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FOOD PRICES, WAGES, AND WELFARE IN RURAL INDIA

HANAN G. JACOBY*

With soaring food prices in recent years has come alarm about rising poverty in the developing world. Less appreciated, however, is that many of the poor in agricultural economies may benefit from higher wages. This study finds that wages for manual labor in rural India, both within and outside agriculture, rose faster in districts growing more of those crops with large producer price run-ups over the 2004–2009 period. Based on a general equilibrium framework that accounts for such wage gains, rural households across the income spectrum are found, contrary to more conventional welfare analysis, to benefit from higher agricultural prices. (*JEL* Q17, Q18, F14)

I. INTRODUCTION

Elevated food prices over the last half decade have provoked a rash of government interventions in agricultural markets across the globe, often in the name of protecting the poor. Of course, it is well recognized that many poor households in developing countries, especially in rural areas, are also food producers and hence net beneficiaries of higher prices.[1] Even so, there is another price-shock transmission channel, potentially more important to the poor, which has received far less attention in the literature: rural wages.[2] To what extent do higher agricultural commodity prices translate into higher wages? For rural India, home to roughly a quarter of the world's poor (those living on less than $1.25/day), the answer to this question can have momentous ramifications. After all, the vast majority of India's rural population relies on the earnings from their manual labor, most of which is devoted to agriculture.[3] Any thorough accounting of the global poverty impacts of improved terms of trade for agriculture must, therefore, confront rural wage responses in India.

Textbook partial equilibrium analysis (e.g., Deaton 1989; Singh et al. 1986) considers only the direct income effect of a price change on household welfare, which, to a first order, is proportional to the household's production of the good net of consumption. While this approach is useful for understanding the very short-run welfare impacts of price shocks, it ignores the inevitable labor market repercussions of persistent price changes. Insofar as higher agricultural prices lead to higher wages, then, there are three channels of general equilibrium welfare effects: (1) higher labor income; (2) lower capital (land) income due to higher labor costs; and (3) higher prices for nontradables. To quantify these effects and obtain the full welfare impact of changes in agriculture's terms of trade, one needs, first and foremost, an estimate of the relevant wage-price elasticity.

A few existing studies estimate wage-price elasticities using long aggregate time series data from countries that were effectively autarkic in

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1. Ivanic, Martin, and Zaman (2012), Wodon et al. (2008), and World Bank (2010) provide recent multi-country assessments of the welfare impacts of food price increases accounting for such producer gains. See also the study by de Janvry and Sadoulet (2009) for an analysis along these lines using Indian data.

2. Ravallion (1990) surveys the debate in development on the nexus between the intersectoral terms of trade and poverty. Sah and Stiglitz (1987) provide an early theoretical treatment. In their cross-country study, Ivanic and Martin (2008) incorporate price-induced changes in wages for unskilled labor derived from nation-level versions of the GTAP computable general equilibrium model.

3. Indeed, rising wages are seen as the major driver of rural poverty reduction in recent decades (Datt and Ravallion 1998; Eswaran et al. 2007; Lanjouw and Murgai 2009).

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the main food staple (pre-1980s Bangladesh in Boyce and Ravallion 1991; the Philippines in Lasco, Myers, and Bernsten 2008), thus raising serious endogeneity issues. Alternatively, Porto (2006) estimates the wage impacts of changes in traded goods prices using several years of repeated cross-sectional household survey data from Argentina. In the case of agricultural goods, which must somehow be aggregated, Porto creates a price index using household expenditure shares as weights (as does Nicita 2009). To appreciate the issue involved with this strategy, consider an extreme example. Suppose that a country is a net exporter of cotton and net importer of wheat, its sole consumption item. Since the cotton industry is a major demander of labor, a rise in the cotton price should lead to higher wages (and, ultimately, higher welfare); conversely, a rise in the wheat price should have little impact on wages (i.e., only through an income effect on labor supply). Hence, in this scenario, the correlation between changes in wages and changes in the *expenditure* share weighted agricultural price index may well be close to zero. Clearly, however, this is not the relevant wage-price elasticity for our purposes. Indeed, as I show in the context of a formal general equilibrium trade model, the relevant elasticity is one based on a *production* share weighted agricultural price index.[4]

Even with the correct wage-price elasticity estimate in hand, one must still wrestle with what to do about non-traded goods. One option is to simply ignore them; that is, by assuming either that they constitute a negligible share of the budget or that their prices are fixed. Unfortunately, the first assumption is counterfactual, at least in the case of India, and the second assumption is inconsistent with theory. As I will show, in a multisector general equilibrium model, in which one of the sectors is nontradable, the price of the nontraded good is increasing in the agricultural price index. Recognizing this possibility, Porto (2006) provides one of the few, if only, econometric estimates of the elasticity of nontraded goods prices with respect to traded goods prices. In India, however, as in most developing countries, reliable data on prices of services and other nontradables are unavailable. One contribution of this paper, therefore, is to quantify the nontradable price elasticity without actually estimating it econometrically.

To evaluate the distributional impacts of changes in agriculture's terms of trade, I integrate a three-sector, specific factors, general equilibrium trade model (e.g., Jones 1975) into a first-order welfare analysis.[5] Appealing to the widely noted geographical immobility of labor across rural India (e.g., Topalova 2007, 2010),[6] I apply this general equilibrium framework at the district level, treating each of these several hundred administrative units as a separate country with its own labor force but with open commodity trade across its borders.[7] This district-level perspective has two implications for empirical implementation of my approach. First, since each district produces a different basket of agricultural commodities, differences in the magnitude of wholesale price changes across crops (even if common across districts), generate cross-district variation in agricultural price (index) changes. Second, following the logic of the model, the wage-price elasticity itself is specific to a district, varying with characteristics of the local labor market.

While my estimation strategy is related to the "differential exposure approach" (Goldberg and Pavcnik 2007) employed in studies of the local wage impacts of tariff reform (most recently in Topalova 2010; McCaig 2011; and Kovak 2010, 2013), there are several novel elements. Kovak, for example, uses the same type of theoretical model to motivate his empirical specification, but he has many industrial sectors; there is no distinctive treatment of agriculture. Moreover, Kovak ignores intermediate inputs, whereas in this paper intermediates play a quantitatively important role in transmitting food price shocks. Finally, Kovak does not consider the welfare or distributional implications of trade shocks, or of food price shocks more particularly, which is a point of departure for this paper. Topalova (2010) finds that tariff reductions during India's trade

4. A related issue is that prices or unit values obtained from household expenditure surveys (as in Marchand 2012; Porto 2006) may not reflect the wholesale prices faced by farmers in a particular region, especially where government intervention is heavy (as in India).

5. Another strand of the literature incorporates second-order (substitution) effects of price increases on the consumption side based on demand-system estimation (most recently, Attanasio et al. 2013). Banks, Blundell, and Lewbel (1996), however, provide evidence that first-order approximations do reasonably well (relative error of around 10%) for price changes on the order of 20%.

6. Kovak (2010) finds no evidence that labor migration matters for local wage responses to trade reform in Brazil, a country with much higher inter-regional labor mobility than India.

7. Capital (land, in agriculture) is also assumed immobile across both districts and production sectors. Longer-run Stolper–Samuelson effects are not of paramount concern in policy discussion of food price shocks.

liberalization led to a fall in wages, including agricultural wages, and to a rise in rural poverty. Although Topalova's analysis is reduced-form and ex-post,[8] she interprets her findings through the lens of a specific-factors trade model with sectorally immobile labor (and mobile capital). Such a model, however, implies that *nonagricultural* wages would fall with higher food prices and, hence, that households would be affected very differently by rising food prices according to the sector in which their members are employed. My evidence will show the contrary, that the wage benefits of higher food prices are similar across employment sectors. More broadly, Topalova's results do not speak directly to the impact of shifts in *agriculture's* terms of trade.[9] This study is thus the first to adapt the differential exposure approach specifically to the agricultural sector and to the question of food-price crises.

My empirical analysis finds that nominal wages for manual labor across rural India respond elastically to higher (instrumented) agricultural prices.[10] In particular, wages rose faster in the districts growing relatively more of the crops that experienced comparatively large run-ups in price over the 2004–2005 to 2009–2010 period. Importantly, the *magnitude* of these wage responses is broadly consistent with the quantitative predictions of the specific-factors model. These results have striking distributional implications. Improved terms of trade for agriculture, rather than reducing the welfare of the rural poor as indicated by the conventional approach (which ignores wage impacts), would actually benefit both rich and poor alike, even though the latter are typically not net sellers of food.[11]

8. In other words, rather than predicting distributional impacts from a model based on estimated elasticities, it looks at changes in poverty rates directly. By contrast, Marchand (2012) uses an ex-ante simulation of household consumption along the former lines to find that the fall in India's trade barriers during the 1990s would have *reduced* rural poverty in India.

