The Welfare Impacts of High Food Prices: Resource Endowments and Spill-Over Effects

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Abstract

Though several studies using simulation based approaches have predicted that rising food prices would lead to worsening of poverty in the developing world, these predictions have not fully realized. This paper empirically examines the impact of high food prices on household welfare in India. Our main contribution is to use a unique identification strategy which exploits the natural suitability endowments of a region for food cultivation to separate the income and consumption effect of food price changes on household welfare. We find that the welfare effects of high food prices vary spatially with the natural suitability of food cultivation with regions highly suitable for food cultivation experiencing lower welfare losses from high food prices. The welfare enhancing income effects are also found for households not directly engaged in food cultivation indicating that the spill-over effects of high food prices are important.

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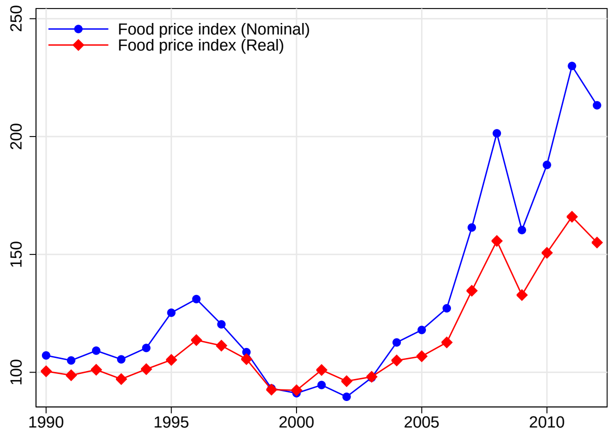
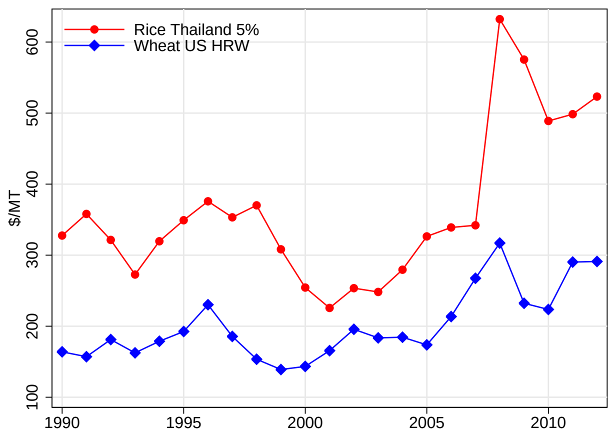
1 Introduction

Global food prices have risen dramatically in the recent past. As can be seen from 1a, the Food and Agriculture Organization's (FAO) global food price index first surged in June 2008 and then again in 2011, and has not reverted to its previous level. A majority of this surge was driven by equally dramatic increase in prices of staples i.e., rice and wheat in the international markets.



(a) FAO Global Food Price Index



(b) Rice and Wheat Prices in the International Markets

Figure 1: Trends in International Food Prices: 1990-2015

Notes: The food price index (2002-2004=100) comes from the Food and Agricultural Organization's database. The international rice and wheat prices at real 2010$ are from World Bank, Global Economic Monitor Commodities price database.

Figure 1b shows trends in real prices of rice and wheat for major exporters of the two staple food commodities. This increase in the prices of staples is unprecedented, as in the past, real prices of rice and wheat have either been declining or remained stable.

In general, the welfare effects of high food prices would be experienced universally as food is a necessity. The major cause of concern among the academics and policymakers is that, as the exposure to high food prices is proportional to its budget share in a households' consumption expenditure, the worst affected population groups would be the ones placed at the bottom of the income distribution. Therefore, rising food prices have become a matter of serious concern for developing countries, which are home to a majority of the world's poor.

Several studies analyzing the impact of high food prices on household welfare concluded that rising food prices would lead to worsening of poverty in the developing world (Ivanic and Martin, 2008; De Hoyos and Medvedev, 2011; Ivanic et al., 2012). These studies relied on variants of Deaton's (1989) net benefit approach to estimate the impact of food price changes on household welfare and poverty. In this approach, the welfare effect of food price changes is approximated as the net income change from a change in food expenditure and change in earnings from food production.

However, the prediction of rising food prices leading to an increase in global poverty have not fully realized. It is argued that estimates based on the net benefit approach provide good approximations of welfare losses when price changes are marginal, but this approach is not suitable to analyze the welfare effects of large and sustained price changes as witnessed during the global food price crisis (De Janvry and Sadoulet, 2009).

There has been a longstanding belief among scholars that the welfare loss from high food prices will not be uniform across all population groups. This belief stems from the understanding that in the long run high food prices can also stimulate demand for labor and increase wages in the agricultural sector (Gulati and Narayanan, 2003; Ravallion, 1990; Jacoby, 2016; Headey, 2016). Greater income in the hands of farmers might increase demand for non-traded goods and therefore increase the local employment and wages. Such effects are welfare enhancing but would be relevant only for those whose earnings are directly or indirectly related to activities in the agricultural sector.

The debate around the short- and long-run welfare impacts of high food prices has led to a few studies re-examining the link between food price changes and household welfare using reduced form empirical approaches. While Deaton's net benefit approach simulates the welfare losses, the reduced form regression of household welfare on food prices directly estimates it. The evidence based on reduced form econometric studies using cross-sectional household level data generally find higher food prices adversely affecting the household welfare (D'Souza and Jolliffe, 2012; D'souza and Jolliffe, 2013). On the contrary, Headey (2016) using country-level panel data finds that rising global food prices between 2005 and 2010 has led to a reduction in global poverty.

Such contradictory findings are probably a reflection of the fact that causal identification of the welfare effects of food price changes is challenging. And this is chiefly on two counts. First, the welfare impacts of food price changes are highly heterogeneous across population groups and it is difficult to capture this heterogeneity empirically as it depends on endogenous household characteristics like budget share of food, production structure and decision to participate in the labor market (Bellemare et al., 2013). Second, there is always the possibility of unobserved omitted variables leading to joint determination of both the price changes and the household welfare outcomes (Bellemare, 2015).

Though there is an agreement that high food prices may benefit some population groups, empirical evidence is scarce. This study aims to bridge this gap by directly focusing attention on a particular population group which can gain from high food prices, i.e., the rural food producers. The first contribution of this work is to use a formal econometric identification strategy to test the commonly-held belief that net food producing households stand to gain from high food prices. Our second contribution is to identify labor market impacts of high food prices without relying on any theoretical formulation of agricultural households. And finally, to the best of our knowledge, this is the first study that identifies spill-over effects of price changes on local economy, and thereby gives a flavor of the general equilibrium effects of a rise in food prices.

