food prices may impact household consumption and income in a developing country. We show that even with modest effects of energy policy on food prices (of the order of 5-11%), the impact on the poor may be significant and can go in either direction. Wage effects are an order of magnitude higher than consumption effects among rural households because they work mainly in agriculture. If world prices pass through perfectly, we show that on net, about 36 million people get out of poverty even though poverty actually increases in urban areas. However, with imperfect pass-through, the big jump in welfare from wage increases disappears, and poverty increases among both rural and urban households.

The broad policy implication of our analysis is that U.S. biofuel policy may lead to significant poverty, mostly in towns and cities where consumption effects dominate. But in rural areas, there may be a reduction in poverty. However, when governments intervene to protect the domestic market from world price shocks, poverty may increase universally. This may be an additional cost of government intervention, beyond the other distortionary losses that are well known.

We have examined the effect of a domestic policy of one large country on another. 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 operation, although not as large as the United States mandate. India and China have mandates in the books.[53] 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 the distributional impacts.

[53] On the other hand, mandates in other nations may be partially offset if the US scales down its mandate in coming years, especially in an environment where oil and gas prices remain highly competitive.

The framework we adopt has several limitations that can be examined in future research. The impact of price increases may change within the country (e.g., by state) depending on geographical factors, market structure or state-specific policies. These differences can be incorporated by estimating state-specific pass-through elasticities. In fact, the pass-through elasticities for key crops such as rice and wheat may be indirectly estimated by computing pass-throughs for crops that are not subject to government intervention, then using these counter-factual estimates in the analysis to better measure the true costs of government intervention in the cereal market. This procedure may be more accurate than the time-series estimations we perform in the paper.

Another important data limitation is that the welfare estimations focus only on the wage income and consumption channel, excluding important channels such as agricultural profits. Third, this paper does 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 nature 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 energy policy induced price shock is 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

Ando, A., Khanna, M., and Taheripour, F. (2010). Market and Social Welfare Effects of the Renewable Fuels Standard. In Khanna, M., Scheffran, J., and Zilberman, D., editors, *Handbook of Bioenergy Economics and Policy*, volume 33 of *Natural Resource Management and Policy*, pages 233–250. Springer New York.

Auffhammer, M. and Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, 46:555–561.

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.

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.

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.

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., Magné, B., and Moreaux, M. (2008). A dynamic model of food and clean energy. *Journal of Economic Dynamics and Control*, 32(4):1181–1203.

Chen, S. and Ravallion, M. (2010). The developing world is poorer than we thought, but no less successful in the fight against poverty. *The Quarterly Journal of Economics*, 125(4):1577–1625.

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.

Cranfield, J., Preckel, P. V., Eales, J. S., and Hertel, T. W. (2002). Estimating consumer demands across the development spectrum: maximum likelihood estimates of an implicit direct additivity model. *Journal of Development Economics*, 68(2):289–307.

Datt, G. and Olmsted, J. (2004). Induced Wage Effects of Changes in Food Prices in Egypt. *Journal of Development Studies*, 40(4):137–166.

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.

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

EIA (2014). International Energy Statistics. 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 (2008). The State of Food and Agriculture. Biofuels: Prospects, Risks and Opportunities. Food and Agricultural Organization, Rome.

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, C. and Salant, S. W. (2012). Alternative climate policies and intertemporal emissions leakage: quantifying the green paradox. *Resources for the Future Discussion Paper*, (12-16).

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.

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.

Jacoby, H. G. (2013). Food prices, wages, and welfare in rural India. The World Bank, Policy Research Working Paper Series, 6412.

Kooten, G., Folmer, H., et al. (2004). *Land and forest economics.* Edward Elgar Publishing.

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).

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).

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.

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.

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*.

Ruttan, V. W. (2002). Productivity growth in world agriculture: sources and constraints. *Journal of Economic Perspectives*, pages 161–184.

Schade, B. and Wiesenthal, T. (2011). Biofuels: A model based assessment under uncertainty applying the Monte Carlo method. *Journal of Policy Modeling*, 33(1):92–126.

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

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

UNDP (2010b). Population Prospects: The 2010 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.

US Congress (2007). Energy Independence and Security Act of 2007. *Public Law*.

World Bank (2014a). Commodity Markets Outlook, Prices (Pink Sheet). World Bank.

World Bank (2014b). World Databank. World Development Indicators.

