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The distributional effect of a large rice price increase on welfare and poverty in Bangladesh*

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This paper studies the distributional effect of a sharp rice price increase on welfare and poverty in Bangladesh. We employ household consumption data and include the indirect effect of price responses to estimate the welfare loss. Our findings suggest that the estimated welfare effect can be misleading if household responses to rice consumption and production are ignored. This study further supports the hypothesis that the poor are the main victims of such a shock. Our examination also indicates that a higher rice price may increase or decrease the poverty head-count ratio, depending on the choice of the poverty line, but worsens the country's poverty situation when it is measured by the per capita consumption gap. Our analysis reveals that the government can play a central role to prevent and mitigate such shocks, particularly in the medium to long run. On the methodological side, we observe that consumption provides a more consistent outcome across different methods of analysis than household income.

Key words: distributional effect, poverty, rice price increase, semiparametric regression, welfare.

1. Introduction

The world recently experienced a severe increase in food prices. Between January 2007 and April 2008, for example, the price of coarse rice in Bangladesh and wheat in Afghanistan nearly doubled. A similar increase was also observed for staple foods in most of the food importing low-income countries. The global price increase was particularly severe for rice and 294 per cent between January 2004 and June 2008, followed by maize (147 per cent) and wheat (61 per cent; World Bank, 2010). A large increase in the prices of staple foods, even if temporary, may force low-income households to adjust their food consumption with potential negative effects on physical and mental health and may even generate social unrest (D'Souza and Jolliffe 2012, 2014; Warr 2014; Bellemare 2015).

The net effect of the price increase in staple foods on household welfare is the sum of the direct effect as well as the effects through labour market,

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change in other prices and transfers.[1] While transfer income is usually exogenous, a common practice in such analysis is to ignore the effect of higher food prices on the prices of other consumption items primarily due to the difficulty in identifying the cross-price effect (Vu and Glewwe 2011; Minot and Dewina 2015). Therefore, a welfare analysis requires information on the direct effect as well as the indirect effect through the labour market (Ferreira *et al*. 2013). The problem lies in the fact that empirical estimates exhibit substantial variations in the long-run response (elasticity) of the wage rate with respect to the food price (Aksoy and Hoekman 2010). For instance, Ravallion (1990), using a partial equilibrium framework, found the labour market channel important in explaining the welfare loss of a higher food price in Bangladesh. In contrast, using time series data from 1976/1977 to 1998/1999, Rashid (2002) found an insignificant effect of the rice price on agricultural wages in Bangladesh. A general equilibrium framework may account for relevant factors. However, relying on complex assumptions may drive the results (Wodon and Zaman 2010). As a consequence, simulation, combined with the use of household survey data, is a preferred practice for the welfare analysis of price shocks.

Simulation-based studies on the welfare effect of higher food prices typically employ the first-order approximation of welfare loss and ignore households' adjustment of consumption and production, which is captured by the second-order approximation (Ivanic and Martin 2008; Attanasio *et al*. 2013; Ferreira *et al*. 2013). Such studies rely on income for the estimation of the welfare loss and routinely investigate the relationship between the two. Studies also focus on the effect of higher food prices on poverty (Chen and Duclos 2011; Mghenyi *et al*. 2011). A common practice in such studies, which compare poverty situations before and after the price shock, is to rely on income for such comparisons.

Against this background, this paper employs household survey data to study the distributional effect of a strong rice price increase on welfare and poverty in Bangladesh. Bangladesh is particularly interesting in this context because it is characterised by a large proportion of low-income households (BBS, 2012). The country has a high consumption share and a low cross-price elasticity of rice, indicating its importance in household consumption.[2] While the majority of households in the country are net rice buyers, a significant proportion of low-income households are associated with growing rice. Therefore, an empirical investigation is essential to confirm the effect on low-income households. Such investigations, despite limiting the focus towards

[1] Higher food prices, for example, may boost the demand for services and nontradables by households whose incomes rise (Aksoy and Hoekman 2010). The substitution of nonfood items for food, which is now relatively costly, may contribute to increasing nonfood prices and stimulate nonfarm household incomes.

[2] With respect to wheat, the second largest food item in consumption in Bangladesh, the cross-price elasticity of rice (coarse type) demand is estimated at 0.01 (Islam *et al*. 2007).

the direct effect of rice price increases, may assist in improving policies aimed to support the poor in low-income countries.

