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Food Prices and Poverty Reduction in the *Long Run*

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ABSTRACT

Standard microeconomic methods consistently suggest that, in the short run, higher food prices increase poverty in developing countries. In contrast, macroeconomic models that allow for an agricultural supply response and consequent wage adjustments suggest that the poor ultimately benefit from higher food prices. In this paper we use international data to systematically test the relationship between changes in domestic food prices and changes in poverty. We find robust evidence that in the *long run* (one to five years) higher food prices reduce poverty and inequality. The magnitudes of these effects vary across specifications and are not precisely estimated, but they are large enough to suggest that the recent increase in global food prices has significantly accelerated the rate of global poverty reduction. The policy implications of these findings are therefore nuanced: short-run social protection is justified in the face of high food price volatility, but passing on higher prices to producers in the long run is an important means of reducing poverty in the poorest countries.

Keywords: food crisis, food prices, poverty reduction, inequality, income growth

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1. INTRODUCTION

Sharp increases in international food prices since 2007 have widely been termed the *global food crisis*. Indexes of staple grains—as well as other higher-value food groups—doubled or tripled over the course of 2007–2008, fell precipitously in the second half of 2008, and then surged again over 2010–2011 in a second food crisis. That these price spikes caused a sense of crisis—including food riots in several places and a range of panicky trade responses (Headey 2010)—is not in dispute. But far less certain are the aggregate impacts of higher food prices on material well-being. The earliest attempts to gauge such impacts—all of which were based on the net benefit ratio approach pioneered by Deaton (1989)—invariably concluded that global poverty would increase sharply as the result of *ceteris paribus* increases in food prices, by an order of 105 million people (Ivanic and Martin 2008) to 160 million people (de Hoyos and Medvedev 2009).[1] Yet the predictive accuracy of those estimates has been questioned. Theoretical commentaries pointed out that the prevailing wisdom prior to the 2008 food crisis was that high agricultural prices were good for the poor (Swinnen 2010). The first multicountry empirical work on the crisis found no evidence of any global increase in self-reported food insecurity (Headey 2013), and a similar analysis of African data also found very modest increases in food insecurity (Verpoorten, Arora, and Swinnen 2011). The most recent World Bank poverty estimates also reveal an almost ubiquitous decline in global poverty, a finding that is at least potentially inconsistent with sizable poverty impacts of higher food prices (The Economist, 2012). And recent macroeconomic models find that higher agricultural prices have large positive impacts on rural wages in the long run, such that higher food prices ultimately reduce poverty (Jacoby 2013; Van Campenhout, Pauw, and Minot 2013).

In this paper we aim to further inform this debate by exploring the relationship between changes in poverty and changes in domestic food prices across a large swathe of developing-country *poverty episodes* that vary between one and five years in length. Although a large and related literature examines statistically the drivers of poverty reduction using cross-country data (Christiaensen, Demery, and Kühl 2011; de Janvry and Sadoulet 2010; Loayza and Raddatz 2010; Ravallion, Chen, and Sangraula 2007), and within that literature a handful of papers explores the links between inflation and poverty reduction (Easterly and Fischer 2000; Ravallion and Datt 2002), the present paper appears to be the first cross-country examination of whether higher food prices help or hinder poverty reduction. While cross-country analyses typically have limitations in terms of causal identification (Durlauf, Johnson, and Temple 2005), we use the exogeneity of international food prices as a natural instrument for domestic food price movements. We also engage in a wide range of robustness tests, as well as tests for structural breaks and parameter heterogeneity.

In terms of results, this paper uncovers a remarkably robust empirical relationship that is strikingly different from those derived from short-run simulation approaches. In the long run—poverty episodes of one to five years in duration—it appears that higher food prices typically *reduce* poverty. The elasticity of the $1.25-per-day ($1.25/day) poverty headcount with respect to domestic food price movements varies between 0.30 and 0.46, and is significantly different from zero (though imprecisely estimated). The $1.25/day poverty *gap* measure yields even larger elasticities, whereas the $2/day headcount measure yields smaller elasticities. Together, these results suggest that the ultra poor may benefit even more from higher prices than the more marginally poor. Reducing the duration of the poverty episodes makes no difference to these results, suggesting factor price adjustments occur relatively quickly. Using robust or instrumental variable regressors also makes no difference to the results, suggesting that the elasticities are not driven by outliers and plausibly represent causation rather than mere correlation. And although the various point estimates are not precisely estimated, taken at face value they suggest that higher food prices from the mid-2000s onward have reduced global poverty by somewhere between 87 to 127 million people.

[1] Subsequent estimates of the impact of the 2010–2011 price surge suggested a further 44 million people would be thrown into poverty (Ivanic, Martin, and Zaman 2011). A number of country studies have also found that higher food prices typically increase poverty. See Headey and Fan (2010) and Compton, Wiggins, and Keats (2011) for reviews.

In the concluding section of the paper, we reflect on explanations and implications of this result. In terms of the former, our results are clearly consistent with macroeconomic models that produce substantial factor price adjustments to higher food prices, particularly wage adjustments. In terms of policy implications, it is clearly critical to distinguish between short-run and long-run impacts. Although the results in this paper are consistent with higher food prices being beneficial for poverty reduction after factor price adjustments have taken place, higher-frequency data on the real wages of unskilled workers in developing countries imply that such adjustments do not happen instantaneously, and that poor net consumers could indeed be hard hit by higher food prices in the short run. This suggests that although many of the policy responses aimed at protecting the poor from food price volatility were indeed justified, passing on higher food prices to farmers in developing countries is also justified, not only in terms of much-needed supply responses, but also on the grounds that higher food prices will ultimately reduce poverty.

The remainder of this paper is structured as follows. Section 2 of the paper briefly reviews existing theory and evidence on the impact of food prices on poverty and welfare, including unskilled wages. Section 3 discusses the data and methods used in this paper. Section 4 reports our results. Section 5 concludes.

2. THEORY AND EVIDENCE TO DATE

The workhorse model of research into food prices and economic welfare has undoubtedly been Deaton's (1989) net benefit ratio approach. In this partial equilibrium approach it is typically only first-order (direct) impacts that are modeled, with the decisive influence on welfare outcomes being whether a household is a net consumer or net producer of food, as in

$$\dot{y} = \left(\dot{s}_F^y - \dot{v}_F^c\right).\dot{p}_{F,} \tag{1}$$

where $\dot{y}$ is the percentage change in real income, $\dot{s}_F^y$ is the share of income directly derived from food production, $\dot{v}_F^c$ is the share of household consumption of food, and $\dot{p}_F$ is the percentage change in real food prices.

Applications of the net benefit ratio approach almost invariably find that higher food prices increase poverty in poor countries. At least three studies have produced global estimates for changes in poverty resulting from higher international food prices. Ivanic and Martin (2008) extrapolate from a nine-country sample to estimate that 105 million people could fall into \$1.25/day poverty by higher food prices, all else equal. Based on a sample of 73 developing countries, de Hoyos and Medvedev (2009) estimate that 155.6 million people would fall into \$1.25/day poverty, with almost all of that increase occurring in South and Southeast Asia (141.2 million). Most recently, Ivanic, Martin and Zaman (2011) extrapolate from a sample of 28 developing countries to estimate that the 2010–2011 price increases led to an additional 44 million people falling into poverty.[2] A superficial explanation of these results is that although many poor people produce food, their productivity (or access to land) is sufficiently low and their food expenditure shares sufficiently high so as to result in them being net food consumers.