A Appendix: Details of Data Used in Estimation

The model used to predict the effect of the biofuel mandate on food prices is adapted from Chakravorty et al. (2014).[54] It is solved using GAMS software. Here we provide additional data and specifications used in the calibration.

Table A.1 shows crop yields and land endowment for the base year 2010 by land quality and region.

Table A.1: Endowment of Land (million hectares) and Crop Yields by Land Quality and Region (tons per hectare)

Land quality	Land available	Wheat	Rice	Sugar	Other Crops
			U.S.		
High	60	6.8 (1.50%)	7.1 (1.19%)	86 (1.10%)	4.5 (1.50%)
Medium	80	5.0 (1.25%)	5.1 (1.10%)	72 (1.10%)	3.5 (1.25%)
Low	30	2.9 (1.00%)	3.5 (0.90%)	65 (1.10%)	2.5 (1.00%)
			India		
High	70	4.0 (1.35%)	3.2 (1.18%)	79 (1.10%)	2 (1.35%)
Medium	50	1.8 (1.15%)	2.8 (1.11%)	60 (1.10%)	1.5 (1.15%)
Low	10	1.5 (0.90%)	3 (0.90%)	52 (1.10%)	1 (0.90%)
			ROW		
High	200	2.8 (1.25%)	4 (1.16%)	70 (1.1%)	2.2 (1.25%)
Medium	950	1.8 (1.10%)	3 (1.10%)	60 (1.10%)	1.8 (1.10%)
Low	950	0.8 (0.90%)	2 (0.90%)	50 (1.10%)	0.9 (0.90%)

Sources: FAO-IIASA (2002) and Fischer et al. (2001). Numbers in parenthesis represent the annual growth rate of yield.

Parameters for the cost of converting new land into farming (equation (9)) are reported in Table A.2.

Table A.2: Parameters for the Cost of Land Conversion

	ψ_1	ψ_2
U.S.	430	431
India	200	200
ROW	26	26

Source: Gouel and Hertel (2006).

The parameters for the production cost (equation (10)) are reported in Table A.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), assumed uniform across regions. A portion

[54]They develop a model to study the effect of the U.S. and E.U. biofuel mandates on the price of a basket of food commodities. We use a disaggregated form of their model for the five commodities of interest.

Table A.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)

of "other crops" is used as animal feed. The quantity of meat and dairy produced from one ton of "other crops" (feed ratio) is region-specific and adapted from Bouwman (1997). We use a feed ratio of 0.4 for U.S. and 0.25 for India and ROW.

Regional demands (for rice, wheat, sugar, meat and dairy, other food and transportation fuel) are given by equation (11). The constant A_i is calibrated to reproduce the demand in the base year and it is given by: $A_i = \dfrac{D_i}{P_i^{\alpha_i} y_i^{\beta_i} N}$. The data used to calibrate A_i is shown in Table A.4.

Population projections are taken from the United Nations Population Division (UNDP, 2010b).[55] India's population is expected to increase to about 1.45 billion people in 2022. GDP per capita is non-stationary and is assumed to increase at an exogenous and declining rate. We assume GDP per capita to be increasing at an annual rate of 1.5% for the U.S., 5% annually for India and 2% annually for ROW (World Bank, 2014b).

Energy is provided by a mix of gasoline and biofuels. We consider an upward sloping curve for crude oil supply. The inverse supply curve is given by: $c_o = Bq_o^{\alpha_o}$ where c_o is the marginal cost of crude oil, q_o is the world supply of crude oil used for transportation, α_o is the supply elasticity from Chen et al. (2012) and equals 0.5. B is a constant to be calibrated and equals $B = q_o^{-\alpha_o} c_o$. For the base year 2010, the marginal cost of crude oil is US$50 per barrel as in Fischer and Salant (2012) and the world supply of crude oil used for transportation is 8.1 billion gallons (EIA, 2014). Thus, the constant B equals 2.70. Crude oil is transformed into gasoline: one gallon of oil produces 0.47 gallons of gasoline. The cost of converting oil into gasoline is the same across different regions and equal to 0.46 per gallon (Chakravorty et al., 2014). Since transport fuel is in energy units, we convert gallons into Megajoules (MJ). A gallon of gasoline yields 120 Megajoules of energy and a gallon of ethanol gives 80 MegaJoules. Finally, transport fuel is transformed into Vehicle Miles Traveled (VMT): one MJ of transportation energy equals 0.177 VMT for a gasoline-powered car (Chen et al., 2012).

