Geography and the Welfare Impact of Food Price Shock

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Abstract:

Several studies have examined the impact of recent surge in food prices on household welfare. Some predict that an increase in food prices would lead to rise in incidence of poverty while others contradict this arguing that in the in the long run high food prices may actually increase income and reduce poverty. This lack of consensus has led to a debate around the welfare impacts of recent food price shocks. This paper contributes to this debate by analyzing the impact of food price shock on welfare of Indian households located in rural and urban areas. Using natural suitability for food cultivation as a source of exogenous variation, the study identifies the causal mechanism through which the welfare impact of food prices vary across rural and urban location. The results also demonstrate that ignoring the heterogeneity in the impact may lead to misleading conclusions about the impact of high food prices on households' welfare.

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1. Introduction

In the recent past, global food prices have risen dramatically and become more volatile. The international food price index surged in June 2008 and then again in 2010 and has not reverted to its previous level. In India too, food prices increased substantially. Between January 2006 and June 2008, India's food price index rose by 22% and the prices of staple cereals like rice and wheat almost doubled.

An immediate concern for academics and policymakers has been the impact of high food prices on welfare and poverty. Several studies analyzing the impact of rising food prices on social welfare concluded that rising food prices would lead to worsening of poverty in the developing world (Ivanic and Martin 2008). But this prediction of adverse effect of rising food prices on global poverty was not realized. It was argued that high food prices would increase profits for producers and also augment wages in the agricultural sector.

Those who predicted rise in global poverty in response to rising food prices relied on cross sectional household surveys and simulations to estimate the impact of food price increase on household welfare and poverty. These simulations were based on the expenditure function of a representative farm household where the possibility of the household being a food producer was internalized. The revisionist view is that higher food prices may reduce poverty. For example, Jacoby (2016) accommodates labor market effects of food price changes and has shown substantial welfare gains due to increase in food prices. Headey (2016), using poverty measures for a panel of countries, has shown that high international food prices have led to reduction in global poverty. He justifies his findings by arguing that in the short-run the high food prices might increase incidence of poverty, but in the long-run as food supply responds and wages adjust in response to food prices changes the poor may eventually gain from higher food prices.

The literature recognize that the losses or gains from change in food prices will vary geographically. Most of the studies however fail to provide convincing causal evidence for this variation. Identification of welfare changes based on the geographical distribution of households may provide better insight as why some households lose and some gain from rising food prices. Tandon (2015) conducts one such exercise for India where he compares welfare losses of rice vs. wheat eating regions and finds rice eating regions losing more due to relatively higher increase in rice prices. The idea behind classifying households by their preference for a particular staple is that tastes evolve from historical abundance and natural suitability of a crop thus partitioning households based on rice and wheat eating regions is exogenous. This point is also echoed in Atkin (2016) who shows that Indian households' preferences for staple foods are so strong that households migrating to different regions forgo calories to maintain their traditional food habits. Although Tandon's (2015) analysis is unique, it does not distinguish between rural and urban locations and also ignores the distinction between food and non-food producing households. It has been recognized that gains from high food prices, if any, will be concentrated among only those who are directly or indirectly engaged in food production (Headey 2016). Food is an essential commodity for everyone irrespective of location and/or economic activity. Therefore any increase in food prices will increase the monetary cost of consumption and reduce welfare in the short run. This is the first order or the direct effect of food price change and is welfare reducing. The debate around the welfare impacts of high food prices stems from the lack of consensus on the medium and long run impacts. It is argued by many authors that in the long run high food prices will stimulate the demand for agricultural inputs (Jacoby 2016; Heady 2016; Ivanic and Martin 2014; De Hoyos and Medvedev 2011; Ravallion 1990). This is the second order or indirect effect of high food prices and is welfare increasing but will be relevant only for those whose earnings are directly or indirectly related to activities in the agricultural sector.

In this paper, using a district level panel data on households' nutritional intakes and dietary diversity, I examine the impact of high food prices on welfare of Indian households. To do so I compare households based on two dimensions. The first dimension is the location of a household, i.e. rural and urban. By definition almost all agricultural activities in India are carried out by rural population. Urban locations, thus, have food consumers only. It is, therefore, conjectured that urban consumers will lose when food prices rise, irrespective of their geographical location. The case of rural households, however, is complex. Most rural households directly or indirectly are engaged in agriculture, as cultivators or agricultural laborers. Rise in food prices will directly benefit food producers. As food supply responds to high prices, the demand for agricultural laborers will also increase in food-producing regions. If labor flow across regions is relatively low, then higher food prices will lead to higher wages. To incorporate this, the second classification is based on food and non-food producing regions. A direct way to classify households or districts as food producing is by the proportion of area allocated to staple food crops such as rice and wheat. But such a classification may not be entirely exogenous because of the possibility of omitted variables as the acreage allocation is also determined by the economic forces. Therefore, to classify the regions as food producing the study uses proportion of area which is naturally suitable for production of rice and wheat based on crop suitability indices derived from FAO's Global Agro-Ecological Zones (GAEZ) database. The idea here is that conditional on roads, irrigation and other infrastructure variables, the suitability index provides an instrument to classify regions as food producing. The variation in the welfare impact of food price increase is identified of the interaction between district specific food prices index which provides time variation and differences in districts' suitability for food cultivation based on time-invariant geographic and edaphic conditions. The identification strategy compares the food price elasticity of household welfare between districts that are more suitable for food cultivation and districts that are less suitable.

To construct welfare outcome variables I 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. These surveys, conducted by the government of India's national sample survey organization, record in detail a household's consumption quantity and value for a variety of food and non food items. I calculate the per capita per day calories from different foods for each household and use the share of calories from rice and wheat in total calories as the main indicator for household welfare.

