Food for Fuel: The Effect of U.S. Energy Policy on Indian Poverty

by

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Abstract

Many countries have adopted energy policies that promote biofuels as a substitute for gasoline in transportation. For instance, 40% of U.S. grain is now used for energy and this share is expected to rise significantly under the current Renewable Fuels Mandate. This paper examines the distributional effects of the U.S. mandate on India. First, we use a model with endogenous land use to estimate the effect of biofuel policy on the world price of food commodities, in particular rice, wheat, sugar and meat and dairy, which provide almost 70% of Indian food calories. We obtain world price increases of the order of 10% for most of these commodities. Using Indian micro-level survey data for consumption and income, we carefully estimate the effect of these price increases on household welfare. We account for negative consumption impacts as well as the positive effects through wages and income. We consider both perfect and imperfect pass-through from world to domestic prices. We show that the net impact on welfare is negative as well as regressive, i.e., U.S. biofuels policy affects the poorest people the most. About 42 million new poor may be created in India alone. Under imperfect pass-through, this number declines to 16 million. The main implication is that U.S. energy policy that mandates the production of fuel from food may lead to a sharp increase in world poverty.

Keywords: Clean Energy, 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 crops in the transportation sector. About 10% of U.S. gasoline now comes from ethanol produced from corn, making it the largest biofuel consumer in the world. This share is expected to rise several-fold because of the U.S. Renewable Fuels Standard (Energy Independence Security Act, 2007). Brazil, the European Union, China and other countries have similar policies that divert corn, sugarcane and other commodities from food to energy. This policy is controversial because it uses scarce land resources that displace food for energy production, leading to an increase in food prices (New York Times, April 2011). Several studies have attributed recent food price shocks to the sharp increase in biofuel production.[2] However, we are not aware of any systematic studies of the welfare impacts of biofuels policy. In this paper, we 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 and also a third of the world's poor (Chen and Ravallion, 2010). Nearly 70% of Indians live on less than $2 a day (World Bank, 2010). 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 (Human Development Report, 2010). 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).

Our analysis on the effect of U.S. biofuel policy focuses on specific crops that are critical to the Indian diet, while aggregating the ones less important.[3] The calibration model we develop traces the effects of diverting corn from food to energy use on the world market for major crops such as rice, wheat and sugarcane. The use of crops for energy will lead to displacement of food production to lower quality lands, which we capture in our dynamic model. Thus, the food price estimates we obtain are in general, inclusive of adjustment processes in the economy, and hence

[2] See for example, Mitchell (2008), Rosegrant *et al.* (2008), Hausman et al (2012) and Roberts and Schlenker (2010). These studies examine the effect of biofuel policy on U.S. and world markets for different time periods. All report significant price increases for food commodities, ranging from 20-70%.
[3] In particular, rice, wheat, sugar and meat and dairy, which supply about 70% of calories for the average Indian household.

in the lower range of most other studies. However, we then take the next step, i.e., examine how these commodity price shocks will affect welfare among households in India.

By using detailed Indian household survey data, we estimate the effect of food price shocks on households through the cost of consumption, as well as the positive effects on household wages and income. This is done by estimating industry-specific wage-price elasticities, accounting for both perfect and imperfect price transmission from world to domestic Indian markets. 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. The net welfare effect experienced by households is then used to compute the poverty rate *ex-post* of the energy-induced price shocks.

We show that even with modest price increases (10-12%) for most food crops, the U.S. biofuel policy may create about 42 million new poor in India alone, if world prices transmit perfectly to the Indian domestic market. With significant government intervention and imperfect pass through, there may be 16 million new poor.[4] If food prices were to increase by a bigger margin (25%) which could happen in the short-run, these estimates rise proportionately. With perfect pass-through, 88 million people become poor.

All households experience welfare losses due to the increased cost of food and fuel consumption. However, there are key differences in terms of who is most impacted. The effect through food consumption is highly regressive – poorer households are hurt more, because they spend a larger share of their budgets on food. However, the consumption effect of transport fuel is progressive – richer households are impacted more. But the magnitude of the food effect dominates that of fuel, leading to a negative and regressive welfare impact because of the increased cost of consumption.

The effect of the commodity price shocks through wages is positive, and progressive for both rural and urban households. This is mainly because of the high number of households employed in the agricultural sector at the low end of the expenditure distribution. However, agricultural

[4] The lower estimate does not incorporate the potentially significant welfare costs of intervening in the food market.

profits accrue to the more affluent rural households since a higher proportion of them are land owners. Both the wage and profit impacts on rural households are an order of magnitude higher than for those living in urban areas.

Aggregating the impacts through consumption, wages and profits, the net effect on households is regressive. Households who are larger, own less land, are less educated, have more female members and have less children are impacted more by the price shocks, *ceteris paribus*. Members of scheduled castes and tribes are also among the ones most impacted, especially among rural populations. Muslims are more adversely affected by the food price shocks than Hindus and other religious groups due to a higher share of meat consumption.

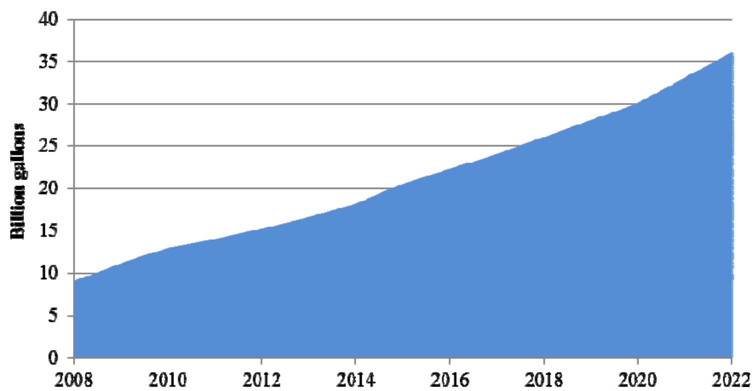
The main contribution of our paper is in linking a calibrated model of the world food market to generate estimates of energy policy-induced commodity price shocks and then using micro-level household data to study the distributional effects of this policy. This enables us to understand how the decisions of an economy (the U.S.) that is a major player in the world energy and food markets impacts individuals and households in a developing country. Many studies have established the link between biofuels and food markets, but none have taken this next step, which is to examine the consequences of energy policy at the household level using consumption and employment data. The main policy implication of the paper is that energy policies that divert food to fuel may create a large number of newly impoverished people. This may occur even if the policy causes “modest” price shocks in the world food market.

In section 2, we outline the calibration technique used and estimate the impact of the US biofuel mandate on the world price of food and fuel. Section 3 develops the theoretical framework underlying the distributional analysis. Section 4 describes the estimation methodology and presents results on the components of welfare changes for Indian households. Section 5 examines the impacts on poverty and section 6 concludes the paper. Details of the calibration and estimation of price pass-through and wage elasticities are provided in the Appendix.

2. A Ricardian Model of Food and Energy

The first step is to impose the US biofuel mandate which requires the share of biofuels (mainly from corn) in transportation to increase from about 11 billion gallons currently to 15 billion by the year 2015 (EPA 2010). This is shown in Fig.1.[5] We calibrate a dynamic partial equilibrium economy with three regions (U.S., India and Rest of the World, called ROW). These regions produce and trade five major food products (rice, wheat, sugar, other crops and meat and dairy). Rice and wheat are chosen because they are the most important cereal crops in terms of providing nutrition for the poor in India and because they consume significant global acreage, hence likely to be impacted the most from diversion of land to energy production.[6] Rice, wheat and sugar together supply 60% of all calories in India (FAOSTAT). The "other crops" we consider include all grains other than rice and wheat, and starches, soybeans and oil crops.[7] Meat and dairy group all meat products as well as milk and butter.[8]

Figure 1: U.S. Biofuel Mandate



These food commodities compete for land with corn and sugarcane which are converted to biofuels. The model allows for the endogenous expansion of acreage into lands currently under alternative uses such as grassland or forest. We use global land quality data from FAO which

[5] The bill also requires an increase in the consumption of newer cellulosic biofuels from near zero to 21 billion gallons per year in 2022. We account for this in the model. We also impose the Indian biofuel mandate, which specifies a 20% share of transport fuels by 2017 (Eisentraut 2010). See Appendix A for details.
[6] Rice accounts for 10% of world farmland and wheat another 14%, according to FAOSTAT.
[7] These "other" crops are not treated separately because they occupy less acreage and are likely to be less important in terms of distributional effects than say, rice and wheat.
[8] We distinguish cereal crops from meat because the two goods have different income elasticities and producing meat is more land intensive than cereals. On average, one hectare of land produces either one ton of meat or three tons of cereals and other crops (Bouwman 1997).

defines three different land classes based on soil and climate characteristics. Crop yields are higher on higher quality land. We build in regional differences in the production costs for food and energy production, as well as the cost of converting new land for farming (see Appendix A).

Transport energy is supplied by a blend of gasoline and biofuel. Gasoline consumption is a fixed share of crude oil production, given by a rising and convex supply curve as in Nordhaus and Boyer (2000). In total, we then have six final consumption goods - namely the five food commodities and blended fuel for transportation.

The social planner maximizes the consumer plus producer surplus for all regions by choosing land and energy (gasoline and biofuels) to supply transportation fuel and the five food commodities. This policy causes grains to be diverted from food to energy and leads to the conversion of new land to farming in regions that have large endowments of low-cost, arable land.[9] World prices for the selected crops – rice, wheat, sugar and meat and dairy, increase relative to the no-mandate case. Below we only report the price shocks for the year 2015. Further details for the calibration model are presented in Appendix A.

U.S. and Indian biofuel mandates

We examine two scenarios. In the benchmark scenario, no biofuel policy is implemented.[10] This serves as the counterfactual. In the second, U.S. and Indian biofuel mandates are introduced in the model.[11] Under the biofuel mandates of the two countries, 20 million additional hectares of land are brought into cultivation globally. Global food production declines by about 2%. Table 1 shows the price increases predicted by the model in year 2015 relative to the counterfactual, expressed as a percentage. It shows that the effect on world food prices is modest relative to other studies (cited earlier) possibly because of supply-side adjustments built into our model.[12]

[9] Because we have made the model tractable by aggregating countries into the three regions, we are unable to say exactly in which country the acreage conversion takes place.
[10] Without biofuel policy, only a small amount is consumed in the US (2 billion gallons) and India (1 billion).
[11] Because of its heavy dependence on imported oil, India has embarked on an ambitious biofuel program (Swarup 2011). For consistency, we consider the joint effect of the US and Indian biofuel mandate. However, the Indian mandate alone adds only a fraction of a percent to world prices. The US mandate is many times larger in scale. For example in 2011, US biofuel consumption was 11 billion gallons, and Indian consumption 450 million gallons.
[12] These include the endogenous expansion of agricultural acreage, and optimistic assumptions with respect to technological change in the form of yield increases in agriculture and efficiency gains in the transport sector (e.g., increased fuel efficiency in automobiles).

Wheat and domestic fuel prices increase the most.[13]

Table 1: Vector of Price Shocks due to Biofuel Policy

World Prices					
Rice	Wheat	Sugar	Meat & Dairy	Other Crops	Indian Transport Fuel
7.8	12.1	0.84	11.8	11.9	38.2

Notes: The figures represent percent increase in price relative to the benchmark case. Since transport fuel is blended domestically, we report the equilibrium domestic transport fuel price.

The model suggests that acreage under biofuel production in the U.S. increases by 21 million hectares relative to no mandate in the year 2015. This represents about 12% of U.S. cropland. Since most of this additional land is released from other crops, U.S. production of food crops falls by about 7%. Wheat prices show the largest increase (among food crops) because the U.S. is a major producer of wheat. Meat prices increase mainly because of the price of cereal inputs. Sugar prices are impacted less because it is mostly produced outside the U.S. and it can be produced in lower quality lands, relative to grains.