9. In particular, as high nontariff barriers on agricultural products remained in force well after India's initial trade liberalization (Anderson 2009), it is not clear what actually happened to the relative price of agriculture in Topalova's post-reform period.

10. In rural India, manual labor by far predominates over nonmanual labor in terms of annual days worked, and much of the latter is in the public (i.e., nonmarket) sector. Thus, unlike, e.g., Porto (2006) or Nicita (2009), I do not attempt to estimate separate wage-price elasticities for skilled and unskilled workers.

11. To be sure, the increase in rural wages may *lag* the increase in consumer prices, and so the conventional analysis may be more appropriate for the very short run. This article does not speak to the timing issue.

In the next section, I sketch the theoretical framework and develop my empirical testing strategy. Section III discusses the econometric issues and the estimates. Section IV presents the distributional analysis of food price shocks, comparing the general to partial equilibrium scenarios. I conclude, in Section V, with a discussion of the Government of India's responses to the 2007–2008 food price spike, notably its export ban on major foodgrains.

II. GENERAL EQUILIBRIUM FRAMEWORK

A. *Model Assumptions*

Consider each district as a separate economy with three sectors: agriculture (A) and manufacturing (M), both of which produce tradable goods, and services (S), which produces a nontradable. The reason it is necessary to distinguish services from manufacturing is simple. Combining the two into one nontradable nonagricultural sector is tantamount to allowing changes in agricultural prices to affect the prices of both manufactured goods and services. Since manufactured goods are, in fact, tradable, this approach would overstate the welfare impact of changes in agriculture's terms of trade.

Continuing with the assumptions, output Y_i in each sector $i = A, M, S$ is produced with a specific (i.e., immobile) type of capital K_i, along with manual labor L_i and a tradable intermediate input I_i, using sector-specific production function $Y_i = F_i(L_i, I_i, K_i)$. In the case of agriculture, K_A is land and I_A is, for example, fertilizer. Intermediate inputs do not play an essential role, except insofar as the model provides quantitative predictions, in which case (as we will see) they make a big difference.

In India, as in most developing countries, agricultural production largely takes place on household-farms using family and hired labor. Moreover, in a given year, these farms typically produce several crops on the same land (contemporaneously via multicropping and/or sequentially in multiple cropping seasons) with largely the same workers and intermediate inputs. Hence, following, for example, Strauss (1984), I treat the representative farm as a multiproduct firm that chooses among a fixed set of c crops $\{Y_1, ..., Y_c\}$ to grow, transforming between them according to the function $Y_A = G(Y_1, ..., Y_c)$, where G is assumed to be homogeneous of degree one. To account for the huge agroclimatic variation across India, one

TABLE 1
Summary Statistics for Major Crops

	Area Share	Value Share	No. of Districts	$\Delta p_j - \Delta p_{rice}$
Rice	0.380	0.408	447	0.000
	(0.320)	(0.328)		
Wheat	0.225	0.199	390	−0.032
	(0.183)	(0.165)		
Soyabean	0.092	0.099	153	0.056
	(0.151)	(0.159)		
Bajra	0.076	0.037	287	−0.064
	(0.146)	(0.091)		
Cotton	0.076	0.128	206	−0.130
	(0.112)	(0.175)		
Maize	0.067	0.054	410	−0.011
	(0.112)	(0.103)		
Jowar	0.065	0.024	317	−0.041
	(0.110)	(0.040)		
Ragi	0.052	0.030	192	0.052
	(0.123)	(0.092)		
Groundnut	0.046	0.050	349	−0.112
	(0.115)	(0.115)		
Gram	0.043	0.045	385	−0.195
	(0.072)	(0.087)		
Sugarcane	0.035	0.090	386	0.001
	(0.082)	(0.164)		
Rapeseed/Mustard	0.034	0.038	367	−0.199
	(0.073)	(0.090)		
Urad	0.028	0.012	409	0.364
	(0.042)	(0.018)		
Moong	0.025	0.014	424	0.586
	(0.041)	(0.030)		
Arhar	0.021	0.019	428	0.253
	(0.033)	(0.033)		
Potato	0.019	0.053	312	−0.146
	(0.061)	(0.105)		
Sunflower	0.014	0.009	271	−0.083
	(0.048)	(0.032)		
Sesamum	0.012	0.008	387	0.053
	(0.022)	(0.022)		

Notes: Means (standard deviations) of district-level data and number of districts growing each crop in 2003–2004. Log-price changes for 2004–2009 are averages across the 18 major states of India weighted by state production shares.

should think of the set of feasible crops as varying across districts.

Farmers then choose the particular quantities to grow, the Y_j, to maximize total revenue, $\sum_{j=1}^{c} P_j Y_j$, where P_j is the price of crop j, subject to the constraint that $G(Y_1,..., Y_c) = Y_A$ for any given Y_A. Thus, in this set-up, production value shares $s_k = P_k Y_k / \sum_{j=1}^{c} P_j Y_j$ are determined by both agroclimatic conditions and by relative crop prices. Given the homogeneity of G, there exists a price index P_A such that $P_A Y_A = \sum_{j=1}^{c} P_j Y_j$, which upon differentiation yields

$$\widehat{P}_A = \sum_j s_j \widehat{P}_j \tag{1}$$

where "hats" denote proportional changes; that is, $\widehat{x} = d \log x$. This establishes our production value share-weighted agricultural price index.

Now, we may write profit per acre in agriculture as $\Pi_A = [P_A F_A(L_A, I_A, K_A) - P_I I_A - W L_A]/K_A$, with analogous expressions for average profit per unit capital in manufacturing, Π_M and in services Π_S, given respective output prices in these sectors, P_M and P_S. I assume that manual labor is perfectly mobile across the three sectors but its overall supply is fixed at $L = L_A + L_M + L_S$ within each district. Thus, in each district economy, there is one type of labor with a single nominal wage, W, and a unique wage-price elasticity

$$\psi \equiv \widehat{W}/\widehat{P}_A \tag{2}$$

that must be solved for.

Because this is a general equilibrium framework, income effects of changes in factor prices are fully accounted for. Thus, total income y

consists of the sum of value-added (revenue net input expenditures) across sectors $i = A, M, S$

$$y = \sum_i P_i Y_i - P_I I_i + E \tag{3}$$

with an additional exogenous component, E. Although a technical nuisance, the presence of E suits an important empirical purpose: A significant portion of household income in rural India comes from (salaried) nonmanual labor; for example, teachers, police/army, and other civil servants. The exogeneity assumption on this income can be motivated by thinking about entry into these professions as requiring an advanced level of education (relative to unskilled labor), which cannot be acquired in the short-run.[12]

B. Solution and Intuition

We are interested in what happens to the equilibrium wage in this model when the agricultural price index changes, holding other tradable prices constant; that is, $\widehat{P}_M = \widehat{P}_I = 0$. Given that farmers are price-takers in all markets, we have (from price equals unit cost)

$$\alpha_L \widehat{W} + \alpha_K \widehat{\Pi}_A = \widehat{P}_A \tag{4}$$

where, under constant returns to scale, the input cost shares in agriculture, the α_l, $l = K, L, I$, are such that $\alpha_K + \alpha_L + \alpha_I = 1$. Similar equations hold for the other sectors, each with its own set of input cost shares. In the interest of clarity and because it will make no appreciable difference empirically (see below), I assume equal input cost shares across sectors from now on.

As I show in the Appendix,

$$\psi = \left(\beta_A + \delta\beta_S\right) / \left(\alpha_L + \alpha_K\right) \tag{5}$$

where the $\beta_i = L_i/L$ are the sectoral labor shares and $\delta \equiv \widehat{P}_S/\widehat{P}_A$. Note that δ, the elasticity of the nontradables price with respect to the price of agriculture, is endogenous and needs to be solved out.[13]

Before doing so, however, we can gain some intuition for the mechanics of the model by considering the special case $\alpha_I = \beta_S = 0$; a two-input, two-sector economy (without nontradables). According to Equation (5), in this case $\psi = \beta_A$, where β_A is the share of the rural labor force in agriculture. Referring to Figure 1, compare equilibrium A, with a high share of labor in agriculture to equilibrium B with a low agricultural share. At A the value of marginal product curve in manufacturing (the supply curve of labor to agriculture) is necessarily very steep; at B it is very flat. Thus, in moving from A to A', a 50% increase in the agricultural price translates into an almost 50% increase in the wage, whereas, in moving from B to B', the same price increase leads to virtually no wage increase whatsoever (in proportional terms).