Despite the consistency of results derived from the net benefit ratio approach, a number of observers of this literature have expressed skepticism. Swinnen (2010) points out that the prevailing consensus prior to the 2007–2008 crisis was that *low* agricultural prices were constraining poverty reduction.[3] Headey and Fan (2008, 2010) make note of the methodological limitations of simulation studies, including underlying data quality,[4] and the important general equilibrium issue of wage adjustments to higher food prices. However, they also note the limited evidence on wage adjustments, with much of the evidence derived from Bangladesh (Ravallion 1990; Palmer-Jones 1993; Rashid 2002).[5] In the last of those studies Rashid extends the datasets used in earlier studies, and finds a large long-run elasticity between agricultural wages and rice prices of 0.69, but relatively low short-run elasticities of 0.25 and 0.32 (depending on the model).[6] Lasco, Myers, and Bersten (2008) conducted a rare study outside Bangladesh. For the rural Philippines, they find somewhat stronger short-run elasticities between agricultural wages and food prices in the range of 0.29 to 0.57.

In the most recent crisis, only two papers that we are aware of have estimated high-frequency real wage series. For Ethiopia, Headey et al. (2012) examine the daily laborer wage series in urban and small town Ethiopia, which they deflate by a poor person's price index (food and nonfood). In Bangladesh, Zhang et al. (2013) examine the wage series of both rural and urban unskilled workers, which they deflate

[2] A range of other country-level simulation studies not reviewed here, but covered in Headey and Fan (2010) and Compton, Wiggins, and Keats (2011), also typically find that poverty increases as food prices rise.

[3] However, this conclusion was often based on trade liberalization scenarios where the focus is often on cash crops rather than staple foods.

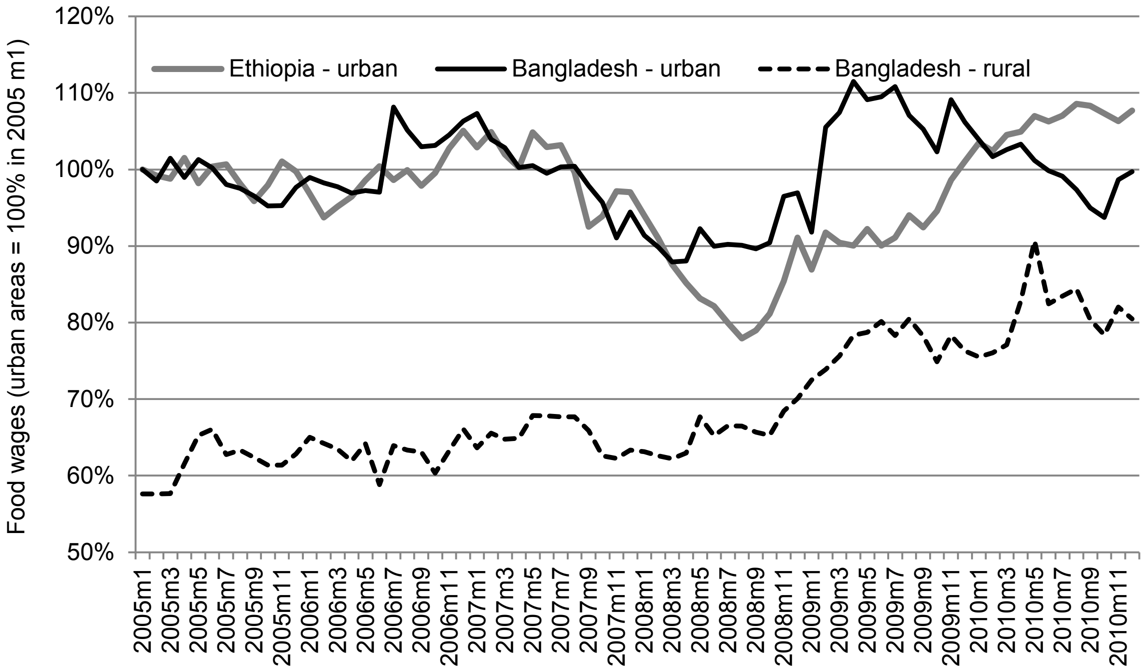
[4] Headey and Fan (2008, 2010) question whether household surveys can really measure net food consumption/production with sufficient accuracy. Consumption modules are based on short recall lengths of one to four weeks, or occasionally on household diaries. In contrast, production modules ask questions that may cover as much as 12 months. With attenuation bias, it is possible that these surveys overestimate the prevalence and depth of net food consumption in developing countries.

[5] Another recent paper focuses on general wage dynamics in Bangladesh over the 2000s (Zhang et al. 2013). They find that rural wages deflated by rice prices declined by one-third during the 2008 food crisis, though wages deflated by the food CPI as a whole were scarcely affected. The authors did not formally test for wage–price adjustments, however.

[6] Also of note is that Ivanic and Martin (2008) incorporate these short-run elasticities into one of their robustness tests.

by food and nonfood consumer price indexes (CPIs), as well as rice prices.[7] In Figure 2.1 we report food wages (wages deflated by the food CPI) for urban areas of Ethiopia and urban and rural areas of Bangladesh. For urban areas in both Ethiopia and Bangladesh, one sees a striking decline in real food wages from early 2007 to mid-2008, when international (and domestic) food prices peaked. This sharp decline in real wages suggests that, in urban areas at least, there is little short-run adjustment of nominal wages to higher food prices. Indeed, food wages in the urban areas of both Ethiopia and Bangladesh declined by 20 to 25 percent from early 2007 to mid-2008. In contrast, in rural Bangladesh there is no evidence of a negative impact of higher food prices on real wages. If anything rural wages start to increase from early 2008 onward. By mid-2009 rural wages were around 25 percent higher than they were in late 2007, and by the end of the period the rural–urban wage gap in Bangladesh had closed substantially. This is consistent with higher food prices inducing factor price adjustments in rural areas, even in the relatively short run.

Figure 2.1 Trends in food wages in Ethiopia and Bangladesh, 2005-2011



Source: Ethiopian data are drawn from Headey et al. (2012); Bangladeshi data are drawn from Zhang et al. (2013).
Notes: Both series pertain to unskilled laborers for urban areas. Both series are deflated by the food consumer price indexes (CPI), although Headey et al. (2012) construct a poor person's food CPI based on the consumption patterns of the bottom two expenditure quintiles. The x-axis refers to monthly (m) data.

A recent paper by Jacoby (2013) makes a strong theoretical case for such a wage response. Jacoby constructs a simple general equilibrium model that assumes constant returns to scale, fixed nonlabor input prices, a nontradable services sector, and labor markets characterized by fluidity between farm and nonfarm sectors, but spatial segmentation across Indian districts. Under those assumptions, the elasticity of rural wages with respect to agricultural prices (φ) is given by

$$\varphi = \frac{\beta_A + \delta\beta_S}{\alpha_L + \alpha_K}, \quad (2)$$

[7] Note that while Headey et al. (2012) are explicitly trying to gauge the impacts of the food crisis in Ethiopia, Zhang et al. (2013) are focused on explaining the long-run evolution of wages in Bangladesh, rather than short-run wage dynamics pertaining to food prices. Hence, Headey et al. (2012) report vector error correction estimates of both short- and long-run elasticities.

where β_A and β_S are the employment shares of agriculture and services in total employment (respectively), δ is the changes in the prices of service outputs relative to agricultural outputs, and α_L and α_K are the input share costs of labor and capital in agriculture. The size of this elasticity therefore depends on several important structural factors.