Since the income elasticity of food is low, any change in income due to food price shock will be reflected in the dietary diversity of households. Use of diet diversity as indicator of household welfare has an additional benefit that it, unlike income or consumption expenditures, does not require additional information on price deflators.

The study uses natural suitability for food cultivation to identify the causal mechanism through which the welfare impact of food prices vary across rural and urban locations. Like other studies I find that high food prices significantly reduced diet diversity and nutrition in India. But comparing food producing and non food producing households across locations, i.e. rural and urban I show that this finding masks geographical variation in welfare losses. I find that although both urban and rural households experience reduction in dietary diversity as a result of food price increase, the reduction in diversity is significantly less for the households in food-producing districts. Therefore the second order or income effect of food price increase does mitigate consumption effect of food price increase for rural households in food producing areas. These results are robust to a triple difference specification where the difference in food price elasticity of dietary diversity between food and non food producing districts is compared across rural and urban locations. Finally, I explore the heterogeneity of impact across household types based on main occupation and find that the dietary diversity of labor households in food producing rural areas is the least sensitive to food price increase. This is in line with the findings of Jacoby (2016) that the food price elasticity of wages in India is positive and income gains for cultivators are to an extent truncated by rising input costs which is not the case for laborer households.

The rest of the paper is laid out as follows. Next section briefly discusses the literature surrounding the debate on the welfare impacts of recent food price shocks. Section 3 is divided into two subsections of which the first provides the details about data sources and variable construction and the second subsection outlines the identification strategy. Section 4 presents the results and establishes their robustness to variety of controls and different specifications. Conclusions are presented in the last section.

2. Literature

The economic effects of food price shocks have been of considerable interest to economist and the literature on it is vast. This section summarize some of the literature which focusses on the welfare impacts of the recent food price shocks. Some of the earliest work on the impacts of food price shocks was based on the agricultural household model of Singh, Squire and Strauss (1986). Deaton's (1989) method which builds upon the agricultural household's model has been a workhorse of the literature analyzing the impact of food price changes on household welfare. This approach is based on the indirect utility function of a representative agricultural household where the welfare impact of a food price change on a household is expressed as the difference between budget share of food and value of production of food as a fraction of total household expenditure. Deaton used this method to analyze the effect of changing rice prices on the distribution of welfare in Thailand, both across geographical location and along the income distribution.

Ivanic and Martin (2008) use Deaton's net benefit approach to look at the short run welfare impact of global food price increase on poverty in the developing world. They use cross sectional household surveys from nine low income countries to estimate the impact of food prices on poverty rates and conclude that recent surge in global food prices will increase global poverty by 4.5%. Another study by Ivanic, Martin, and Zaman (2012) which considers a sample to 28 countries finds considerable heterogeneity in the welfare impacts of global food price increase but predicts an increase in poverty of 1.1% points in low income countries and 0.7% points in middle income countries.

Heady (2016) has questioned these findings on the grounds that in the long run high food prices will cause agriculture supply response which in turn will lead to restructuring of the demand and supply in the markets for agricultural inputs. Heady points out that this can also have spillover effects on other sectors and can affect the whole rural economy. Unlike the earlier studies based on simulation, Heady (2016) takes an empirical approach to examine the relationship between changes in food prices and poverty. Using a 20 year panel data of head count poverty for a number of developing countries and instrumental variable techniques Heady identifies a negative long term impact of food price rise on poverty. Jacoby (2016) shows that the adjustment in rural labor market and rural wages is another important price-shock transmission channel through which the poor may gain in the long run. Jacoby in the context of India, using a three sector general equilibrium model, shows that the food price elasticity of wages is large and positive and that higher food prices would lead to substantial gains to the rural population of India.

Another parallel strand of literature has looked at the impact of rising food prices on the households' food security and nutritional intakes. Jenson and Miller (2008) use panel data for April, September, and December of 2006 from two Chinese provinces to examine the impact of recent food price increase on the consumption and nutrition of poor households. They find that households could maintain their nutritional intakes as domestic prices of staple foods remained low due to government intervention. As noted by D'Souza and Jolliffe (2012) one reason for this finding can be that the data used by Jenson and Miller was for the time period which did not experience the stark increase in the price of staples during the crisis. D'Souza and Jolliffe (2012, 2013) use a nationally representative survey of Afghan households to study the impact of sharp increase in staple food prices on real expenditures and dietary diversity. They find that increases in the price of wheat flour led to large decline in real monthly per capita food consumption and reduction in dietary diversity and that this effect was stronger for urban households and households without access to agricultural land. Similar findings are also reported by Friedman et al. (2011) for Pakistan.

One finding common among all studies is the difference in welfare impacts of food price shocks across households in rural and urban locations. Almost all studies report that the welfare losses due to food price increase will be lower in rural areas in comparison to urban areas.

3. Data and Empirical Strategy

The Government of India intervenes heavily in the domestic markets for staple cereals; viz. rice and wheat through fixing a floor price called the Minimum Support Price (MSP) and procures cereals in the open market to maintain market prices over and above MSP. This is done with the objective to insure both consumers and producers from price fluctuations. Although domestic markets in India are insulated from global price shocks due to heavy government intervention, domestic food prices especially of rice and wheat did shoot up in India as well. Figure 1 shows the trends in consumer prices for rice and wheat and the MSP for four time periods. Even with government intervention in the domestic food market the prices for rice and wheat rose substantially between 2004-05 and 2009-10.

(a) Data and descriptive statistics

India provides ideal set up to look at the impact of high food prices on welfare. India is home to a significant proportion of the world's poor concentrated mainly in the rural areas of the country. Almost half of the Indian workforce is still engaged in agricultural activities and own and cultivate small landholdings. Some of the poorest and most vulnerable regions in the country depend mainly on agriculture for their livelihood and allocate significant proportion of their land to rice and wheat cultivation. India is also suitable to investigate the labor market effects of the high food prices as district labor markets in India are spatially segregated with relatively low inter district migration rates (Topalova 2007, 2010).