The production of ethanol in India goes up by about 2 billion gallons compared to the benchmark case. This causes a modest diversion of land from food to energy production.[14] Only one percent of cultivated land in India is allocated to energy production in the model. Indian food production decreases by less than 2%. Since ethanol in India is produced from sugar, sugar prices increase by a small margin. The main impact of the Indian mandate is felt in the gasoline market with a 38% increase in the price of fuel.[15] However, it reduces gasoline consumption by only 6% because transportation fuel consumption is highly inelastic (see Appendix Table A1).

3. The Model for Estimating Distributional Impacts

We measure the distributional impacts of biofuel policy by comparing the net expenditures of households before and after the price shock. We estimate the percentage gain or loss in

[13] Our analysis of welfare effects is predicated on modest shocks to food prices induced by the biofuel mandate. Later we repeat the welfare analysis for a larger across-the-board increase (25%) in food prices.
[14] Unlike the US, India does not have much fallow land that can be used to expand acreage.
[15] The rise in the price of transport fuel price (which is a blend of gasoline and ethanol) is mainly due to a rise in the world price of ethanol due to an increase in the cost of supply.

household welfare with respect to their net expenditure in the baseline (no mandate) scenario. This is done by computing the negative compensating variation for each household as a percentage of their initial expenditure, which yields a nonparametric distribution of welfare impacts across the per capita expenditure spectrum. We allow households to respond to price shocks by adjusting their expenditure patterns. This micro-level approach allows us to differentiate between households based on their expenditure patterns, factor endowments and other household-specific characteristics. The heterogeneity across households in consumption and income-generating activities interacts with differential price shocks across commodities. We can identify which households are most affected, and analyze the channels through which this takes place.

We adopt the approach of Deaton (1989) modifying it to allow for second order adjustments in the household consumption basket.[16] Consider the following household net expenditure function:

$$B(p,u) = E(p,u) - w(p) - \pi(p) \tag{6}$$

where p is the vector of prices, $E(p,u)$ is expenditure required to reach utility level u, $w(p)$ denotes the wage income of the household and $\pi(p)$ are profits obtained by selling agricultural goods. A second-order Taylor series expansion of $B(p,u)$ around an initial price level p^0 and utility level u^0 yields

$$B(p,u) = B(p^0,u^0) + \sum_i \left(\frac{\partial e}{\partial p_i} - \frac{\partial w_i}{\partial p_i} - \frac{\partial \pi}{\partial p_i}\right) dp_i + \frac{1}{2}\sum_i \sum_j \left(\frac{\partial^2 e}{\partial p_i \partial p_j}\right) dp_i dp_j. \tag{7}$$

By the envelope theorem, $\partial e/\partial p_i$ is the Hicksian demand so that $h_i(p_i,u) = x_i$.[17] The compensated price elasticity of good i with respect to good j is then given by $\varepsilon_{ij} = (\partial^2 e/\partial p_i \partial p_j)(p_j/x_i)$. The term $dB(p,u) = B(p,u) - B(p^0,u^0)$ 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. 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

[16] Porto (2006, 2010), Nicita (2009) and Ural Marchand (2012) use a similar approach to analyze the distributional impacts of price changes caused by trade liberalization.
[17] Household subscripts are omitted to simplify the notation.

initial expenditure by multiplying the right hand side of (7) by p_i/p_i and both sides with $1/e$ to obtain:

$$dlnW = -\frac{dB(p,u)}{e} = -\frac{1}{e}\sum_i \left(x_i p_i - \varepsilon_{w_i} w_i - \varepsilon_{\pi_i}\pi_i\right)\frac{dp_i}{p_i} - \frac{1}{2e}\sum_i\sum_j \varepsilon_{ij} x_i p_i \frac{dp_i}{p_i}\frac{dp_j}{p_j} \quad (8)$$

where $dlnW$ is defined as the compensating variation as a fraction of household initial net expenditure, ε_{w_i} is the elasticity of wage income and ε_{π_i} is the elasticity of profits with respect to the price of good i.

Each member of the household contributes to household income, which may be affected by the vector of commodity price shocks. Therefore, we can express household wage income and profits respectively as $w_i = \sum_h w_i^h$ and $\pi_i = \sum_h \pi_i^h$ where $h = 1, \dots, H$ represents members of the household. Equation (8) can then be simplified to

$$\begin{aligned} dlnW = &-\sum_i \theta_i dlnp_i - \frac{1}{2}\sum_i\sum_j \theta_i \varepsilon_{ij} dlnp_i dlnp_j \\ &+ \sum_h\sum_i \theta_{w_i}^h \varepsilon_{w_i} dlnp_i + \sum_h\sum_i \theta_{\pi_i}^h \varepsilon_{\pi_i} dlnp_i \end{aligned} \quad (9)$$

where $\theta_i = x_i p_i/e$ is the expenditure share of good i, $\theta_{w_i}^h$ is the share of wage income and $\theta_{w_i}^h$ is the share of profits from good i in the household budget contributed by member h.

The terms on the right hand side of (9) represent the different components of the compensating variation. The first term gives the direct consumption impact from the change in the price vector, $dlnp_i$, induced by biofuel policy. Households that consume goods $i = 1, \dots, n$ will be impacted negatively due to the increase in their cost of consumption. Its magnitude is proportional to the importance of these goods in their budget given by budget shares θ_i. This share is computed for each household from survey data. The second term in (9) 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 increases 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 six by six elasticity matrix ε_{ij}.[18]

The last two terms in (9) measure the effect of the price shocks on household incomes. They enter as positive terms in the household net expenditure. These income shocks are measured individually for each household member h, and then aggregated up to the household. Individuals who are affiliated with industry i experience an increase in their wages by $\varepsilon_{w_i} dlnp_i$ where ε_{w_i} is the wage-price elasticity.[19] We estimate these elasticities by using two rounds of the Indian NSS Employment and Unemployment Survey, detailed in Appendix B. The impact on household net expenditure is then proportional to the contribution of member h to the household budget, given by weight $\theta_{w_i}^{h}$ and estimated using the above NSS survey data. A similar interpretation applies to the last term in (9) which measures the effect of price shocks on profits of household farms, although the estimation is less straightforward due to data limitations discussed below. Note that (9) is not exhaustive, i.e., it does not include all possible sources of household income and focuses only on the types of income which are likely to be most affected by the price shocks. For instance, detailed household-level income data for remittances, rents and transfers is not available and thus not included in our analysis.

4. Estimation Results

Welfare Loss through Consumption

Table 2 presents the expenditure shares of the commodities we study. In general, food takes a larger budget share than fuel for rural households. Urban households consume more wheat, sugar and fuel, while all other items are more important for rural households. Rice and meat are relatively more important than other foods. Sugar does not account for a large budget share. Although not reported in the table, the share of these commodities decreases significantly with expenditure, because the budget share of other non-food items and more expensive foods increases.

[18] For each good i there are 36 second-order terms that summarize the behavioral response of the household. The set of elasticities used is given in Appendix Table A1. The cross-price elasticities for fuel are set to zero as this commodity is assumed to be separable.

[19] Here, the terms *good* and *industry* are used interchangeably. We distinguish between the two in the next section.

Table 2: Average Expenditure Shares for Food and Fuel (%)

	Rice	Wheat	Sugar	Meat and Dairy	Other Food	Total Food	Fuel
Rural	7.48	4.17	2.66	7.64	25.02	46.97	4.09
Urban	6.44	4.62	1.76	11.09	22.24	46.16	6.11

Notes: Average monthly expenditure shares as a fraction of total expenditures (including non-food) are obtained from the 61st round of the NSS Expenditure Survey. Sampling weights are used in estimation of the mean expenditure shares. Only purchased items are included. The "other food" category includes starchy foods, other cereal, fruits and vegetables, oil, spices and beverages.

The household consumption effect CE can be written as:

$$CE = -\sum_i \theta_i dlnp_i - \frac{1}{2}\sum_i \sum_j \theta_i \varepsilon_{ij} dlnp_i dlnp_{j.} \tag{10}$$

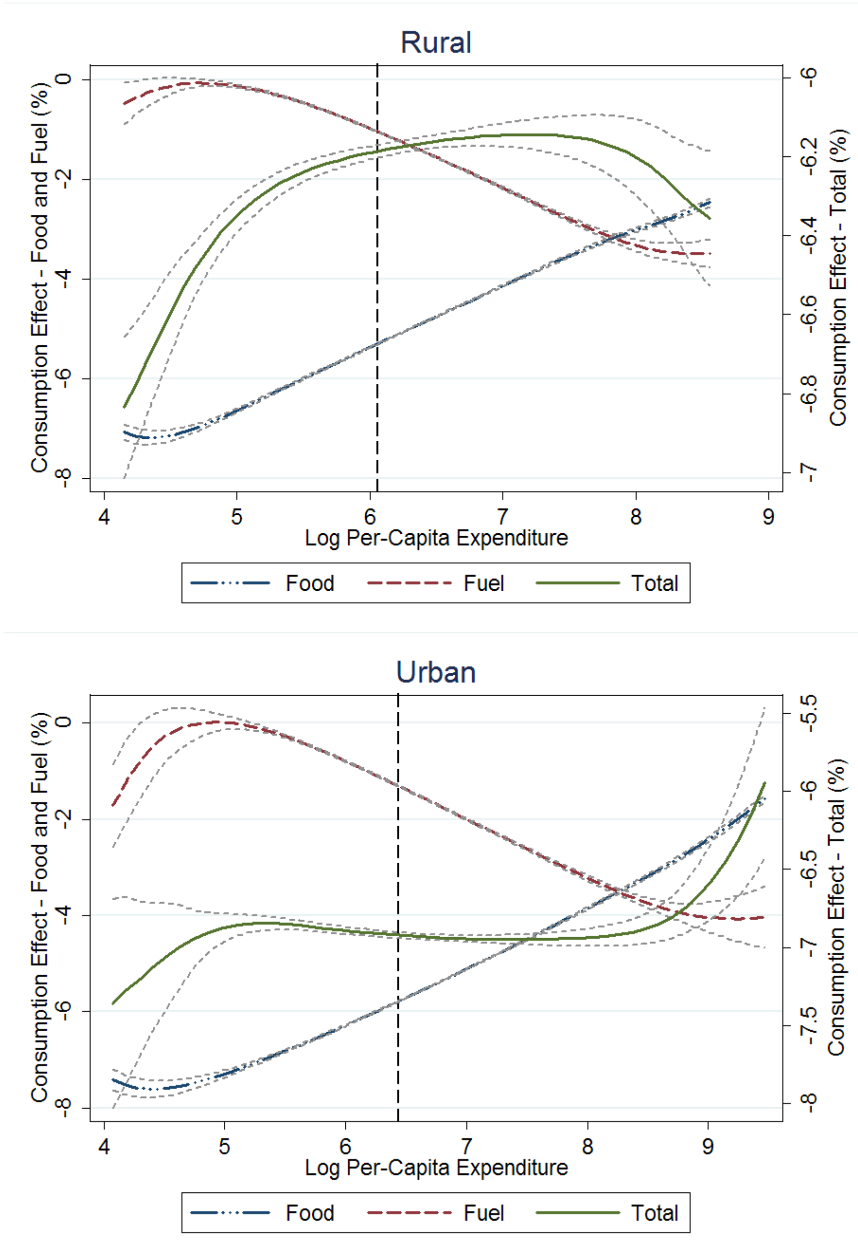
Each household is affected by a price change in good i proportional to the budget share of good i, and a price change in good j to the extent there is substitution between i and j. We get the distribution of consumption effects across households with different expenditure levels by estimating a nonparametric local linear regression conditional on log per capita expenditure. At each point in the expenditure distribution, we minimize the following expression

$$\sum_k (CE_k - a - bx_k)^2 K\left(\frac{x_k - x}{s}\right) \tag{11}$$

where a and b are parameters, x_k is the log of per capita expenditure for household k, $K(.)$ is the Epanechnikov kernel function, and s is the bandwidth. Parameters a and b define the linear relationship between the consumption effect CE_k and expenditure x_k within each neighborhood around the evaluation point x, where the size of the neighborhood is defined by the bandwidth. As the bandwidth increases, the neighborhood contains a wider segment of the expenditure scale and the estimated line becomes smoother, hence s is also called the smoothing parameter. The advantage of this method is that it does not require an assumption about the functional form and allows the data to determine the shape of the distribution.