Our analysis provides a more precise estimate of welfare loss in two ways. First, we include the second-order approximation which, relying on earlier parameter estimates like the price elasticity of rice demand/supply, accounts for the responses to price changes. Second, we employ consumption, which is more appropriate than the use of income as the latter is typically prone to measurement error in household surveys.[3] We also investigate the relationship between welfare effects and consumption to test which is a better measure of well-being than income (Ravallion 1992; Meyer and Sullivan 2012). Using consumption, on which the usual poverty estimates rely on, also improves the poverty analysis in our study.

Our empirical analysis indicates that accounting for responses in household production and consumption is important in examining the welfare effect. Relying on nonfarm income as an instrument to address endogeneity, our investigation confirms a typical quadratic relationship between consumption and welfare loss. Finally, a higher rice price may either increase or decrease the poverty head-count ratio (HCR), depending on the choice of the poverty line, but unambiguously worsens the per capita consumption gap throughout the country.

This paper contributes to the literature on higher food prices. On the empirical side, we provide additional evidence for a quadratic relationship between the welfare effect and consumption. On the methodological side, our findings indicate that the use of consumption and including the second-order effect may generate more precise estimates of the welfare loss compared to estimates based on income or excluding the second-order effect. Additionally, we find that substituting consumption for income appears to provide results that are more consistent with our expectations.

2. Data

Our analysis uses data from the 2010 Bangladesh Household Income and Expenditure Survey (HIES). The HIES is a repeated cross-sectional household survey that generates nationally representative socioeconomic information at the household level. The survey includes detailed information on household production, income and consumption, essential to analyse the effect of price hikes on household welfare. The total number of households in the survey is 12,240 (BBS, 2012). We exclude 379 implausible observations with nonpositive income or rice consumption from our sample. Thus, our analysis relies on a sample of 11,861 households.

[3] Household income suffers from measurement error to a greater extent than consumption. Reasons include a lack of knowledge about assets and returns, the measurement of income from self-employment, the presence of agricultural households consuming their own products and the seasonality of income. See Deaton (1997) for detail.

Geographical factors influencing crop production like rainfall and soil quality are mainly determined by agro-ecological zones (Quddus 2009). As districts in Bangladesh belong to a single agro-ecological zone, our models include district fixed effects. However, differences in important socioeconomic variables across regions motivate us to conduct the analysis separately for each division. Table 1 presents the proportions of rice growers and sellers together with information on household consumption and income across divisions. Because input costs for a particular agricultural product are difficult to identify and vary with the methodology used, we use the gross value of harvested rice to calculate incomes from rice production. Interestingly, rice consumption and prices are similar across divisions, indicating similar preferences and a well-integrated rice market throughout the country (see Tables A1 and A2 in Supporting information). In our data, the expenditure share on rice decreases with income/consumption, indicating a larger negative impact on low-income households in the country (data not presented).

Income data in household surveys usually suffer from measurement error, which is typically severe in agrarian economies (Bhalotra and Attfield 1998). Consistent with such arguments, we observe a significant number of households with income lower than consumption in our data. For example, at the 10th percentile, consumption is 125 per cent higher than income in the Barisal division (see Table A1 in main text). In the division, the respective numbers are 52 and 27 per cent at the 25th and 50th percentiles. A similar pattern is observed for other divisions and for the entire country. An income lower than consumption for such a significant proportion of households appears implausible and indicates that our income data can be quite unreliable.

3. Methodology

3.1 Welfare loss estimation

Considering savings as a good that is consumed in the future (i.e. to support future consumption), the effect of a price increase on welfare may be explained by an indirect utility function v, with household income, x, depending on the rice price p_r

$$u_i \equiv v_i(p_i, x_i) = v_i[p_i, y_i + \pi_i(p_{ir})] \tag{1}$$

where for each household i, p_i is the price vector (not including the rice price p_r), y_i is nonrice income, and π_i is income from rice farming.

