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The logo for 'Food Prices for Nutrition' features a row of stylized human figures in various colors (blue, green, orange, purple) standing on a blue base.

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**Food Inflation, Poverty, and Urbanization**

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## INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

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## **Abstract**

After a long secular decline in the 20th century, food prices spiked sharply in 2007-08, 2010-11 and again in 2021-22. While often termed “food crises”, economists disagree on whether rising food prices increase or decrease poverty: poor people have high food expenditure shares but also produce and sell food, and higher food prices trigger food supply responses and growth in rural wages. One limitation of previous econometric studies is their focus on medium-run multi-year impacts, even though simulation analyses typically find negative impacts in the short run. In this study we therefore construct and analyze a novel short run panel of annual poverty and food price data for 33 middle income countries (MICs) over 2000-2019. Using standard panel data techniques, we find that increases in the real price of food predict reductions in \$3.20/day poverty in less urbanized countries but increases in poverty in the most urbanized MICs.

**Key words:** Food price crisis; poverty; food security; food inflation; urbanization.

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The authors conceptualized the idea for the study, constructed and analyzed the dataset, and contributed to writing and editing.

## 1. Introduction

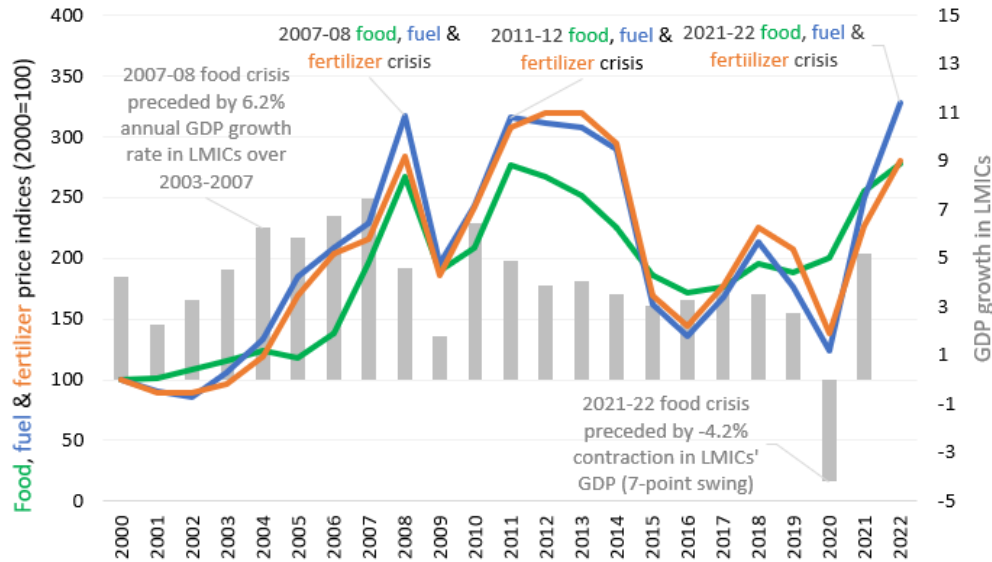
If the real price of food increases in a country, does that country's poverty rate go up, or go down? Do the impacts of higher food prices depend on whether a country is predominantly urban (who are typically net food consumers) or rural (who are often net food producers)? Does the net poverty impact vary over time as economies adjust to higher food prices?