First, a larger agricultural sector (β_A) increases the wage elasticity since a larger sector demands more labor in absolute terms from the smaller nonfarm sector, which requires a larger wage adjustment to induce intersectoral shifts in labor. Second, the larger the service sector (β_S), the larger the wage elasticity. As a nontradable and very labor-intensive sector, a large increase in agricultural prices will require a large increase in service sector prices to keep sufficient labor in services. This means that manufacturing has to make a larger contribution to the supply of agricultural labor, resulting in a larger rise in wages. Third, the higher the elasticity of service prices to agricultural prices (δ), the higher the wage elasticity. This will likely depend on the income elasticity of demand for services as well as the aggregate income effects of higher agricultural prices. Finally, the greater the importance of labor (α_L) and land (α_K) in agricultural production (or conversely, the smaller the importance of intermediate inputs such as fertilizers, pesticides, and traction services), the smaller the elasticity.

For India, Jacoby uses this model to deterministically illustrate that existing economic structures in India predict a positive wage–price elasticity on the order of 1.09 to 1.17, while econometric estimates of this elasticity cannot reject the null that it is equal to unity. In terms of welfare outcomes, Jacoby uses an extended version of the net benefit ratio approach that includes factor income responses to higher agricultural prices (θ):

$$\dot{y} = \left(\theta \dot{s}_F^y - \dot{v}_F^c\right) . \dot{p}_F, \tag{3}$$

where $\theta = \frac{\omega_K^y (1-\alpha_L \varphi)}{\alpha_K} + \varphi \omega_L^y - \delta v_S$, ω is the share of income derived from land (K) or labor (L), and v_S is the share of expenditures on services. Jacoby uses equation (3) to predict that the elasticity between household expenditures and agricultural prices for rural Indians varies from 0.25 for the poorest quintile to 0.40 for the richest. For rural India he shows that this directly contradicts the predictions of the net benefit approach, in which expenditure goes down for all but the richest groups.[8]

What Would this Model Predict for Other Developing Regions?

First, any country with large shares of employment in agriculture and services should ultimately benefit from higher food prices (unless there was sharp labor market segmentation between sectors, which would confine any wage responses to the agricultural sector only). This structural feature alone would imply a wage elasticity of close to unity, which in turn would predict that rural populations benefit from higher food prices, since they largely consist of net producers and unskilled wage earners. Thus, while poor populations do indeed spend more of their budgets on food, their incomes are also much more responsive to agricultural prices.[9]

Second, while Jacoby's model could predict that even urban wages rise in response to higher food prices (if there is no substantial segmentation between rural and urban labor markets), it is still likely that urban people are somewhat worse off in the short run when food prices increase, because there are presumably little or no first-round effects of higher food prices on urban income. Yet in the poorest countries it must be remembered that the urban poor typically make up only a small fraction of the total poor (at least, at lower poverty lines). Moreover, it is not inconceivable that spatial mobility is reasonably

[8] Van Campenhout, Pauw, and Minot (2013) also model trade effects, particularly impacts on the exchange rate that might result from changes in a country's terms of trade.

[9] One might claim that, relative to Asia, Africa has less-developed labor markets and would therefore benefit less from this type of general equilibrium wage effect. On the other hand, if many rural Africans are indeed net food consumers, it is difficult to argue that they are not dependent on wage incomes, since their cash incomes must come from manual labor.

high among many poor populations, suggesting some scope for migration as a response to higher agricultural prices over the longer run.[10]

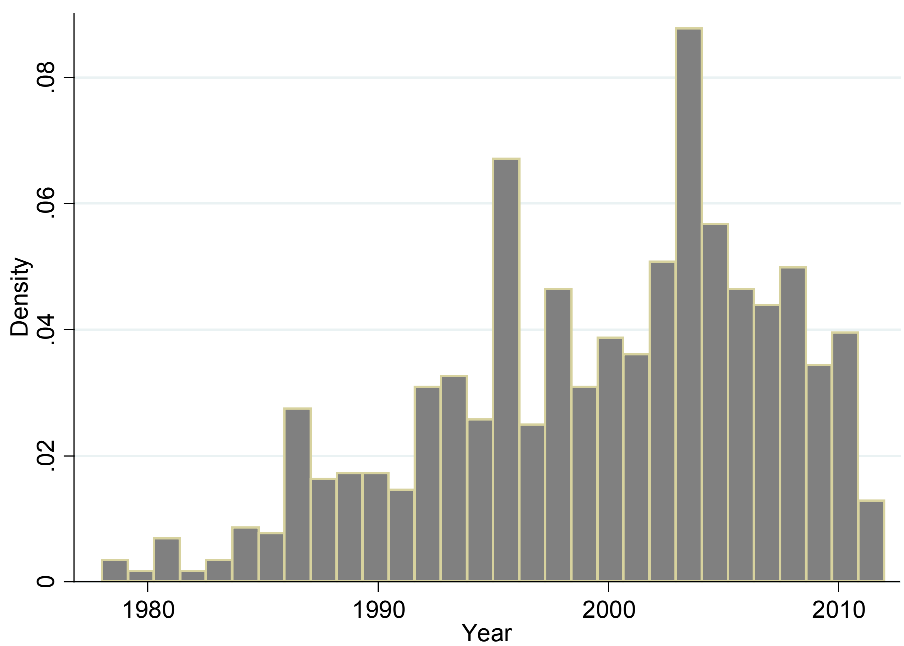
In summary, whereas general equilibrium approaches to assessing the welfare benefits of higher agricultural prices suggest that poorer countries may well benefit from higher food prices, partial equilibrium approaches that prohibit factor price adjustments imply that poverty rates will increase. In the next section we describe the data and methods used to derive reduced-form tests of these alternative predictions, because very few of the structural parameters in equation (3) are measurable in international data.

[10] Headey et al. (2012) reported that the vast majority of urban construction workers in Ethiopia come from rural households, suggesting they may return to rural areas during peak agricultural seasons.

3. DATA AND METHODS

In this paper we use a cross-country dataset that merges data from a variety of sources. Poverty, income, and inequality data are from the World Bank's Povcal dataset (World Bank 2013a). These data are measured at the national level for most countries, at the urban level for a few middle-income countries, and at both the rural and urban level for China, India, and Indonesia. In addition to poverty headcounts—which can be measured for any given international poverty line—Povcal also yields data on higher-order poverty indicators such as the poverty gap, mean household income or expenditure, and inequality indicators such as the Gini coefficient. We also note that while such data have been widely used in previous research, the most recent version of Povcal constitutes a major extension over previous versions in terms of sample size and country coverage. Moreover, a large proportion of these observations fall in the 2005–2010 window, when there was considerable volatility in food and nonfood commodity prices (Figure 3.1). This provides us with much-needed variation in food prices across countries and across time. We also note that the Povcal data determine the duration of our poverty episodes, which vary between 1 and 17 years. But given that very long poverty episodes are probably ill-suited to identifying the impacts of food price changes on poverty (since many other unobservables will change over longer periods of time), we restrict our analysis to episodes no longer than six years. Hereafter, this one-to-six-year period is what we refer to as the *long run*.