Empirical studies widely use two monetary measures of welfare change, equivalent variation (EV) and compensating variation (CV). EV describes the change in the consumer's net wealth that would have a welfare impact equivalent to the impact of the price change. CV describes the amount of

Table 1 Means (SD in parenthesis) of analysis sample (weighted)

	Divisions							
	Barisal	Chittagong	Dhaka	Khulna	Rajshahi	Rangpur	Sylhet	Bangladesh
Farming Status								
Rice farmer	0.28	0.30	0.26	0.41	0.43	0.52	0.36	0.35
Nonrice farmer	0.72	0.70	0.74	0.59	0.57	0.48	0.64	0.65
Net rice seller	0.05	0.09	0.08	0.14	0.17	0.22	0.10	0.12
Self-sufficient in rice	0.11	0.09	0.08	0.13	0.11	0.13	0.10	0.10
Net rice buyer	0.84	0.83	0.84	0.73	0.72	0.65	0.81	0.78
Finance (in Tk.)								
Household consumption	9,814	14,520	11,748	9,547	9,326	8,386	12,183	11,147
	(8,248)	(13,297)	(10,054)	(7,486)	(7,282)	(6,472)	(9,581)	(9,840)
Household rice consumption	1,854	1,836	1,815	1,779	1,731	1,887	2,419	1,846
	(887)	(990)	(938)	(861)	(921)	(932)	(1,431)	(974)
Household income	10,355	17,017	14,285	10,228	8,787	7,616	13,209	12,450
	(13,134)	(30,083)	(20,218)	(48,768)	(12,938)	(9,433)	(21,144)	(25,714)
Household rice income	535	679	656	1,016	1,323	1,785	1,131	945
	(1,441)	(1,853)	(1,958)	(2,124)	(3,378)	(3,520)	(2,977)	(2,486)
N	940	2,165	3,452	1,694	1,492	1,267	851	11,861

Notes Farming status indicates their proportions in the sample. We define self-sufficient households as those who produce 60–125 per cent of their consumption of rice.

income compensation required to keep the consumer as well off after the price change as before (Mas-Colell *et al.* 1995). We employ the latter, which relies on the final price vector for estimating changes in welfare and is therefore more appropriate for an ex post analysis.

Assuming households are facing the same price and denoting mi as the proportional change in household *i*'s welfare, a second-order approximation and standard mathematical manipulation yields[4]

$$m_i = \left(s_i^s - s_i^d\right)\lambda + 0.5\left[s_i^s \xi_i^{ps} - s_i^d \xi_i^{pd}\right]\lambda^2 + 0.5\left\{\left(R_i - \xi_i^{yd}\right)\left[(s_i^d)^2 - 2s_i^d s_i^s\right] + R_i (s_i^s)^2\right\}\lambda^2, \quad (2)$$

where for each household i, s^s and s^d denote the value of the rice harvest and consumption as a proportion of total income, respectively; λ denotes $(p^1 - p^0)/p^1$; ζ^{ps} ζ^{pd}, ζ^{yd} and R_i denote the elasticity of supply, the elasticity of demand, the income elasticity and the coefficient of relative risk aversion (CRRA), respectively.

The first part on the right-hand side of Equation (2), $\left(s_i^s - s_i^d\right)\lambda$, constitutes the first-order effect, whereas the remaining parts form the second-order effect. The first-order effect indicates the direct effect in which net rice seller households benefit from higher sale revenue while net rice buyer households lose from higher expenditure on rice. On the other hand, the second-order effect indicates the indirect effect, specifically the substitution of rice with other items in consumption and the substitution of rice growing for other activities in production. When the rice price increases, a higher supply elasticity will positively affect welfare of seller households as the benefit increases with supply. At the same time, a higher demand elasticity of rice (absolute value) will reduce the welfare loss through reduction in consumption. In contrast, a higher income elasticity offsets welfare gains (losses) of net rice sellers (buyers) who consume more (less) rice due to increased (decreased) income. Therefore, for rice seller households, a highly elastic supply and demand combined with a low-income elasticity for rice demand will provide large impact on welfare in the second order. For buyer households, who experience a reduction in real income due to the price shock, a high price and income elasticity of rice demand will do the same.

Based on actual household data and using Equation (2), we simulate the welfare loss of an increase in the rice price. To obtain a more precise estimate of the welfare loss, we define *ss* and *i* as value of the rice harvest and consumption as a proportion of total consumption (rather than income), respectively. Furthermore, we use a value of 0.30 for the supply elasticity and 0.45 for the demand elasticity. In case of the income elasticity, we assume a value of 0.60 for rural and 0.40 for urban households, while the value of CRRA (which varies with wealth ownership) is assumed to be 1.0. The

[4] See Mghenyi *et al.* (2011) and Minot and Dewina (2015) for detail.

employed numbers are similar to those used in earlier studies (World Bank 2010). Our entire analysis is based on a 50 per cent rice price increase which, while not unprecedented, is useful to demonstrate the contribution of the second-order effect.