Our setting is same as in Tandon (2015) who estimates the causal impact of rising staple food prices on nutritional intakes and dietary diversity of households in India. Tandon's identification strategy is based on a difference-in-difference approach that exploits the cross-sectional heterogeneity in budget shares of rice and wheat, two staple foods in India, and differential increase in rice and wheat prices to identify the causal impact of food price changes on welfare. He finds households most exposed to higher food prices have significantly reduced dietary diversity, investment on labor saving productive assets and schooling of children.

Although Tandon's analysis offers critical insights into the effects of higher prices on welfare outcomes, his identification strategy is designed to captures only the consumption effect of food price changes. But, the households' exposure to food price changes also depends on their production structure. Though an increase in price of staple foods will increase the monetary cost of consumption and consequently reduce welfare, but it would also lead to an increase in income for food-producing households. This possibility of welfare gains from high food prices is ignored by Tandon (2015). The objective of this paper is therefore to devise an econometric strategy that can capture both the consumption and production effects of price changes.

The main contribution of this study is to design a formal identification strategy to disentangle the consumption and income effects of food price changes on household welfare. To do so, we construct a district-level panel of dietary diversity, defined as the share of calories from rice and wheat in the total calories, and staple food price index constructed as weighted average of state-specific rice and wheat retail prices. The panel structure of the data allows us to control for time invariant differences and aggregate time trends that may be correlated with food price changes and household welfare. Our identification strategy is similar in spirit to Edmonds and Pavcnik (2005) who estimate the impact of changes in rice price on child labor in Vietnam. Edmonds and Pavcnik (2005) capture the consumption and income effects of food price change by allowing the welfare effects of price changes to vary with households' rice production status at the baseline. We add a further innovation to this identification strategy by using spatial variation in natural suitability endowments to identify the food producing regions. We exploit the fact that natural geo-climatic endowments are a major determinant of the types of crops grown in a particular region, and are exogenous to a household's decision problem. This exogenous variation is available in the form of crop suitability indices from the Food and Agricultural Organization's (FAO) Global Agro Ecological Zones (GAEZ) database .

The identification strategy relies on the exogenous cross-sectional variation in the natural suitability for food cultivation to bifurcate rural households into net consumers and net producers of food; thus separating the total effect into consumption and income effect. This is econometrically implemented by interacting the staple food price index with the computed food suitability variable. The interaction allows the food price elasticity of welfare to vary with the natural suitability for food production; hence captures the heterogeneity attributable to income effect. In the final specification, we consider a triple interaction between food price index, food suitability and an indicator variable for rural areas. This strategy compares the difference in food price elasticity of dietary diversity between food and non-food producing districts across rural and urban locations. Finally, to identify how households engaged in different sectors of local economy within the food producing regions are affected by changes in food prices, the consumption and income effects are estimated for different household groups based on their primary occupation.

We find a robust negative consumption effect of high food prices on household welfare and dietary diversity. But this effect is found to be smaller for rural households in the districts suitable for food production. Therefore, the welfare effects of high food prices vary spatially with the natural suitability of food production; with regions highly suitable for food production experiencing lower welfare losses from high food prices. The welfare enhancing income effects are strong for the laborer and cultivator households and almost offset their negative consumption effects. Interestingly, the income effects of high food prices are also present for the households not directly engaged in cultivation and agricultural activities within the food suitable rural regions. This provides for a direct evidence of the spill-over effects and induced general equilibrium responses of high food prices on the local economy.

Rest of the paper is organized as follows. Next section presents a review of literature studying the welfare impacts of recent food price shocks. Section 3 provides details about the data sources and construction of variables. Section 4 presents the empirical strategy. Section 5 presents the results and establishes their robustness to a variety of controls and different specifications. Conclusions are presented in the last section.

2 Literature

A modification of Deaton's (1989) net benefit approach to quantify the welfare impact of an increase in food prices is given by the following expression:

$$\Delta W_i \approx [(Q_i - C_i) + \eta L_i]\Delta p_F \tag{1}$$

where, ΔW_i is the welfare change as a proportion of total income for household i , C_i is the share of income spent on food, Q_i is the share of income from food production and sale, η is the wage food price elasticity, L_i is the share of household labor income in total income and Δp_F is the percentage change in food price. The basis for the argument that high food prices may actually benefit some population groups can be examined using equation 1. For a net food producer household, the first term in the above expression is positive, and hence it gains from an increase in food prices. A net food buyer household, on the other hand, would experience a welfare loss from such an increase. A higher share of labor income increases the food price elasticity of welfare but the degree of change depends on the wage food price elasticity. Note that, equation 1 gives the direct effect of price changes and hence approximates the change in welfare due to small price changes. The indirect or substitution effects of high food prices both in terms of consumption and production are ignored under the assumption that with small price changes these second order effects are infinitesimal.

Deaton (1989) while studying the impact of rice price changes on Thai households assumed the labor market responses of high food prices to be negligible. The induced wage response to high food prices may be marginal when price changes are small or persist for a short duration. Nevertheless, with the extent of food price increase witnessed during the recent global food price surge, the induced wage response may be significant enough to benefit the rural poor even if they are net food consumers (Gulati and Narayanan, 2003; Ravallion, 1990; Headey, 2016; Jacoby, 2016).

Studies looking at the immediate impact of 2007-08 food price crisis have primarily relied on Deaton's net benefit approach and have ignored the second order effects of price changes (see, Wodon and Zaman, 2010). For example, Ivanic and Martin (2008) use equation 1 to simulate the welfare impacts of 2005-2007 global food price increase for nine low income countries on the assumption of perfect transmission between global and local prices. They find that high global food prices will in general increase poverty both in rural and urban areas, but the impact would be greater in urban areas. They also conclude that wage adjustment in unskilled labor markets partially offsets the welfare reducing effects of high food prices. Similar findings are also reported by De Hoyos and Medvedev (2011). Improving on their earlier work Ivanic et al. (2012) use data on country level local food price changes to estimate their impact on poverty. This modification builds on the criticism that pass-through rates between global and local prices may vary across countries because of the differences in domestic policies, market structure and transportation costs.

Another set of studies has focused on the long run impacts of high food prices by using the general form of equation 1 where both direct and indirect substitution effects are taken into account. Examples of such studies are Minot and Dewina (2013) and Robles et al. (2010) who provide long run estimates either by estimating the cross elasticities or relying on other studies to parametrize their simulations. Attanasio et al. (2013) estimate a Quadratic Almost Ideal Demand System (QAIDS) to account for the possible cross substitution across food commodities due to price increase. The demand system estimation approach is also adopted by Vu and Glewwe (2011) and Friedman and Levinsohn (2002) to estimate the welfare effects of high food prices. Vu and Glewwe (2011) go a step further and allow for differential rate of increase in consumer and producer prices. Ivanic and Martin (2014) add a further layer to the general version of the net benefit approach by accounting for the direct response of output to price changes and the indirect effect through induced change in wages, and the cross effects of price change on the amount of labor sold off farm.