Figure 3.1 A histogram of Povcal observations



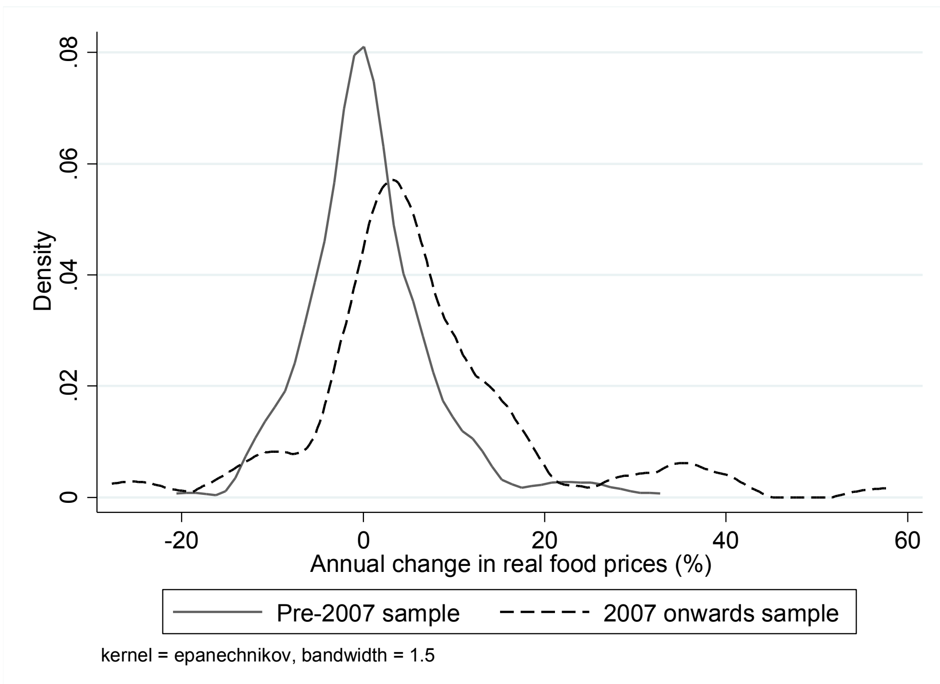
Source: Author's estimation from World Bank (2013a) data.

A second important source of the data is the International Labour Organization (ILO 2013), which provides consumer price indexes for food and other items. These data are measured monthly, though we have cleaned and aggregated the data to yearly series. Food price changes are measured as the percentage change in the ratio of the food CPI to the nonfood CPI.[11] The use of domestic price data is

[11] Previous analyses of the impact of food prices on global welfare have also used these data. De Hoyos and Medvedev (2009) use the ratio of the food CPI to the total CPI, while Headey (2013) uses the food CPI to the nonfood CPI. However, like Headey (2013), the nonfood CPI must be imputed. In this paper we take food expenditure shares from the FAO for a relatively narrow range of countries and years, and then fit cross-country Engel-type relationships between food expenditure shares and the

advantageous relative to studies that simply assume transmission rates between international and domestic prices, but a potential drawback of domestic price series is that such price trends may not be strictly exogenous, as we discuss subsequently. Figure 3.2 shows kernel densities of the distribution of annualized real food price changes for the poverty episodes analyzed in this paper, but splits the sample into a pre-crisis period and a crisis period based on the last year of the poverty episode. It is evident from the graph that the pre-crisis and crisis distributions are very different. Prior to the crisis the average real food price change was just 0.47, and not significantly different from zero (the 95 percent confidence interval is -0.42, 1.35). But from 2007 to 2011 the average annual change in real food prices was a significantly larger 5.75 (95 percent confidence intervals of 3.26 and 8.23), and the tail of the distribution extends further out to the right. Thus there was a significant and quite rapid acceleration of real domestic food prices in this period, consistent with imported food price inflation. We rely on that fact in several of our identification tests discussed subsequently.

Figure 3.2 Changes in relative food prices before and after the food crisis



Source: Author's estimation from World Bank (2013a) data.

Although domestic food prices are clearly influenced by higher international food prices, a number of domestic shocks may also drive food price changes and that have independent effects on poverty. There are many such examples. A drought could increase domestic food prices and reduce farm incomes and wages. A financial crisis could influence the exchange rate (which influences international price transmission) but also separately affect unemployment and incomes. Expansionary government policies could increase employment but also have inflationary impacts. And increases in real food prices might simply be highly correlated with rapid aggregate inflation, which may have its own impacts on poverty. Although some of the shocks that might induce these simultaneity biases are unobservable, many are observable. To control for such factors we augment the Povcal and ILO data with changes in agricultural gross domestic product (GDP), M2 money supply, exchange rates, terms-of-trade indexes,

log of GDP per capita. This relationship yields a very high R-squared of 0.86. We then use predicted food expenditure shares to derive the nonfood CPI from the total CPI and food CPI data reported by the ILO.

and aggregate consumer price indexes. These data are derived from either the World Development Indicators (World Bank 2013b) or the Food and Agriculture Organization (FAO 2013), with the exception of CPI inflation, which is drawn from the aforementioned ILO database.

Table 3.1 presents some basic descriptive statistics for our key variables. The table shows descriptive statistics for the full sample, as well as a cropped sample in which we make several exclusions. First, we exclude poverty spells where the initial poverty headcount was less than 5 percent. Inclusion of countries with very low initial poverty rates can create changes in poverty that are exceptionally high in percentage terms, as indicated by the maximum values in the first three columns of Table 3.1. Thus we follow Bourgignon (2002) and others in excluding these values from our analysis. This cuts the sample size by around 200 observations, but at little informational cost because countries with poverty headcounts close to zero are of little material interest in the present analysis. Second, we exclude poverty episodes that are longer than five years in duration (though there are relatively few of these). Very long poverty episodes are likely picking up secular changes in food prices that are qualitatively different from short- to medium-term changes. In some of our robustness tests we will further shorten the duration of poverty episodes. Finally, we crop the top and bottom 2.5 percent of changes in food prices (13 observations) to purge the data of episodes in which there were extreme increases or decreases in real food prices that were unlikely to be related to international price movements and more likely related to domestic macroeconomic crises. For example, we dropped all the recent poverty episodes for Zimbabwe, as well as well-known hyperinflationary episodes from Latin America in the 1980s and early 1990s (Brazil and Mexico in the early 1990s, for example) and an episode covering Indonesia's financial crisis.

Table 3.1 Summary statistics for key variables

	Full sample			Cropped sample		
Statistics	**\$1.25/day poverty**	**Change in poverty (%)**	**Change in food prices (%)**	**\$1.25/day poverty**	**Change in poverty (%)**	**Change in food prices (%)**
Observations	523	509	493	273	262	278
Mean	14	90	2	19.9	-7.7	4.3
Median	7	-10	0	14.7	-9.5	1.6
Standard deviation	18	1155	18	17.5	27.6	14.4
Minimum	0	-98	-47	0.1	-74.3	-21.9
Maximum	81	20950	143	78.2	85.3	75.7

Source: Author's estimates.

Notes: The poverty, Gini coefficient, and mean income data are from World Bank (2013a). Changes in food prices are from ILO (2013). Changes in the terms of trade are from the World Bank (2013b).

The next question is how best to analyze these data. Our basic model takes the form

$$\dot{H}_{i,t} = \varepsilon_p \dot{p}_{i,t} + \beta \dot{X}_{i,t} + v_{i,t}, \tag{4}$$

where H is a poverty indicator, p is the relative price of food, X is a set of control variables, v is an error term, and dots above the variables denote percentage changes for country i from the beginning to the end of a poverty episode (subscript t).

While an ordinary-least-squares (OLS) version of equation (4) describes our basic model, it is important to engage in a number of different tests of the key parameter, ε_p. We first use nonparametric regressions, particularly the LOWESS regressor, and Stata's robust regressor. Both are used to minimize the influence of outliers (the former does so locally, which allows us to look for nonlinearities). Although we have already cleaned the data (as discussed earlier), outliers are potentially an important problem in this relatively small sample.

Second, we use regressions that add fixed effects to the model, following the approach of Christiaensen, Demery, and Kühl (2011), who also analyze these types of poverty episodes. Of course, the model's variables are already specified in percentage differences, so these fixed effects really represent country-specific trend effects rather than time-invariant unobservables. But adding the country trend effects is potentially important because secular changes in real food prices could be correlated with other unobserved poverty-relevant secular trends.