In the 21<sup>st</sup> Century these questions have taken on paramount importance. Despite several food and fuel price crises in the 1970s, most of the 20th century saw a secular decline in the real price of food, and relatively little price volatility.<sup>1</sup> However, this trend reversed dramatically in the early 21st century (Figure 1) when the FAO's real cereal price index first increased gradually in the early 2000s and then spiked in 2007-2008, peaking at 180 points above its 2000 value (Panel A, Figure 1). Prices plummeted during the global financial crisis in late 2008 and 2009 but rose again in 2010 and 2011 to similar "crisis" levels. More recently, the unprecedented fiscal and monetary measures that governments used to respond to the COVID-19 pandemic,<sup>2</sup> along with associated supply chain disruptions and the food, fuel and fertilizer impacts of the war in Ukraine,<sup>3</sup> resulted in the cereal price index again rising sharply in 2021 and 2022, reaching the levels it did in 2008 and 2011. In Panel B of Figure 1 we plot local polynomial regression trends in the ratio of the food component of the consumer price index (food CPI) to the general CPI as a measure of trends in the real domestic price of national food baskets in 110 low- and middle-income countries (LMICs). Consistent with rising international prices, LMICs have witnessed much faster increases in food prices than in the general cost of living, by 20% on average over 2000-22.<sup>4</sup> The 21st century have therefore already witnessed three acute spikes in international prices, all closely connected to equally acute energy price volatility, and a steep rise in real food prices for consumers in poorer countries.

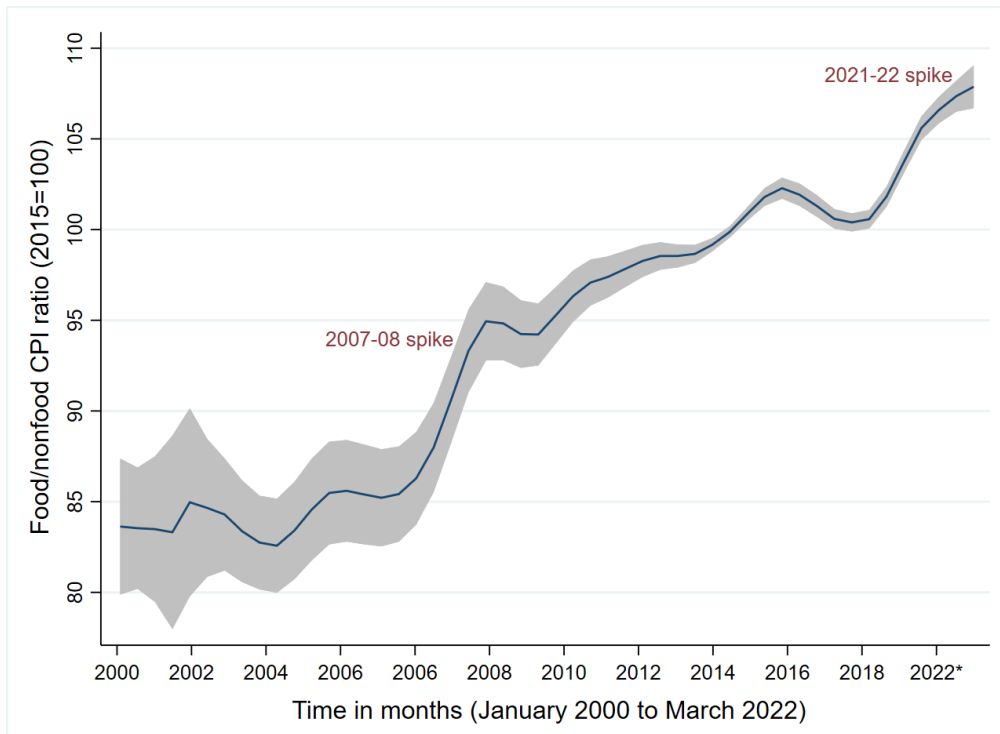
Whether these increases in real food prices translated into increasing poverty is a matter of considerable debate, however. Intuitively, higher food prices would seem to reduce disposable income for the poor because they spend large shares of their income on food (e.g., 50% or more for the extreme poor). On the other hand, many of the world's extreme poor are rural<sup>5</sup> and therefore often engaged in food production and marketing, so high food prices could also increase their incomes. In the short run – without any responses or adjustments at the household or economywide level – the poverty impacts of higher prices therefore depend on whether a household is a net food consumer or a net food producer, or what Deaton called the "net benefit ratio".<sup>6</sup>