Another advantage of choosing India for the study is the availability of large scale household surveys which collect detailed information on the monthly consumption of food and non food items. These surveys are conducted on an annual basis by the government of India's National Sample Survey Organization (NSSO). For this study I use the thick rounds of consumption and expenditure surveys conducted in years 1999-00, 2004-05, 2009-10 and 2011-12 (55th, 61st, 66th and 68th rounds). These rounds have a larger sample size and allow me to estimate outcome variables for rural and urban areas at the district level. I use the item wise food consumption data available in these surveys to convert it into calorie equivalent and then calculate the per capita per day calorie intake from different food groups for each household. Using the population multipliers provided by the NSSO as weights I then estimate the district level rural and urban average calorie intake from different food groups. Estimates of calorie intake from different food groups serve as my outcome variables.

Data on minimum support prices and state wise retail prices of rice and wheat comes from the Ministry of Agriculture and Farmers' Welfare, Government of India. I generate food price index as a weighted average of rice and wheat prices. 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 the welfare loss due to preference for a particular staple. It penalizes a household more if it resides in a district which has a stronger preference for rice than wheat.

I use the natural suitability of a district for rice and wheat cultivation as an instrument for food producing or food surplus regions. I refrain from using acreage allocated under rice and wheat to identify food producing district as area allocation is a joint outcome of natural suitability and economic forces. Natural suitability of a region for a crop can be a good predictor of the proportion of area in the region allocated to that crop. Information on a particular crop's suitability based on the edaphic conditions is available from the Food and Agriculture Organization (FAO)'s Global Agro-Ecological Zones (GAEZ) 2002 database. The

GAEZ dataset was designed to assist government agencies in crop planning based on agronomic models of how crops grow under different edaphic and geo-climatic conditions. The GAEZ dataset provide simulated potential yields and crop suitability index for a number of crops at a high spatial resolution. Since the suitability of a crop comes 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 region based on alternative scenarios of irrigation and intensity of input use. For this study I use crop suitability based on rain fed conditions and low input use and traditional management practices. More details about the GAEZ dataset can be found in Nunn and Qian (2011). Many studies have utilized 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, Caprettini, and Ponticelli (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 Ozak (2015) using the potential yields in the GAEZ database construct a Caloric Suitability Index (CSI) to examine the effect of land productivity on comparative economic development.

The GAEZ dataset provides the crop suitability index in latitude and longitude grids with cells of approximately 100 square kilometers (see IIASA/FAO (2012)). The index varies from 0 to 100 where higher number means higher suitability. The gridded food suitability index is generated as a simple average of suitability index for rice and wheat (figure 2). To generate district level proportion of area suitable for food cultivation I calculate the proportion of area in a district where the suitability index is higher than the country average. Figure 3 shows on the Indian district map, the actual area under cultivation and the area which is naturally suitable for food crops. Areas with higher color intensity correspond to greater area suitable for or cultivated with rice and wheat. Figure 3 shows that natural suitability for food cultivation 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 actual area under food cultivation. For example, the Indo gangetic planes are highly suitable for food production and also specialize in food production. Figure 4 shows the scatter plot of area under food cultivation in 1999-2000 and area suitable for food cultivation. There is a strong a positive association between share of land suitable for food cultivation and actual area under cultivation. The correlation coefficient between actual area and suitable area is 0.70 and is statistically significant at 1% level.

To construct the final dataset I merge the outcome variables estimated from consumption and expenditure rounds with other district level agricultural variables like cropping patterns, area under irrigation and fertilizer use which are extracted from the International Crops Research Institute for the Semi-Arid Tropics ICRISAT-VDSA database compiled from various official sources. District level population density and population composition by gender, social groups and employment also comes from the ICRISAT-VDSA database compiled from census of India. Other district level infrastructure access variables like access to medical, education and communication facilities, electrification, and roads infrastructure is calculated from the village amenities data of census of India 2001. To maintain consistency and comparability across NSSO survey rounds and other databases I maintain the district boundaries considered in the ICRISAT-VDSA database (see VDSA/ICRISAT (2015)).

Table 1 presents the summary statistics for the variables used in the study. The variables have been 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 cross sectional variables.

India experienced significant macroeconomic changes during the decade under consideration in this study. This was a period of high income growth in India where the income per capita grew at an annual rate of 6%, almost double in comparison to the growth rate in previous decades. As noted by many authors, high economic growth during the 1990s and 2000s led to a significant reduction in poverty in India (Datt and Ravallion 2011; Panagariya and Mukim 2014). This high growth in incomes is also evident in table 1 by the fact that between 1999-2000 and 2011-2012 an average household's share of non food expenditure increased by 10 percentage points from 44% to 54%. High income growth in India was also accompanied by a general rise in consumer prices as the average consumer price index almost doubled during this period. Mishra and Roy (2012) examine inflation in India during 1990s and 2000s and find food price inflation to be consistently higher than non-food price inflation during the period with items like milk, fish, edible oils, fruits and vegetables and cereals like rice and wheat being the primary drivers of food price inflation in India.

Another major event during this period was the launch of the government of India's flagship workfare program the National Rural Employment Guarantee Act (NREGA). The

NREGA guarantees every willing households in rural India 100 days of work per year at a minimum wage. The act was initially introduced in 200 of the poorest districts in 2006, and then was gradually extended to the rest of rural India in 2008. Imbert and Paap (2015) examine the labor market effect of the NREGA and find that the large scale work provision by public sector under the employment guarantee act led to crowding out of private sector work and pushed private sector wages upwards. This was also the period when the public distribution system of the government of India which distributes food grains at heavily subsidized prices to poor households underwent major reforms. Table 1 shows that for an average household in India the proportion of rice and wheat consumed from public distribution system also increased during the period. There were also changes in the structure of rural employment as the proportion of cultivators reduced and the proportion of agricultural laborers increased in the total workforce. Inputs use in agriculture intensified as both irrigated area and fertilizer use show increasing trends. Finally because of the large scale rural road building programs like the Pradhan Mantri Gram Sarak Yojana and the national highway building program (Golden Quadrilateral project) the average road density also increased in India.