3.2 Distribution of the welfare effect

Examining whether the welfare loss is related to a household's financial condition is important from a policy perspective. A specific aim of such an examination is to identify whether the poor lose from shocks. This allows national governments to take necessary measures to protect them. A solid understanding about the association of such impacts with household's financial strength also allows governments to play a role in improving national distributions.

Studies typically employ income as an indicator of households' financial condition (Mghenyi *et al*. 2011). However, a household's financial status is better reflected in its consumption compared to income. Consumption captures flows from the ownership of durable goods, the insurance value of government programs, access to credit and the accumulation of assets, while income cannot (Meyer and Sullivan 2012). For certain life events or for changes in savings or debt, compared to income, consumption is more stable over time and therefore constitutes a better measure of welfare and economic well-being of households (Friedman 1957). Therefore, we examine the relationship between the welfare effect and consumption. Since larger households may have a bigger financial outlay, we employ adult equivalent consumption by using an equivalence scale for Bangladesh (Hasan 2012).

Nonparametric and semiparametric techniques are particularly popular in examining the distribution of the welfare loss (Mghenyi *et al*. 2011). Our identifying assumption is that the change in proportionate welfare depends linearly on socioeconomic variables but nonlinearly on consumption. As a result, we use the following SP model

$$m_i = F(x_i) + Z_i\beta + u_i \tag{3}$$

where for each household i, m_i represents proportionate welfare change, x_i represents (the log of) adult equivalent consumption, Z_i is a vector that includes regional, demographic and socioeconomic variables entering the model linearly, β is a vector of parameters, F is an unknown function, and the error term is $u_i \sim NID(0, \sigma^2)$.

Important explanatory variables in our model include agricultural input expenditure, household size, age and gender of the household head, urban/rural status, the presence of a disabled member and the socioeconomic status of a household. Socioeconomic status in our model is proxied by a households' electricity connection status, roof construction materials and agriculture asset value. We additionally control for data collection time and whether a household experienced a natural disaster. As returns to education can be nonlinear, we consider dummies of educational categories for household heads/spouses (see Table A3 in Supporting information). Means and SDs of important independent variable are presented in Table 2.

Unfortunately, the proportionate welfare loss and consumption may be jointly determined.[5] Engel curve estimation has a long history of substituting income with consumption due to the measurement error in the former. Interestingly, studies routinely employ income as an instrument for consumption, which suffers from endogeneity in such models (Blundell *et al*. 1998, 2007). Income, which includes farm income from rice, does not satisfy the exclusion restriction in our case. Nonfarm income, in contrast, satisfies the exclusion restriction and has high correlation with consumption (coefficient 0.47). Therefore, we employ nonfarm income as an instrument to control for the endogeneity of consumption. For that we follow the control function approach, outlined in Newey *et al*. (1999) and widely used in empirical studies (Blundell *et al*. 1998, 2007), which involves the generation of residuals through the nonparametric regression of the endogenous variable on instruments and the use of the residuals as an additional covariate in the SP model. This methodology generates consistent estimates of the covariates, while the significance of the residuals provides a test of endogeneity.

3.3 The effect on poverty

In addition to the effect on welfare, policymakers are often interested in the effect on poverty. To study this effect, we employ a poverty measure proposed in Foster *et al*. (1984; FGT from here on). Specifically, let F: $R_+ \rightarrow [0,1]$ represent the distribution of ordered real income such that $F(z)$ is the proportion of the population, p, with an income below or equal to z. Then for each $\alpha \geq 1$, a poverty index P_α is given by

$$P_\alpha(F, z) = \frac{1}{Z^{\alpha-1}} \int_0^{F(z)} \left[z - F^{-1}(p)\right]^{\alpha-1} \mathrm{d}p, \tag{4}$$

where the measure P_1 is the poverty HCR, P_2 is the per capita income gap, and P_3 is the weighted sum of income shortfalls of the poor (Foster and Shorrocks 1988a).

Uncertainty in comparing the extent of poverty arises from the disagreement about poverty lines, z, or disagreement about the poverty measures, P_α (Fields 2002). Therefore, some broader criteria are useful for ordering distributions. We follow Foster and Shorrocks (1988a,b) in which the poverty

[5] For instance, a higher rice price may simultaneously affect consumption and welfare.