If we now let $\alpha_I > 0$, then we have $\psi = \beta_A/(\alpha_L + \alpha_K) > \beta_A$. So, while the qualitative prediction is the same, the *magnitude* of the wage-price elasticity can increase quite a lot after accounting for the cost share of intermediate inputs. The source of this amplification effect is the increase in intermediate input use induced by higher agricultural prices, which boosts the marginal product of labor in agriculture. Because of a greater exodus of labor from manufacturing in response to agriculture's improved terms of trade, there must be an even larger wage increase than was the case in the absence of intermediates.

Finally, let us return to δ in Equation (5). To solve out this parameter, we must equate the demand and supply of services, which I discuss in the Appendix. For purposes of exposition, set $\alpha_I = 0$ again and consider the special case $E = 0$, in which there is no exogenous source of income outside of the three sectors. As shown in the Appendix, $\psi = \delta = \beta_A/(1 - \beta_S) > \beta_A$ in this case. Thus, the introduction of a nontradable sector also amplifies the wage-price elasticity. In this economy, a rise in the wage induced by higher agricultural prices reduces the supply of services; it also increases the *demand* for services due to an income effect. Both forces put upward pressure on the price of services, so that $\delta > 0$. With the expansion of the service sector as agricultural prices rise, the supply curve of labor to agriculture becomes even more inelastic, making the rural wage even more sensitive to these price changes.

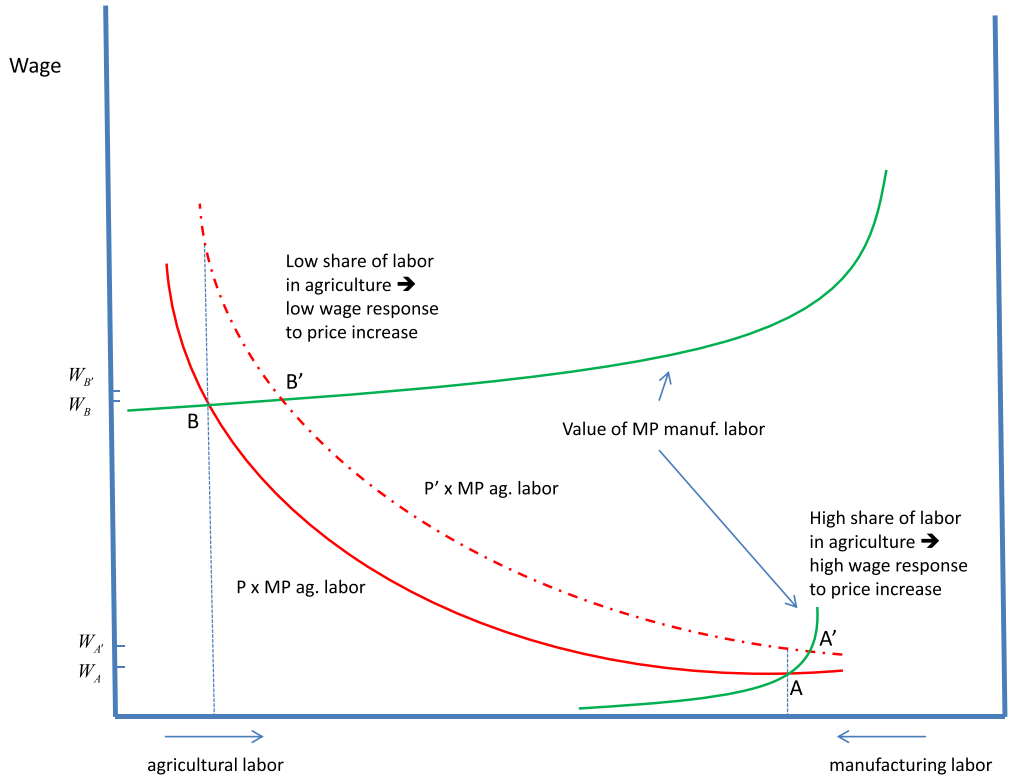
C. Empirical Validation

The advantage of the above machinery is twofold: First, the model tells us what the relevant

12. We can also think of rural nonmanual labor as paid for out of a central government budget financed by urban taxpayers and not contributing directly to output in any rural sector.

13. Combining (4) and (5) also gives $\widehat{\Pi}_A/\widehat{P}_A = \left(1/\alpha_K\right)\left(1 - \alpha_L\psi\right)$. So the elasticity of the return on land with respect to the agricultural price index incorporates the direct (positive) effect of price changes on farm profits as well as the indirect (negative) effect of price induced wage changes.

FIGURE 1
Labor Market Equilibrium



wage-price elasticities are and, second, it delivers explicit expressions for these elasticities in terms of input cost shares, sectoral labor shares, and other parameters, all of which can be computed from nationally representative data collected by India's National Sample Survey (NSS) Organization.[14] I thus calculate district (d) specific wage-price elasticities, ψ_d, assuming equal input cost shares across sectors,[15] for 472 districts in the 18 major states of India (see Table A2 for descriptive statistics).[16] Generally speaking, the estimated elasticities are high ($\overline{\psi} = 1.15$), reflecting large values of β_A. Indeed, for the average rural district, around three-quarters of *manual* labor days (adjusted for efficiency units; see *Sectoral Labor Shares* section in Appendix) are spent in agriculture. Note also that intermediate inputs play a quantitatively important role in the elasticity calculation; if I assume that $\alpha_I = 0$, then $\overline{\psi}$ would drop to 0.85. In other words, the input amplification effect on the wage-price elasticities, discussed in the previous section, is substantial.

In principle, one could econometrically estimate separate wage-price elasticities for each district and compare them to their theoretically

14. An exception is the share of aggregate income from exogenous sources, or E/y (cf., Appendix), which is computed at the state-level from IHDS data described below.

15. While it is straightforward to allow for sector-specific input cost shares using the results in Appendix, it is somewhat messy. Fortunately, it hardly matters, because they yield virtually identical elasticity results as in the equal shares case. Cost shares of value-added for Indian manufacturing and service sectors based on national accounts are available from Narayanan, Aguiar, and McDougall (2012). As it turns out, however, the ratio of capital to labor shares is what is most relevant to our calculations, and these are quite similar across sectors.

16. Excluded are the peripheral states of Jammu/Kashmir in the far north and Assam and its smaller neighbors to the north and east of Bangladesh. Included states, organized into five regions, are *North*: Harayana, Himachal Pradesh, Punjab, Uttar Pradesh, and Uttaranchal; *Northwest*: Gujarat and Rajastan; *Center*: Chhattisgarh, Madhya Pradesh, Maharashtra, and Orissa; *East*: Bihar, Jharkhand, and West Bengal; *South*: Andhra Pradesh, Karnataka, Kerala, and Tamil Nadu.

implied counterparts above. In practice, however, this would require long time-series of wages and prices for each district over a period of structural stasis.[17] In lieu of such data, I estimate the regression analog to the identity given by Equation (2), or

$$\Delta w_d/\psi_d = c + \gamma \sum_j s_{d,j} \Delta p_j + \varepsilon_d \tag{6}$$

where c is an intercept, γ is a slope parameter, and ε_d is a disturbance term for each district d. Thus, Equation (6) replaces $\hat{W}$ and $\hat{P}_A$ by their empirical counterparts; Δw_d is the difference in log wages between years $t-k$ and t and the Δp_j are the corresponding time-differences in log prices of crop j, which are weighted by production value shares $s_{d,j}$ as already discussed.

Under the null hypothesis, which is that the model and all its auxiliary assumptions holds true *on average*, we have $\gamma = 1$. In other words, under the null, the magnitude of observed wage responses to actual changes in the agricultural price index corresponds (in an average sense) to what the theory says it should be. Several econometric issues arise in implementing Equation (6), including potential endogeneity of price changes. These are left for Section III.D.