Figure 5 shows the trends in ratio of calories from rice and wheat in total for rural and urban locations. The rural areas of the country consume more calories from rice and wheat i.e. rural diets are less diversified. One explanation for this can be that since food is cultivated in rural areas it may be cheaper there due to low transportation costs. It can also be that rural areas of the country are poorer and thus have lower dietary diversity than urban areas. Another observation worth noting from the figure 5 is the declining trend in the ratio of calories from rice and wheat over the period from 1999-2000 to 2011-2012.

This declining trend can be attributed to the increase in real incomes in both rural and urban areas.

(b) Empirical strategy

A simple specification to estimate the impact of surge in domestic food prices between 2004-05 and 2009-10 on the welfare of Indian households can be

$$Y_{dt} = \phi Ln(PRICE)_{dt} + X_{dt}\beta + \alpha_d + \mu_t + \varepsilon_{dt} \qquad (1)$$

Where Y is the welfare outcome of interest for district d at time period t. The variable $Ln(PRICE)_{dt}$ is the food price. 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. A similar specification is used by D'Souza and Joilliffe (2013) to look at the impact of surge in wheat flour prices on welfare of households in Afghanistan. The specification in equation (1) however does not reveal anything about the geographical variation in impacts.

To identify the first order and the second order effect of food price changes the identification strategy in this paper is designed around two classifications of households. The first is of rural vs. urban regions and the second is food producing vs. non food producing districts. Specification (1) is modified in the following manner.

$$Y_{dt} = \delta Ln(PRICE)_{dt} \times FOOD_d + \eta Ln(PRICE)_{dt} + X_{dt}\gamma + \alpha_d + \mu_t + \epsilon_{dt} \qquad (2)$$

I introduce an interaction between food prices and the proportion of area in a district suitable for food cultivation. As discussed before $FOOD_d$ acts as an instrument for differentiating food producing and non food producing districts. Conditional on time and district fixed effects and additional controls in vector X the edaphic and geographical conditions captured in food suitability index provides exogenous variation to identify the welfare impacts of high food price on welfare. The coefficient on the interaction term δ gives us the impact of food price increase on welfare of households in food producing districts relative to non food producing districts.

Separate specification are estimated for rural and urban areas to bring out the heterogeneity of welfare impacts of high food prices. For urban households the hypothesis is that high food prices will unambiguously reduce welfare irrespective of them being located in a food or non food producing district therefore the first order consumption effect will dominate. This implies that for the urban subsample estimate of η should be negative and δ should be close to zero. On the other hand, the welfare loss to rural households residing in food producing district may not be as much as rural households in non food producing households as the second order income effect to will mitigate the consumption effect of high food prices. This implies that for the rural subsample η should be negative but δ should be positive.

A third specification can be where the difference in outcomes of rural and urban households is compared across food and non food producing districts.

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

This can be expressed as a triple interaction between food price, a household being in either rural or urban region and the natural potential of a district for food production. The coefficient of interest in this equation is θ^1 which gives the differential impact of surge in food prices for rural households residing in food producing districts.

4. Results

I follow the literature in using nutritional intakes from different food groups as outcome variables. Nutritional intakes are more sensitive to food price shocks as they capture food and nutrition security of poor households. D'Souza and Jolliffe (2012) document strong association between commonly used nutrition indicators and measures of household level food security like dietary diversity. Figure 6 shows the all India trends in the food price generated as the weighted average of state specific rice and wheat retail prices. The food price starts trending upward only after 2004 and more than doubles by 2010.

As mentioned before the minimum support prices are set by the government of India and thus are exogenous. I want to consider only the welfare effect of exogenous price variation. To begin with I look at the transmission elasticity between the constructed retail food price and the minimum support price and whether the transmission systematically varies between the districts which are suitable for food cultivation and districts which are not. This is in sprit of the parallel trends check that the data has to satisfy for a difference-in difference identification strategy to work. Another concern is that if price shocks are because of supply shocks, while the farmers gain from price shocks, they would lose from supply shocks therefore we want to investigate and net out the variation in food prices due to supply shocks.

Table 2 shows the results from regression where the dependent variable is the log of weighted average of rice and wheat retail prices and the independent variable is the log of weighted average of minimum support prices of rice and wheat. The transmission elasticity is high and statistically significant and is same for both food suitable and non suitable districts. Although standardized district rainfall deviation which is a proxy for supply shocks does show inverse association with food prices the magnitude of coefficient on rainfall drops drastically and becomes statistically insignificant with addition of district fixed effects. The issue of district level supply shocks influencing our food price variable is thus not a major concern because the retail price data is at the state level and is exogenous to district level supply shocks. Irrespective of the lack of statistical significance I will still include rainfall deviations along with other variables as a control in all of the regression specifications.

(a) Impact of food prices on diet diversity of households

Table 3 presents the estimated coefficients from equation (1) for urban and rural households pooled together. The dependent variable is the dietary diversity i.e. the ratio of calories from rice and wheat to total calories and the independent variable is log of weighted food price. The results show that surge in food prices significantly reduced the diet diversity of households in India. The ratio of calories from staple cereals to total calories which is a direct indicator of diet diversity of households in inversely related to food prices. More precisely, a one per cent increase in the food price is associated with a 4 percentage point decline in the ratio of calories from staple cereals to total calories. These findings are similar to D'Souza and Joilliffe (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.