Table 2 Means (SD in parenthesis) of independent variables (weighted)

	Division							Bangladesh
	Barisal	Chittagong	Dhaka	Khulna	Rajshahi	Rangpur	Sylhet	
Agricultural input expenditure	566	832	875	2,201	1,879	1,573	871	1,225
	(1,373)	(2,615)	(3,189)	(4,870)	(3,859)	(3,178)	(2,121)	(3,364)
Agricultural asset value	7,461	2,766	2,408	7,796	7,800	5,351	6,205	4,691
	(78,172)	(22,473)	(16,318)	(28,454)	(43,959)	(33,354)	(29,838)	(32,995)
Family size	4.57	4.97	4.38	4.28	4.15	4.27	5.51	4.50
	(1.82)	(2.05)	(1.77)	(1.65)	(1.70)	(1.67)	(2.47)	(1.87)
Age of household head	48.06	46.44	45.23	45.54	44.90	45.50	47.57	45.76
	(14.54)	(14.23)	(13.76)	(13.32)	(13.91)	(14.01)	(14.16)	(13.94)
Female headed	0.15	0.21	0.14	0.09	0.11	0.10	0.18	0.14
Urban	0.17	0.27	0.42	0.24	0.18	0.13	0.16	0.28
Disabled member	0.29	0.24	0.26	0.29	0.36	0.31	0.28	0.28
Lean Season	0.16	0.16	0.22	0.18	0.16	0.21	0.13	0.19
Disaster	0.14	0.06	0.11	0.24	0.08	0.22	0.10	0.13
Electricity	0.41	0.61	0.68	0.55	0.52	0.30	0.47	0.56
Brick roof	0.05	0.12	0.15	0.11	0.05	0.03	0.11	0.11
CI roof	0.91	0.76	0.81	0.70	0.90	0.90	0.79	0.81
Wooden roof	0.02	0.01	0.01	0.10	0.03	0.00	0.02	0.02
Bamboo roof	0.02	0.11	0.03	0.07	0.01	0.07	0.08	0.05
Other roof	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.01
N	940	2,165	3,452	1,694	1,492	1,267	851	11,861

Note For dummy variables, we only present proportions.

ordering P_α is such that for two distributions F and G with the same population size n

$$\begin{aligned} &FP_\alpha G \text{ if and only if } P_\alpha(F;z) \leq P_\alpha(G;z) \text{ for all } z \in R_{++} \\ &\text{and } P_\alpha(F;z) < P_\alpha(G;z) \text{ for some } z \in R_{++}, \end{aligned} \tag{5}$$

where $F\ P_\alpha\ G$ indicates that distribution F implies a lower poverty level than distribution G with respect to the poverty index P_α for all possible poverty lines. In other words, distribution F 'poverty dominates' distribution G, for a given α.

To compare poverty before and after the rice price increase, instead of income, we compare actual and counterfactual consumption. In generating the latter, we adjust the actual consumption with the proportionate welfare loss. We start with the first order, check whether one distribution 'poverty dominates' the other, and repeat the analysis with higher order if no poverty dominance is found. We additionally investigate the effect of the higher rice price on the poverty HCR using official poverty lines in Bangladesh.

4. Results and discussion

4.1 Estimated welfare loss

Means and standard deviations of households' first-order (Δ_1), second-order (Δ_2) and total proportionate welfare losses (m) across divisions are presented in Table 3. For all divisions, Δ_1 and Δ_2 are significantly different from zero. The means of Δ_1 in Rajshahi and Rangpur, which have higher proportions of rice-producing households, are lower than those of other divisions. The second-order effect, which accounts for a household's adjustment of consumption and production pattern, compensates the welfare lost in the first order. While this holds true for all divisions, the ratio of Δ_2 to Δ_1 is

Table 3 High rice price and households' proportionate welfare loss (weighted)

Division	1st order (Δ_1)		2nd order (Δ_2)		$\bar{\Delta}_2/\bar{\Delta}_1$ (%)	Total	
	Mean	SD	Mean	SD		Mean	SD
Barisal	−0.0884	0.0717	0.0237	0.0148	26.87	−0.0646	0.0745
Chittagong	−0.0533	0.0693	0.0174	0.0193	32.70	−0.0359	0.0801
Dhaka	−0.0682	0.0951	0.0240	0.0383	35.23	−0.0442	0.1214
Khulna	−0.0595	0.1173	0.0304	0.0524	51.07	−0.0291	0.1563
Rajshahi	−0.0496	0.1715	0.0383	0.2439	77.21	−0.0113	0.3898
Rangpur	−0.0443	0.1696	0.0452	0.0661	101.90	0.0008	0.2240
Sylhet	−0.0738	0.1164	0.0303	0.0607	41.06	−0.0435	0.1637
Bangladesh	−0.0607	0.1185	0.0284	0.0974	46.71	−0.0324	0.1926