Simulation studies based on Deaton's approach explicitly accommodate the different channels through which price changes influence household welfare. But they assume other variables like prices of other commodities and incomes to be constant that can simultaneously affect household welfare. Further, small errors in estimation of parameters and elasticities can lead to significant bias in the final estimates of household welfare. The true advantage of the simulation based approach lies in the ex-ante prediction of welfare impacts. One such example is the study by Friedman and Levinsohn (2002), which using cross-sectional household data at the baseline, demonstrates the utility of this method in predicting the welfare impacts of an increase in food prices on Indonesian households

An alternative approach is to use reduced form econometric estimation to study the welfare impacts of food price changes. This approach uses observational data to attribute a change in a welfare indicator to food price changes. While the simulation approach uses data to estimate few parameters (e.g., budget shares) necessary to predict the welfare outcome of a given change in food prices, econometric estimations allow the data to directly estimate the impact of such changes in food prices. This paper is a contribution to the econometric evaluations of the welfare impact of food prices.

A simple reduced form specification to estimate the welfare impact of food price increase can be of the following form

$$W_{it} = \varphi p_{it} + X_{it}\beta + \alpha_i + \mu_t + v_{it} \tag{2}$$

where W is the welfare measure of interest which is regressed on food price p conditional on a set of controls in vector X, and individual (α_i) and time fixed effects (μ_t). Adequate controls are important as the dependent variable might be affected by a variety of shocks that are either common to all households or specific to an individual household.

The benchmark specification in 2 assumes a price effect that is uniform across all households. However, the objective of analysis is often to assess the impact of food prices on different population groups. Indeed, the simulation analysis points to the fact that impacts may be different across consumers, producers and workers. To allow for such a differential impact, either equation 2 must be estimated separately for different population groups or just the price effect should be allowed to differ across population groups.

D'Souza and Jolliffe (2012); D'souza and Jolliffe (2013) estimate a cross-sectional counterpart of equation 2 using nationally representative household surveys from Afghanistan and find a large decline in real monthly per capita food consumption and reduction in dietary diversity due to the increase in prices of staple foods. They find welfare loss to be stronger for urban households and for households with no access to agricultural land. Headey (2016), on the other hand, estimates equation 2 using country level panel of poverty rates and finds an inverse relationship between food prices and poverty. He argues that, as long as agricultural wages in developing countries are indexed to food prices, rural populations in these countries would be beneficiaries of higher food prices.

A more refined empirical approach can be to focus on just one dimension of heterogeneity in equation 1. Tandon (2015) designs his identification strategy such that it focuses on the welfare loss due to the consumption aspect of food price changes. He exploits the differential increase in rice and wheat prices in a difference-in-difference strategy to compare welfare losses of rice vs. wheat consuming regions in India. His identification strategy is based on one of the main insights from the net benefit approach that welfare impact of price change of a particular commodity will be proportional to its share in household consumption. We draw parallel between this identification strategy and equation 1.

$$\begin{aligned} \Delta W_R - \Delta W_W = {} & [(Q_R - C_R) + \eta L_R]\Delta p_R \\ & - [(Q_W - C_W) + \eta L_W]\Delta p_W \end{aligned} \tag{3}$$

where subscript R and W denote the welfare change for rice and wheat consuming regions. Tandon's simplification is:

$$\Delta W_R - \Delta W_W = C_R \Delta p_R - C_W \Delta p_W \tag{4}$$

If, $\Delta p_R > \Delta p_W$, then rice consuming regions would experience greater welfare loss than wheat consuming regions. The assumption required for this simplification is that terms involving food production and labor income shares are either canceled out with the differencing strategy or accounted for using control variables. This seems more convincing for urban areas that are primarily food consumers and hence also independent of the induced labor market response to high food prices but perhaps an oversimplification in case of rural areas. Note that a sound difference-in-difference strategy would also control for other macroeconomic shocks, changing incomes and other commodity prices, which are held constant in Deaton's approach.

This paper builds on Tandon's analysis by empirically modeling household's exposure to high food prices on consumption and production sides and considers the welfare impacts of this exposure on producers and agricultural workers separately.

3 Data

3.1 Dietary Diversity as an Indicator of Household Welfare

The study uses dietary diversity as the main measure of household welfare as unlike monetary indicators it captures the food and nutrition security of households (Lele et al., 2016). The dietary diversity is defined as the ratio of calories from rice and wheat in total calories from all food sources. Staples such as rice and wheat are the primary source of dietary energy in India. The rational of using dietary diversity as an indicator of welfare is that with a reduction in real incomes from higher food prices, households would reduce calories from more nutritious sources to protect their consumption of primary staple foods. This association between income levels and the shares of staples in total calorie intake is known as Bennet's law due to Bennett (1941) who first observed such an association in aggregate data. Also, since the poorest households devote highest share of their income on staple foods, their food security and welfare are more sensitive to this measure (Lele et al., 2016). Using nutritional intakes and dietary diversity as indicators of household welfare has an additional advantage that it, unlike income or consumption expenditure, does not require information on price deflators.

To construct the outcome variables we use data from four thick rounds of large scale consumption and expenditure sample surveys of Indian households conducted in years 1999-2000, 2004-2005, 2009-2010 and 2011-2012 (55th, 61st, 66th and 68th rounds). These surveys, conducted by the Government of India's National Sample Survey Organization (NSSO), record in detail a household's consumption in quantity and value for a variety of food and non food items. We use item wise food consumption to convert it into calorie equivalent, and then calculate the per capita per day calorie intake from different food groups for each household. The population multipliers provided by the NSSO are then used as weights to estimate the district level rural and urban average calorie intake from different food groups.

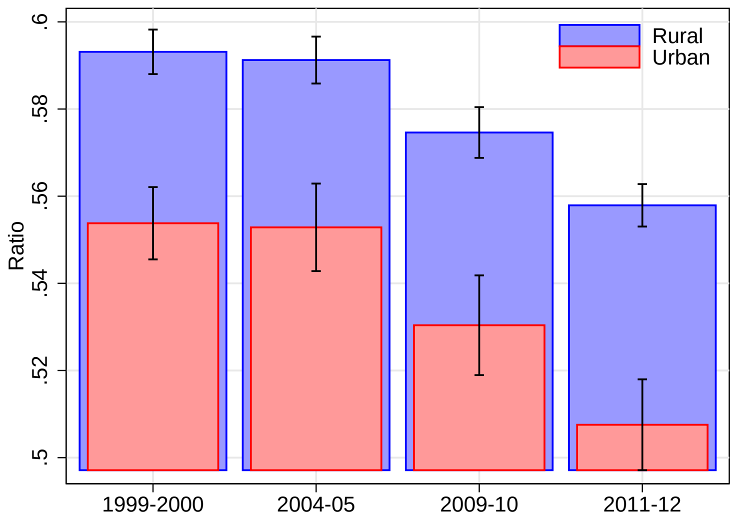


Figure 2: Trends in Ratio of Calories from Rice and Wheat in Total Calories

Notes: Authors' estimates based on National Sample Survey Organizations (NSSO) 55th, 61st, 66th and 68th rounds of consumption and expenditure surveys.