The next set of result presented in table 4 are based on equation 2. The coefficient of the interaction between food prices and area suitable for food cultivation is negative and statistically significant in all three specification. This is clear evidence that second order income effects of food price increase does mitigate the welfare reducing consumption effect of high food prices. Results presented in table 4 however mask important geographical variation in welfare losses across India. Table 5 presents the estimates of equation 2 for urban and rural subsample. Comparing the sign and statistical significance of coefficients across urban and rural subsamples clearly brings out the geographical variation of welfare losses. As hypothesized, the second order effect of high food price act as a buffer to households in rural areas of the food suitable districts. For urban households the welfare impact of high food price is same irrespective of the districts suitability for food cultivation. These findings are not only in line with the current literature but also provides evidence on causal mechanism through which the welfare impact of food prices vary across rural and urban location.

Table 6 presents the results from triple difference specification. Result from the triple difference specification reinforce my earlier results. The coefficient for the triple interaction term is negative, statistically significant and close in magnitude to the estimates in table 6.

(b) Robustness checks

This section presents the findings from some sensitivity checks I conduct to establish the robustness of the results. The first concern relates to the way in which I construct the dietary diversity variable. It is constructed as the ratio of calories from rice and wheat in total calories. As food becomes expensive, households would substitute rice and wheat with cheaper coarse cereals. Although the substitution effect will depend upon 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 substituting to cheaper substitutes rather than diversification of diets. To check the robustness of the results against this bias I reconstruct the dependent variable as ratio of calories from rice and wheat in total calories excluding calories from coarse cereals.

Second exercise I conduct is to check the sensitivity of the results to the construction procedure of the food suitability variable. I 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 I recalculate the proportion of area in a district where the suitability index is higher than the country average. The third robustness test I conduct is to see the sensitivity of the results to district specific linear time trends.

Table 7 presents the results from the robustness checks based on the triple difference specification. The dependent variable in specification 1 is the reconstructed dietary diversity variable. In specification 2 the interaction is with the new food suitability variable and specification 3 has district specific linear time trends. The coefficient on the triple interaction term is negative and statistically significant in all three specification. Additional results based on triple difference specification are presented in table A1 in the appendix.

(c) Heterogeneity in impact of food price on diet diversity of households

In this section I evaluate the heterogeneity of impact across different household types based on main source of occupation. Table 8 presents the estimates of equation (2) by household types based on their main occupation and income source. Comparing the food price elasticity of calorie intake among household types in food vs. non food producing regions I find that the laborer households' diet diversity was least sensitive to food price increase. This implies that laborers household had the highest income gains from food price increase. Laborer households would only gain from food price increase if wages in food producing district increase as food supply responds to higher food prices. This is also in line with Jacoby's (2016) finding that the food price elasticity of wages in India is positive. The results also indicate that income gains for cultivator households were truncated by the rising input costs which is not the case for laborer households.

5. Conclusion

Several studies have examined the impact of recent surge in international food prices on household welfare. The findings were mixed. Some predicted that an increase in food prices would lead to rise in incidence of poverty while others contradicted this arguing that in the in the long run high food prices may actually increase income and reduce poverty. This lack of consensus has led to a debate around the welfare impacts of recent food price shocks. In this paper I contribute to this debate by analyzing the response of welfare outcomes to rising food prices in India for different types of households located in rural and urban areas.

Using natural suitability index for crop cultivation as an instrument, the study finds significant geographical variation in the impact of high food prices on household welfare. The results demonstrate that ignoring the heterogeneity in the impact may lead to misleading conclusions about the impact of high food prices on households' welfare. Finally, the study identifies the most vulnerable households for targeting policies aimed at minimizing the impact of food price shocks.