The results are presented in Figure 2 separately for rural and urban households. For each household, the x-axis represents the log per capita expenditure and the y-axis shows the percentage welfare effect due to the policy-induced increase in the cost of consumption. The vertical line denotes the international poverty line, which corresponds to an expenditure of $1.25 per day, equivalent to Rs 429 for rural and Rs 628 for urban households.[20]

Figure 2: Welfare Impacts through Cost of Consumption



Notes: Results of local linear regression: 95 percent confidence intervals are shown. The vertical line represents the PPP-adjusted international poverty line.

[20] Conversion is done using 2005 purchasing power parity (PPP) of Rs 14.3 per day for rural and Rs 21.6 rupees per day for urban households. PPP conversions are obtained from the World Bank. A month is assumed to be 30 days.

We see that the distributional impact through food consumption is highly regressive for both rural and urban households. Those at the low end of the distribution are impacted the most, and this effect declines almost monotonically with expenditure. This is mainly because the poor allocate a higher share of their budget to food. However, the effect through fuel consumption is the opposite. Households at the high end of the distribution are affected the most, since they spend a bigger share of their budget on fuel. Because the magnitude of the fuel effect is smaller, the consumption effect is generally regressive for the poorer rural households and for urban households at both ends of the expenditure scale. Overall, welfare declines by approximately 6% in rural areas and 7% in urban areas. Welfare losses from food and fuel are somewhat higher for urban households relative to rural. This can be seen from Table 3 where we disaggregate the impacts by expenditure quartiles. This is mainly because urban households spend more on meat and dairy and fuel than those in rural areas.

Table 3: Composition of Welfare Loss through Cost of Consumption (%)

	Rural			Urban		
Quartiles	Food	Fuel	Total	Food	Fuel	Total
1	-5.81	-0.67	-6.33	-6.34	-0.80	-6.94
	(1.72)	(1.09)	(1.89)	(1.31)	(1.43)	(1.66)
2	-5.31	-0.98	-6.13	-5.82	-1.40	-7.03
	(1.70)	(1.31)	(2.08)	(1.29)	(1.70)	(1.92)
3	-4.87	-1.29	-6.02	-5.24	-2.02	-7.09
	(1.70)	(1.55)	(2.22)	(1.33)	(1.97)	(2.13)
4	-4.24	-2.07	-6.18	-4.24	-2.96	-7.05
	(1.83)	(2.25)	(2.77)	(1.54)	(2.53)	(2.71)
Overall	-5.20	-1.14	-6.18	-5.32	-1.89	-7.04
	(1.82)	(1.59)	(2.19)	(1.57)	(2.14)	(2.18)

Notes: Quartiles are based on household log per capita expenditure. The mean and standard deviation are shown. Sampling weights are used in estimation.

Effect of Price Shocks on Household Income

Households that are net sellers of agricultural products, as well as wage earners in these industries are expected to benefit from food price increases. Neglecting these effects may lead to first-order bias in the estimates. The NSS Employment Survey records the industry affiliation by 5-digit NIC categories for each labor market activity undertaken by an individual. There are about 460 (226) thousand observations for rural (urban) households. Approximately 14 (7) percent of rural (urban) individuals record more than one activity. These activity-specific industry codes are matched to the food product categories used in the calibration model, namely rice, wheat, sugar, meat, other food and fuel (see Appendix D). Approximately 53 percent of rural and 15 percent of urban residents are affiliated with industries that are impacted by our price shocks. The concentration of industries such as services and manufacturing is higher for urban households, and individuals affiliated with these industries are less likely to be affected.[21] Given that about 75 percent of India's population is rural, almost half of the country's population is directly impacted.

Table 4 shows that a large portion of rural households are in crop production, but this share is much smaller among urban households. The fuel sector accounts for a larger employment share among urban households, although still small in terms of magnitude. This suggests that the welfare gains through increased incomes are likely to mitigate poverty impacts to a greater degree among rural households.

Table 4: Employment Shares by Commodity

	Crops	Sugar	Meat & Dairy	Other Food	Fuel	Other Non-food
Rural	41.29	0.83	1.87	4.46	4.08	47.47
Urban	4.60	0.07	1.10	1.08	8.17	84.98

Notes: Employment shares are computed by matching 5-digit NIC affiliation of workers to the commodity groups as in Appendix D. "Crops" represent all crops including rice and wheat except sugar: industry codes are not provided separately for rice and wheat. The "Other non-food" category includes all product groups with no change in prices. Sampling weights are used in estimation of mean employment shares.

From (9), the total income effect of the price change denoted by IE is given by

$$IE = \sum_h \sum_i \theta_{w_i}^h \hat{\varepsilon}_{w_i} dlnp_i + \sum_h \sum_i \theta_{\pi_i}^h \varepsilon_{\pi_i} dlnp_i \,. \tag{14}$$

Some of the above terms can be directly recovered from the data. At the individual level, $\theta_{w_i}^h$ is the share of wage income of member h in industry i. These shares are then matched to the wage-price elasticity in industry i, $\hat{\varepsilon}_{w_i}$, and the predicted price shock, $dlnp_i$. We estimate wage-price elasticities based on two rounds of the NSS Employment and Unemployment Survey conducted in 2000 and 2004. This is done by exploiting district and time variation in prices in order to

[21] We do not incorporate general equilibrium impacts that arise from factor reallocations across industries.

identify the elasticities for each industry separately. The detailed estimation methodology and results are provided in Appendix B.

The wage effects are estimated at the individual level, and aggregated to the household level, thus recognizing differential wage effects within households. Neither the NSS Employment Survey nor the NSS Expenditure Survey provides information about production in household farms. This may be an important component of household income, especially in agriculture, given that our focus is on food prices. In addition, some members of the household may be wage-earners while others receive income from sales of agricultural products. Although agricultural profits are not explicitly recorded, it is possible to identify self-employed agricultural workers who are employers or unpaid family workers from information on their reported activities. A worker is assumed to be self-employed in agriculture if both of the following conditions are satisfied: (s)he identifies herself as a "self-employed worker" and the reported industry code indicates affiliation with an agricultural industry, but no wage income is reported.[22] In order to be conservative with respect to our welfare estimates, these individuals are assumed to have received their entire profit income from agricultural activities, which are directly affected by the increase in commodity prices.

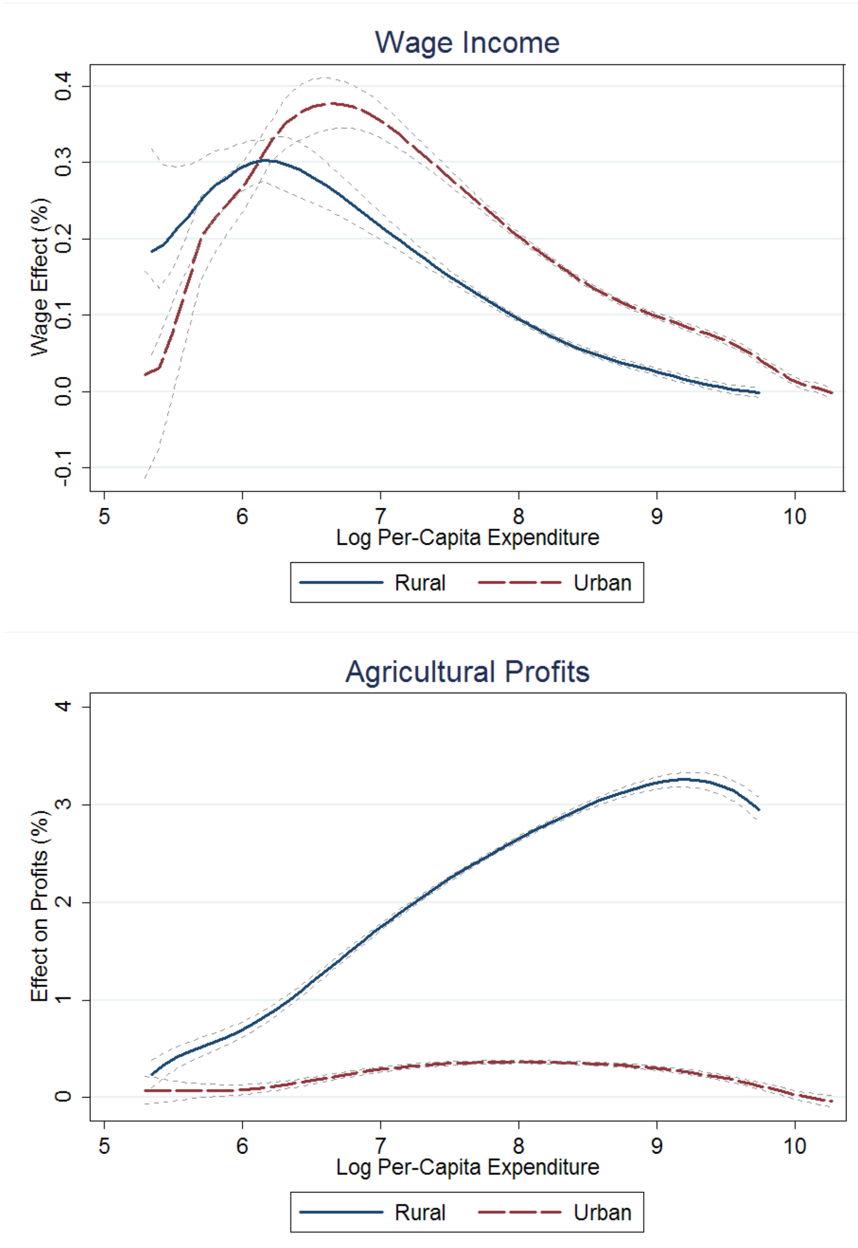
Once these individuals are identified, the increase in their income is assumed to be proportional to the price shock, which are then aggregated across individuals by household. That is, the income-price elasticities ε_{π_i} are set to unity and an average increase in the price vector $dlnp_i$ is computed for each household to approximate the household-level increase in agricultural profits. Although we cannot estimate the price elasticities for this channel due to data restrictions, our technique captures the highest possible income effect through this channel, leading to conservative poverty estimates.

The distribution of impacts from wage income and profits is shown in Figure 3. The effect on wage income is pro-poor, because the proportion of wage-earners in agriculture is higher at the lower end of the expenditure distribution. This holds both for rural and urban households. Except

[22] NSS data distinguishes between own-account workers and employers. We include both in our definition of an agricultural worker (activity codes 11 and 12).

among the very poor, the magnitude of the effect is larger among urban households, mainly due to their higher reliance on wages.

Figure 3: Impacts through Wages and Profits



Notes: Results of local linear regression: 95 percent confidence intervals are shown.