Figure 2 shows the trends in ratio of calories from rice and wheat in total calories for rural and urban households. Rice and wheat provide more that half of the dietary energy for households in our sample. The figure also shows that this measure of welfare is responsive to real income changes. The rural population consumes more calories from rice and wheat i.e. rural diets are less diversified possibly because rural households have lower real incomes than urban. Also dietary diversity shows a declining trend which again can be attributed to the increase in real incomes.

3.2 The Natural Suitability for Food Cultivation

The geo climatic conditions of a region are major determinant of the type of crops cultivated in that region. Therefore, this paper relies on the indicators of natural suitability of a region for rice and wheat cultivation to identify food producing and supplying regions.

Data on indicators of a particular crop's suitability based on the geo climatic conditions are available from the Food and Agriculture Organization (FAO)'s Global Agro-Ecological Zones (GAEZ) 2002 database. The GAEZ dataset was designed to assist governments in crop planning based on agronomic models of crops. The GAEZ dataset provides simulated potential yields and crop suitability indices for a number of crops as grids at a very high spatial resolution. Since the suitability of a crop is simulated from agronomic models where the only inputs are average climatic factors and edaphic conditions, these indices are entirely exogenous and uninfluenced by economic processes. The GAEZ dataset simulates crop suitability for each grid with different scenarios of irrigation and intensity of input use. For this study we use crop suitability based on rainfed conditions and low input use and traditional management practices. More details about the GAEZ dataset can be found in Nunn and Qian (2011).

Several studies utilize the exogenous variation in GAEZ simulated potential yields and suitability indices to devise compelling identification strategies. For example, Nunn and Qian (2011) use the regional variation in suitability of potato cultivation and time variation from introduction of potato to the Old World, to estimate the impact of potatoes on historical world population and urbanization. Similarly, Bustos et al. (2016) use the simulated yields from the GAEZ database as instruments to study the effects of the adoption of new agricultural technologies on structural transformation. Galor and Özak (2015) use simulated potential yields from GAEZ database to construct a Caloric Suitability Index and use it to examine the effect of land productivity on comparative economic development.

The GAEZ dataset provides crop suitability indices in latitude and longitude grids with cells of approximately 100 square kilometers (see, IIASA, 2012). The index varies from zero to 100 where higher number means better suitability or vice versa. The gridded food suitability index is generated as a simple average of suitability index for rice and wheat.

The food suitability grid for India is presented in Figure 3. The food suitability grid and geographical district boundaries are used to estimate the proportion of area in a district where the suitability index is higher than the national average. The district level proportion of area suitable for food cultivation is used in the empirical analysis.

Figure 4 shows, the actual area under cultivation and the area which is naturally suitable for food crops in India. Areas with higher color intensity correspond to the areas more suitable for and cultivated with rice and wheat. Figure 4 shows that natural suitability is a major determinant of a district's area under food cultivation as there is significant overlap in the regions which are naturally suitable and actually cultivate food. For example, the Indo Gangetic plains are highly suitable for food cultivation

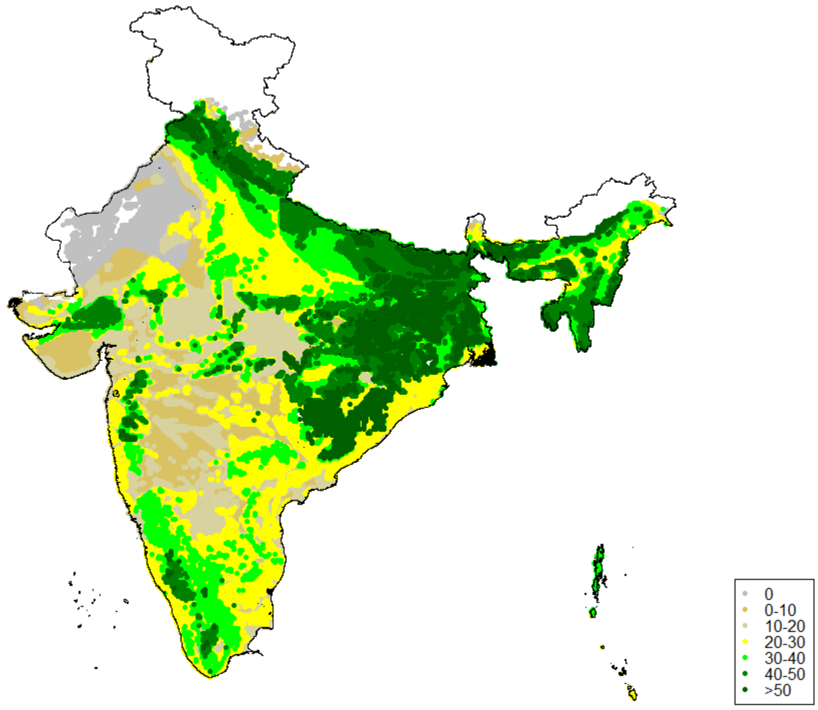


Figure 3: Gridded FAO-GAEZ Food Suitability Index

Notes: The food suitability for each grid point is constructed as the simple average of suitability index for rice and wheat. The gridded crop suitability indices are available from FAO GAEZ database.

and also specialize in its production.

Figure 5 shows scatter plot of area under food cultivation in 1999-2000 and area suitable for food cultivation. There is a strong positive association between share of land suitable for food cultivation and actual area under cultivation. The correlation coefficient between actual and suitable area is 0.70 and is statistically significant at 1% level.

3.3 Food Prices

Data on government administered producer prices and state wise retail prices of rice and wheat are extracted from the publications of Ministry of Agriculture and Farmers' Welfare, Government of India.