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Figures

Figure 1: Trends in rice and wheat prices

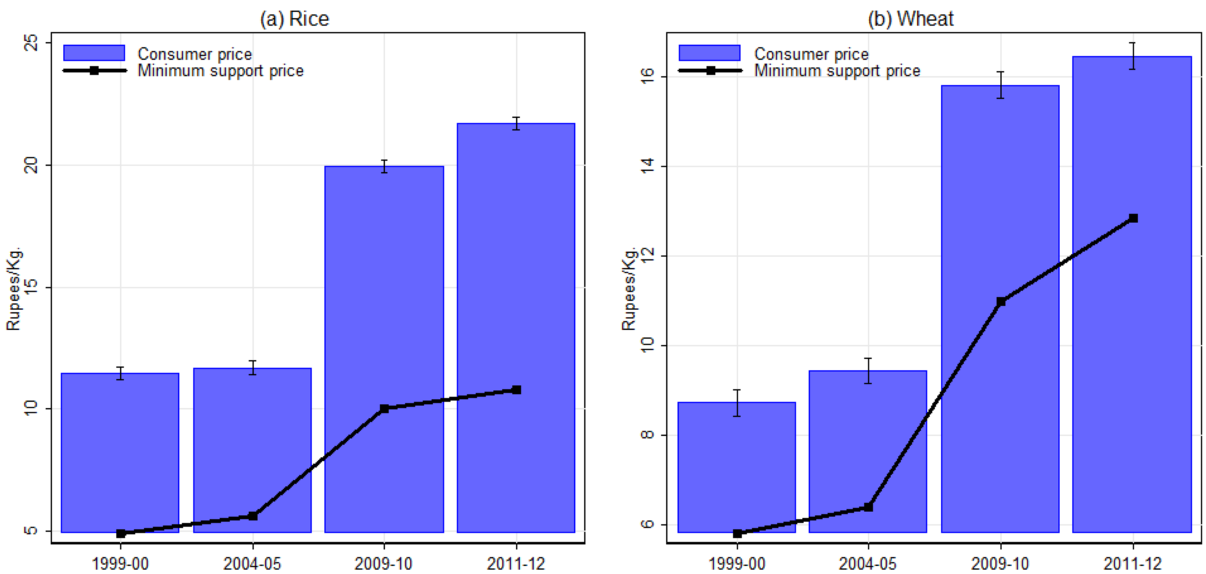


Figure 2: Gridded FAO-GAEZ food suitability index

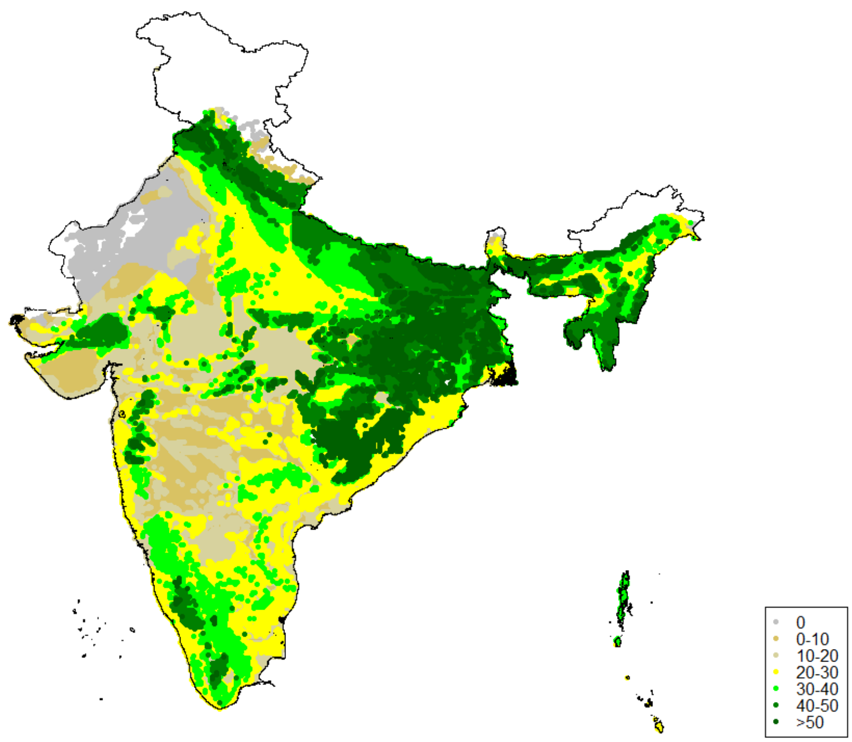


Figure 3: Area cultivated in 1999-2000 and area naturally suitable for cultivation of rice and wheat