Notes $\Delta_1 = \left(s_i^s - s_i^d\right)\lambda$ and $\Delta_2 = 0.5\left[s_i^s\xi_i^{ps} - s_i^d\xi_i^{pd}\right]\lambda^2 + 0.5\left\{\left(R_i - \xi_i^{yd}\right)\left[(s_i^d)^2 - 2s_i^d s_i^s\right] + R_i(s_i^s)^2\right\}\lambda^2$. The total proportionate welfare loss $\approx \Delta_1 + \Delta_2$. $\bar{\Delta}_1$ and $\bar{\Delta}_2$ are divisional means.

relatively large for Rajshahi and Rangpur. As a result, the aggregate welfare loss remains insignificant in case of Rangpur at the 5 per cent and Rajshahi at the 1 per cent level. Thus, our results indicate that reliance on the first-order effect overestimates the welfare effect even more for the case of rice-producing regions. Note that the conventional way of using income generates levels of Δ_2 which is implausibly higher than Δ_1 (see Table A4–A8 in Supporting information, for estimates under different settings).

An important implication of our analysis is that including the second-order effect can alter the rankings of the welfare loss. For example, the first-order effect indicates Khulna will be affected more than Chittagong while including the second order reverses the scenario. Therefore, the use of geographical targeting, relying exclusively on the first-order effect, can be inappropriate to compensate for the welfare loss. This is particularly applicable when the duration of the price shock is longer, as people take time to adjust their consumption and production pattern.

Supply side measures like the reduction of the import duty and the agricultural subsidy can stabilise the domestic rice price and thus offset the effect on welfare in the short run. In the medium to long run, public investment in agricultural research and rural infrastructure may also contribute to both preventing such shocks (through a permanent increase in production) and mitigating the effect of shocks on welfare (through increasing response of supply; Warr 2014). Measures to increase the elasticity of demand can also be useful. For example, a campaign for more reliance on potato, which is a relatively cheaper food in the country, might contribute in such situations.

4.2 The distribution of the welfare effect

Our SP regression results indicate that m is positively related to household's agricultural input expenditure and negatively related to the family size, female head, urban/rural status of their usual place of residence and disability of a household member (see Table A9 in Supporting information). Input expenditure may indicate the farm size and the use of technology in farming (e.g. growing of HYVs), which may positively affect welfare. Families with larger size and urban households, who are more likely to be net rice buyers, lose with higher rice prices. Households with a female head or a disabled member suffer a loss in welfare that cannot be explained otherwise. The occurrence of a disaster, seasonality of data collection and household's socioeconomic status also appear important in our models. An important point in our results is that the residuals, used to control for the endogeneity of consumption in our models, are significant in two cases (at the 5 per cent level) indicating consumption to be endogenous in our models.

To verify the type of relationship between welfare change and consumption, we present the SP regressions together with quadratic fits (see Figure A1 in Supporting information). As a visual inspection is not conclusive, we start with testing a linear relationship between the two. Following Hardle and Mammen (1993), for each case we investigate whether the SP fit can be approximated by a linear fit. The test results indicate a nonlinear relationship between the welfare effect and consumption in five out of seven cases (tests conducted at the 5 per cent level, results not presented).

Next, we test whether the change in welfare and consumption has a quadratic relationship. The test results, presented in column 3 of Table 4, indicate that we cannot reject the null hypothesis in six out of the seven cases at the 5 per cent and all seven at the 1 per cent level. Using consumption, either household level or adjusted for per capita or adult equivalence (by OECD/square root of family size scale), provides similar results (Table 4). Thus, our results confirm those of Deaton (1989), who using socioeconomic survey data for 1981–1982, finds that the rice price increase in Thailand benefits the rural middle class. Failing to reject the quadratic fit can be a result of several facts. First, richer households that are associated with agriculture benefit from selling rice at a higher price. Second, wealthier households that are not associated with farming rice may only lose marginally as their consumption share on rice is usually low. Third, low-income households are hit hard as they exhibit a larger share of rice in consumption.

Interestingly, we cannot reject a quadratic relation between welfare change and adult equivalent income for any of the seven divisions. Again, relying only on the first-order effect rejects the quadratic fit for three out of the seven divisions and indicates a higher order relation between the two. However, we put less emphasis on those results because of the imprecision on the estimates (see Tables A9–A22 in Supporting information, for results under different settings).