The positive effect on profits, however, is increasing as we move to the right of the distribution. Because the proportion of individuals who own land and operate farms is higher among better-off households, this channel has a regressive effect among the rural population. The profit channel benefits rural households more than those in urban areas. Urban households in the middle of the expenditure scale benefit the most. This is mainly due to the composition of industry affiliation. High-expenditure urban households are mostly affiliated with manufacturing and services, and therefore, their share of profits from agriculture is small.

Net Distributional Effects of Price Shocks

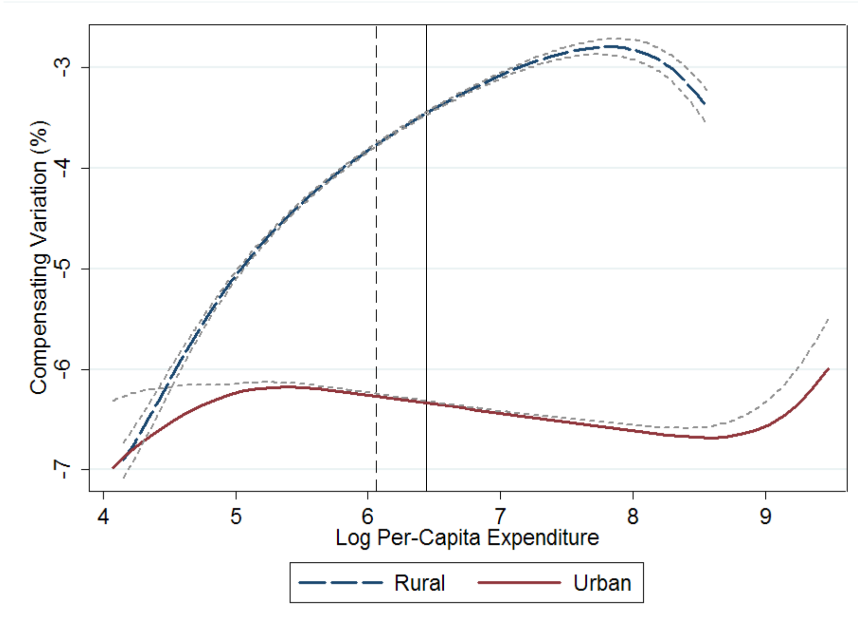
The consumption, wage and profit effects are combined as in (9) to obtain the net welfare effect or compensating variation for each household, shown in Figure 4. The effect is negative for all households and generally regressive. The poorest households experience the highest level of welfare loss – about 7 percent of their initial expenditure. The effect diminishes steadily for rural households as we move towards higher per capita expenditures, with a 3 percent loss at the extreme right of the distribution. Note that the distribution of welfare effects is sharply different between rural and urban households. Income effects are much smaller for urban households, hence the distributional effect is mainly driven by the cost of consumption. The regressivity is evident only in the two tails of the urban distribution. Because the urban consumption effect is regressive through food but progressive through fuel, these effects partly compensate each other, leading to the flat segment in the middle. For rural households, the regressivity of the welfare impacts is mainly driven by food since their budget share of transport fuel is small. The net effect is smaller at the high end of the distribution, as these households tend to generate income from agricultural profits, which increase with prices. The profit effect is relatively small for high-end urban households, because they are likely to work in the service and manufacturing industries.

According to Table 5, which summarizes the results within each expenditure quartile, the rural households experience an average 3.55 percent (6.39 percent for urban) net welfare loss. These households within the lowest decile incur an average 4.34 percent net loss with respect to their initial expenditure. The poorest urban households suffer a larger loss of 6.29 percent due to their higher share of transportation and fuel expenditures in their budget, and lower reliance on income from food commodities.

Welfare Impacts under Imperfect Price Transmission

India has a history of strong intervention in the domestic market, in the form of agricultural

Figure 4: The Distribution of Compensating Variation (%)



Notes: Results of local local linear regression with 95 percent confidence intervals: vertical dashed and solid lines denote rural and urban poverty lines, respectively.

subsidies and large-scale government procurement and distribution of food. This regulatory environment is expected to restrict the extent to which world prices are transmitted to domestic prices. Even with no government regulation, price transmission may be low due to other distortions, such as transportation costs, or imperfect substitution between imported and domestic goods.

In this section we estimate welfare effects with imperfect transmission of prices. We estimate the pass-through elasticities for each commodity using monthly time-series data, available for the period 2005-11. This period is somewhat unusual because of the spike in commodity prices in 2008 and the resulting aggressive short run response by the Indian government.[23] Due to limited data availability, it is not possible to identify the transmission mechanism independently of these policies. These measures may have mitigated the effect of rising world prices in the short run, but they are potentially costly and infeasible in the long run. The welfare impacts we estimate under imperfect pass-through may therefore be interpreted as lower bounds.

[23] 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 (see Jones and Kwiecinski (2010)). Some of these measures were in effect only for a few months, but they were effective in insulating the domestic market from price increases during the crisis. Most of these policies were removed eventually.

We estimate pass-through elasticities separately for each commodity using methodology from recent exchange rate and tariff pass-through studies (Campa and Goldberg,2005; Campa and Minguez, 2006). The estimation strategy and results are provided in Appendix C. Rice and sugar pass-through elasticities are significant but well below unity, while meat and wheat yield insignificant elasticities. Because the calibration model generates the domestic fuel price, a pass-through elasticity of unity is assigned to the price of fuel.

These results are summarized in Table 5 and Figure 5. As expected, welfare losses are lower when prices do not transmit perfectly although the effect remains regressive. Because the elasticities reduce the impact of food prices, but not the domestic fuel price, food becomes less important under imperfect pass-through leading to a relatively lower compensating variation for rural households.

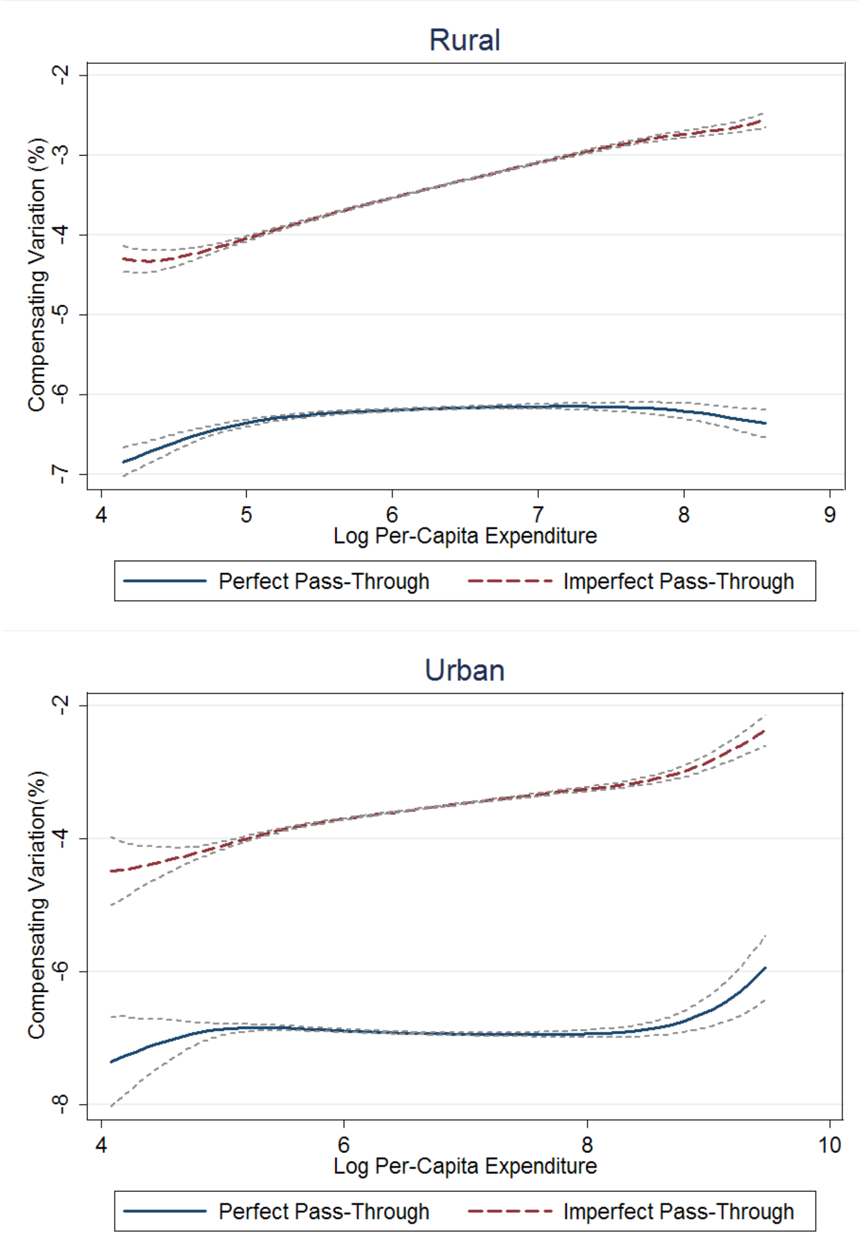
Table 5: Distribution of Compensating Variation: Perfect and Imperfect Pass-through

	Rural			Urban		
Quartile	Quartile Cutoffs (Rs. per cap)	Perfect Transmission	Imperfect Transmission	Quartile Cutoffs (Rs. per cap)	Perfect Transmission	Imperfect Transmission
1	<399	-4.34	-1.82	<519	-6.29	-3.15
		(1.95)	(1.30)		(1.71)	(1.25)
2	399-547	-3.60	-0.99	519-810	-6.25	-2.93
		(2.16)	(1.25)		(1.96)	(1.27)
3	547-779	-3.03	-0.27	810-1363	-6.38	-2.87
		(2.33)	(1.27)		(2.15)	(1.38)
4	>779	-3.21	-0.07	>1363	-6.64	-3.01
		(2.85)	(1.40)		(2.73)	(1.58)
Overall		-3.55	-0.79		-6.39	-2.99
		(2.40)	(1.47)		(2.18)	(1.38)

Notes: Quartiles are based on log per capita household expenditure. Mean and standard deviation are shown. Sampling weights are used in estimation.

Rural households in the highest decile experience a 3.6 percent welfare loss under perfect transmission but only a 0.2 percent loss under imperfect transmission (Table 5). The net effect on urban households is reduced by a half under imperfect transmission. The distributional impacts are regressive for both rural and urban households, although the effect is much less pronounced for the latter. The average welfare impact under imperfect price transmission is -0.8 percent for rural and -3 percent for urban households.

Figure 5: Compensating Variation with Perfect and Imperfect Pass-Through



Notes: Results of local linear regression with 95 percent confidence intervals. Imperfect pass-through results are based on estimated transmission elasticities (see Appendix C).

Variation in Welfare Effects

The analysis so far is based on the heterogeneity among households in terms of their consumption baskets, sources of income, industry affiliation, skill endowments and location. These sources of variation may also be correlated with other household socio-economic characteristics such as caste and tribal affiliation, household size and composition or geographical concentration. In this section, we regress the compensating variation and its three components - consumption, wage and profit income on a vector of household characteristics in order to check whether the welfare impacts are systematically correlated with certain socio-economic characteristics (see Tables 6 and 7).

Better-off households experience smaller welfare losses, analogous to what we have observed from the nonparametric estimation (Figure 4).[24] The wage effect is progressive, as suggested by the negative sign, and its magnitude is smaller than that of the consumption and profit channels. The coefficient is negative for agricultural profits although the coefficient with no control variables indicates a positive correlation.