Third, we estimate multivariate regression models that control for some of the potentially confounding factors described earlier: changes in agricultural GDP, exchange rates, M2 money supply, the terms of trade, the total CPI, and the size of the population.

Fourth, we apply an instrumental variables approach. We first construct an international food price index for every country, where the weights in the index are the share of a country's calories derived from the particular food type, with a focus on those foods for which there is substantial international trade and an international price series: wheat, maize, rice, sorghum, soybean, and banana. The logic of this approach is that a country's domestic food CPI is an index broadly weighted by consumption patterns, so the food CPI should be more sensitive to international food price movements when international price changes are larger for the foods that a country consumes more of.[12] We then regress domestic food price changes against changes in this country-specific international food price index, as well as its interaction with changes in the exchange rate (to allow for variation in price transmission). Hence our first-stage regression takes the form

$$\dot{p}_{i,t} = \gamma^{f}\dot{p}^{f}_{i,t} + \gamma^{fx}\dot{p}^{f}_{i,t}.\dot{x}_{i,t} + T + u_{i,t}, \qquad (5)$$

where the dependent variable is the change in real food prices, p^f is the change in each country's international food price index, x is each country's exchange rate with respect to the US dollar (the currency in which food and gasoline are also denominated), T is a global time trend, and u is the error term.

An important aspect of equation (5) worth noting is that while international prices are exogenous, exchange rate movements are potentially endogenous, since there are several ways in which they might influence poverty in addition to food price effects. On the other hand, in the recent global food crisis the US dollar devalued against the majority of the world's currencies, suggesting that some exchange rate movements (particularly those in recent years) are largely exogenous. We will therefore also estimate a sample of observations that is restricted to the 2000s, since this period has sufficient variation in international prices as well as exchange rate movements that are largely driven by global macroeconomic imbalances weakening the US dollar. In any case, results reported in the appendix show that movements in the country-specific international food price index explain substantial variation in domestic price movements even when exchange rates are excluded from the first-stage model.

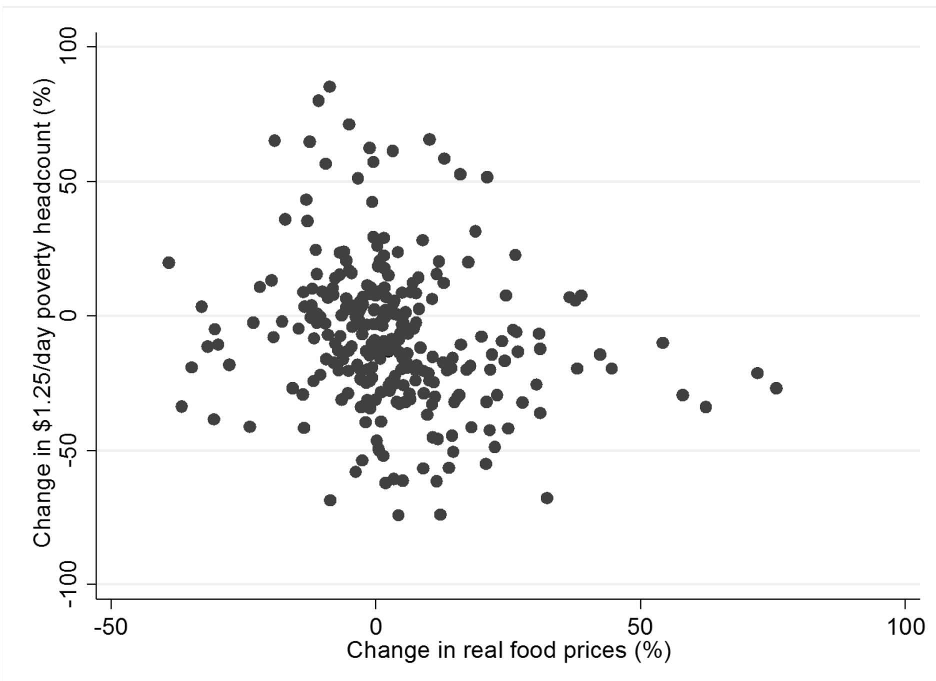
Finally, in addition to the various estimation approaches we have described, we also vary the poverty measure used in the left-hand side of equation (4). As per international norms, we chiefly focus on the \$1.25/day poverty headcount. To examine the impact on the ultra poor, we also use the \$1.25/day poverty gap, which attaches more weight to the depth of poverty below this line, and the \$2/day poverty line, which includes populations that are more marginally poor (and generally somewhat more urbanized).

[12] The food CPI is typically weighted by expenditure shares on particular items, but these were not available for all the countries in our sample. Another alternative available to us was to use trade shares of different foods to weight this index. We did indeed experiment with such an index, though the consumption-weighted index performed slightly better at explaining domestic food price movements in the first-stage regressions. Also note that both sets of indexes were constructed from FAO (2013) data.

4. RESULTS

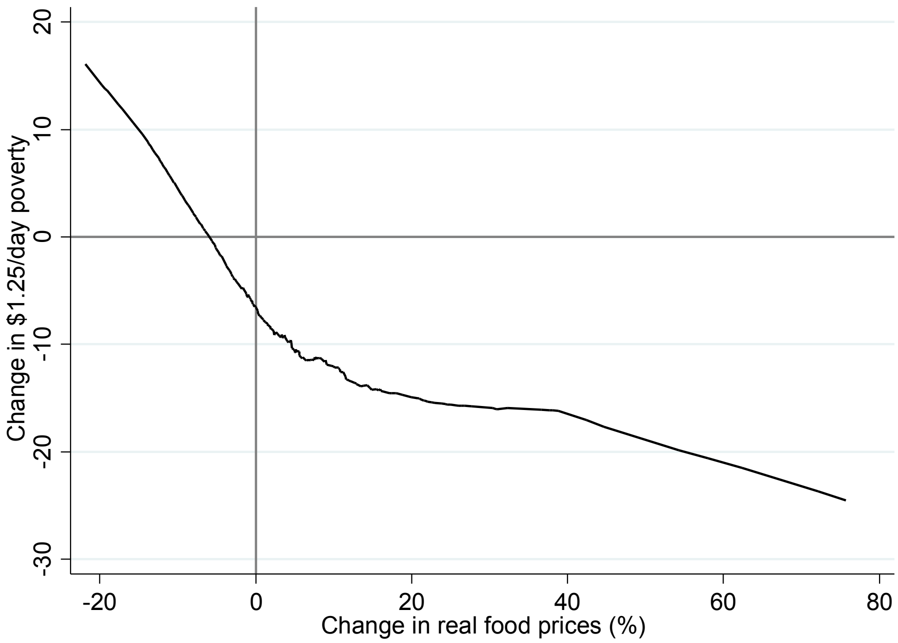
We begin our empirical analysis by focusing on the relationship between changes in $1.25/day poverty headcounts and changes in real food prices. Figure 4.1 shows a basic scatterplot of changes in the $1.25/day poverty headcount and changes in real food prices. There is some suggestion of a negative relationship, though it is also evident that the data are reasonably noisy. Figure 4.2 therefore presents the LOWESS-predicted relationship between the two variables. It is now immediately clear that a negative and reasonably steep relationship exists between food prices and poverty. The relationship is approximately linear, although the gradient is flatter over the range in which food prices increase by 10 to 40 percent.

Figure 4.1 A scatterplot of the relationship between changes in $1.25/day poverty headcounts and changes in real food prices



Source: Author's estimates.
Notes: This graph shows a scatterplot of percentage changes in the $1.25/day poverty headcount against percentage changes in real food prices. The scatterplot labels are World Bank three-letter country codes along with the time span of the poverty episode. Thus, ZMB:91:93 refers to food price changes and poverty change in Zambia from 1991 to 1993.