**Figure 1. Trends in international and national food price indices in low- and middle-income countries only over 2000 to the first quarter of 2022**

**Panel A: Trends in international food, fuel and fertilizer prices and GDP per capita**



**Panel B: Annual trends in average national food/nonfood CPI: 2000 to Q1 of 2022**



Source: Panel A data are the author’s construction from the FAO cereal price index,<sup>7</sup> IMF data on fuel and fertilizer costs<sup>8</sup> and World Bank<sup>9</sup> data on growth in GDP per capita. Panel B data reports local polynomial regression of the food CPI/general CPI ratio sourced from FAO<sup>10</sup> against time in months (range 1-267) for 116 LMICs.

In response to the 2007-2008 food crisis, an extensive body of simulation-based research concluded that higher food prices increase poverty in the short run,<sup>11-19</sup> precisely household surveys indicated a surprising number of poor households are net food consumers, even in rural areas.<sup>20</sup> Yet even early on in the crisis, there was skepticism of these findings. As Swinnen<sup>21</sup> noted, agricultural economists were historically concerned about the harmful impacts of falling agricultural prices, since these dis-incentivize adoption of new agricultural technologies, reduce farm profits, and weakened the spillovers that vibrant agricultural development creates for the rural non-farm economy. Subsequent theoretical and empirical work indeed demonstrated that the average medium-term impacts of higher food prices on poverty are more beneficial, particularly because higher prices increase demand for agricultural labor and raise rural wages, including for the landless poor. This somewhat revisionist body of research included a theoretical and empirical model for rural India,<sup>22</sup> an economywide simulation model for Uganda,<sup>23</sup> a cross-country panel analysis of food prices and poverty at the national level,<sup>24</sup> and a series of World Bank national poverty assessments.<sup>25-28</sup> Most of these studies conclude that, in the medium term (in the space of several years) higher food prices reduced poverty in aggregate because of poverty reduction in rural populations that were much poorer at baseline. Moreover, an in-depth review of these issues also conjectured that the household surveys upon which short run simulation models rely under-estimate food production and hence over-estimate the share of the population that are net food consumers.<sup>29</sup>

While the 2007-08 crisis clearly catalyzed an extensive body of research founded on ex ante simulations and ex post empirical analysis, the sharp escalation in food prices in 2021-22 has again raised concerns that higher food prices drastically increase poverty in the short run. However, if simulation models are potentially unreliable for accurately estimating short run net benefit ratios,<sup>29</sup> then a potentially more insightful alternative is to analyze poverty and food price movements at a higher frequency.

That is precisely the objective of the present study, which examines whether short run (annual) increases in food prices predict increases or decrease in poverty in 33 middle income countries (MICs) over 2000-2019. This short run focus is a contrast to the medium run focus (2-5 year) of previous cross-country research on this issue. A second innovation we introduce is to model the association between changes in food price changes and changes in *national* poverty changes as conditional upon each country's urban population share under the plausible hypothesis that urban populations are more likely to experience falling real incomes when food prices increase.

Of course, there are limitations to this kind of empirical "ecological" analysis. We examine associations between changes in food prices and changes in poverty without any assumption that these associations are causal, and without any assertions that these historical results over 2000-2019 are predictive of the impacts

of rising food prices under the unusual economic circumstances that post-COVID economies face in 2021-2022,<sup>30</sup> including protracted losses of incomes, depletion of assets, higher rates of household and public debt, foreign exchange shortages, and significant disruptions to international trade in food, fuel and fertilizers. Thus, while it remains important to acknowledge the potential for higher food prices to have very different impacts on rural and urban populations, we also emphasize that many LMICs currently face unique economic challenges at the time of writing.

## **2. Data and methods**

We combine World Bank<sup>31</sup> poverty, income and inequality data from 2000-2019 with disaggregated consumer price index (CPI) data sourced from the International Monetary Fund<sup>32</sup> and the FAO<sup>7</sup>, and real GDP per capita and urban population shares from the World bank's *World Development Indicators*<sup>9</sup> to form the panel dataset used in this study. More details on the specific indicators we use are described below, as well as the econometric methods we use to explore the association between poverty and food price changes.