III. EMPIRICAL ANALYSIS

A. Domestic Agricultural Markets

Since at least the 1960s, Indian governments, both at the national and state level, have intervened extensively in agricultural markets. Interstate trade in foodstuffs is often severely circumscribed through tariffs, taxes and licensing requirements (see Atkin 2010, for a review) with some states (e.g., Andhra Pradesh) going so far recently as to prohibit the exportation of rice to other *states* (Gulati 2012). The Government of India also sets minimum support prices (MSPs) at which major food crops are, or at least can be, procured for eventual release into the nationwide public distribution system (PDS). In practice, however, the level of procurement, and thus the extent to which the MSPs are binding, varies greatly by crop and state, and even within states (Parikh and Singh 2007). The principal foodgrains, rice and wheat, have, in recent years, been the overwhelming focus of government procurement efforts, concentrated in the states of Punjab and Haryana, often for lack of storage capacity and marketing infrastructure elsewhere. By contrast, procurement of pulses and oilseeds has been minimal, as market prices have consistently exceeded MSPs.[18]

During and after the sharp run-up in international food prices in 2007–2008, the Government of India imposed export bans on rice, wheat, and a few other agricultural commodities in an attempt to tamp down domestic price increases. Meanwhile, over several consecutive years, MSPs for rice and wheat (and most other major crops) were raised substantially, partly in response to international prices; huge stockpiles of foodgrains were subsequently accumulated through government procurement (Ahmed and Jansen 2010; Himanshu and Sen 2011).

The upshot of these interventions is that output prices faced by Indian agricultural producers do not always perfectly track those in international markets.[19] Moreover, as domestic market integration is somewhat limited (especially in the case of rice), there is considerable variability across states in crop price movements. On the one hand, this variation may reflect differential transmission of exogenous price pressure (e.g., because of varying levels of state procurement or exposure to trade, both with other countries and with other states); on the other hand, it may reflect localized supply or demand shocks, which can also drive rural wages directly.

B. Crop Prices

Wholesale crop price data averaged at the state level from observations at several district markets per state (and weighted by district production), are compiled by the Ministry of Agriculture,

17. India's quinquennial labor force survey, available since 1983, would yield, at best, five first-differenced wage observations per district. Alternatively, Jayachandran (2006) examines a 30-year agricultural wage series for Indian districts. Although these data fall entirely within the pre-reform (largely autarkic) trade regime, Jayachandran estimates a national-level wage elasticity with respect to agricultural TFP, instrumented with rainfall shocks. One of the difficulties with interpreting this as an estimate of ψ, however, is that the year-to-year TFP shocks induced by annual rainfall deviations are *unanticipated* and thus are unlikely to give rise to the sectoral labor reallocations underlying the general equilibrium model of this paper.

18. See the reports by the Commission for Agricultural Costs and Prices on http://cacp.dacnet.nic.in/ for more details.

19. This is true for the principal intermediate input in agriculture as well. Despite a substantial upsurge in the international prices of chemical fertilizers beginning in 2007, retail prices in India, which are set by the central government, remained uniform and unchanged over the 2004–2009 period (Sharma 2012).

TABLE 2
Rural Wage Impacts of Crop Price Changes: 2004–2009

	(1)	(2)	(3)	(4)	(5)	(6)
(A) Wages for all manual labor ($N = 462$)						
γ	0.429	0.547	0.864	0.822	0.847	0.846
	(0.100)	(0.105)	(0.305)	(0.302)	(0.318)	(0.320)
ΔPW[a]						0.042
						(0.215)
p-values						
$H_0 : \gamma = 1$	0.000	0.014	0.672	0.579	0.660	0.663
$H_0 : \gamma = 0$	0.000	0.001	0.006	0.009	0.014	0.018
Cragg-Donald F-stat (weak identification test)		1384.1	61.0	50.0	39.0	38.5
(B) Wages for nonagricultural manual labor ($N = 445$)						
γ	0.672	0.779	0.988	0.844	0.900	0.851
	(0.109)	(0.104)	(0.263)	(0.245)	(0.249)	(0.250)
ΔPW[a]						−0.228
						(0.242)
p-values						
$H_0 : \gamma = 1$	0.010	0.461	0.969	0.585	0.733	0.613
$H_0 : \gamma = 0$	0.000	0.000	0.004	0.008	0.006	0.010
Cragg-Donald F-stat (weak identification test)		1522.6	73.1	59.0	48.2	49.8
Instrument	—	$IV1_d$	$IV2_d$	$IV3_d^{100}$	$IV3_d^{200}$	$IV3_d^{200}$

Notes: Standard errors robust to spatial dependence in parentheses. All *p*-values based on Bester et al. (2014) bootstrapped critical values ($R = 10000$). Dependent variable is the change in log wage district fixed effect between 2004 and 2009 scaled by the district wage-price elasticity. All regressions include a constant term and are weighted by the inverse estimated sampling variance of the dependent variable. See text for definition of instruments.

[a]Difference in average days of public works employment per week in district between 2004 and 2009.

as are production and area data at the district level. So as to focus on a period of substantial price movement, as well as to match the NSS wage data (see below), I consider state-level price changes between the 2004–2005 and 2009–2010 crop marketing seasons. Given the relative ease of moving produce across district (as opposed to state) lines, state-level wholesale prices appear the appropriate measure of farmer production incentives.[20]

I base the crop value shares, the $s_{d,j}$ in Equation (6), on production data from the 2003–2004 crop-year, which has the best district/crop coverage for the pre-2004–2005 period. Value of production is calculated at 2004–2005 state-level prices. Note, however, that I do not take the value-weighted sum of price changes across every single agricultural product grown in India. Price data for many of the minor field crops and the tree crops are incomplete or not reliable. Moreover, the associated production data are often inaccurate (especially for vegetables and tree products). I thus select *major field crops* according to the criteria that they cover at least 1% of total cropped area nationally *or* that at least five districts had no less than 10% of their cropped area planted to them in 2003–2004. These 18 crops, listed in Table 1 in descending order of planted area, comprise some 92% of area devoted to field crops in 2003–2004 in the major states of India. Table 1 also reports national average log-price changes (weighted by the state share of total production) *relative to rice*. Thus, in the first row, the relative price change for rice is zero, quite negative for several important crops (e.g., cotton, gram, groundnut, and mustard/rapeseed) and highly positive for pulses (Urad, Moong, and Arhar).

C. Wages

Wage data are derived from the NSS Employment-Unemployment Survey (EUS), normally conducted every 5 years. The most recent round, the 66th, collected in 2009–2010, is the first conducted in the wake of the food price "crisis" of 2007–2008, whereas the 61st round of 2004–2005 most closely preceded it. Once again, in the spirit of the theoretical model, I focus on *manual* labor, which constitutes nearly 83% of

20. As sugarcane is sold mostly to mills and not in wholesale markets, I use the national MSP or, when relevant, "State Advised Prices," which tend to be much higher and, hence, closer to international cane pricing standards (see Gulati 2012).

days of paid employment in rural areas.[21] The first-stage of the estimation takes individual log daily wages in the last week and regresses them on district fixed effects as well as a quadratic in age interacted with gender. Thus, I estimate the respective log-wage district fixed effects, $\overline{w}_{d,09}$ and $\overline{w}_{d,04}$, separately for each round, removing, via the constant terms, year effects due to, for example, general inflation. Estimates of the standard errors of the fixed effects $\sigma\left(\overline{w}_{d,09}\right)$ and $\sigma\left(\overline{w}_{d,04}\right)$, which I use below to construct regression weights, are obtained following the procedure of Haisken-DeNew and Schmidt (1997).

D. Identification

Rewriting Equation (6) to reflect the price data discussed above, I wish to estimate

$$\Delta w_d/\psi_d = c + \gamma \sum_j s_{d,j} \Delta p_{STATE_d,j} + \varepsilon_d. \tag{7}$$

where $STATE_d$ denotes the state in which district d is located. There are two endogeneity issues to contend with: measurement error and simultaneity between wage and price changes.

As to the first issue, both the crop value shares, $s_{d,j}$, and the crop-specific log-price changes, $\Delta p_{STATE_d,j}$, may be measured with error. Putting aside the latter concern momentarily and assuming that measurement error is confined solely to value shares, I could deploy the instrument

$$IV1_d = \sum_j a_{d,j} \Delta p_{STATE_d,j} \tag{8}$$

where $a_{d,j}$ is the area share of crop j in district d. To be sure, cropped areas may also be measured with error, but these errors should not be correlated with those of crop production and prices.

Clearly, $IV1_d$ does not deal with measurement error in price changes, which could arise if, for example, the marketed varieties or grades of a certain crop in a certain state change over time. Another concern is unobserved district-level shocks (or trends) correlated with both wage and price changes. For instance, suppose that a particular district has been industrializing relatively rapidly over the 2004–2009 period, or that it has experienced comparatively rapid technological improvement in agriculture. Both types of shocks would tend to raise district wages. And, they may influence crop prices as well insofar as the state's agricultural markets are insulated from the rest of India (and the world) and the district is important relative to that market, or the shocks are strongly spatially correlated.