Figure 4.2 A LOWESS prediction of the relationship between changes in real food prices and changes in $1.25/day poverty headcounts



Source: Author's estimates.
Notes: This graph shows kernel-weighted local polynomial predictions of the percentage changes in the $1.25/day poverty headcount against percentage changes in real food prices, along with the 95% confidence intervals in grey shade. LOWESS predictions are locally weighted regressions estimates, in this case implemented in STATA v13.

We now turn to multivariate regression models. Table 4.1 reports results from a number of variations in our estimation strategy. Regression 1 reports a simple OLS regression of changes in $1.25/day poverty headcounts against changes in food prices and a basic time trend. The elasticity with respect to changes in food prices is large in absolute magnitude and highly significant. A 1 percent increase in the price of food relative to nonfood items is predicted to reduce poverty by 0.46 points. That said, this estimate is not very precisely estimated, with 95 percent confidence intervals ranging from -0.23 to -0.69. Regression 2 uses Stata's robust regressor, which downweights outlying values. The point estimate is somewhat lower than the OLS result in regression 1, but still highly significant. Regression 3 adds a wide range of control variables. The coefficient on changes in food prices falls somewhat but is again highly significant and still large in economic magnitude. In regression 4 we added country fixed effects, which, as we noted above, really represent country trend effects. The point estimate of the coefficient on food price changes is the same as regression 2 in which we used the robust regressor, and still significant at the 1 percent level.

Finally, regression 5 uses the instrument variables (IV) approach with international prices weighted by domestic consumption patterns as the main instrument (see the appendix for full first-stage results). The point estimate on food price changes is very similar to the previous regressions and still significant at the 5 percent level. The IV test statistics at the bottom of Table 4.1 are also encouraging. First, the Wu-Hausman test suggests that changes in food prices may well be exogenous (and certainly the IV results are very close to the OLS and robust regression results). Second, the instruments are quite strong. The partial R-squared from the first-stage regression is a high 0.29, and the F-statistic on the significance of the instrument coefficients is a high 41, well above the suggested requirement of 10. Finally, the Hansen over-identification test easily rejects the null hypothesis that the instruments are correlated with the second-stage error term. Hence, the instruments appear to be exogenous to changes in poverty (though not obviously necessary), as one would expect.

Table 4.1 Regressions of changes in $1.25/day poverty headcounts against changes in real food prices

Regression number	R1	R2	R3	R4	R5
Modeling variations	**OLS**	**Robust**	**Robust with controls**	**Fixed effects**	**IV**
Change in food price (%)	-0.46*** (0.12)	-0.39*** (0.11)	-0.32*** (0.11)	-0.39*** (0.14)	-0.32** (0.16)
Time trend	-0.08 (0.29)	-0.01 (0.26)	0.49 (0.31)	-0.44 (0.34)	-0.10 (0.33)
Change in exchange rate (%)			0.31*** (0.08)		
Change in CPI (%)			-0.26*** (0.08)		
Change in agricultural GDP (%)			0.05 (0.11)		
Change in terms of trade (%)			-0.13 (0.12)		
Change in M2/GDP ratio (%)			0.08 (0.08)		
Population growth (%)			0.36 (0.55)		
R-squared	0.06	0.05	0.13	0.05	0.06
N	262	262	195	262	248
Wu-Hausman test: p-value					0.33
Partial R-squared, first stage					0.29
Hansen over-id test: p-value					0.75

Source: Author's estimates.
Notes: OLS = ordinary least square; IV = instrumental variables; CPI = consumer price index; M2/GDP = M2 money supply over GDP. See text for descriptions of the various tests and definitions of the variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are reported in parentheses. See the appendix for first-stage regression results.

The results in Table 4.1 therefore consistently suggest that changes in food prices are typically poverty reducing, at least in the one-to-five-year poverty episodes in these data. But one limitation of the poverty headcount data is that it treats all the $1.25/day poor equally. Conceivably, changes in food prices might have different effects on the ultra poor. In Table 4.2 we therefore regress changes in the $1.25/day poverty gap measure, which attaches more weight to the ultra poor. We still find negative elasticities with respect to food prices, but the elasticities are actually larger in absolute magnitude than the elasticities for poverty headcounts reported in Table 4.1. With the exception of the robust regression model with a full set of controls, the point estimates of these elasticities are all greater than -0.5, though somewhat imprecisely estimated. If anything, then, higher food prices tend to be just as beneficial to the ultra poor as the more marginally $1.25/day poor.

Table 4.2 Regressions of changes in $1.25/day poverty gap against changes in real food prices

Regression number	R1	R2	R3	R4	R5
Modeling variations	**OLS**	**Robust**	**Robust with controls**	**Fixed effects**	**IV**
Change in food price (%)	-0.64***	-0.50***	-0.35**	-0.53**	-0.52**
	(0.20)	(0.13)	(0.15)	(0.24)	(0.26)
Time trend	-0.35	0.09	0.59	-0.83	-0.46
	(0.48)	(0.32)	(0.40)	(0.60)	(0.57)
Change in exchange rate (%)			0.41***		0.01
			(0.10)		-0.02
Change in CPI (%)			-0.36***		
			(0.11)		
Change in agricultural GDP (%)			0.21		
			(0.14)		
Change in terms of trade (%)			-0.05		
			(0.15)		
Change in M2/GDP ratio (%)			0.13		
			(0.1)		
Population growth (%)			0.36		
			(0.71)		
R-squared	0.05	0.05	0.09	0.04	0.05
N	262	262	195	262	248
Wu-Hausman test: p-value					0.55
Partial R-squared, first stage					0.29
Hansen over-id test: p-value					0.62

Source: Author's estimates.
Notes: OLS = Ordinary least square; IV = instrumental variables; CPI = consumer price index; M2/GDP = M2 money supply over GDP. See text for descriptions of the various tests and definitions of the variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are reported in parentheses. See the appendix for first-stage regression results.

Are the results sensitive to the choice of poverty line? In Table 4.3 we switch to $2/day poverty headcounts instead of $1.25/day headcounts. There is substantial evidence that higher food prices are less beneficial for the $2/day poor. The OLS and robust regression coefficients are significantly different from zero, but the robust regression coefficients are about half as large as the $1.25/day poverty elasticities. The coefficients in the fixed effects and IV regressions are similar in magnitude to the robust regression coefficients, but neither are significant at the 10 percent level. We suggest that the somewhat weaker result for $2/day poverty headcounts is likely related to the rural–urban decomposition of poverty. In many poor countries urban poverty rates at the $1.25/day poverty line are relatively low, and much lower than rural poverty rates (Ravallion, Chen, and Sangraula 2007). In contrast, urban areas contain quite large numbers of $2/day poor. For these urban poor, higher food prices are obviously expected to have lower net benefits because they are net food consumers (almost by definition), and since spatial segmentation in labor markets may limit the urban wage response to higher food prices (Section 2).