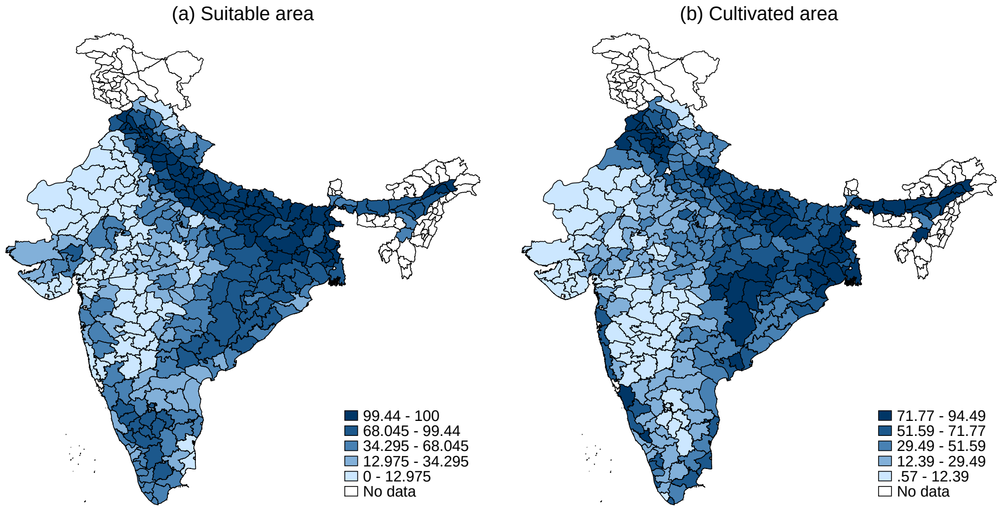


Figure 4: Area Cultivated in 1999-2000 and Area Naturally Suitable for Cultivation of Food Crops

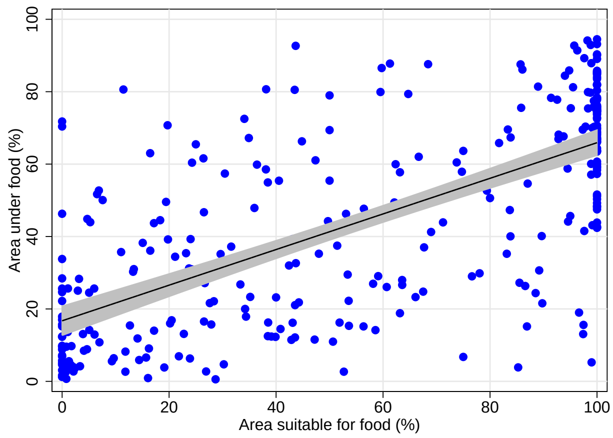


Figure 5: Association between Food Suitability and Food Cultivation in 1999-2000

Figure 6 shows the trends in consumer prices for rice and wheat and the government administered Minimum Support Prices (MSP). The MSP are price floors maintained by the Government of India in the domestic markets primarily for rice and wheat in order to protect domestic producers from price slumps. With international prices increasing dramatically around 2007 the Indian government was unable to maintain stable price levels with the result that both the administered producer prices and the consumer prices of rice and wheat shot upwards in the domestic market as well.

The food price variable is constructed as a weighted average of state specific

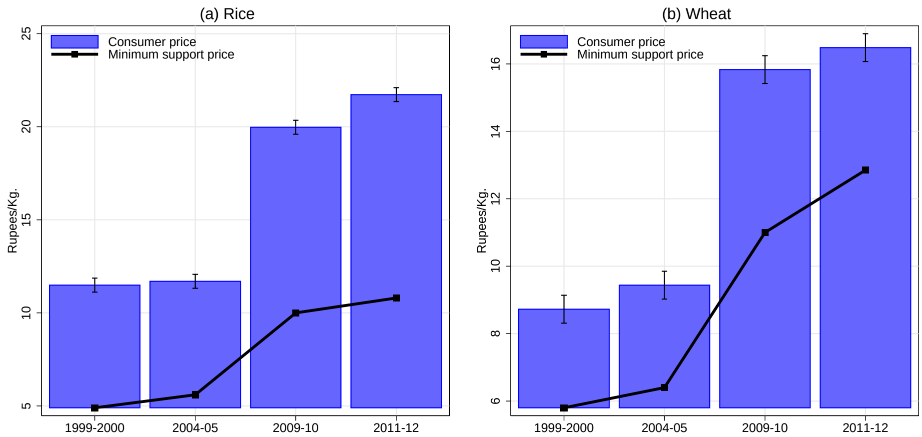


Figure 6: Trends in Rice and Wheat Prices

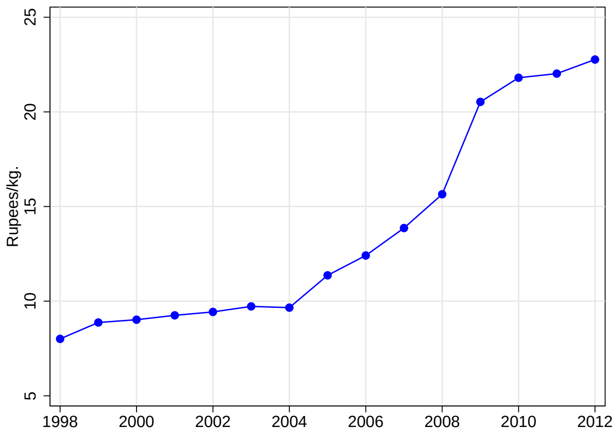


Figure 7: Weighted Food Price

average retail prices of rice and wheat where the weights are district averages of households' expenditure share of rice and wheat in the total spent on both. These shares are estimated from 1999-2000 consumption expenditure survey and are same for all rounds. There is evidence that increase in rice prices was higher in comparison to wheat in India and therefore rice consuming households lost more compared to wheat consuming households (Tandon, 2015). The weighted food price variable captures a district's exposure to increasing food price based on the preference for a particular staple. The exposure is higher for a household residing in a district having stronger preference for a staple whose relative price increase is higher. Figure 7 plots the average of food price index for different years. It shows that constructed food price index is capable of capturing the dramatic increase in food prices between 2004 and 2010.

3.4 Summary Statistics

Table 1 presents the source and summary statistics for the control variables used in this analysis. The variables are divided into two groups, (1) variables for which the information is available for all time periods are the panel variables, and (2) variables for which the information is available for only the initial period are the initial conditions. To maintain consistency and comparability across NSSO survey rounds and other databases we maintain the district boundaries considered in the ICRISAT-VDSA database (see, ICRISAT, 2015).

Table 1: Summary Statistics

Control variables	Source	1999-2000	2004-2005	2009-2010	2011-2012
(a) *Panel controls*					
Standardized total rainfall	Indian meteorological department gridded rainfall data	0.16	-0.24	-0.42	0.26
		(0.94)	(0.74)	(0.85)	(1.04)
Proportion of population in rural areas	ICRISAT VDSA database	0.37	0.37	0.36	0.36
		(0.07)	(0.07)	(0.08)	(0.08)
Proportion of literate in total population	ICRISAT VDSA database	0.51	0.56	0.61	0.63
		(0.13)	(0.12)	(0.10)	(0.09)
Proportion of agricultural laborers in total workers	ICRISAT VDSA database	0.27	0.30	0.33	0.34
		(0.15)	(0.16)	(0.17)	(0.17)
Proportion of area irrigated of total cropped	ICRISAT VDSA database	0.42	0.43	0.46	0.49
		(0.28)	(0.29)	(0.30)	(0.31)
Fertilizer use per hectare (kg/ha)	ICRISAT VDSA database	94.51	97.35	136.54	138.18
		(64.00)	(67.66)	(89.01)	(85.41)
Road density (km/1000 persons)	ICRISAT VDSA database	1.97	1.84	2.17	2.24
		(1.63)	(2.41)	(3.10)	(3.38)
Proportion of PDS rice and wheat in total consumed	NSS consumption and expenditure surveys	0.27	0.35	0.38	0.39
		(0.14)	(0.14)	(0.08)	(0.08)
State wise consumer price index	Ministry of Labor and Employment	714.75	824.80	1232.76	1479.22
		(92.8)	(132.26)	(173.94)	(238.96)
Proportion of households with NREG job card	NSS unemployment and employment surveys	0.00	0.00	0.37	0.39
(b) *Initial conditions*				(0.27)	(0.24)
Percent villages with communication facilities	Census of India, 2001	0.59			
		(0.3)			
Percent villages with banking facilities	Census of India, 2001	0.22			
		(0.17)			
Percent villages with electricity	Census of India, 2001	0.90			
		(0.16)			

Note: Figures in parenthesis are standard errors.