The next step, therefore, is to develop an instrument that is uncorrelated both with district-level wage shocks and with measurement error in price changes (and crop value shares). Consider, then,

$$IV2_d = \sum_j a_{d,j} \Delta \overline{p}_{STATE_d,j} \tag{9}$$

where $\Delta \overline{p}_{STATE_d,j}$ is the production share weighted mean change in the log-price of crop j across states *excluding the state to which district d belongs*.[22] In other words, $IV2_d$ replaces the state price changes in $IV1_d$ with a national average price change uncontaminated by state-specific shocks or measurement error because no price data from that state or production data from that district are used in its construction. The idea, then, is that $\Delta \overline{p}_{STATE_d,j}$ reflects exogenous international price changes transmitted to other states of India as well as shifts in demand and supply in the vast domestic market outside of the particular state.

A problem with $IV2_d$, however, is that it does not meet the exclusion restriction if ε_d are correlated across state boundaries. In other words, if industrialization or agricultural innovation (or even weather) in, say, southern Andhra Pradesh and northern Tamil Nadu move together, then the $\Delta \overline{p}_{STATE_d,j}$ for a district in Andhra Pradesh may reflect these shocks inasmuch as price changes from Tamil Nadu contribute to the weighted average. To deal with this concern, I first establish some notation: Let $BSTATE_d^r$ be the set of states within a radius of r kilometers around district d; of course, $STATE_d \subseteq BSTATE_d^r$. Thus, $BSTATE_d^r$ for the district in southern Andhra Pradesh, depending on r, may include Karnataka and Tamil Nadu (in addition to AP itself), whereas,

21. The NSS-EUS categorizes jobs in terms of manual and non-manual labor only for rural, not urban, workers. Based on the 61st round sample of nearly 39,000 individuals, the population-weighted proportions in each category are as follows: 58% in manual-agricultural; 24% in manual nonagricultural; and 18% in nonmanual (virtually all in nonagriculture). For the 66th round sample of some 30,000 individuals, the corresponding proportions are 51%, 30%, and 19%, respectively.

22. To be precise, $\Delta \overline{p}_{STATE_d,j} = \sum_{k \in STATE_d^C} \omega_{kj} \Delta p_{k,j}$, where $STATE_d^C$ is the set of states excluding $STATE_d$ and ω_{kj} is state k's share of total production of crop j among all states in $STATE_d^C$.

if d were instead in northern AP, $BSTATE_d^r$ might include Maharashtra and Chhattisgarh. With this definition, my instrument becomes

$$IV3_d^r = \sum_j a_{d,j} \Delta\overline{p}_{BSTATE_d^r,j} \tag{10}$$

where $\Delta\overline{p}_{BSTATE_d^r,j}$ is the production share weighted mean change in the log-price of crop j across states *excluding those in* $BSTATE_d^r$. Here, again, the logic is that the price instrument should not directly, or, in this case, even indirectly, be driven by local shocks that also determine *differential* wage growth across districts (and states).

The choice of r, the radius of "influence" of local wage shocks on prices in bordering states may seem arbitrary. As, on average, districts are 57 kilometers apart (centroid-to-centroid), at $r = 100$ kilometers, the sets $BSTATE_d^r$ and $STATE_d$ differ only for districts relatively close to their state's border with another Indian state. Indeed, $IV3_d^{100} = IV2_d$ for half of the 462 districts in my estimation sample (those in the deep interior of states or along the coasts or international borders). By contrast, $IV3_d^{200} = IV2_d$ for fewer than 10% of sample districts. This suggests a strategy of comparing alternative estimates of γ from Equation (7) based on $IV3_d^r$ with successively higher values of r to determine at what point increasing the radius of influence ceases to matter.

Finally, as Equation (10) makes evident, differences in price trends *across* crops is key to identification; if the $\Delta\overline{p}_{BSTATE_d^r,j}$ are the same for all j, then $IV3_d^r$ collapses to $\Delta\overline{p}_{BSTATE_d^r}$, essentially a constant. Given the inclusion of the constant term c, γ is virtually nonidentified in this scenario. Equally as important is variation in crop composition across districts (see Table 2). If $a_{d,j} = a_j$ for all d, then even if the $\Delta\overline{p}_{BSTATE_d^r,j}$ are not all equal, $IV3_d^r$ again essentially collapses to a constant. The adjusted R^2s of the first-stage regressions using $IV1_d$, $IV2_d$, $IV3_d^{100}$, and $IV3_d^{200}$ are, respectively, 0.788, 0.121, 0.103, and 0.091.

E. Inference

As already alluded to, the error term ε_d is likely to be correlated across neighboring districts, if only because geographically proximate regions experience similar productivity shocks over time. I use a nonparametric covariance matrix estimator or spatial HAC (Conley 1999) to account for heteroskedasticity and spatial dependence. A familiar alternative to the spatial HAC is the clustered covariance estimator. But clustering standard errors by state or region assumes independence of errors across state or regional boundaries, a serious lacuna given the large fraction of districts bordering an adjacent state.[23]

Bester et al. (2014) show that the asymptotic normal distribution, typically used to obtain critical values for inference in HAC estimation, is a poor approximation in finite samples. I thus follow their suggestion of bootstrapping the distribution of the relevant test-statistics. For this reason, inference should be guided by p-values rather than by standard errors, although I will follow convention and report both. In particular, bootstrapped p-values are much less sensitive than standard errors to choice of the tuning or bandwidth parameter (i.e., the degree of kernel smoothing).[24]

Both numerator, $\Delta w_d = \overline{w}_{d,09} - \overline{w}_{d,04}$, and denominator, ψ_d, of the dependent variable in Equation (7) are district-level summary statistics derived from micro-data. This gives rise to a particular form of heteroskedasticity and renders least-squares estimation inefficient. The standard solution is to use weighted least-squares, taking the inverse of the estimated sampling variances as weights. While the sampling variance of Δw_d is $\sigma^2\left(\overline{w}_{d,09}\right) + \sigma^2\left(\overline{w}_{d,04}\right)$ (see above), there is no equally straightforward "plug-in" estimate of the sampling variance of ψ_d. I, therefore, bootstrap this variance as well by drawing 1000 random samples of individuals from each district's original sample and computing ψ_d repeatedly. From these two components, then, I obtain the sampling variance of $\Delta w_d/\psi_d$ using the delta-method.[25]

F. Estimation Results

Estimates of γ based on Equation (7) are reported in Table 2A, in which identifying

23. Also note that with only a single (5-year difference) observation per district, serial correlation is not an issue in my set-up.

24. Bandwidth here is the distance cutoff, in degrees of lat/long, beyond which spatial dependence is assumed to die out. Based on simulation evidence from Bester et al. (2014), I choose a bandwidth of 16; i.e., given the area of my "sampling region" (the 18 major states of India), this choice should yield minimal test-size distortion across a range of possible spatial correlations. I find these p-values to be highly robust to bandwidth deviations of at least ± 4.

25. Although this procedure ignores correlation between numerator and denominator arising from the fact that these two statistics are calculated from partially overlapping samples of the same underlying micro-data, it should serve adequately as a first approximation.

assumptions become progressively less restrictive across columns. Thus, column 1 estimates are by ordinary (weighted) least squares, column 2 uses $IV1_d$ as an instrument, column 3 uses $IV2_d$, column 4 uses $IV3_d^{100}$, and column 5 uses $IV3_d^{200}$. Instrument diagnostics are problematic given the spatial error structure discussed above. However, for lack of a better alternative, I report Cragg-Donald F-stats, which assume i.i.d. errors, in Table 2 for all IV regressions. The critical value for the associated weak instrument test, based on 10% maximal size for a 5% Wald test, is 16.4 in all cases (Stock and Yogo 2002). Hence, subject to the caveat already noted, I can strongly reject weak identification, even using $IV3_d^{200}$.

While a comparison of the first two columns suggests that measurement error in crop shares leads to a modicum of attenuation bias, even the column 2 estimate is well below unity as indicated by the p-values from the bootstrapped-based t-test of $H_0 : \gamma = 1$.[26] Relaxing the assumption of no measurement error or simultaneity bias in price changes in columns 3–5 delivers a $\hat{\gamma}$ much closer to unity, albeit one much less precisely estimated. The specifications in columns 4 and 5, however, which allow shocks to be correlated across state borders, do not give much different results from that of column 3, which ignores such correlation. The pattern of coefficients across columns suggests a rough balance between measurement error in prices (attenuation bias) and simultaneity bias.

None of the p-values for $H_0 : \gamma = 1$ in columns 3–5 are anywhere near rejection levels, evidence in favor of the specific-factors model. To assess power, I use the bootstrapped t-distribution to answer the question: How likely would I have been to reject $H_0 : \gamma = 1$ had the true γ been at or very near zero? Based on this empirical power functions, at a true γ of zero, $H_0 : \gamma = 1$ would be rejected with 95% certainty in the column 3 specification, and with closer to 90% certainty in the column 5 specification. In this sense, then, power is reasonably good: The evidence does not support the view that rural wages are unresponsive to agricultural price changes over a half-decade period.