### **Poverty, income, and inequality measurement**

We analyze 33 MICs that report poverty on annual basis. The exclusion of low-income countries is unfortunate, but no low-income country conducts consumption or income surveys annually (we deliberately exclude high-income countries). However, as Table A1 in the appendix demonstrates, the 33 MICs are characterized by large variation in average poverty headcounts at the \$3.20/day poverty line (e.g., 45.3% in Indonesia in the early 2000s). The dataset is spread across Latin America (156 observations), Europe and Central Asia (193) and East Asia and Pacific (40), but is in no way representative, even of MICs, given the exclusion of several MICs from sub-Saharan Africa as well as large MICs like India. Table A1 also illustrates that the panel is unbalanced as some countries have more observations (surveys) than others. However, we do ensure that each countries' time series does not contain gaps and does not switch between income-based poverty measures and consumption-based measures.

In contrast to earlier studies on food prices and poverty, we principally focus on the \$3.20/day poverty headcount rather the \$1.90/day "extreme poverty line", since the \$3.20 line was recommended for lower middle-income countries to better reflect their national poverty lines. An additional welfare rationale is that the \$3.20 line better represents appropriate nutritional standards for the food component of the poverty line.<sup>33-35</sup> We also use the mean poverty gap index, which captures depth of poverty as the mean income of the poor as a percentage of the \$3.20 poverty line.

## Measurement of real food price changes

The income or consumption data used to measure poverty is already deflated by total CPIs that incorporate food and non-food components. Hence, the direct impact of overall nominal inflation on poverty is already addressed in the World Bank poverty database. Here, we study “real” food price increases – or changes in the composition of inflation – measured as annual changes in the ratio of the food CPI to the non-food CPI. This is easily calculated from a new IMF<sup>32</sup> CPI database containing detailed information on different CPI components and their weights in the overall consumer basket for most countries. For countries not reporting weights in the IMF database, and for all countries in the FAO<sup>7</sup> CPI database (which never includes weights), we impute weights from cross-country regressions of the IMF food CPI weights against the log of GDP per capita (essentially an Engel curve). We did a further check to verify that the imputation technique works well by assessing the correlation in actual and imputed food/nonfood CPI ratios for the IMF sub-sample reporting food and nonfood CPI shares; correlations are very high, assuaging concerns that imputation for some countries introduces any significant measurement error.

## Statistical analysis

We first use descriptive analysis to get a sense of the patterns in the data as well as trends in real food prices by estimating fitted regression lines of annual changes in food prices against binary variables capturing each year. We also produce a scatterplot of changes in the poverty headcount against changes in food prices, with linear regression lines for less urbanized and more urbanized countries (with the threshold at a 60% average urban population share).

We then turn to more formal panel regression techniques by first modeling the poverty headcount or poverty gap index ( $pov_{i,t}$ ) in a country  $i$  in year  $t$  as a function of its real food price level ( $foodprice_{i,t}$ ) in the same year:

$$(1) \quad \Delta pov_{i,t} = \beta \Delta foodprice_{i,t} + t_t + \varepsilon_{i,t}.$$

The estimated relationship between real food prices and poverty is given by  $\beta$ . We purge time-invariant country characteristics using first-differencing (i.e., subtracting the previous year’s value from each observation). As a result,  $\beta$  is identified from annual within-country variation in real food price levels. Mindful of the limited degrees of freedom in our dataset, we explore sensitivity by including year fixed effects ( $t_t$ ), i.e., binary variables for each year in the dataset to control for time effects.