4 Empirical Strategy

The benchmark specification is the following

$$Y_{dt} = \varphi Ln(PRICE)_{dt} + X_{dt}\beta + \alpha_d + \mu_t + \varepsilon_{dt} \tag{5}$$

where Y_{it} is the share of calories form rice and wheat in total calories consumed in district d at time t and $Ln(PRICE)_{dt}$ is the food price index. Vector X contains control variables described in table 1. District fixed effects and time dummies are included to control for district specific time invariant un-observables and aggregate time trends.

Equation 5 ignores the heterogeneity based on consumers and producers of food. One classification of consumer and producers of food can be based on rural and urban areas, as most of the agricultural activities are carried out by the rural population and urban households are primarily food consumers. Therefore, we estimate equation 5 for subsamples of rural and urban households.

Even within rural regions one would expect the exposure of high food prices to vary across households based on whether they are net food producers or consumers. The main identification strategy of this paper is designed to incorporate this heterogeneity. In order to identify the net income effect of food price changes on household welfare, we allow coefficient φ in equation 5 to vary across districts with the spatial variation in natural suitability of food cultivation. We estimate the following equation

$$\begin{aligned} Y_{dt} = {} & \delta Ln(PRICE)_{dt} \times FOOD_d + \eta Ln(PRICE)_{dt} \\ & + X_{dt}\gamma + \alpha_d + \mu_t + \epsilon_{dt} \end{aligned} \tag{6}$$

where $FOOD_d$ is the proportion of area in a district suitable for food (rice and wheat) cultivation, $Ln(PRICE)_{dt} \times FOOD_d$ is the interaction of food price index with area suitable for food cultivation and other variables are same as equation 5. The interaction term allows the food price elasticity of dietary diversity to vary across districts based on their natural suitability for food cultivation. The identification strategy relies on geo climatic endowments to identify districts as net food producing. Conditional on control variables in vector X, the natural suitability for food cultivation is exogenous to the factors associated with changes in dietary diversity between 1999-2012.

The food suitability endowments exogenously separates districts into net food consumers and producers, or separates the total effect into consumption and income effects. Therefore, η captures the consumption effect and δ captures the income effect.

Urban households will experience pure consumption effect, therefore our hypothesis is that $\eta_{URBAN} > 0$ and $\delta_{URBAN} = 0$ or higher food price will unambiguously reduce dietary diversity in urban areas irrespective of suitability endowments of the districts. On the other hand, for rural households there will be an additional income effect based on their food suitability endowments. Hence, for rural regions our hypothesis is that $\eta_{RURAL} > 0$ but $\delta_{RURAL} < 0$.

The third specification combines the distinction between rural and urban regions and food suitability variable in the following manner.

$$
\begin{aligned}
Y_{sdt} = {} & \theta^1 Ln(PRICE)_{dt} \times RURAL_{sdt} \times FOOD_d \\
& + \theta^2 Ln(PRICE)_{dt} \times RURAL_{sd} \\
& + \theta^3 Ln(PRICE)_{dt} \times FOOD_d \\
& + \theta^4 Ln(PRICE)_{dt} \\
& + \theta^5 RURAL_{sd} \times FOOD_d \\
& + \theta^6 RURAL_{sd} \\
& + X_{sdt}\eta + \alpha_d + \mu_t + v_{sdt}
\end{aligned} \tag{7}
$$

where the dependent variable is rural-urban sector specific dietary diversity. This specification expresses the heterogeneity of price effects between rural-urban households and food suitable regions as a triple interaction between food price index, an indicator variable for rural households $(RURAL)$ and the share of area suitable for food cultivation. The coefficient of interest in this equation is θ^1 which is equivalent to $(\delta_{RURAL} - \delta_{URBAN})$ where δ is the coefficient on the interaction term in equation 6. Therefore, θ^1 gives the differential impact of food price changes for rural households residing in food suitable districts. Note that if our hypothesis $\delta_{URBAN} = 0$ is true then $\theta^1 = \delta_{RURAL}$.

To assess the labor market effects of food price changes, the analysis is limited to rural areas. Equation 6 is re-specified at the individual household level as

$$
\begin{aligned}
Y_{idt} &= \delta Ln(PRICE)_{dt} \times FOOD_d + \eta Ln(PRICE)_{dt} \\
&\quad + Z_{idt}\rho + X_{dt}\gamma + \alpha_d + \mu_t + \epsilon_{idt}
\end{aligned}
\tag{8}
$$

where the dependent variable is the dietary diversity for an individual household i, residing in rural region of a district d at time t. Use of household level data has the advantage that we can now control for household specific control variables. Vector Z has controls for household characteristics along with district level controls in vector X. To capture the heterogeneity of effects across laborer households, cultivator households and other household, equation 8 is estimated for subsamples of rural households based on their primary occupation types.

5 Results

5.1 Benchmark Specification

Table 2 presents the estimated coefficients from equation 5. In panel A, where we consider log calories from staple foods as the dependent variable, the coefficient on log food price is statistically insignificant. This suggests that Indian households' demand for calories from staple foods is price insensitive. In comparison, the staple food price elasticity of demand for calories from foods other than staples is negative and statistically significant (table 2 panel B). Negative and statistically significant food price elasticity is also found for calories form more nutritious sources like pulses, milk, meat, eggs fruits and vegetables (panel C). This suggest that Indian households cope with high food prices by reducing their consumption of calories from more nutritious sources in order to maintain their consumption of staple foods such as rice and wheat. Therefore, food prices would be positively correlated with the share of calories from staples in total calories. This is indeed the case in panel D where the dependent variable is the share of calories from staples in total calories and the coefficient on food price is positive and statistically significant. These results are robust to addition of controls listed in table 2.