A quadratic relation between the welfare effect and consumption indicates that expenditure groups that are in the middle typically suffer less. This highlights the need for intensified support for the poor in the face of a food price shock. Policy makers need to consider the fact that the poor households

Table 4 Hardle and Mammen test results: *P*-value

Division	Consumption		With consumption equivalised by		
	Household (1)	Per capita (2)	SP scale (3)	OECD scale (4)	SRFS scale (5)
Barisal	0.12	0.68	0.64	0.24	0.18
Chittagong	0.30	0.18	0.30	0.28	0.22
Dhaka	0.00	0.00	0.06	0.00	0.00
Khulna	0.14	0.02	0.56	0.06	0.16
Rajshahi	0.42	0.50	0.14	0.28	0.52
Rangpur	0.32	0.00	0.04	0.02	0.00
Sylhet	0.24	0.64	0.58	0.20	0.28
Bangladesh	0.00	0.00	0.00	0.00	0.00

Notes H_0: Nonparametric fit can be approximated by a parametric adjustment of order 2, H_1: H_0 is false. A low *P*-value rejects H_0. For detail, see Hardle and Mammen (1993).

are distributed throughout the country while the rural poor are usually excluded from support (Pinstrup-Andersen 2014).

4.3 The effect on poverty

Our analysis provides no evidence of first-order poverty dominance of one distribution over the other, for any division or for the whole country when we consider poverty lines of up to Tk. 5,000 (that corresponds to 2.5–4 times the official poverty lines in Bangladesh).[6] Critical values, at which price shocks improve the poverty HCR, are lower for rice-producing divisions compared to other divisions. This is due to the presence of a higher proportion of surplus rice farmers who benefit from a higher rice price. A higher rice price would thus improve the poverty HCR in those regions for a comparatively lower poverty line.

The second-order poverty dominance indicates that, with the price shock, the poverty situation worsens in the country and in all divisions except Rangpur.[7] Thus, if we consider the per capita consumption gap as the measure of poverty, while the increase in the rice price unambiguously makes the other divisions worse off, the poverty situation in Rangpur improves for any poverty line above the critical value (around Tk. 3,000). Given that the official poverty lines for Rangpur range between Tk. 1,223 and 1,312, we may conclude that the price shock also worsens the poverty situation in the division for a reasonable range of poverty lines (see Figure A4–A13 in Supporting information, for poverty dominance graphs under different settings). Thus, the poverty analysis confirms our earlier finding that poor households are the most hard-hit in the presence of higher rice prices.

Finally, when we use the official poverty lines for each region, we find that a higher rice price increases the poverty HCR in all divisions (see Table A23 in Supporting information). A similar result for divisions with higher proportions of rice growers may seem paradoxical given that the critical values, at which the distributions with a price shock poverty dominate the distributions without any shock, are lower for them. The data reveal that a lot of households have a consumption level that is close to the poverty line. As a result, a small reduction in consumption now redefines a significant proportion of households as poor. This result confirms the dependency of

[6] See Figure A2 (Supporting information), where the difference between the two poverty incidence curves (cumulative distributions of the population at each poverty line) is given on the vertical axis, while the horizontal axis indicates the poverty lines. Any positive value in the vertical axis indicates that the distribution with higher rice price results in a higher poverty HCR at the corresponding poverty line and vice versa.

[7] See Figure A3 (Supporting information), where the vertical axis denotes the difference between the FGT indices, while the horizontal axis indicates the poverty lines. Any positive value in the vertical axis indicates that a higher rice price results in a higher per capita consumption gap at the associated poverty line. As we employed consumption for comparing poverty, the per capita income gap measure refers to the per capita consumption gap in our case.

poverty HCR on the poverty line used. In particular, it confirms that we may obtain a completely different conclusion regarding the incidence of poverty, depending on the poverty line we employ. Therefore, using poverty lines when assessing the successes or failures of the public programs may provide a wrong signal to policymakers.

Repetition of the previous analysis with household income leads to a similar conclusion but demonstrates a higher variability in the difference between the two cumulative distributions. An alternative analysis that relies only on the first-order effect provides lower critical values at which poverty HCR improves with the price shock. More importantly, it fails to capture the effect on the rice-producing regions when we consider the per capita consumption gap measure of poverty.