Land owners experience smaller losses.[25] Households with more land tend to gain from the increase in prices (stronger effect for rural households), and experience smaller increases in their cost of consumption, indicated by a positive coefficient on this variable. For land-owning households, wage gains tend to be smaller as most of them do not work for wages.

Larger households experience smaller losses, and this effect increases with size. This can be explained by the consumption effect – they spend a disproportionately lower budget share on food and fuel. The wage effect declines with the number of children in the household, which may be due to the fact that non-agricultural households tend to have fewer children, and their wages do not increase as much as farming households.[26] The share of females in the household is negatively correlated with consumption and wage effects.

Productivity related characteristics of the head of the household turn out to be important determinants of who loses more from price shocks. Households with older heads experience smaller welfare losses through the consumption channel. This effect diminishes with age. Somewhat counter-intuitively, educated households experience higher losses. This effect is mainly driven by consumption impacts, and may be due to higher fuel expenditure among educated individuals who are likely to be better-off. Educated households gain through higher

[24] The dependent variables are negative for the first two columns, therefore a positive coefficient indicates a smaller loss, *ceteris paribus*. They are positive in the last two columns where a positive coefficient indicates a higher gain.
[25] Land owned is defined as the total land owned, possessed and leased-in minus the land leased out.
[26] A child is defined as a household member who is 14 years of age or younger.

Table 6: Variation in Compensating Variation (CV): Rural Households

	(1) CV	(2) Consumption	(3) Wages	(4) Profits
Expenditure (monthly per capita, log)	0.0092***	0.0026***	-0.0004***	-0.0024***
	(0.000)	(0.001)	(0.000)	(0.001)
Household Size	0.0021***	0.0020***	-0.0001***	-0.0013***
	(0.000)	(0.001)	(0.000)	(0.000)
Household Size ^2 / 100	0.0040***	0.0049***	0.0009***	0.0036***
	(0.000)	(0.001)	(0.000)	(0.001)
Land Owned (hectares, log)	0.0026***	0.0025***	-0.0002***	0.0081***
	(0.000)	(0.000)	(0.000)	(0.000)
Share of Children (age less than 15 years)	0.0013***	0.0012***	-0.0016***	0.0040***
	(0.000)	(0.000)	(0.000)	(0.001)
Share of Females	-0.0036***	-0.0032***	-0.0013***	0.0001
	(0.001)	(0.001)	(0.000)	(0.001)
Age of Household Head	0.0002***	0.0002***	-0.0000	0.0007***
	(0.000)	(0.000)	(0.000)	(0.000)
Age of Household Head ^2 /100	-0.0001***	-0.0001***	-0.0000	-0.0008***
	(0.000)	(0.000)	(0.000)	(0.000)
Education of the Household Head (control group: 'illiterate')				
Primary and Below	-0.0012***	-0.0016***	-0.0001	0.0015
	(0.000)	(0.000)	(0.000)	(0.001)
Middle	-0.0019***	-0.0025***	-0.0001	0.0001
	(0.000)	(0.000)	(0.000)	(0.001)
Secondary	-0.0045***	-0.0050***	0.0000	0.0007
	(0.000)	(0.000)	(0.000)	(0.001)
Higher Secondary and Above	-0.0103***	-0.0101***	0.0001*	-0.0070***
	(0.000)	(0.001)	(0.000)	(0.001)
Social Group of the Household (control group: 'other')				
Scheduled Tribe	0.0028***	0.0032***	0.0000	-0.0026**
	(0.000)	(0.001)	(0.000)	(0.001)
Scheduled Caste	-0.0008***	-0.0007*	0.0001*	-0.0049***
	(0.000)	(0.000)	(0.000)	(0.001)
Religion of the Household (control group: 'Hindu')				
Islam	-0.0019***	-0.0020**	0.0002**	-0.0072***
	(0.000)	(0.001)	(0.000)	(0.001)
Other non-Hindu	0.0035***	0.0032**	-0.0000	-0.0095***
	(0.000)	(0.001)	(0.000)	(0.001)
Regional Indicators (control group:'West')				
East	0.0020***	0.0023	-0.0003**	-0.0016
	(0.000)	(0.002)	(0.000)	(0.002)
North	0.0018***	0.0026*	-0.0002	-0.0010
	(0.000)	(0.002)	(0.000)	(0.001)
Northeast	-0.0038***	-0.0035*	-0.0002	-0.0031**
	(0.000)	(0.002)	(0.000)	(0.001)
South	-0.0061***	-0.0053***	0.0001	-0.0042***
	(0.000)	(0.002)	(0.000)	(0.001)
Observations	78,785	78,785	74,561	74,561
R-squared	0.120	0.156	0.019	0.202

Notes: Dependent variables are shown in columns, defined by Equation (9). Standard errors are clustered at the district level and reported in parentheses. Sampling weights are used in estimation. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Variation in Compensating Variation (CV): Urban Households

	(1) CV	(2) Consumption	(3) Wages	(4) Profits
Expenditure (monthly per capita, log)	0.0012**	0.0027***	-0.0012***	-0.0025***
	(0.001)	(0.001)	(0.000)	(0.000)
Household Size	0.0071***	0.0071***	-0.0009***	0.0004**
	(0.001)	(0.001)	(0.000)	(0.000)
Household Size ^2 / 100	0.0064***	0.0067***	0.0051***	-0.0025**
	(0.001)	(0.001)	(0.002)	(0.001)
Land Owned (hectares, log)	0.0011***	0.0011***	-0.0001*	0.0035***
	(0.000)	(0.000)	(0.000)	(0.000)
Share of Children	0.0007***	0.0006***	-0.0010***	0.0016**
	(0.000)	(0.000)	(0.000)	(0.001)
Share of Females	-0.0058***	-0.0053***	-0.0053***	0.0010
	(0.001)	(0.001)	(0.002)	(0.001)
Age of Household Head	0.0002***	0.0002***	0.0002***	0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)
Age of Household Head ^2 /100	-0.0002**	-0.0002**	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Education of the Household Head (control group: 'illiterate')				
Primary and Below	-0.0010***	-0.0011***	-0.0002	-0.0012
	(0.000)	(0.000)	(0.000)	(0.001)
Middle	-0.0007*	-0.0009**	0.0007***	0.0000
	(0.000)	(0.000)	(0.000)	(0.001)
Secondary	-0.0021***	-0.0023***	0.0005*	-0.0001
	(0.000)	(0.000)	(0.000)	(0.001)
Higher Secondary and Above	-0.0058***	-0.0057***	0.0013***	-0.0029***
	(0.001)	(0.001)	(0.000)	(0.001)
Social Group of the Household (control group: 'other')				
Scheduled Tribe	0.0030**	0.0029**	-0.0003	0.0013
	(0.001)	(0.001)	(0.000)	(0.001)
Scheduled Caste	0.0003	0.0004	0.0000	-0.0018***
	(0.000)	(0.000)	(0.000)	(0.000)
Religion of the Household (control group: 'Hindu')				
Islam	-0.0022***	-0.0020***	-0.0003	-0.0024**
	(0.000)	(0.000)	(0.000)	(0.001)
Other non-Hindu	-0.0012	-0.0012	-0.0006	-0.0033***
	(0.001)	(0.001)	(0.000)	(0.001)
Regional Indicators (control group: 'West')				
East	0.0017	0.0018	0.0003	-0.0048***
	(0.002)	(0.002)	(0.000)	(0.001)
North	0.0037**	0.0039**	0.0012**	-0.0035**
	(0.002)	(0.002)	(0.000)	(0.001)
Northeast	0.0014	0.0014	0.0001	-0.0031**
	(0.002)	(0.002)	(0.000)	(0.001)
South	-0.0007	-0.0006	0.0003*	-0.0034**
	(0.002)	(0.002)	(0.000)	(0.001)
Observations	44,717	44,717	31,200	31,200
R-squared	0.044	0.043	0.007	0.130

Notes: Dependent variables are shown in columns, defined by Equation (9). Standard errors are clustered at the district level and reported in parentheses. Sampling weights are used in estimation. *** p<0.01, ** p<0.05, * p<0.1.

wages especially in urban areas, but their profits go up only marginally. Individuals with education are likely to be wage earners and less likely to earn income from food commodities.

Social characteristics of the household play an important role in determining who is impacted from the rise in commodity prices, especially in rural settings. Tribal members experience smaller net losses, and they gain less through the profit channel relative to non-tribals, simply because they do not own significant assets. On the other hand, caste members experience higher losses, especially in rural areas. This may be due to a preponderance of caste membership among the rural poor, especially in the farming sector. There is some evidence to suggest that the incidence of poverty is higher among scheduled castes and tribes than among the non-scheduled population (Gang, Sen and Yun, 2008). This effect is not observed among urban residents, possibly because of dilution of caste relations in metropolitan areas. Compared to Hindus, Muslim households are hurt more while other non-Hindu households are impacted less. This effect is significant both for urban and rural populations. The Indian Human Development Report (Desai et al., 2010, p.15) attests to a higher state of poverty among the Muslim population in the country relative to Hindus and other religious groups, both in the rural and urban population.

Finally, regional differences are more pronounced for rural households.[27] Those living in the East and North of the country experience smaller losses, and those in the Northeast and South experience higher losses than the control group - people living in the Western part of the country. Urban households in the north are affected significantly less than those in other areas. Agricultural profit shocks appear to be highest in the rural Western states, since the coefficients for other regions are negative and significant.

5. The Effect on Poverty

We examine the impact of the above price shocks on poverty by computing how many more people fall below the poverty line *ex-post* of the policy. Let the poverty line be defined by z. Then the share of the population below the poverty line, called the headcount ratio (HCR) is defined as:

[27] The Indian Ministry of Home Affairs definitions are used for classifying states into regions.

$$HCR = \frac{1}{N}\sum_{k=1}^{N} I(x_k \leq z) \tag{15}$$

where N is the total number of individuals, x_k is per capita expenditure, $I(\cdot)$ is an indicator function that picks the households for which $x_k \leq z$. After the policy change, per capita expenditures are impacted through adjustments in their wage incomes and profits. Households that are net producers will see a rise in their per capita expenditure, and those people who were marginally poor prior to the price shock may no longer be poor *ex-post* of the policy change. This may happen if the budget share of profits obtained by selling goods, $\sum_h \theta_{\pi_i}^h$, or the wage incomes of household members affiliated with industries $\sum_h \theta_{w_i}^h$, is high. Higher profits from assets are likely to accrue to better-off households, while landless workers are more likely to benefit through wages.

A second effect on the poverty rate is through a price-induced shift in the poverty line z. An increase in the cost of consumption will shift the poverty line to the right, because the same basket of goods is now costlier. This change is given by

$$dz = \sum_i \bar{\theta}_i dlnp_i + \frac{1}{2}\sum_i \sum_j \varepsilon_{ij}\bar{\theta}_i (dlnp_i)(dlnp_j) \tag{16}$$

where $\bar{\theta}_i$ is defined as the average expenditure share of the "marginal" poor.[28] For poverty analysis, household expenditures are adjusted for incomes, but not for the cost of consumption. Instead, the increase in the cost of consumption is reflected in a shift in the poverty line (see de Janvry and Sadoulet (2010) and Porto (2010)).

The impact on the poverty rate depends on the expenditures of households that are initially close to the poverty line and change their status once prices increase. Therefore, the estimates are sensitive to the impacts only on marginally poor individuals. Although poverty estimates provide a summary of the distributional impacts, they are likely to ignore the effect on the left tail of the distribution, which is significantly higher than the effect on the marginally poor.

[28] de Janvry and Sadoulet (2010) define "marginal poor" as households within a 5 percent range of the poverty line.