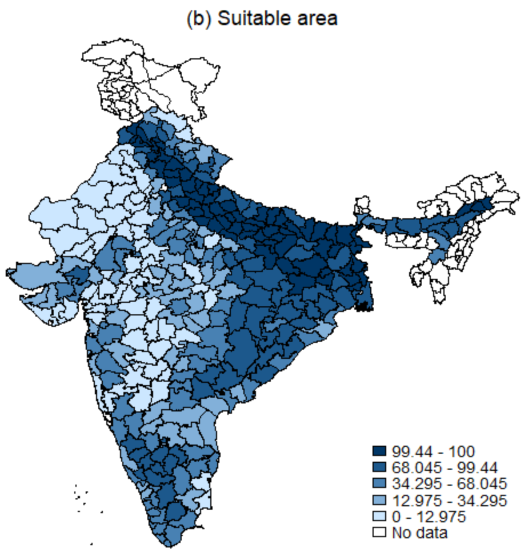


Figure 4: Association between food suitability and food cultivation in 1999-2000

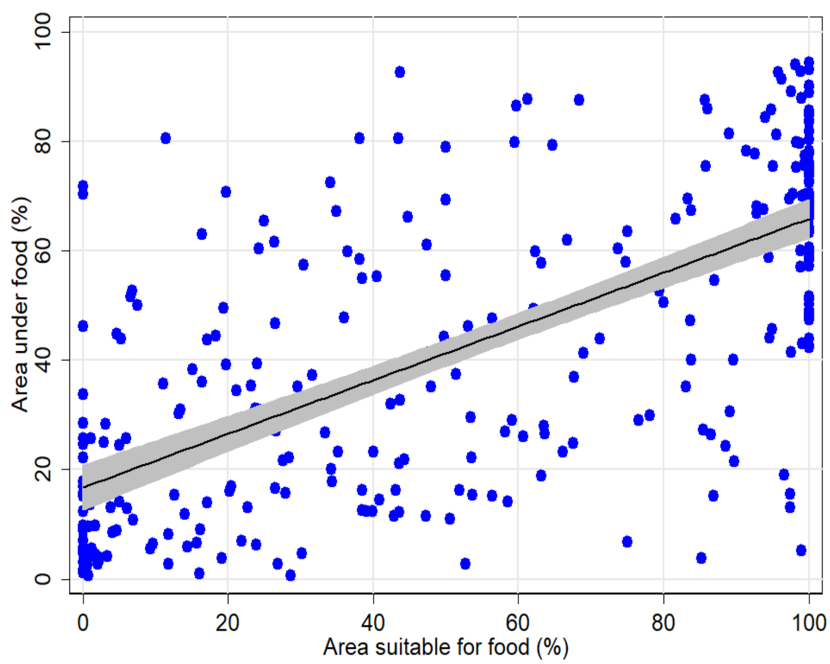


Figure 5: Trends in ratio of calories from rice and wheat in total

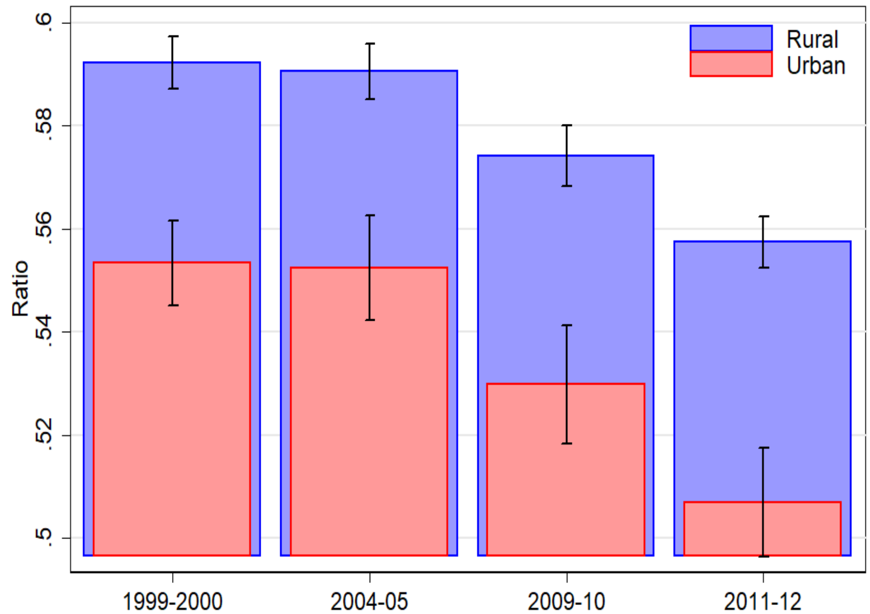
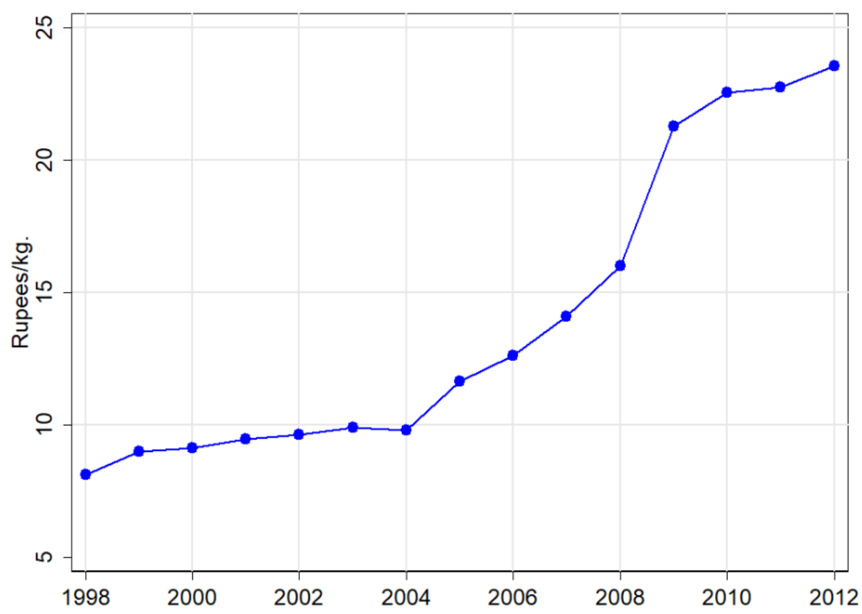


Figure 6: Weighted food price



Tables

Table 1: Summary statistics

Variables	Source	1999-2000	2004-2005	2009-2010	2011-2012
A. *Panel variables*					
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)
Share of nonfood items in total expenditure	NSS consumption and expenditure surveys	0.44	0.49	0.50	0.54
		(0.07)	(0.08)	(0.08)	(0.07)
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 cultivators in total workers	ICRISAT VDSA database	0.40	0.38	0.35	0.34
		(0.17)	(0.18)	(0.17)	(0.17)
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
				(0.27)	(0.24)
B. *Cross sectional variables*					
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.

Table 2: Transmission between minimum support prices and retail prices

	(1)	(2)	(3)
Ln(MSP)	0.832***	1.225***	1.255***
	(0.035)	(0.013)	(0.023)
Ln(MSP) × FOOD			-0.052
			(0.033)
Standardized rainfall deviations	-0.012*	-0.006	-0.007
	(0.006)	(0.005)	(0.005)
District fixed effects	No	Yes	Yes
Observations	1232	1232	1232
Adjusted R2	0.543	0.911	0.911
F statistic	282.8	5124.9	3396.7

Notes: Dependent variable is the log of weighted average of retail prices of rice and wheat. Rainfall deviations are at the district level. 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: Estimates from equation 1 for pooled rural and urban households

A. Log of per capita per day calories from rice and wheat	(1)	(2)	(3)
Ln(PRICE)	0.036	0.024	0.028
	(0.037)	(0.038)	(0.042)
Panel controls	No	Yes	Yes
Cross sectional controls × Time	No	No	Yes
Observations	2456	2452	2452
Adjusted R2	0.710	0.725	0.730
F statistic	18.5	13.9	13.6
B. Log of per capita per day calories from food items other than rice and wheat			
Ln(PRICE)	-0.172***	-0.147***	-0.154***
	(0.049)	(0.051)	(0.055)
Panel controls	No	Yes	Yes
Cross sectional controls × Time	No	No	Yes
Observations	2456	2452	2452
Adjusted R2	0.632	0.645	0.652
F statistic	118.7	44.4	31.5
C. Log of per capita per day calories from pulses, fruits, vegetables and animal sources			
Ln(PRICE)	-0.173***	-0.121**	-0.129**
	(0.055)	(0.056)	(0.060)
Panel controls	No	Yes	Yes
Cross sectional controls × Time	No	No	Yes
Observations	2456	2452	2452
Adjusted R2	0.654	0.673	0.677
F statistic	77.1	29.8	21.0
D. Ratio of calories from rice and wheat in total calories			
Ln(PRICE)	0.045***	0.034***	0.037***
	(0.013)	(0.013)	(0.014)
Panel controls	No	Yes	Yes
Cross sectional controls × Time	No	No	Yes
Observations	2456	2452	2452
Adjusted R2	0.783	0.795	0.797
F statistic	15.1	16.1	13.5