Table 2: Estimates from Benchmark Specification

A. Log of per capita per day calories from rice and wheat			
$Ln(PRICE)$	0.023	0.021	0.014
	(0.029)	(0.031)	(0.033)
R^2	0.731	0.738	0.739
F	207.666	77.607	57.468
B. Log of per capita per day calories from items other than rice and wheat			
$Ln(PRICE)$	-0.144***	-0.145***	-0.151***
	(0.051)	(0.051)	(0.055)
R^2	0.679	0.683	0.691
F	122.291	46.887	32.907
C. Log of per capita per day calories from pulses, fruits, vegetables and animal sources			
$Ln(PRICE)$	-0.168***	-0.150***	-0.159***
	(0.056)	(0.055)	(0.058)
R^2	0.698	0.706	0.711
F	78.631	30.222	20.928
D. Ratio of calories from rice and wheat in total calories			
$Ln(PRICE)$	0.038***	0.036***	0.038***
	(0.013)	(0.013)	(0.014)
R^2	0.811	0.820	0.822
F	14.303	18.344	13.618
Panel controls	No	Yes	Yes
Initial conditions*Time	No	No	Yes
Observations	2456	2452	2452

Notes: All specifications include district fixed effects, time dummies and rural region dummy. Panel and initial conditions are listed in table 1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In terms of magnitude, a one per cent increase in the food price is associated with a 4 percentage point increase in the ratio of calories from staple cereals to total calories. These findings are similar to D'Souza and Jolliffe (2012) who find that rising food prices in Afghanistan led to households shifting from animal based calorie sources and vegetables toward staple foods. Tandon (2015) also finds similar results for India.

5.2 Rural Urban Heterogeneity in Price Effects

The results presented in the previous section are based on pooled sample of rural and urban households. In this section we present the estimates of equation 5 for the sub-samples of rural and urban households.

Table 3: Rural Urban Heterogeneity in Price Effects

	(1)	(2)	(3)	(4)	(5)	(6)
		Rural			Urban	
Dependent variable: ratio of calories from rice and wheat in total calories						
$Ln(PRICE)$	0.034*	0.038**	0.036*	0.043**	0.037**	0.038*
	(0.019)	(0.017)	(0.019)	(0.018)	(0.018)	(0.020)
N	1232	1232	1232	1224	1220	1220
R^2	0.914	0.926	0.927	0.842	0.847	0.849
F	7.165	20.141	13.283	18.326	10.554	7.510
Panel controls	No	Yes	Yes	No	Yes	Yes
Initial conditions*Time	No	No	Yes	No	No	Yes

Notes: Specification 1 to 3 are for rural households and specifications 4 to 5 are for urban households. All specifications include district fixed effects, time dummies and rural region dummy. Panel controls and initial conditions are listed in table 1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3 presents the results from a regression of share of calories from staples in total calories on log of staple food price index. For both rural and urban households, the coefficient on food price index is positive and statistically significant. Hence higher food prices reduce dietary diversity for both rural and urban households. The comparable price elasticity estimates across rural and urban households points to the fact that this specification is unable to identify the income and consumption effects.

5.3 Effects by Food Suitability Endowments

Table 4: Heterogeneity of Effects for Rural and Urban Households by Food Suitability Endowments

	(1)	(2)	(3)	(4)	(5)	(6)
	Rural			Urban		
Dependent variable: ratio of calories from rice and wheat in total calories						
$Ln(PRICE)$	0.067***	0.059***	0.058***	0.041**	0.038*	0.039*
	(0.021)	(0.019)	(0.020)	(0.019)	(0.020)	(0.022)
$Ln(PRICE) \times FOOD$	-0.056***	-0.034***	-0.035**	0.004	-0.002	-0.002
	(0.012)	(0.012)	(0.014)	(0.010)	(0.012)	(0.015)
Panel controls	No	Yes	Yes	No	Yes	Yes
Initial conditions*Time	No	No	Yes	No	No	Yes
N	1232	1232	1232	1224	1220	1220
R^2	0.918	0.927	0.928	0.843	0.847	0.849
F	18.813	19.145	13.417	14.589	9.907	7.225

Notes: Specification 1 to 3 are for rural households and specifications 4 to 5 are for urban households. All specifications include district fixed effects and time dummies. Panel controls and initial conditions are listed in table 1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 presents the estimates of equation 6 for rural and urban subsamples. As hypothesized the estimated coefficient η which captures the consumption effect of change in food price is positive and statistically significant for both rural and urban households. The coefficient δ on interaction term ($Ln(PRICE) \times FOOD$) is negative and statistically significant for rural households but is close to zero and statistically insignificant for urban households. This implies that both rural and urban households experience a reduction in dietary diversity as food price increase. But the income effect of high food prices, visible in the negative and statistically significant coefficient on the interaction term for rural regions, mitigates the welfare reducing consumption effect. The absence of income effects for urban subsample is proof that this empirical strategy is capable of identifying the income effect of price changes.

Table 5 presents the results from triple interaction specification. Conceptually, the coefficient on triple interaction is just the difference between the interaction coefficients for rural and urban subsamples in table 4. Considering specification (3) in table

Table 5: Triple Interaction Specification

	(1)	(2)	(3)
Dependent variable: ratio of calories from rice and wheat in total calories			
$RURAL$	-0.130***	-0.124***	-0.124***
	(0.029)	(0.028)	(0.028)
$RURAL \times FOOD$	0.213***	0.200***	0.199***
	(0.037)	(0.037)	(0.037)
$Ln(PRICE)$	0.036**	0.041***	0.039**
	(0.015)	(0.015)	(0.016)
$RURAL \times Ln(PRICE)$	0.036***	0.033***	0.032***
	(0.009)	(0.009)	(0.009)
$FOOD \times Ln(PRICE)$	-0.004	-0.014	-0.007
	(0.010)	(0.010)	(0.011)
$RURAL \times FOOD \times Ln(PRICE)$	-0.045***	-0.041***	-0.041***
	(0.012)	(0.012)	(0.012)
Panel controls	No	Yes	Yes
Initial conditions*Time	No	No	Yes
N	2456	2452	2452
R^2	0.835	0.843	0.844

Notes: All specifications include district fixed effects and time dummies. Panel controls and initial conditions are listed in table 1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5 as the main specification the estimated coefficient on the triple interaction term is -0.04. This estimate is equal to the interaction coefficient from comparable specification (3) in table 4. This is so because the income effect in urban areas in negligible hence the coefficient on the triple interaction term in table 5 is equal to income effects estimated for rural areas.

5.4 Labor Market and Spill-Over Effects

Table 6 presents the estimates of equation 8 by household types based on main occupation and income source.