Transport energy supply q_e is given by equation (12). The parameter λ is a constant which is calibrated to reproduce the base-year production of transport fuel. It is given by

[55] We use estimates from the United Nations (UN Population Division, 2010) based on medium range fertility projections. It predicts a 2050 world population of 9 billion.

Table A.4: Calibration of Per Capita Demand Functions (Base Year = 2010)

	US	India	ROW
Population *(millions)*	310	1.224	5.360
Consumption *(dollars per capita)*	47,200	3,500	10,000
		Rice	
Consumption *(kg per capita)*	9	70	53
Price *(dollars per ton)*	400	400	400
Price elasticity	-0.1	-0.5	-0.15
Income Elasticity	0.01	0.11	0.65
Constant (A_i)	0.0147	0.5705	0.0003
		Wheat	
Consumption *(kg per capita)*	85	60	65
Price *(dollars per ton)*	300	300	300
Price elasticity	-0.1	-0.50	-0.15
Income Elasticity	0.01	0.11	0.65
Constant (A_i)	0.1350	0.4235	0.0004
		Sugar	
Consumption *(kg per capita)*	67	24	28
Price *(dollars per ton)*	400	400	400
Price elasticity	-0.50	-0.74	-0.15
Income Elasticity	0.01	0.62	0.65
Constant (A_i)	1.2033	0.0128	0.0002
		Other food	
Consumption *(kg per capita)*	119	80	116
Price *(dollars per ton)*	350	350	350
Price elasticity	-0.10	- 0.50	-0.15
Income Elasticity	0.01	0.62	0.65
Constant (A_i)	0.192	0.010	0.001
		Meat/dairy	
Consumption *(kg per capita)*	375	75	70
Price *(dollars per ton)*	1,960	1,960	1,960
Price elasticity	-0.50	-1.10	-0.19
Income Elasticity	0.89	0.70	1.20
Constant (A_i)	0.001	1.036	4.684E-06
		Transport fuel	
Per capita demand *(VMT per capita)*	9,250	69	752
Price *(dollars per VMT)*	0.14	0.23	0.23
Price elasticity	-0.7	-0.21	-0.25
Income Elasticity	0.97	1.12	1.05
Constant (A_i)	0.069	0.005	0.032

Sources: Consumption figures for food commodities: FAO (2014), transport fuel: EIA (2014); prices: World Bank (2014a); own-price and income elasticities for transport fuel: Hertel et al. (2007) and Dimaranan et al. (2007); own-price and income elasticities for food commodities (U.S.):Hertel et al. (2007) and Regmi et al. (2001); own-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); own-price and income elasticities for food commodities (India): Paul (2011), Hertel et al. (2007) and Mittal (2006); population figures: United Nations Population Division (UNDP, 2010b); and per capita income: World Bank (2014b).

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

The data used to calibrate λ is reported in Table (A.5).

Table A.5: Calibration of the Transport Fuel Production Function (2010)

	US	India	ROW
Transport fuel supply q_e (MJ)	16,200	480	22,800
Gasoline supply q_g (MJ)	15,840	466	21,840
Biofuels supply q_{bf} (MJ)	800	16	720
Share of gasoline μ_g	0.10	0.05	0.05
Elasticity of substitution ρ	2	2	2
Constant λ	1.189	1.115	1.130

Notes: MJ: MegaJoules; Production of transport fuel (q_e) equals consumption in our framework 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 A.6: Elasticities Used in the Econometric Estimation (ε_{ij})

	Wheat	Rice	Sugar	Meat	Other food
			Cross-price Elasticities		
Wheat	-0.50	0.10	0.05	-0.10	0.05
Rice	0.10	-0.50	0.05	-0.10	0.05
Sugar	0.05	0.05	-0.74	0.10	0.05
Meat	-0.10	-0.10	0.10	-1.10	-0.10
Other food	0.05	0.05	0.05	-0.10	-0.50
			Wage-price Elasticity = 0.826		

Notes: Own-price elasticities are from Paul (2011), Hertel et al. (2007) and Mittal (2006). Cross-price elasticities are assumed symmetric and adapted from Regmi et al. (2001). Wage-price elasticity is from Jacoby (2013).

Table A.7: 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	5001	Fishing on commercial basis in ocean, sea and coastal areas
	186	Others: birds, crab, oyster, tortoise, etc.	5002-5005	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