26. The p-value is the proportion of times the bootstrapped, re-centered, t-statistic of Bester et al. (2014) exceeds the conventional t-statistic for the null in question computed for the original sample. I use 10,000 bootstrap replications.

G. Robustness: NREGA

India's National Employment Rural Guarantee Act (NREGA) is meant to provide every rural household with 100 days of manual labor at a state-level minimum wage, which is typically above the market wage. Imbert and Papp (2012), using NSS-EUS data and exploiting the gradual phase-in of the program since 2006, find that NREGA increased overall public works employment while (modestly) raising private-sector wages in rural India. As these labor market changes were contemporaneous with rising food prices, they are worth taking seriously as possible confounding factors. Given my estimation strategy, however, NREGA will only affect the results insofar as the local expansion of the program was systematically related to the (instrumented) change in the agricultural price index.

Based on 7-day employment recall information in the NSS-EUS, I compute the population weighted district average days spent in public works employment (both NREGA and other) for rounds 61 and 66.[27] Including the 2004–2009 change in this public works employment variable (ΔPW) in regression (Equation (7)) results in no appreciable changes in my estimates of γ (compare columns 5 and 6 of Table 2). Of course, the coefficient on ΔPW does not necessarily reflect the *causal* impact of NREGA or any other public works employment program in India on rural wages; this specification merely serves as a robustness check.

H. Sectoral Labor Mobility

My framework assumes perfect mobility of labor across production sectors over the relevant horizon. However, as noted above, Topalova (2010) proposes an alternative specific-factors model to rationalize her empirical results for India in which labor is perfectly immobile, but capital moves freely, across sectors. It is easy to see that, in this set-up, agricultural wages respond positively to an increase in food prices but nonagricultural wages respond *negatively*, as capital is reallocated away from the sector whose terms of trade have deteriorated and toward agriculture.

To test perfect intersectoral mobility of labor, I use the same procedure just employed to

27. This is essentially the same variable considered by Imbert and Papp (2012). In 2004–2005, public-works employment accounted for just 0.22% of a day of work on average, increasing to a still minuscule 1.44% of a day in 2009–2010. Note, however, that NREGA employment is concentrated in the agricultural off-season.

construct log-wage district fixed effects for the 2004–2005 and 2009–2010 NSS-EUS rounds, except in this case using only wage data for *nonagricultural* jobs. The dependent variable is again the time difference of these district fixed effects scaled by ψ_d. Relative to the previous analysis, 17 districts are dropped for lack of data on nonagricultural wage jobs. The estimates, in panel (B) of Table 2, differ little from their counterparts in panel (A), nor can I reject $H_0 : \gamma = 1$ in the specifications with the least restrictive identifying assumptions. Hence, it appears that nonagricultural wages, contra Topalova's implication, respond as positively to higher food prices as do wages overall. Consequently, the resulting welfare gains accruing to manual laborers (through wages) should not depend on the sector in which they happen to be employed.

IV. FOOD PRICES AND WELFARE

A. Welfare Elasticities

Now consider a rural household embedded within the economy sketched out in Section II. Its contribution to aggregate income consists of value-added from its enterprises, both farm and nonfarm, its *net* earnings from manual labor, and its exogenous income E. The second of these components, which I will denote by $W(L^S - L^D)$, is not present in Equation (3) because manual labor supply (L^S) and demand (L^D) are equal in the aggregate.

Household indirect utility is a function of income and prices, P_M, P_S, and $P_j, j = 1,..., c$. Following the conventional derivation, the proportional change in money-metric utility m is

$$\widehat{m} = \sum_j \left(\Omega s_j - \nu_j\right) \widehat{P}_j \tag{11}$$

where $\Omega = \lambda_A + (\lambda_S - \nu_S)\delta + \lambda_L \psi$, υ_j is the expenditure share of good j (S in the case of services), $\lambda_A = P_A Y_A / y$ is the ratio of gross farm revenue to income, $\lambda_S = P_S Y_S / y$ is the ratio of gross revenue from service enterprises to income, and $\lambda_L = [W(L^S - L^D)]/y$ is the ratio of the net earnings of manual labor to income. The term $\Omega s_j - \nu_j$ is reminiscent of Deaton's (1989) well-known *net consumption ratio* (revenue minus expenditures on crop j divided by total consumption expenditures) except that, unlike Deaton's partial equilibrium result, it fully accounts for the changes in factor income induced by a given price change, as well as for changes in the price of nontradables. There are also several differences between Equation (11) and the compensating variation formula used by Porto (2006), and earlier by Ravallion (1990). First, Ω allows not just for changes in labor earnings but for changes in capital (land) income, which is obviously critical in my setting. Second, whereas the λs vary by household, as in Porto's application, the elasticities δ and ψ vary in my case by the sectoral composition of the district labor market. Moreover, rather than plugging in reduced-form econometric estimates of these elasticities (which are infeasible for reasons already discussed), I compute them based on an empirically validated theoretical model.

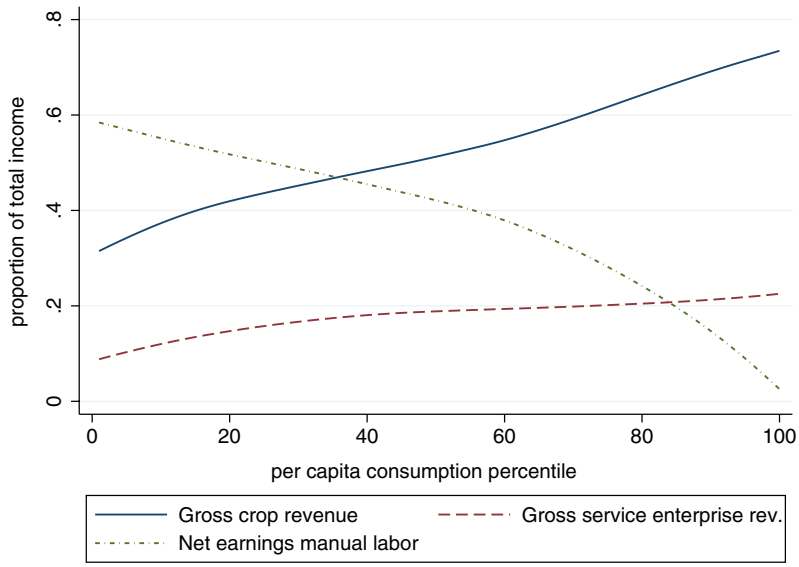
In what follows, I consider the distributional consequences of a *uniform* percentage increase in all agricultural commodity prices *relative* to the price of manufactures, the numeraire. According to Equation (11), the corresponding household welfare elasticity is simply $\varepsilon = \Omega - \nu_A$, where ν_A is the expenditure share of food crops.

B. Distributional Analysis

The India Human Development Survey (IHDS) of 2005 is a nationally representative household survey of both rural and urban India (Desai, Vanneman, and National Council of Applied Research 2008). Within the 18 major states already discussed, the IHDS covers nearly 24 thousand rural households spread over 254 districts, collecting information on consumption expenditures and income, including revenues and costs from household enterprises, both agricultural and nonagricultural. Figure 2 shows the patterns of λ_A and λ_S smoothed across percentiles of per-capita expenditures, as represented by the IHDS rural sample. Relative to total household income, gross revenues from both farming and service enterprises increase by percentile, though the former increases much faster. By contrast, because the demand for hired labor across household enterprises increases with wealth, λ_L decreases and essentially goes to zero for the highest percentile. On the consumption side (Figure 3), the behavior of the food share is familiar, falling steadily and quite rapidly by percentile, whereas the share of expenditures on nontraded goods has the opposite, though a less steep, distributional gradient.[28]

28. Nontraded goods expenditure categories include: firewood, entertainment, conveyance, house rental, repair and maintenance, medical care, education, and other services.