We consider a number of robustness checks to confirm our findings. For example, an analysis with smaller price changes (25 per cent) produces a proportionately lower second-order effect but reveals a similar conclusion. Our results are also insensitive to reasonable modifications (± 10 per cent) of the CRRA. Furthermore, using models that include the rice price (to control for the endogeneity of consumption) or principal component analysis (to control for the socioeconomic status of households) also provides similar outcomes. We also conduct the entire analysis separately on rural households and arrive at the same conclusions. However, biases in analysis which relies either on income or on the first-order effect supports our argument that the analysis of welfare loss or poverty can be improved through using consumption and including the second-order effect.

5. Conclusion

This paper studies the distributional effect of a sharp rice price increase on welfare and poverty in Bangladesh. We find that the use of consumption and including the second-order effect improves the estimates of welfare loss. Our analysis confirms that low expenditure households, compared to the middle of the distribution, experience proportionally greater loss in welfare with such price shocks. We also find that changes in the poverty HCR across regions are not invariant to the choice of poverty lines but the per capita expenditure gap indicates that price shocks worsen the poverty situation throughout the country. It appears that employing consumption, compared to income, is more appropriate for comparing poverty situations associated with programs and policies. The inclusion of the second-order effect of a price change may also improve policy decisions.

While poverty estimates that rely on official poverty lines fail to indicate the regional difference in the effect of the rice price shock, our findings with poverty dominance indicate that regions with higher proportions of rice-growing households suffer less. Nonetheless, rice price shocks unambiguously worsen poverty situations throughout the country. Such findings confirm the results with estimated welfare losses. As consumption patterns are assumed similar across regions (with reasonable rural/urban variation), the supply elasticity plays the primary role in offsetting the welfare loss in regions with a higher proportion of rice-growing households. A higher price offers a better incentive for rice growers who, in the medium to long term, shift from other agricultural and nonagricultural activities towards rice growing to increase their welfare. Thus, the government can play a major role by removing the supply bottlenecks (e.g. through the provision of agricultural loans and inputs). Increasing supply responses by providing incentives (e.g. price incentives) can also play a key role. Promoting diet diversification in the long run, by increasing the price elasticity of rice demand, may also contribute to mitigating such effects.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table A1. Monthly household consumption of rice (in kg) by division (weighted)

Table A2. Rice price (BDT/kg) by division (weighted)

Table A3. Proportion of households for each educational category (weighted)

Figure A6. First-order poverty dominance with CRRA 1.1
Figure A7. Second-order poverty dominance with CRRA 1.1
Figure A8. First-order poverty dominance with first-order effect
Figure A9. Second-order poverty dominance with first-order effect
Figure A10. First-order poverty dominance with income
Figure A11. Second-order poverty dominance with income
Figure A12. First-order poverty dominance with 25 per cent price change
Figure A13. Second-order poverty dominance with 25 per cent price change

Appendix

Table A1 Percentiles of household income and consumption

	Divisions							
	Barisal	Chittagong	Dhaka	Khulna	Rajshahi	Rangpur	Sylhet	Bangladesh
Percentiles of household income								
1	229	868	512	331	290	333	464	406
5	1,017	1,994	1,500	1,100	865	1,131	1,575	1,332
10	1,790	3,000	2,433	1,757	1,645	1,905	2,522	2,120
25	3,686	5,133	4,702	3,025	3,000	3,044	4,235	3,800
50	6,287	9,631	8,770	5,355	4,983	4,793	7,417	6,997
75	12,035	19,250	16,885	9,767	9,350	8,764	14,725	13,933
90	21,747	35,106	31,667	17,873	19,147	15,567	27,525	26,667
95	33,618	52,358	45,498	27,300	29,835	22,200	41,667	39,660
99	62,975	117,650	82,500	51,018	59,226	46,118	84,833	78,333
Percentiles of household consumption								
1	1,472	3,117	1,943	1,459	1,642	1,587	1,856	1,814
5	3,069	4,917	3,511	3,067	2,760	2,639	3,870	3,273
10	4,027	6,018	4,405	3,857	3,682	3,384	4,686	4,170
25	5,609	8,233	6,095	5,384	5,234	4,787	6,478	5,871
50	8,009	11,177	8,981	7,619	7,261	6,587	9,429	8,634
75	11,376	16,583	13,859	11,231	10,966	9,772	14,487	13,016
90	16,656	24,641	21,987	16,780	17,058	14,720	22,664	20,354
95	21,169	32,813	29,471	22,899	21,208	19,899	29,048	26,592
99	43,180	69,487	52,452	38,927	41,088	37,053	49,857	49,340

Note Number of observations 11,861.