From Table 8 we see that the rural poverty line shifts to the right by 6.55 percent and the urban poverty line by 5.85 percent. Assuming that the expenditure shares remain constant, some marginally non-poor households will now move below the poverty line because the line itself has shifted to the right due to the increased cost of consumption. Therefore, the headcount ratio (HCR) poverty rates go up proportionately. The rural poverty rate is estimated to increase by 3.4 points and the urban rate by 2.9 points. As a result, 30 million rural and nearly 12 million urban individuals will move below the $1.25 international poverty line.[29]

Next, the poverty impacts are re-estimated under imperfect transmission. The rural poverty rate increases by about 1 percentage point and the urban rate by about 1.5 points. This represents about 15.5 million newly poor individuals.

Table 8: Poverty Impacts

	Shift in poverty line (%)	Increase in poverty rate	New poor (millions)	Shift in poverty line (%)	Increase in poverty rate	New poor (millions)
	Perfect Pass-Through			Imperfect Pass-Through		
Rural	6.55	3.39	29.96	3.64	1.08	9.54
Urban	5.85	2.85	11.70	3.16	1.46	5.99
Total	6.35	3.24	41.66	3.51	1.19	15.53

Notes: The poverty line is defined as $1.25 per day converted to Indian Rupees using PPP. Shifts in the line are based on (16). UN population projections for the year 2015 are used for the estimation of the number of new poor. Results with imperfect pass-through are based on price transmission elasticities (see Appendix C).

A Larger Food Price Shock

Many studies in the literature predict larger impacts of biofuels on food prices, and they may well be more accurate, especially in the short-run, when supply-side adjustments have not worked through the world economy. It may be reasonable to examine the effect of a bigger shock in food prices to check the sensitivity of the poverty estimates.[30] To simplify matters, we assume a 25% increase in the price of all the six crops, namely rice, wheat, sugar, meat and dairy and

[29] We repeated the analysis with another poverty measure, the National Poverty Line which is less stringent. The International Line translates to Rs 429 (for rural) and Rs 628 (for urban households) while the National Line is defined as Rs 356 (rural) and Rs 538 (for urban) respectively. The aggregate poverty estimates were lower for the National measure by about a million and a half. These results are not reported.

[30] Roberts and Schlenker (2010) estimate a price increase of 20-30% depending on whether recycling of by-products takes place. During the production process of ethanol only one part of the plant is used. The other part can be wasted or used to produce by-products such as cattle feed. In the former case, the effect on food prices is likely to be higher. Many other studies have come to similar or higher price estimates.

fuel.[31] The entire exercise described above is repeated by estimating the compensating variation through the three channels of consumption, income and profits. Poverty rates increase (see Table 9) by approximately 7 percentage points with perfect pass-through, increasing the number of poor individuals in India by 88 million. This estimate decreases to 2 percentage points with imperfect pass-through, which translates to about 27 million new poor.[32]

An immediate question that arises is the role of the biofuel mandate on world poverty. How big could the numbers be? This would depend on a list of factors that may be country-specific, such as the composition of diets across countries and ethnic groups, as well as domestic policies and institutions that mitigate the impacts of price shocks. This analysis needs to be done in order to evaluate the complete welfare effects of energy policy, but is beyond the scope of our research. However, a simple extrapolation of our estimates for India can be performed to get some crude estimates of global poverty caused by the US mandate. If we combine our rural and urban estimates by using population shares as weights, the poverty rates in India are estimated to be between 1.19 and 3.24 percentage points higher than the benchmark poverty rates with no change in the biofuel policy. Assuming that the proportion of new poor individuals is the same globally, we get a range of about 87 to 234 million new poor individuals at the global level, depending on pass-through rates.[33]

Table 9: Poverty Impacts of a 25 percent Price Shock

	Shift in poverty line (%)	Increase in poverty rate	New poor (millions)	Shift in poverty line (%)	Increase in poverty rate	New poor (millions)
	Perfect Pass-Through			Imperfect Pass-Through		
Rural	15.54	6.87	60.71	8.03	1.66	14.67
Urban	13.52	6.58	27.01	6.92	2.95	12.11
Total	14.97	6.79	87.72	7.72	2.02	26.78

Notes: The poverty line is defined as $1.25 per day converted to Indian Rupees using PPP. Shifts in the line are based on (16). UN population projections for the year 2015 are used for the estimation of the number of new poor. Results with imperfect pass-through are based on price transmission elasticities (see Appendix C).

[31] This implies a higher increase in food prices, but a lower rise in fuel prices relative to the earlier analysis (see Table 1).
[32] Using the national poverty line yields an estimate of 83 million and 25 million respectively.
[33] The projected population in 2015 is 7,284 million individuals (UN Population Division (2010)).

6. 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, the impact on the poor may be significant. About 16 to 42 million new poor may be created in India alone.

The methodology followed in this paper has the advantage of mapping the different components of welfare at the household level. We are able to identify which groups are more or less impacted based on their expenditure, location and a host of other socio-economic characteristics. We find that the welfare effects are quite regressive. The poor spend a higher share of their budget on staples such as rice and wheat, and are impacted most by an increase in food prices. They also benefit the most from rising food prices because of wage effects. However, consumption effects dominate wage and profit income. The richer households are hurt mainly by higher fuel prices. We find that households who are larger, own less land, are less educated, have more female members and have fewer children are likely to be impacted more, *ceteris paribus*. Members of scheduled castes and tribes are also among the ones most impacted, especially among rural populations. Muslims are more adversely impacted by these price shocks than Hindus and other religious groups.

The broad implication of our analysis is that U.S. biofuel policy may lead to significant poverty at the global level, especially if the impact of large scale diversion of food crops to produce transportation fuel is not mitigated by supply-side responses. The impacts are expected to be worse if other countries with rapidly-growing transport sectors also turn to biofuels as a way of reducing their energy dependence. In the long-run, these price effects may be mitigated by bringing new land under production and technological improvements in farming. However, to the extent that supply costs of growing more crops increases, the food price shocks may linger for an extended period. Other factors such as climatic shifts and droughts may also affect commodity prices and exacerbate the impacts we discuss.

The framework we adopt has several limitations that can be examined in future research. The impact of price increases may be higher in coastal states relative to states located in the interior. Our estimates are based on a uniform pass-through of prices across the country as price series data for each state is not available. State-specific pass-through elasticities could be estimated with more data. Another important limitation is in the estimation of agricultural profits at the household level. Because they are not directly reported in the survey, we use the most conservative estimates possible – a one-to-one transfer of prices into profits. Future work can take into account general equilibrium impacts on other sectors of the economy. This will require price data from other sectors including services such as education are health, not readily available. Although it is not possible to speculate on the direction of general equilibrium impacts, the magnitude of GE effects may be small because 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 as well. We can compare the micro-level impacts in India with that in other countries with significant poor populations to see if the nature of the welfare effects is fundamentally different and idiosyncratic to diet and other cultural factors. For example, cultures 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 can be hand-matched to its calorie, fat and protein content using the FAO nutritional database. The energy-induced price shock is likely to alter the consumption structure of each household. We can then 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.

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Appendix A: Calibration Technique and Data

The model used to predict the effect of the biofuel mandate on food prices is modified from Chakravorty *et al.* (2012).[34] It uses a partial equilibrium, dynamic framework, solved using GAMS software. The reference year for calibration is 2010.

Demand for final products Regional demands (for rice, wheat, sugar, meat and dairy, other crops and transportation fuel) are modeled using a Cobb-Douglas specification, and are functions of regional per capita income and population. Thus demand D_l for final product l takes the form

$$D_l = A_l P_l^{\alpha_l} \prod_{-l} P_{-l}^{\alpha_{-l}} w_l^{\beta_l} N \qquad (A1)$$

where P_l and P_{-l} are output prices of goods l and goods other than l (in dollars), α_l and α_{-l} are similarly the regional own-price and cross-price elasticities, β_l is the income elasticity for good l, w is regional per capita income, N is regional population and A_l is the constant demand parameter calibrated from data.[35] Demand for food products is expressed in kilograms per capita per year while the demand for the transport fuel is in Vehicles Miles Travelled (VMT).

Table A1 reports the own and cross-price elasticities for food products in India. These elasticities are also used to estimate the distributional effects of biofuel policy (see (9)). Indian demands have the same structure shown in (A1) above. Population projections are taken from the United Nations Population Division (UNDP 2010).[36] India's population is expected to increase to about 1.3 billion people in 2015. GDP per capita is non-stationary and is assumed to increase at an exogenous and declining rate. We assume US GDP per capita to be increasing at an annual rate of 1.5% and Indian GDP per capita at 5% annually (World Bank, 2010).

Land Use: Land can be used to produce one of the five food products or energy. Since land quality differs across geographical areas, we define three different land classes based on soil and climate characteristics using the FAO-IIASA database (Fischer *et al.* 2002), land

[34] They use the model to examine the effect of the U.S. and E.U. biofuel mandate on the price of a basket of food crops. We use a disaggregated form of their model to investigate the effect on the five food commodities.
[35] Cross-price elasticities are only defined for food commodities. Food-fuel elasticities are assumed to be zero.
[36] We use the *medium variant scenario of the* United Nations (UN Population Division, 2010) which is based on medium fertility projections. It predicts a 2050 world population of 9 billion.

Table A1: Food and Fuel Price Elasticities for India

	Rice	Wheat	Sugar	Other food	Meat/ Dairy	Fuel
Rice	-0.20	0.10	0.05	0.05	-0.10	0
Wheat	0.10	-0.37	0.05	0.05	-0.10	0
Sugar	0.05	0.05	-0.14	0.05	-0.10	0
Other crops	0.05	0.05	0.05	-0.20	-0.10	0
Meat/Dairy	-0.10	-0.10	-0.10	-0.10	-0.20	0
Fuel	0	0	0	0	0	-0.21

Source: Own-price elasticities are from Hertel *et al.* 2008 and FAPRI (2012). Cross-price elasticities are assumed symmetric and are adapted from Regmi *et al.* (2001).

class 1 being the most productive.[37] For each land class, the data base gives information on the area available as well as the yield for each crop. In addition, the definition of the land classes is conditional on the level of technology and the use of irrigation.[38]

Available land as well as yields per land class are reported in Table A2. Crop production is just yield times the land area, given by $k_i^j L_i^j$ where k_i^j represents production per unit of land for use j and L_i^j is the acreage from land class i allocated to use j.

Table A2: Crops Yields by Land Class and Region (tons per hectare)

		Wheat	Rice	Sugar	Other crops
USA	1	6.8	7.1	86	4.5
	2	5.0	5.1	62	3.5
	3	2.9	3.5	45	2.5
India	1	4.0	3.2	79	2.0
	2	1.8	2.8	60	1.5
	3	1.5	3.0	42	1.0
ROW	1	2.8	4.0	70	2.2
	2	1.8	3.0	60	1.8
	3	0.8	2.0	50	0.9

Source: FAO-IIASA.

[37] The database identifies four land classes - very suitable, suitable, moderately suitable and marginally suitable. We group into three classes, by consolidating the two intermediate classes into one, since their yield differences are small.

[38] 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 and choose the level of input that matches the data. For the US, observed yields were closest to the high input level and for India and the ROW region, the FAO data matched the low input scenario.