Table 4.3 Regressions of changes in the $2/day poverty headcount against changes in real food prices

Regression number	R1	R2	R4	R3	R5
Modeling variations	OLS	Robust	Robust with controls	Fixed effects	IV
Change in food price (%)	-0.27***	-0.18**	-0.14*	-0.13	-0.14
	(0.09)	(0.08)	(0.08)	(0.10)	(0.20)
Time trend	-0.22	-0.27*	-0.02	-0.32	-1.00
	(0.19)	(0.17)	(0.20)	(0.22)	(1.00)
Change in exchange rate (%)			0.05		0.01
			(0.05)		(0.01)
Change in CPI (%)			-0.02		
			(0.06)		
Change in agricultural GDP (%)			0.03		
			(0.07)		
Change in terms of trade (%)			-0.19**		
			(0.08)		
Change in M2/GDP ratio (%)			-0.08		
			(0.05)		
Population growth (%)			-0.01		
			(0.37)		
R-squared	0.05	0.04	0.08	0.02	0.01
N	262	264	200	264	248
Wu-Hausman test: p-value					0.43
Partial R-squared, first stage					0.29
Hansen over-id test: p-value					0.45

Source: Author's estimates.
Notes: OLS = Ordinary least square; IV = instrumental variables; CPI = consumer price index; M2/GDP = M2 money supply over GDP. See text for descriptions of the various tests and definitions of the variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are reported in parentheses. See the appendix for first-stage regression results.

Another question of some importance is whether these results are robust to shorter time periods. In the main regression results reported earlier, the sample included poverty episodes ranging between one-year gaps and five-year gaps between successive surveys. In our theoretical section we defined the long run in a conventional economic way: the long run is the state of affairs after which all possible adjustments to higher food prices have taken place. Conceivably, an agricultural supply response to higher prices, and the corresponding labor market adjustments, could take several years (or seasons) to eventuate. In Table 4.4 we therefore restrict our poverty episodes to shorter and shorter durations, and apply the robust regressor to the very simple model that includes only a time trend. We choose the robust regressor in case the smaller sample sizes create increased sensitivity to outliers, and we use the parsimonious model because the results in Table 4.1 suggest that using IV, fixed effects, or larger sets of control variables makes very little difference to the results (and also that the IV approach may be unnecessary). Moreover, the limited degrees of freedom associated with smaller sample sizes could create problems with these more elaborate models.[13]

Strikingly, Table 4.4 shows that using shorter poverty episodes makes no substantial difference to the point estimates. The point estimates in Table 4.4 vary within a tight range of -0.35 to -0.44, though as expected the standard errors consistently increase as we reduce the sample size. This suggests that higher food prices typically reduce poverty, even in the comparatively short run.

Table 4.4 Regressions of changes in the $2/day poverty headcount against changes in real food prices under shorter poverty episodes

Regression number	**R1**	**R2**	**R3**	**R4**	**R5**
Length of poverty episodes	1–5 years	1–4 years	1–3 years	1–2 years	1 year
Change in food price (%)	-0.39***	-0.38***	-0.44***	-0.35**	-0.41**
	(0.11)	(0.11)	(0.12)	(0.15)	(0.19)
R-squared	0.05	0.04	0.06	0.05	0.05
N	262	242	226	182	144

Source: Author's estimates.
Notes: See text for descriptions of the various tests and definitions of the variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are reported in parentheses.

In Table 4.5 we engage in two types of tests for structural breaks. The motivation for this paper largely centered on the uncertainty surrounding the impacts of the 2007–2008 and 2010–2011 food price spikes on poverty. There are justifications for this approach. First, although it is difficult to conceive of an economic argument as to why the recent price spikes should be different from previous spikes, some unobservable factors may be present that alter the impact of higher food prices, such as differences in foreign aid flows and the spread of social safety nets. Hence, Table 4.5 first reports regression models that include an interaction between changes in food prices and a dummy for poverty episodes that ended in the period 2007–2012 (and are thus more likely to contain episodes of *imported* food inflation). We test this interaction term for OLS, the robust regressor, and the fixed-effects model in regressions 1 through 3 respectively.[14] Although the interaction terms with the 2007–2012 period dummy are positive, they are highly insignificant, suggesting that the recent food price spikes did not produce significantly different poverty outcomes to previous price spikes.

Second, regressions 4, 5, and 6 engage in a slightly different kind of test by restricting the sample to the 2000s only. The rationale for this restriction is that it may strengthen our claims to causal identification. From 2000 to 2005 international food prices were very low by historical standards, before rising rapidly in the second half of the 2000s. This combination of a low and a high food price period provides the necessary variation in imported food price inflation, but it also means we are excluding some episodes of food inflation that clearly create endogeneity problems. In particular, the 1980s and 1990s were periods of much greater macroeconomic instability in developing countries, including debt crises and structural adjustment programs that often influenced food prices through exchange rate adjustments. In contrast, the 2000s have been a period of remarkable macroeconomic stability in most developing countries, with the food and fuel crises being the main (exogenous) exception.[15] Regressions 4, 5, and 6

[13] For example, as the sample size increases the number of countries in the panel shrinks relatively little, meaning that adding country trend effects absorbs a large share of the degrees of freedom in the model, which is obviously unadvisable.

[14] Of course, it makes little sense to use the interaction term for the IV model, since the IV model relied on international price transmission in the first place.

[15] Note that even the global financial crisis had surprisingly muted effects on developing countries. Moreover, our sample of countries with initial poverty headcounts of 5 percent or more actually excludes many of the Eastern European and Central Asian countries that were worst affected by the global financial crisis.

show that restricting to the 2000s makes little difference to the results derived from using the full sample. The coefficients vary between -0.30 and -0.39, and with the exception of the fixed-effects model, are all highly significant. Lack of significance in the fixed-effects model is again unsurprising given the limited degrees of freedom (in particular, the ratio of countries to total observations is high, with 44 countries for just 164 observations).

Table 4.5 Testing for structural breaks, and restricting the sample to the 2000s only

Regression number	R1	R2	R3	R4	R5	R6
Modeling variations	OLS	Robust	Fixed effects	OLS	Robust	Fixed effects
Sample	Full	Full	Full	2000s only	2000s only	2000s only
Change in food price (%)	-0.58***	-0.53***	-0.47**	-0.38**	-0.31**	-0.30
	(0.17)	(0.16)	(0.19)	(0.15)	(0.13)	(0.20
Food prices*2007–2012 dummy	0.17	0.18	0.05			
	(0.25)	(0.23)	(0.30)			
2007–2012 dummy	4.29	4.62	7.56	12.95**	13.99**	16.50**
	(5.9)	(5.37)	(6.64)	(7.61)	-6.64	-8.31
R-squared	0.07	0.06	0.06	0.06	0.06	0.05
N	262	262	262	164	164	164

Source: Author's estimates.
Notes: OLS = ordinary least square. See text for descriptions of the various tests and definitions of the variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are reported in parentheses.

Finally, although there are no signs of structural breaks over time, there may be stronger grounds to expect parameter heterogeneity across countries. The theoretical model outlined in the previous section suggested that wage responses to higher food prices should be stronger in economies with larger agricultural sectors, so regression 1 of Table 4.6 interacts food price changes with the initial share of the size of agriculture. The coefficients of the interaction terms are counterintuitively positive, although highly insignificant. Another hypothesis is that more urbanized countries are more adversely affected by higher food prices. Again, though, there is no support for this in the data, as reflected by an insignificant and positive coefficient in regression 2 of Table 4.6. In regressions 3 and 4, we test interactions with Africa south of the Sahara and Asian dummy variables (South Asia and Southeast Asia), but the interactions do not yield significant coefficients. Finally, regression 5 interacts food price changes with initial poverty levels, but again, there is no evidence of significant parameter heterogeneity.

Of course, these results do not preclude the possibility that there is systematic heterogeneity in the impacts of food prices. One possibility is that the noisy nature of the data prevents identification of such heterogeneity. Another limitation is measurement related; the impact of higher food prices will depend on many factors that are simply not observable in international datasets, such as the functioning of labor markets. These limitations suggest that whereas higher food prices typically lead to poverty reduction in the long run, the reality may be that there is substantial variation in the impacts, which justifies some caution in interpretation and policy responses, and further country-level research.