The surprising finding from table 6 is that the coefficient on the interaction term is negative and statistically significant for all household types. This we take as an indication of the spill-over effects, as in the absence of spill-overs, the income effect of food price changes should have been limited to cultivator households. For laborer households the income effect can be attributed to the induced wage responses of food

Table 6: Labor Market and Spill-Over Effects

	(1)	(2)	(3)	(4)	(5)
	Non agricultural households	Agricultural laborer households	Other laborer households	Cultivator Households	Other households
Dependent variable: ratio of calories from rice and wheat in total calories					
$Ln(PRICE)$	0.043***	0.083***	0.074***	0.046***	0.039**
	(0.014)	(0.020)	(0.023)	(0.016)	(0.016)
$Ln(PRICE) \times FOOD$	-0.030***	-0.073***	-0.067***	-0.038***	-0.019*
	(0.011)	(0.018)	(0.017)	(0.011)	(0.010)
N	50242	39590	28948	73701	36646
R^2	0.583	0.639	0.518	0.596	0.449

Notes: The household types are based on the major source of the household's income during the year preceding the survey. Households under others include regular salaried earners. All specifications include district fixed effects and time dummies. Panel controls and initial conditions are listed in table 1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

price changes. But the presence of statistically significant and negative coefficients on the interaction term for non agricultural and other households is evidence of spill-overs effects of high food prices on other sectors of the local economy.

5.5 Robustness Checks

The main identification strategy in this paper relies on the use of natural suitability endowments as exogenous variation. As shown before natural suitability for food cultivation is highly correlated with actual food production. Our first concern is that the coefficient δ in equation 6 may be capturing the fact that districts with higher food suitability experience lower price increases than districts with lower food suitability. We test this empirically by running a regression of the following form

$$Ln(PRICE)_{dt} = \rho FOOD_d \times \mu_t + \mu_t + X_{dt}\pi + \sigma_d + \epsilon_{dt} \quad (9)$$

where we interact the proportion of area suitable for food cultivation with time dummies. We want to test the hypothesis that $\rho = 0$. This is to rule out systematic variation between change in food prices and the crop suitability variable $FOOD_d$. Note that this is similar to a parallel trends check that the data has to satisfy for a difference-in-difference identification strategy to work.

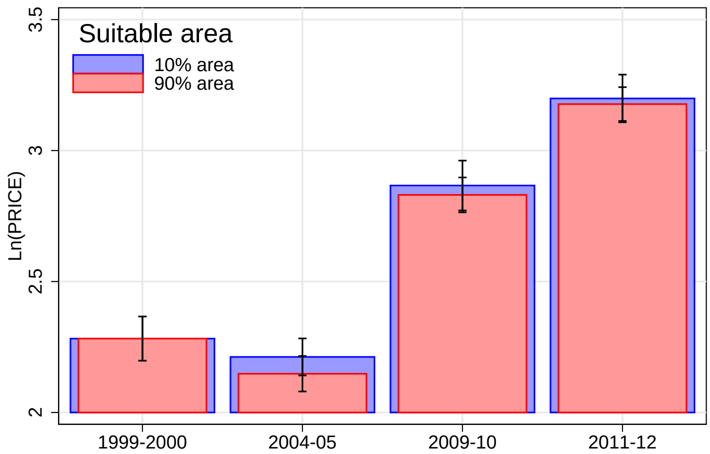


Figure 8: Parallel Trends in Food Prices

Figure 8 presents the simulated price trends from equation based on 10% area suitable for food cultivation (unsuitable for food cultivation) and 90% area suitable for food cultivation (suitable for food cultivation). Figure 8 shows that food prices follow common trends and do not vary systematically with food suitability status.

The second concern relates to the way in which the dietary diversity variable is defined. It is constructed as the ratio of calories from rice and wheat in total calories. As food becomes expensive, households can substitute rice and wheat with cheaper coarse cereals [1]. Although the substitution effect will depend on how strongly households prefer rice and wheat in relation to coarse cereals, it still has the potential to introduce bias in our results. The bias can be introduced in the following sense; since calories from coarse cereals is part of the denominator it is possible that we are capturing households substitution to cheaper cereals rather than diversification of diets.

[1] Coarse cereals include pearl millet, finger millet, Sorghum, barley and maize.

To check the robustness of the results against this bias we reconstruct the dependent variable as ratio of calories from rice and wheat in total calories excluding calories from coarse cereals.

The third exercise is conducted is to check the sensitivity of the results to the construction procedure of the food suitability variable. We generate the food suitability index as the maximum of suitability indices of rice and wheat rather than their average as was done earlier. Using the new food suitability index we recalculate the proportion of area in a district where the suitability index is higher than the national average. Finally, we test for the sensitivity of the results to district specific linear time trends.

Table 7: Robustness Checks

	(1)	(2)	(3)
$RURAL \times FOOD \times Ln(PRICE)$	-0.020**		-0.046***
	(0.010)		(0.014)
$RURAL \times FOOD \times Ln(PRICE)$		-0.022*	
		(0.011)	
District linear time trends	No	No	Yes
N	2452	2452	2456
R^2	0.805	0.815	0.815

Notes: Dependent variable in specification 1 is the ratio of calories from rice and wheat in total calories excluding calories from coarse cereals. Dependent variable in specification 2 and 3 is the ratio of calories form rice and wheat in total calories. Specification 2 uses an alternative procedure to calculate the area suitable for food cultivation in a district. All specifications include district fixed effects and time dummies. Panel controls and initial conditions are listed in table 1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7 presents the results from the robustness checks based on the triple interaction specification in equation 7. The dependent variable in specification 1 is the reconstructed dietary diversity variable. In specification 2 we use the new food suitability variable and specification 3 controls for district specific linear time trends. The coefficients on the triple interaction for all three specifications are negative and statistically significant. Hence our results remain unaffected by these robustness tests.

6 Conclusions

Though several studies using Deaton's (1989) net benefit approach have predicted that rising food prices would lead to worsening of poverty in the developing world, these predictions have not fully realized. In this paper we take an empirical approach to estimate the welfare impact of food price shocks. Our primary innovation is to use the spatial variability in the natural suitability of food cultivation to disentangle the consumption and income effect of food price changes on household welfare.

We find a statistically significant welfare improving income effect of high food prices for households located in regions suitable for food cultivation. The income effects are present for both laborer and cultivator households and offset the negative consumption effects to a large extent. This finding is especially important in the light of the trade policy responses of countries during global food price shocks. Countries often rely on restrictive trade policy to insulate households from food price shocks on the grounds that high food prices would hurt the poor. Our results show that laborer and cultivator households within food producing regions are completely insured from food price shocks. Therefore, countries with larger share of population engaged in food production either as cultivator or as wage laborer will be least affected by such events. The households most vulnerable to food price shocks are primarily urban or food importer households. Urban households only experience increase in consumption expenditures as food price rise without offsetting increase in income but as long as richer households reside in urban areas the consumption effect may not be of much consequence to them.

Finally, we also find income effects of high food prices for households not directly engaged in food cultivation within food producing regions. These results indicate that different sectors within food producing regions are closely linked and hence the spill-over effects of high food prices are important.

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