Area under crop cultivation can be expanded by converting bringing new land under production. The initial stock of available land at $t = 0$ is denoted by $L_i^s(0)$. At each period, $l_i^s(t)$ units of new land may be cultivated. This relationship is given by $L_i^s(t) - L_i^s(t-1) = -l_i^s(t)$. The land constraint for each land class in period θ is given by $\sum_j L_i^j(\theta) \leq \bar{L} + \sum_{t=0}^{\theta} l_i^s(t)$ where j denotes land use. The initial global endowment of agricultural land is 1.5 billion hectares (FAOSTAT). About 1.6 billion hectares of land are available for conversion to farming, most of it located in Africa, Latin America and in Eastern Europe (FAO 2008).[39] In the US, nearly 170 million hectares (Mha) are under crop cultivation (FAOSTAT) and another 10.5 Mha of land may be used (Chen *et al.* 2012). In India, about 140 Mha are currently allocated to crop production. We make the plausible assumption that no new land in India is available for crop production (Ravindranath *et al.* 2011).

The cost of converting new land is assumed to be increasing and convex with respect to acreage converted. New land is converted when the endogenous land rent is higher than the cost of conversion. We adopt the same functional form as in Gouel and Hertel (2006) given by:

$$C_s = -\psi_1 \ln\left(\frac{L_i^s(0) - l_i^s}{L_i^s(0)}\right) + \psi_2 \qquad (A2)$$

The parameters are region specific but independent of land class. Their values are reported in Table A3.

Table A3: Cost Parameters for Land Conversion

	ψ_1	ψ_2
USA	430	431
India	200	200
ROW	26	26

Source: from Gouel and Hertel (2006).

Improvements in agricultural productivity are allowed to vary by region and land class. All regions exhibit increasing productivity over time, mainly because of the adoption of biotechnology (e.g., high-yielding crop varieties), irrigation and pest management. *Ceteris*

[39] Forests under plantation or under legislative protection are not included in the model.

paribus, the rate of technical progress is likely to be low for the lowest land quality. This is because biophysical limitations such as topography and climate reduce the efficiency of high-yield technologies and tend to slow their adoption in low quality lands (Fischer *et al*. 2002).[40]

The total cost of crop production (which may be converted to food or biofuel) in each region is assumed to be increasing and convex. The higher the production, the cost of factors such as fertlizers and pesticides increases more than in proportion (van Kooten and Folmer 2004). Total production cost for product j in a given region is defined as

$$C_j(\sum_i k_i^j L_i^j) = \eta_l \left[\sum_i k_i^j L_i^j\right]^{\eta_2} \tag{A3}$$

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

Transportation fuel: Energy in the model is provided by gasoline and biofuels. We consider an upward sloping curve for gasoline supply.[41] Biofuel supply is region-specific, with a representative biofuel for each region. This assumption is quite reasonable since only one type of biofuel dominates in each region. 94% of production in the US is ethanol from corn (EIA 2011). In India, sugarcane ethanol is the main source of biofuel. The premier producer in the ROW region is Brazil where ethanol is only produced from sugarcane. Table A4 shows the representative crop for each region and its production cost. Second generation biofuels are assumed to be available in the US alone. We only consider cellulosic ethanol since it has been identified as the most promising second generation fuel (IEA 2009). Since these crops are less demanding in terms of land quality, we assume that their yields are uniform across different land qualities. Around 2,000 gallons of ethanol per hectare are produced from cellulosic ethanol (IEA 2009). The unit production cost of second generation biofuels is taken to be \$3.5 per gallon.[42] Transportation energy q_e is produced from gasoline and biofuels in a convex linear combination using a CES specification, as in Ando *et al.* (2010) given by

[40] Productivity growth rates are specific to each crop and region. They are based on historical rates and taken from FAOSTAT. To determine the growth rate per land class, we assume a uniform depreciation rate from the highest to the lowest land quality (Fischer *et al.* 2002). To illustrate for rice, the annual growth rate for highest land quality (land class 1) is 1.20% and declines to 1.05% for the lowest land quality (land class 3).
[41] Unlike Chakravorty *et al.* (2012) who consider crude oil to be a nonrenewable resource, we assume an upward sloping supply curve for oil since we only focus on prices in the immediate future (2015).
[42] IEA (2010) defines a range for production costs for cellulosic ethanol between \$3-5 per gallon.

$$q_e = \lambda \left[\mu_g q_g^{\frac{\rho-1}{\rho}} + (1-\mu_g)(q_{bf}+q_{bs})^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho-1}{\rho}} \tag{A4}$$

where λ is a constant, μ_g the share of gasoline in transportation energy, ρ the elasticity of substitution, and q_g, q_{bf} and q_{bs} are the respective input demands for gasoline, first generation and second generation biofuels. The parameters λ and μ_g are calibrated from observed data. The elasticity of substitution is region-specific and depends upon the technological barriers for displacing gasoline by first gen fuels in each region. Elasticity estimates are from Hertel *et al.* (2010).

Table A4. Unit Cost of First Generation Biofuels

	US	India	ROW
Representative crop	Corn (94%)	Sugar (76%)	Sugar (80%)
Unit cost of production ($/gallon)	1.01	1.66	0.74

Notes: Production costs are from FAO (2008), Ravindranath *et al.* (2011); the numbers in parentheses are the percentage of first-generation biofuels produced from the representative crop (e.g., corn). For ROW, sugarcane is the representative crop because Brazil is the dominant producer of biofuels from sugarcane with 75% of ROW production.

Appendix B: Wage-Price Elasticities

The response of wages to price shocks is given by:

$$w = w(p, \gamma) \tag{B1}$$

where p is the vector of commodity prices, given a set of personal characteristics γ such as education, age, marital status, or location. Since we plan to isolate the effect of prices on wages, a reduced form Mincerian wage model is estimated. The elasticity of wages with respect to prices is therefore given by $\beta = \partial lnw/\partial lnp$.

The main issue in estimating wage-price elasticities is the availability of price data that reflects the economic activity by district over time. Employment surveys are conducted infrequently, and often do not offer time variation that is sufficient to identify elasticities for specific product groups. In order to deal with this problem, we use the unit values in the 55th and 61st rounds of the NSS Household Expenditure Survey and aggregate them to the district level. We then merge these unit values with the corresponding rounds of the NSS Employment Survey by district and use them as a proxy for the price levels of each product within that district. This technique is similar to that used in other studies, such as Deaton (2000), Porto (2006, 2010) and Ravallion (1990).

The sub-sample on which the wage equation is estimated includes workers in the informal sector as well as self-employed individuals, such as household farm workers, who are between the ages of 15 and 65. Since our focus is on the distributional aspects of labor market responses, this model is estimated for skilled and unskilled workers separately, where a skilled worker is defined as someone with at least a middle school education.[43] We estimate the following double-log model for each skill level:

$$ln\, w_{idt}^{l} = \alpha + \beta ln\ p_{dt}^{l} + \delta\gamma_{idt}^{l} + \mu_t + \varepsilon_{idt} \tag{B2}$$

where the variable $ln\, w_{idt}^{l}$ is the logarithm of the hourly wage rate of individual i in district d at time t employed in industry l; β is the wage-price elasticity estimated for each industry l; lnP_{dt}^{l} is the logarithm of the price of product l in district d at time t and γ_{idt}^{l} is a vector of individual characteristics that includes age and age-squared as well as indicator variables for male workers, married workers, education level, the geographical region in which they are located and whether they live in a rural area, and μ_t is the year fixed effects.[44]

Some adjustments needed to be made for this estimation. The number of workers in the *sugar* industry is insufficient to obtain meaningful elasticities, therefore they are combined with the *other food* category. Second, the industry affiliations in the NSS survey do not distinguish between rice and wheat workers, but it classifies them under the general category called *crop production*. Therefore, these two elasticities are estimated on a common sample. Third, unit prices are not available for *fuel for transportation* as the NSS Household Expenditure Survey does not record the quantity consumed for this item. We set the wage-price elasticity for this industry to unity in order to obtain results that are as conservative as possible. However, the impact of this assumption is likely to be small due to the low number of workers employed.

[43] Estimates are largely robust to changes in the cut-off skill level to primary or secondary education. Note that approximately one third of individuals in these industries are classified as illiterate.
[44] A work day is assumed to be 8 hours.

The results of the wage-price estimation are shown in Table B1. The wages of workers who are

Table B1. Wage-Price Elasticity Estimation

	Rice		Wheat		Meat & Dairy		Sugar / Other	
	Skilled	Unskilled	Skilled	Unskilled	Skilled	Unskilled	Skilled	Unskilled
	(1)	(2)	(3)	(4)	(5)	(6)	(9)	(10)
log (price)	0.679***	0.682***	0.367***	0.172***	0.157**	0.083	0.128**	0.125***
	(0.108)	(0.071)	(0.064)	(0.059)	(0.063)	(0.056)	(0.051)	(0.035)
Male	0.358***	0.361***	0.380***	0.378***	0.391**	0.499***	0.337***	0.288***
	(0.021)	(0.011)	(0.022)	(0.011)	(0.170)	(0.069)	(0.048)	(0.038)
Age	0.025***	0.019***	0.024***	0.019***	0.091***	0.055***	0.015	0.021***
	(0.005)	(0.002)	(0.005)	(0.001)	(0.023)	(0.015)	(0.013)	(0.005)
Age-Squared	-0.000***	-0.000***	-0.000**	-0.000***	-0.001**	-0.001***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.035***	-0.001	-0.031***	-0.004	-0.040	-0.003	-0.026	0.003
	(0.010)	(0.004)	(0.010)	(0.004)	(0.052)	(0.032)	(0.027)	(0.010)
Below Primary		0.061***		0.057***		0.385***		0.151***
		(0.013)		(0.014)		(0.051)		(0.038)
Primary		0.095***		0.098***		0.454***		0.203***
		(0.013)		(0.013)		(0.065)		(0.039)
Secondary	0.059***		0.066***		0.064		0.084*	
	(0.019)		(0.019)		(0.075)		(0.045)	
Graduate	0.348***		0.318***		0.324*		0.688***	
	(0.070)		(0.066)		(0.187)		(0.139)	
Observations	4,881	30,141	4,879	30,139	306	1,279	933	4,422
R-squared	0.264	0.278	0.257	0.243	0.328	0.355	0.381	0.252

Notes: The regressions are based on 55th and 61th rounds of NSS Employment Survey. 5-digit NIC codes are used to determine industry affiliations as defined in Appendix D. A skilled worker is defined as a worker with at least middle school education. Illiterate individuals are used as the control group in the unskilled regressions, and middle-school educated individuals for skilled regressions. All regressions include a constant as well as year, rural and regional indicators. All standard errors are clustered at the district level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sampling weights are used in estimation.

affiliated with crop production are more responsive to changes in the price of rice than wheat. A one percent increase in the price of rice increases wages (both skilled and unskilled) by 0.68 percent: a one percent increase in wheat prices increases wages by 0.37 percent for skilled workers and 0.17 percent for unskilled workers. These elasticities are estimated to be 0.16 for skilled meat and dairy workers, insignificant for unskilled meat workers and approximately 0.13 for sugar and other food workers. *Ceteris paribus*, male workers earn between 34 and 50 percent more than their female counterparts. An additional year of experience increases wages by 2 to 9 percent, whereas skilled married workers who are engaged in crop production earn 3 percent less than their unmarried counterparts. Education indicators have the expected coefficients and returns to education increase with the degree obtained (primary and secondary) for both skilled and unskilled workers.

Appendix C: Transmission of World Prices to the Indian Market

This section analyzes the extent to which world prices are transmitted to Indian domestic prices. 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.[45] Meat prices are obtained from the Indian Ministry of Agriculture.[46] Exchange rates are obtained from the Federal Reserve Bank of India. All world prices are obtained from the World Bank Commodity Price database.[47] The summary statistics for price increases and expenditure shares of the main crops are presented in Table C1. It shows that between January 2005-May 2011, for rice and meat, the domestic price increases were somewhat similar to world prices with approximately 6 and 15 percentage point deviations, respectively. However, there were substantial differences between the wheat and sugar price series. This can be seen more clearly in Figure C1 which shows the price series for all four commodities. Movements in world prices are transmitted to the domestic market but not to the full extent. This suggests that the pass-through coefficients may vary across commodities and may need to be estimated individually.