FIGURE 2
λ_A, λ_S, and λ_L by Percentile



Turn now to the main results in Figure 4, showing the relationship between the welfare elasticity with respect to food prices, ε, and per capita expenditure percentile. Observe that ε is positive across the income spectrum, never falling below 0.4. Thus, higher food prices confer substantial and broad-based *benefits* to the rural population of India, although the pattern of proportional welfare gains is mildly hump-shaped, with the poorest and richest households gaining least. This latter feature is driven by changes in non-traded goods prices and the relatively large share of expenditures devoted to these goods by the rich. In other words, if δ is artificially set to zero, then ε would be essentially flat across the top per capita expenditure quintile.[29]

Finally, let us compare the general equilibrium welfare analysis to a more conventional partial equilibrium one. Of course, the latter *assumes* that $\psi = \delta = 0$ so that, from Equation (11), $\Omega = \lambda_A$. The distribution of partial equilibrium welfare elasticities looks dramatically different than that of ε (Figure 4). Without the large and beneficial adjustment in rural wages, the poorest rural households in India would experience a welfare *loss* of around 0.2% for a 1% uniform increase in agricultural prices. However, the relative advantage of the general equilibrium scenario erodes rapidly with income as manual labor earnings become progressively less important in the higher percentiles. Indeed, because in partial equilibrium, the richest households do not have to pay higher prices for services or higher wages to hired labor, they would benefit even more than in general equilibrium from higher food prices.

29. In Jacoby (2013), I further account for India's vast Public Distribution System (PDS), under which eligible households (generally, those below the poverty line) can purchase fixed rations of either rice, wheat, or sugar in "Fair Price Shops" at below-market prices. If I assume that PDS prices remain stable even as market prices rise, I obtain modestly better welfare outcomes for all but the top two deciles.

V. CONCLUSIONS

In reaction to the food price spike of 2007–2008, the Government of India imposed export bans on certain major crops. Such efforts to restrain consumer prices can have the unfortunate side-effect of restraining producer prices as well. My analysis shows that, in the face of higher agricultural commodity prices, a stand-alone export ban, or any policy that mimics its effects, would reduce welfare for the vast bulk of India's population. Moreover, it is precisely the poorest rural households (and, hence, the poorest in India as a whole) that are most harmed by forestalling, or at least delaying, the substantial trickle-down effects of higher crop prices via rural wages.

FIGURE 3
Expenditure Shares by Percentile

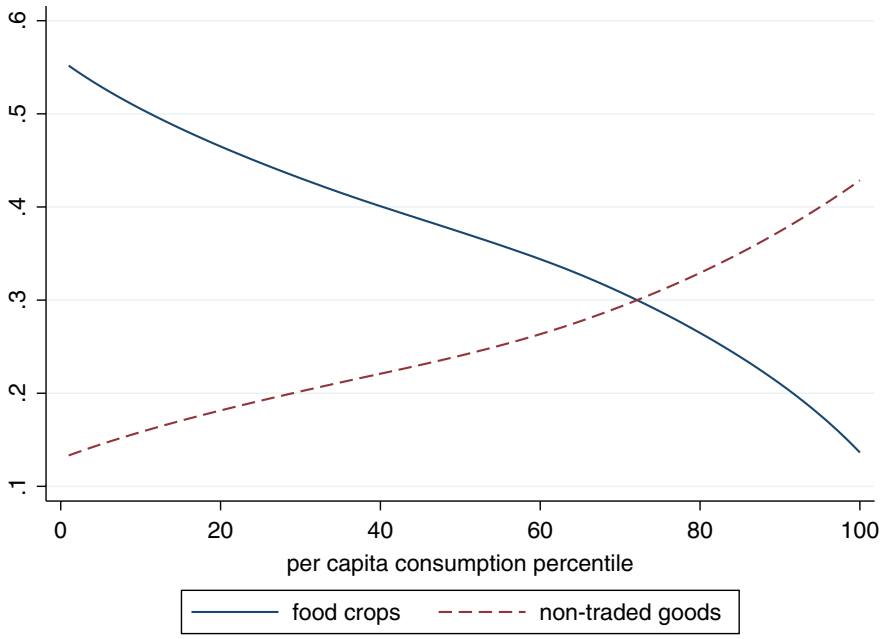
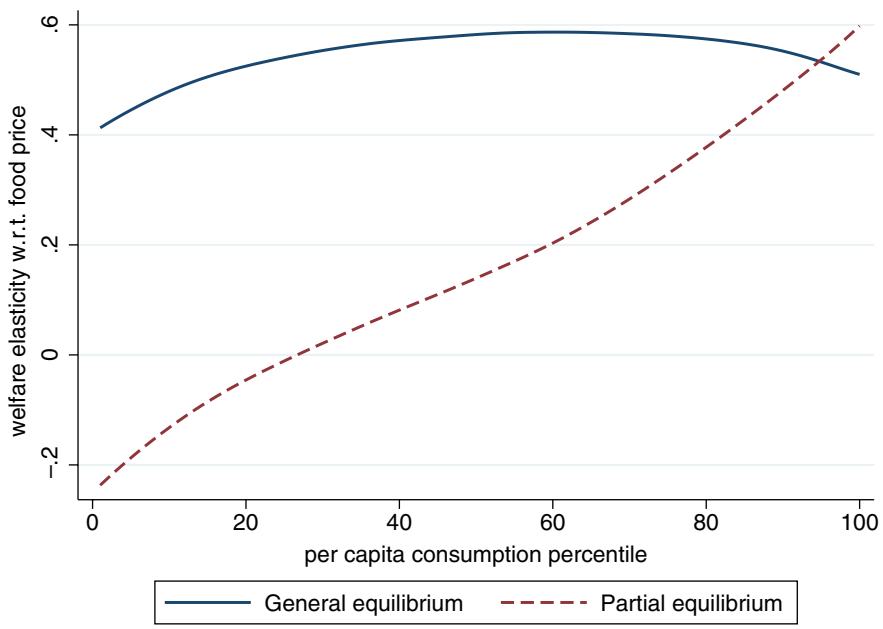


FIGURE 4
Welfare Elasticities by Percentile



Partial equilibrium analysis, which assumes fixed wages, provides a highly misleading picture of the distributional impacts of food price shocks among India's vast rural population. To be sure, the story may be quite different in metropolitan India, where the poor, arguably, benefit little from rising rural wages.[30] Even though not much more than a quarter of India's population resides in cities, urban constituencies are obviously more concentrated than rural ones and, hence, from a political-economy standpoint, are likely to be more pivotal in shaping government policy on such matters as food security.

Finally, this study speaks to the broader debate on the link between trade and poverty. Consistent with the WTO's Doha agenda, my results imply that lowering barriers to trade in agricultural goods on the part of developed countries, if only by improving the lot of the rural poor in India, can make a significant dent in global poverty.

APPENDIX

MODEL SOLUTION

I assume Cobb–Douglas production functions with input cost shares $\alpha_{Li}+\alpha_{Ii}+\alpha_{Ki}=1$ in each sector $i=A,M,S$. The first step is to solve the following system of four equations:

$$\alpha_{LA}\widehat{W}+\alpha_{KA}\widehat{\Pi}_A=\widehat{P}_A$$

$$\alpha_{LM}\widehat{W}+\alpha_{KM}\widehat{\Pi}_M=0$$

$$\alpha_{LS}\widehat{W}+\alpha_{KS}\widehat{\Pi}_S=\widehat{P}_S$$

$$\beta_A\widehat{\Pi}_A+\beta_M\widehat{\Pi}_M+\beta_S\widehat{\Pi}_S=\widehat{W} \tag{A1}$$

for $\hat{W}$ and $\widehat{\Pi}_i$ (recall, $\widehat{P}_M=\widehat{P}_I=0$ by assumption). The first three equations are the sectoral price-equals-unit-cost conditions, whereas the last equation is derived from the labor constraint (which implies $\sum_i \beta_i\widehat{L}_i=0$) and the fact that $\widehat{L}_i=\widehat{\Pi}_i-\widehat{W}$ in the Cobb–Douglas case.

The solution for the wage-price elasticity is given as follows:

$$\widehat{W}/\widehat{P}_A=\left(\beta_A/\alpha_{KA}+\beta_S\delta/\alpha_{KS}\right)/D, \tag{A2}$$

where $D=1+\sum_i\beta_i\alpha_{Li}/\alpha_{Ki}$. In the case of equal input cost shares across sectors, $D=1+\alpha_L/\alpha_K$ and Equation (A2) reduces to Equation (5) in the text.

Solving for the elasticity of the services sector price with respect to the agricultural sector price, δ, involves equating changes in service sector supply $\hat{Y}_S$ and demand $\widehat{X}_S$. If the Marshallian demand function for services takes the form $X_S=\eta y/P_S$ (i.e., Cobb–Douglas preferences), where η is a share parameter, then

$$\widehat{X}_S=\widehat{y}-\widehat{P}_S=(1-E/y)\left(\omega_A\widehat{P}_A+\omega_S\widehat{P}_S\right)-\widehat{P}_S \tag{A3}$$

30. A full analysis of rural–urban labor market linkages is beyond the scope of this study, but is an important topic for future research.

where $\omega_j=(1+\alpha_{Kj}/\alpha_{Lj})\beta_j/(1+\sum_i\beta_i\alpha_{Ki}/\alpha_{Li})$.