Notes: All specifications include district fixed effects, time dummies and rural region dummy. Panel and cross sectional controls 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: Estimates from equation 2 for pooled rural and urban households

	(1)	(2)	(3)
Ln(PRICE)	0.060***	0.054***	0.053***
	(0.014)	(0.015)	(0.016)
Ln(PRICE) × FOOD	-0.027***	-0.034***	-0.028***
	(0.008)	(0.008)	(0.010)
Panel controls	No	Yes	Yes
Cross sectional controls × Time	No	No	Yes
Rural dummy	Yes	Yes	Yes
Observations	2456	2452	2452
Adjusted R2	0.784	0.797	0.798
F statistic	19.9	17.5	14.1

Notes: Dependent variable is the ratio of calories form rice and wheat in total calories. All specifications include district fixed effects, time dummies and rural region dummy. Panel and cross sectional controls 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 5: Results from rural and urban subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
		Rural			Urban	
Ln(PRICE)	0.075***	0.057***	0.056***	0.045**	0.035*	0.036*
	(0.020)	(0.019)	(0.020)	(0.018)	(0.020)	(0.021)
Ln(PRICE) × FOOD	-0.054***	-0.034***	-0.035***	0.001	-0.005	-0.005
	(0.012)	(0.012)	(0.013)	(0.009)	(0.011)	(0.014)
Panel controls	No	Yes	Yes	No	Yes	Yes
Cross sectional controls × Time	No	No	Yes	No	No	Yes
Observations	1232	1232	1232	1224	1220	1220
Adjusted R2	0.890	0.902	0.901	0.788	0.793	0.794
F statistic	19.5	17.9	12.8	14.8	9.1	7.0

Notes: Specification 1 to 3 are for rural households and specifications 4 to 5 are for urban households. Dependent variable is the ratio of calories form rice and wheat in total calories. All specifications include district fixed effects and time dummies. Panel and cross sectional controls 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 6: Triple difference specification

	(1)	(2)	(3)
RURAL	-0.124***	-0.132***	-0.132***
	(0.028)	(0.028)	(0.028)
RURAL × FOOD	0.210***	0.204***	0.204***
	(0.036)	(0.036)	(0.036)
Ln(PRICE)	0.043***	0.039***	0.038**
	(0.014)	(0.015)	(0.016)
Ln(PRICE) × RURAL	0.033***	0.031***	0.031***
	(0.009)	(0.009)	(0.009)
Ln(PRICE) × FOOD	-0.005	-0.014	-0.007
	(0.009)	(0.010)	(0.011)
Ln(PRICE) × RURAL × FOOD	-0.043***	-0.042***	-0.042***
	(0.012)	(0.012)	(0.012)
Panel controls	No	Yes	Yes
Cross sectional controls × Time	No	No	Yes
Observations	2456	2452	2452
Adjusted R2	0.811	0.822	0.823
F statistic	28.4	22.6	18.7

Notes: Dependent variable is the ratio of calories form rice and wheat in total calories. All specifications include district fixed effects and time dummies. Panel and cross sectional controls 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: Robustness checks

	(1)	(2)	(3)
Ln(PRICE) × RURAL × FOOD	-0.023**	-0.024**	-0.045***
	(0.010)	(0.011)	(0.013)
Panel controls	Yes	Yes	No
Cross sectional controls × Time	Yes	Yes	No
District specific linear trends	No	No	Yes
Observations	2452	2452	2456
Adjusted R2	0.810	0.818	0.814

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 and cross sectional controls 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 8: Spillover effects; heterogeneity of impact by type of households

	(1)	(2)	(3)	(4)	(5)
	Non agriculture	Agricultural labor	Other labor	Agriculture	Others
Ln(PRICE)	0.058***	0.073***	0.087***	0.030*	0.036**
	(0.016)	(0.022)	(0.026)	(0.017)	(0.018)
Ln(PRICE) × FOOD	-0.028**	-0.072***	-0.062***	-0.023**	-0.016
	(0.011)	(0.018)	(0.019)	(0.011)	(0.009)
Household controls	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes
District initial conditions × Time	Yes	Yes	Yes	Yes	Yes
Observations	49052	38345	28388	72712	35466
Adjusted R2	0.575	0.638	0.515	0.591	0.443

Notes: Dependent variable is the ratio of calories form rice and wheat in total calories. 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. District controls and district 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.

Appendix A

Table A1: Additional results on triple difference specification

	(1)	(2)	(3)	(4)	(5)
	Log of per capita per day calories from rice and wheat	Log of per capita per day calories from items other than rice and wheat	Log of per Capita per Day calories from pulses, fruits, vegetables and animal source	Log of per capita per day protein intake	Log of per capita per day fat intake
Ln(PRICE) × RURAL × FOOD	0.028	0.107***	0.139***	0.049**	0.157***
	(0.018)	(0.037)	(0.042)	(0.021)	(0.037)
Controls	No	No	No	No	No
Observations	2456	2456	2456	2456	2456
Adjusted R2	0.694	0.647	0.664	0.608	0.749
F statistic	123.2	69.7	52.8	39.5	64.0
Ln(PRICE) × RURAL × FOOD	0.035*	0.096***	0.123***	0.049**	0.143***
	(0.019)	(0.037)	(0.041)	(0.021)	(0.036)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	2452	2452	2452	2452	2452
Adjusted R2	0.706	0.667	0.686	0.627	0.765
F statistic	45.4	28.4	21.5	17.7	28.9

Notes: All specifications include district fixed effects and time dummies. Control variables 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.