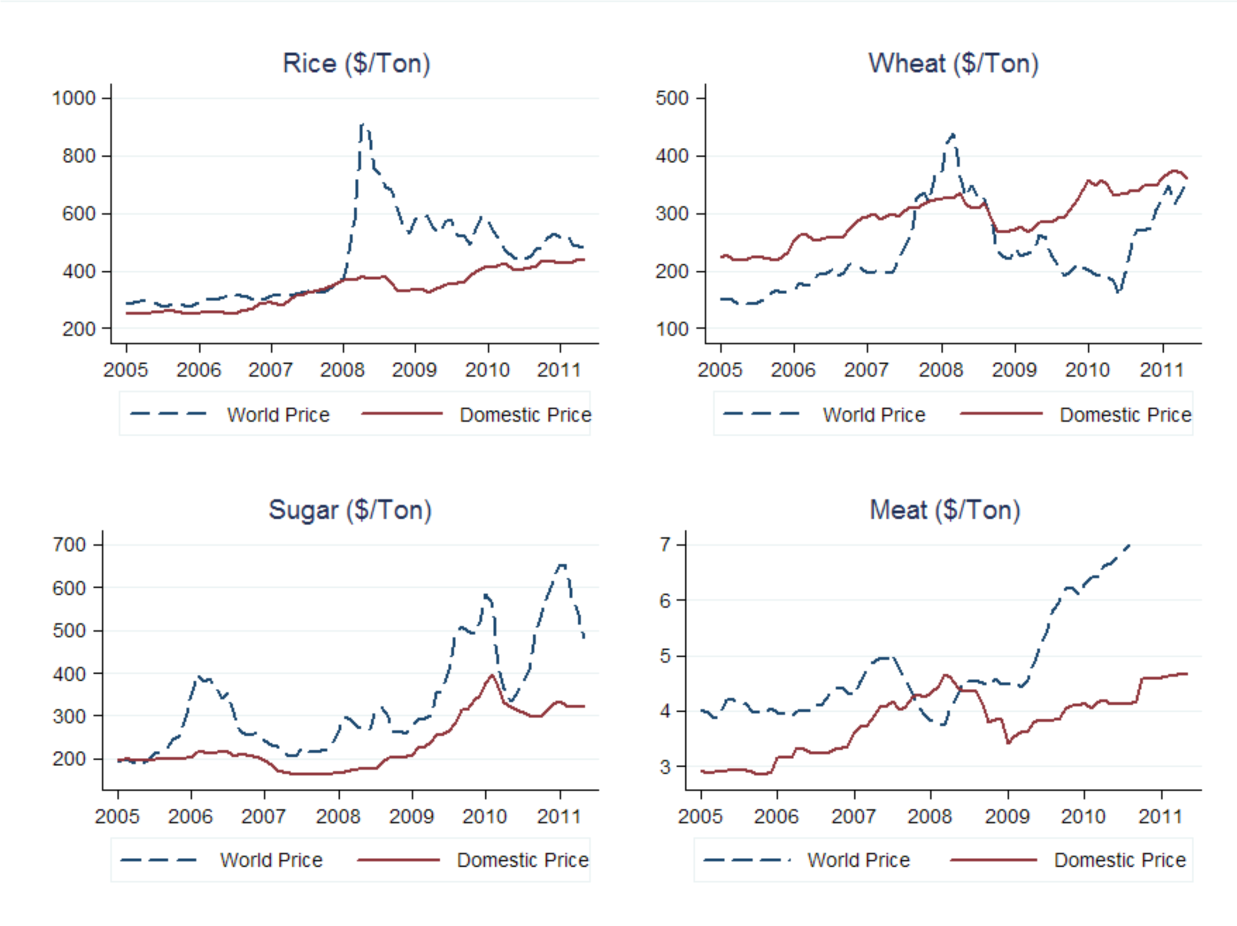
Table C1: Increase in Commodity Prices (Jan 2005 - May 2011)

	Rice	Wheat	Sugar	Meat
World	67.74	131.31	151.72	74.33
Domestic	61.86	61.16	64.11	59.16

Notes: The prices are first converted to USD by using exchange rates from the Federal Reserve Bank of India. The period 2005-11 represents the longest period available for all four commodities.

[45] The Ministry of Public Affairs collects information from Northern, Western, East, Northeastern and Southern zones of India. The prices are then averaged to obtain a nationwide price level for each product.
[46] The average meat (mutton) prices are across Hyderabad, Gujarat, Karnataka, Orissa, Maharashtra, Delhi, Tamil Nadu and Uttar Pradesh, and West Bengal. The 2010 and 2011 prices are extrapolated using the wholesale price index for meat.
[47] For rice prices, Thai 5 percent 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 C1: Domestic and World Prices for Major Crops (current US Dollars)



Different techniques can be used to estimate the transmission elasticity. De Janvry and Sadoulet (2010) interpret the ratio of growth rates in domestic and world prices as transmission elasticity. 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 way 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 Minguez (2006). The estimating equation is

$$\Delta \ln p_t^d = \sum_k \beta_k \Delta lnp_{t-k}^w + \gamma \Delta \ln(1+\tau_t) + \delta \Delta lne_t + \varepsilon_t \tag{C1}$$

where p_t^d represents 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_t is an *i.i.d.* error term at time t. All prices are expressed in nominal terms.[48] 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. The reason for choosing quarterly lags is the dimensionality problem: given the length of our data series, it is not possible to estimate the model with all 12 lags. The short term elasticity is thus given by the coefficient on the contemporaneous price level β_0. The long-term elasticity captures the effect within one year and is defined as the sum of the coefficients, $\sum_{i=0}^{12} \beta_i$.

The results (see Table C2) show that during 2005-2011, the transmission of sugar and rice prices

Table C2: Price Transmission Elasticities of World Prices into Domestic Prices

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

Notes: Standard errors for short run elasticities are reported in parenthesis and F-statistics for long-run elasticities are reported in brackets. *** denotes p<0.01, **p<0.05 and *p<0.1.

[48] We obtain similar results 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.

is statistically significant, although the magnitude of the pass-through transmission elasticity is small. A one percent increase in the world price of sugar yields a 0.219 percent increase in the domestic price in the short run and 0.383 percent in the long run. The magnitude of the rice transmission elasticity is significant, but smaller in magnitude. Transmission elasticities for meat and wheat are statistically insignificant.

Appendix D: Matching between Commodities, Expenditure Categories and Industries

Products	**NSS Categories**		**5-Digit NIC 1998 Categories**	
	Codes	Description	Codes	Description
(1)	(2)	(3)	(4)	(5)
Rice	101, 102	Rice	01111	Growing of food grain crops (cereals and pulses)
	103	Chira	01403	Activities establishing a crop, promoting its growth or protecting it from disease and insects. Transplantation of rice in rice fields.
	104	Khoi, lawa	01404	Harvesting and activities related to harvesting, such as preparation of crop cleaning, trimming, grading, drying.
	105	Muri		
	106	Other rice products		
Wheat	107, 108	Wheat, atta	01111	Growing of food grain crops (cereals and pulses)
	110	Maida	01403	Activities establishing a crop, promoting its growth or protecting it from disease and insects. Transplantation of rice in rice fields.
	111	Suji, rawa	01404	Harvesting and activities related to harvesting, such as preparation of crop cleaning, trimming, grading, drying.
	112	Sewai, noodles		
	113	Bread, bakery		
	114	Other wheat products		
Sugar	269	Sugar (sub-total)	01115	Growing of sugarcane or sugar beet
Meat & Dairy	160	Milk: liquid (litre)	01407	Activities to promote propagation, growth and output of animals and to obtain
	161	Baby food	01409	Other agricultural and animal husbandry service activities, n.e.c.
	162	Milk: condensed/ powder	01211	Farming of cattle , sheep, goats, horses, asses, mules and hinnies; dairy farming
	163	Curd	01212	Rearing of goats, production of milk
	164	Ghee	01213	Rearing of sheep; production of shorn wool
	165	Butter	01214	Rearing of horses, camels, mules and other.
	166	Ice-cream	01221	Raising of pigs and swine
	167	Other milk products	01222	Raising of poultry (including broiler) and other domesticated birds; production of eggs and operation of poultry hatcheries
	180	Eggs (no.)	01223	Raising of bees; production of honey
	181	Fish, prawn	01224	Raising of silk worms; production of silk worm cocoons (production of raw silk is classified under class 1711)
	182	Goat meat/mutton	01225	Farming of rabbits including angora rabbits

Meat & Dairy	183	Beef/ buffalo meat	01229	Other animal farming; production of animal products n.e.c. (Includes: raising in captivity of semi domesticated or wild live animals including birds and reptiles,
	184	Pork	01500	Hunting, trapping and game propagation including related service activities
	185	Chicken	05001	Fishing on commercial basis in ocean, sea and coastal areas
	186	Others: birds, crab, oyster, tortoise, etc.	05002	Fishing on commercial basis in inland waters.
			05003	Gathering of marine materials such as natural pearls, sponges, coral and algae.
			05004	Fish farming, breading and rearing including operations of hatcheries for fin an shell fish
			05005	Service activities related to marine and fresh water fisheries and to operators of
Other Food	115-122	Jowar, bajra, maize, barley, small millets other cereal	01112	Growing of oilseeds including peanuts or soya beans
	139	Cereal substitutes: tapioca, jackfruit, etc.	01119	Growing of other crops, n.e.c. (Includes growing of potatoes, jams, sweet
	159	Pulses & pulse products	01121	Growing of vegetables
	179	Edible oil (sub-total)	01122	Growing of horticultural specialties including: seeds for flowers, fruit or
	229	Vegetables (sub-total)	01131	Growing of coffee or cocoa beans
	249	Fruits (fresh, sub-total)	01132	Growing of tea or mate leaves including the activities of tea factories associated
	259	Fruits (dry, sub-total)	01133	Growing of edible nuts including coconuts
	289	Spices (sub-total)	01134	Growing of fruit: citrus, tropical pome or stone fruit; small fruit such as berries;
	290-293	Tea and coffee	01135	Growing of spice crops including: spice leaves (e.g. bay, thyme, basil); spice
Fuel	500	Air fare	60100	Transport via railways
	501	Railway fare	60210	Other scheduled passenger land transport
	502	Bus/tram fare	60221	Other non-scheduled passenger land transport by motor vehicles
	503	Taxi, auto-rickshaw fare	60222	Other non-scheduled passenger land transport by other
	504	Steamer/boat fare	60231	Freight transport by motor vehicles
	508	Petrol	60232	Freight transport by other
	510	Diesel	60300	Transport via pipelines
	511	Lubricating oil	61100	Sea and coastal water transport
	512	School bus/van	61200	Inland water transport
	513	Other conveyance expenses	62100	Scheduled air transport
			62200	Non-scheduled air transport

Notes: The table presents NSS and NIC codes under each product group. The price vector is merged with the NSS Consumer Expenditure Survey according to the expenditure categories in column (2), and with the NSS Employment Survey according to the 5-digit NIC industry categories according to the column (4). To illustrate for meat, NSS categories 160 through 186 (with gaps) are aggregated as household meat consumption, and individuals affiliated with 5-digit NIC categories 01407 through 05005 (with gaps) are assumed to be workers in meat & dairy production.