On the supply side, from the services production function and the specificity of capital, we have:

$$\widehat{Y}_S=\alpha_{LS}\widehat{L}_S+\alpha_{IS}\widehat{I}_S. \tag{A4}$$

Meanwhile, the condition that input prices equal respective marginal value products delivers $\widehat{W}=\widehat{P}_S+\widehat{F}_{L_S}=\widehat{P}_S-\widehat{L}_S+\widehat{Y}_S$ and $\widehat{P}_S=-\widehat{F}_{I_S}=\widehat{I}_S-\widehat{Y}_S$, where the second equality in each case follows from the total differentiation of the marginal product functions F_{L_S} and F_{I_S}. Solving these two equations, after first substituting out $\hat{I}_S$ from the second using Equation (A4), yields

$$\widehat{Y}_S=\frac{\alpha_{LS}+\alpha_{IS}}{\alpha_{KS}}\widehat{P}_S-\frac{\alpha_{LS}}{\alpha_{KS}}\widehat{W}. \tag{A5}$$

Substituting Equation (A2) into Equation (A5), equating the result to Equation (A3), and solving gives:

$$\delta=\frac{\alpha_{KS}(1-E/y)\,\omega_A D+\alpha_{LS}\beta_A/\alpha_{KA}}{D\left(1-\alpha_{KS}(1-E/y)\,\omega_S\right)-\alpha_{LS}\beta_S/\alpha_{KS}}. \tag{A6}$$

With equal input cost shares, Equation (A6) simplifies to $\delta=R\beta_A/(\alpha_K+\alpha_L-R\beta_S)$ where $R=\alpha_L+\alpha_K(\alpha_K+\alpha_L)(1-E/y)$. Finally, as mentioned in the text, $E=0$ and $\alpha_I=0\Rightarrow R=1\Rightarrow\delta=\beta_A/(1-\beta_S)$.

PARAMETERS COMPUTED FROM NSS DATA

Input Cost Shares in Agriculture

The 59th round of the National Sample Survey (NSS59) collected nationally representative farm household data in 2002–2003, including information on agricultural inputs and outputs for over 40,000 farms. The labor cost share is $\alpha_L=W(\ell_h+\ell_f)/\sum_j P_jY_j$, where ℓ_h and ℓ_f are, respectively, hired and family labor in agriculture and the denominator is the value of crop production. We may write the numerator as $W\ell_h(1+f)$, where $f=\ell_f/\ell_h$ is the ratio of family to hired labor. For a labor market in equilibrium, f should equal the ratio of the number of agricultural laborers working on their own farm to the number working for wages on other farms. Thus, we can calculate f for each of the five regions (north, northwest, center, east, and south) from individual employment data in NSS61-EUS. Comparable data on hired labor expenses (for regular and casual farm workers), $W\ell_h$, and on total value of crop production are available at the farm-level by season from NSS59. Summing up $W\ell_h$ across seasons and households within each region (using sampling weights) multiplying by $(1+f)$ and dividing by a similarly computed sum of production value gives the regional labor shares. I use the same approach for the intermediate input shares $\alpha_I=P_II_A/\sum_jP_jY_j$, where the numerator is the total expenditures on non-labor variable inputs as reported in NSS59 (seed, fertilizer, pesticide, and irrigation). The results of these calculations are as follows:

TABLE A1
Estimated Input Shares

	North	Northwest	Center	East	South
α_L	0.331	0.304	0.258	0.317	0.260
α_I	0.264	0.325	0.258	0.250	0.238

TABLE A2
Summary Statistics for Major States of India

	Annual PC Expend.	ψ	β_A	β_S	β_M	No. of Districts
North						
Haryana	4.559	1.177	0.785	0.142	0.073	19
	(0.817)	(0.136)	(0.138)	(0.111)	(0.081)	
Himachal Pradesh	4.094	1.161	0.772	0.165	0.063	12
	(0.551)	(0.112)	(0.120)	(0.095)	(0.049)	
Punjab	4.535	1.145	0.731	0.203	0.067	17
	(0.891)	(1.145)	(0.160)	(0.135)	(0.041)	
Uttaranchal	3.296	1.177	0.761	0.187	0.052	13
	(0.474)	(0.163)	(0.180)	(0.147)	(0.058)	
Uttar Pradesh	3.108	1.182	0.781	0.149	0.070	70
	(0.596)	(0.127)	(0.124)	(0.090)	(0.068)	
Northwest						
Gujarat	3.136	1.316	0.835	0.088	0.078	25
	(0.579)	(0.169)	(0.136)	(0.084)	(0.093)	
Rajasthan	3.317	1.266	0.758	0.168	0.075	31
	(0.503)	(0.103)	(0.091)	(0.073)	(0.057)	
Center						
Chhattisgarh	2.244	1.253	0.870	0.092	0.038	13
	(0.481)	(0.085)	(0.113)	(0.093)	(0.041)	
Madhya Pradesh	2.489	1.249	0.860	0.104	0.035	45
	(0.608)	(0.092)	(0.117)	(0.103)	(0.050)	
Maharashtra	2.752	1.204	0.825	0.118	0.057	33
	(0.558)	(0.137)	(0.120)	(0.071)	(0.058)	
Orissa	1.964	1.131	0.759	0.151	0.090	30
	(0.557)	(0.135)	(0.137)	(0.114)	(0.076)	
East						
Bihar	2.408	1.183	0.802	0.142	0.055	37
	(0.391)	(0.155)	(0.167)	(0.126)	(0.068)	
Jharkhand	2.257	1.040	0.697	0.210	0.093	18
	(0.441)	(0.282)	(0.243)	(0.210)	(0.073)	
West Bengal	2.667	0.951	0.603	0.223	0.174	17
	(0.363)	(0.189)	(0.139)	(0.075)	(0.113)	
South						
Andhra Pradesh	2.486	1.073	0.717	0.174	0.109	22
	(0.308)	(0.081)	(0.090)	(0.099)	(0.052)	
Karnataka	2.595	1.159	0.828	0.094	0.078	27
	(0.593)	(0.208)	(0.176)	(0.081)	(0.117)	
Kerala	4.355	0.686	0.370	0.458	0.172	14
	(0.877)	(0.289)	(0.223)	(0.172)	(0.096)	
Tamil Nadu	2.386	0.891	0.588	0.225	0.187	29
	(0.369)	(0.228)	(0.174)	(0.114)	(0.139)	

Notes: Means (standard deviations) of district-level data. Annual per capita expenditures are in thousands of 2004 Rupees.

Sectoral Labor Shares

Despite being a so-called "thin" round, NSS64, collected in 2007–2008, fielded the standard Employment–Unemployment Survey questionnaire on a "thick"-round sample of nearly 80,000 rural households. I use these data to compute district-level sectoral labor shares at roughly the mid-point between 2004–2005 and 2009–2010. As the survey was carried out throughout the whole year in most districts, agricultural labor seasonality is not a major issue at the district level. For each individual, I compute the total manual labor days in the last week in both agricultural and nonagricultural jobs, apportioning the latter (based on industry codes) between services and manufacturing sectors. I then take a population-weighted sum of days across individuals in each district to get total district labor days (per week) by sector, $D_{d,m}$, $m = \text{MA}$ (manual ag. labor), MNA (manual nonag. labor), and MNAS (manual nonag. labor in services).

There is a persistent daily wage gap between agriculture and nonagriculture, present across all NSS-EUS rounds, which suggests that days spent in agriculture are substantially less productive than those spent in nonagriculture. In particular, an agricultural sector dummy included in a log-wage regression using the NSS64 rural sample attracts a coefficient of −0.243, after controlling flexibly for gender, age, education, and district. Thus, labor productivity is around 24% lower per day in agriculture. To account for this productivity difference, I incorporate an efficiency units assumption into the model. In other words, the labor constraint becomes $L = L'_A + L_M + L_S$, where $L'_A = L_A e^{-0.243}$. The district-level sectoral labor shares, in efficiency units, can hence be

calculated using

$$\beta_{d,A} = \frac{e^{-0.243} D_{d,MA}}{e^{-0.243} D_{d,MA} + D_{d,MNA}}$$

$$\beta_{d,S} = \frac{D_{d,MNAS}}{e^{-0.243} D_{d,MA} + D_{d,MNA}}.$$

Descriptive statistics for sectoral labor shares and other key variables are shown in Table A2.

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