Table 4.6 Robust regressions of interactions between food price changes and structural and regional indicators

Regression number	R1	R2	R3	R4	R5
Change in food prices (%)	-0.53**	-0.78**	-0.46***	-0.44***	-0.59***
	(0.24)	(0.31)	(0.12)	(0.13)	(0.19)
Food prices*ag GDP share	0.54				
	(1.01)				
Ag GDP share	0.19				
	(0.18)				
Food prices*rural pop share		0.71			
		(0.54)			
Rural population share		-5.58			
		(9.34)			
Food prices*SSA dummy			0.21		
			(0.24)		
SSA dummy			2.59		
			(4.58)		
Food prices*Asia dummy				0.22	
				(0.23)	
Asia dummy				-6.4	
				(4.52)	
Food prices*initial poverty					0.01
					(0.01)
Initial poverty					-0.04
					(0.09)
R-squared	0.06	0.06	0.06	0.06	0.06
N	257	262	262	262	262

Source: Author's estimates.
Notes: ag GDP= share of agriculture in gross domestic product rural population. Share= share of rural population in total population; SSA = Africa south of the Sahara. See text for descriptions of the various tests and definitions of the variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are reported in parentheses.

Bearing these caveats in mind, we conclude our results section by delving more into the economic importance of these elasticities. Specifically, we use the estimated elasticities in Table 4.1 to retrospectively estimate the extent to which food price increases in the late 2000s might have contributed to global $1.25/day poverty reduction. In Table 4.1 the point estimates of this elasticity vary between 0.32 and 0.46, while Figure 3.2 demonstrates that domestic food prices increased substantially in the latter half of the 2000s. These two parameters—the elasticity of poverty with respect to food prices and the observed changes in food prices—can therefore be used to do some *poverty accounting* so as to retrospectively estimate the contribution of higher food prices to the evolution of poverty in the past decade. To do so, we use data for 37 developing countries for which we have observations prior to the food crisis (which began in 2007) and during or after the food crisis. Note that these 37 countries represent about 80 percent of the developing world population.

Strikingly, these elasticities and the observed changes in food prices suggest that higher international food prices reduced global poverty by somewhere between 87 to 127 million people. In contrast, short-run simulation approaches suggest that higher food prices increased global poverty by around 160 million people (de Hoyos and Medvedev 2009). Thus, the long-run impacts of higher food prices appear to be very different from the short-run impacts. Part of this difference may be explained by error. Simulation approaches rely on a number of questionable assumptions as well as on imperfect data. And the econometrically derived estimates used here are certainly imprecisely estimated. To demonstrate the latter, the lower bound of the 95 percent confidence interval for the robust regression estimate (regression 2 in Table 4.1) is an elasticity of just -0.09, which would suggest that higher food prices reduced global poverty by just 25 million people. Nevertheless, the results strongly suggest a positive impact of higher food prices on global poverty reduction, even if the magnitudes of that impact remain uncertain.

5. CONCLUSIONS

When international food prices first rose sharply in 2007 and 2008, it was widely claimed that higher prices constituted a crisis for the world's poor. Although several authors expressed skepticism at the idea that higher food prices were unambiguously harmful for the poor (Headey and Fan 2008; Swinnen 2010), robust evidence to support that claim is only now emerging. Jacoby's (2013) analysis of food price, wage, and welfare dynamics in India casts doubt on the hypothesis that higher food prices increased poverty in India, which has more poor people than any other country on earth. Van Campenhout, Pauw, and Minot (2013) also predict that factor price adjustments mean that higher food prices are ultimately poverty reducing in Uganda, which is an extremely poor African country.

In this paper we generalize these country-specific results with international data: on the whole, increases in the real price of food tend to be poverty reducing. This generalization is robust to sample selections, to the addition of a wide array of control variables, and to different estimators. Restricting to shorter poverty episodes suggests that higher food prices help achieve faster poverty reduction even in the space of just one year, which suggests that factor price adjustments may take place relatively quickly.

What do these results imply for policy responses to food price volatility? As we demonstrated in Section 2, there is evidence from high-frequency wage series that higher food prices could indeed have adverse welfare consequences for net food consumers in the short run, particularly in urban areas. That evidence—though unfortunately very thin—certainly provides a justification for a variety of interventions that either reduce food price volatility or minimize the adverse short-run consequences of that volatility. Similarly, longer-term investments designed to increase global agricultural production obviously still make sense, since higher global food prices clearly signal scarcity.

But the surge in global food prices also prompted policy responses that clearly favored vocal urban consumers at the expense of more politically disenfranchised farmers and rural wage earners, with grain export restrictions being a prominent case in point (Headey 2010). On the basis of the evidence in this paper, these actions were ultimately poverty increasing, at least relative to the counterfactual. Although the conclusion that higher food prices may ultimately be good for the poor (in net terms) is not necessarily intuitive to policymakers, it is consistent with two facts that are admittedly in need of further quantification. First, the world's $1.25/day poor are still overwhelmingly rural and still highly dependent on farming or on nonfarm sectors that are sensitive to agricultural production. Second, rural wages are highly responsive to food prices, at least in the long run. Together these two facts suffice to create a situation in which higher food prices ultimately result in a redistribution of income in favor of the poor rural masses.

APPENDIX: FIRST-STAGE REGRESSION RESULTS

The IV regressions reported in the main text involve first-stage estimation of changes in domestic food prices (the potentially endogenous variable) against changes in international prices, exchange rates, and interactions between the two. To improve the explanatory power of international price indexes by accounting for domestic consumption patterns, we constructed country-specific weights of staple food consumption patterns using calorie shares from the FAO's Food Balance Sheets (FAO 2013) for the following staple foods: wheat, maize, rice, sorghum, soybean, and banana. Thus we construct an international food price index (IFPI) that incorporates domestic consumption weights. Note that we experimented with using international meat prices, but this variable was not robust and added little to the explanatory power of the first-stage regressions. We also experimented with using trade data to construct weights, but that proved a weaker instrument than the index that used calorie shares. Finally, to model heterogeneous price transmission, we interacted changes in international food prices with changes in exchange rates.

The results are reported in Table A.1. The coefficient on exchange rates is insignificant, but the coefficients on the international price index and its interaction with exchange rates are both highly significant, with relatively large marginal effects. The elasticity of domestic food prices with respect to international food prices is 0.36, exchange rates constant (regression 1). The R-squared is also a relatively high 0.33, suggesting that this relatively simple model can account for around one-third of the variation in domestic prices. In regression 2 of Table A.1, we report a regression in which changes in exchange rates are omitted, because this is potentially an endogenous variable. The R-squared is still relatively high and the coefficient on international price changes is still highly significant, suggesting that this indicator constitutes a sufficiently powerful instrument for domestic price movements.

Table A.1 First-stage regressions of changes in domestic food prices against changes in international food prices and exchange rates

Regression number	R1	R2
Change in exchange rate (%)	0.0021	
	(0.0040)	
Change in weighted international food price index (IFPI) (%)	0.3643***	0.3136***
	(0.0626)	(0.0621)
Change in weighted IFPI (%)*change in exchange rate (%)	-0.0036***	
	(0.0009)	
Time trend	0.2351	0.2087
	(0.1514)	(0.1465)
R-squared	0.33	0.22
N	263	270

Source: Author's estimates.
Notes: These are first-stage regression results of changes in domestic food prices against changes in exchange rates against the US dollar, and changes in an index of international food prices, where the weights are country-specific estimates of the share of each food item in average per capita calorie consumption.

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