To explore heterogeneity across countries’ urbanization level, we then add an interaction term between real food prices and a country’s average urbanization rate ( $\overline{urb}_i$ ):

$$(2) \quad \Delta pov_{i,t} = \beta \Delta foodprice_{i,t} + \beta (\Delta foodprice_{i,t} * \overline{urb_i}) + t_t + \varepsilon_{i,t}.$$

Note that the urbanization rate is expressed as an average and therefore does not vary within a country. We use the average urbanization rate across observations in a country for two reasons. First, for many of our sample countries the time dimension of the panel is quite short such that urbanization levels do not change much. Second, in most MICs censuses are conducted infrequently, such that the vast majority of annual observations on urbanization are imputed rather than observed. Using each country's mean urbanization rate means that any cross-country variation in urbanization levels is removed by first-differencing (along with all other time-invariant factors).

Theoretically, changes in domestic food prices would be exogenous only in small open economies that act as price takers with respect to international markets and avoid interference in food markets. In reality, most governments intervene in the agri-food system through agricultural subsidies, price controls and consumer subsidies.<sup>36</sup> Moreover, food prices could be affected by domestic shocks (e.g., droughts, conflict) that affect poverty through non-price mechanisms such as loss of farmer income, leading to omitted variable bias.

To explore the potential problem of confounding factors, we append equation (2) as follows:

$$(3) \quad \Delta pov_{i,t} = \beta \Delta foodprice_{i,t} + \beta (\Delta foodprice_{i,t} * \overline{urb_i}) + t_t + \Delta X'_{i,t} \delta + \varepsilon_{i,t},$$

where  $X'_{i,t}$  represents a vector of time-varying control variables, including log GDP per capita, money supply, exchange rate, food production, terms of trade, and the number of battle related deaths in country  $i$  in year  $t$ . All these variables are sourced from the World Bank,<sup>9</sup> and motivated by Headey's earlier cross-country panel analysis of food prices and poverty in the medium run.<sup>24</sup> In particular, one might be concerned that the association between changes in food prices and changes in poverty reflects other things that are going on in an economy. For example, increases in food prices might be part of a general shift in a country's terms of trade given the association between food and non-food commodity prices. Exchange rate movements can strongly the price of food but could reflect other economic factors in a country (e.g., currencies tend to depreciate in severe economic downturns). Conversely, food prices might increase when an economy is overheating due to rapid growth in money supply or strong economic in general. To explore the sensitivity of our estimates to these control variables, we add them in to the model one-by-one as well as together. Table A2 in the appendix provides summary statistics for these control variables.

Finally, our main regressions are estimated using Ordinary Least Square (OLS) with standard errors clustered at the country level to account for any remaining serial correlation after first-differencing. Because there is evidently some noise in the World Bank poverty estimates we also explore sensitivity of our

estimates by using a robust regressor to down-weight influential outliers. All statistical analyses were implemented in Stata v17<sup>TM</sup>.

### 3. Descriptive results on changes in poverty and food prices in the short run

Table 1 reports summary statistics for the cross-country panel used to analyze associations between poverty headcounts and food/nonfood CPI ratios. The average \$3.20/day poverty headcount in the dataset is 13%, but this varies between 0% for some observations and 75% as a maximum. The mean annual change in \$3.20/day poverty headcount in our dataset is -0.43 percentage points with a standard deviation of 1.2 percentage points. The mean poverty gap index is 4.3% but also quite variable. GDP per capita has a mean of just over five thousand dollars per annum, varying between a minimum of \$742 and a maximum of \$12,735. The urban population shares also varies markedly, between 36% and 84%.

**Table 1. Summary statistics for key indicators of poverty, income, inequality, food/nonfood CPI ratio over 2000-2019: 396 years in 33 countries**

Variable	N	Mean	Std. dev.	Min	Max
Poverty headcount (%), \$3.20/day	396	13.0	13.7	0.0	74.6
Poverty gap index (%), \$3.20/day	396	4.3	5.07	0.0	26.6
Food/nonfood CPI ratio (%)	396	95.2	11.8	57.3	134.7
GDP per capita (2017 \$)	396	5,164.0	2,668.1	742.4	1,2735.1
Mean urban population share (%)	396	62.5	11.5	35.5	84.3

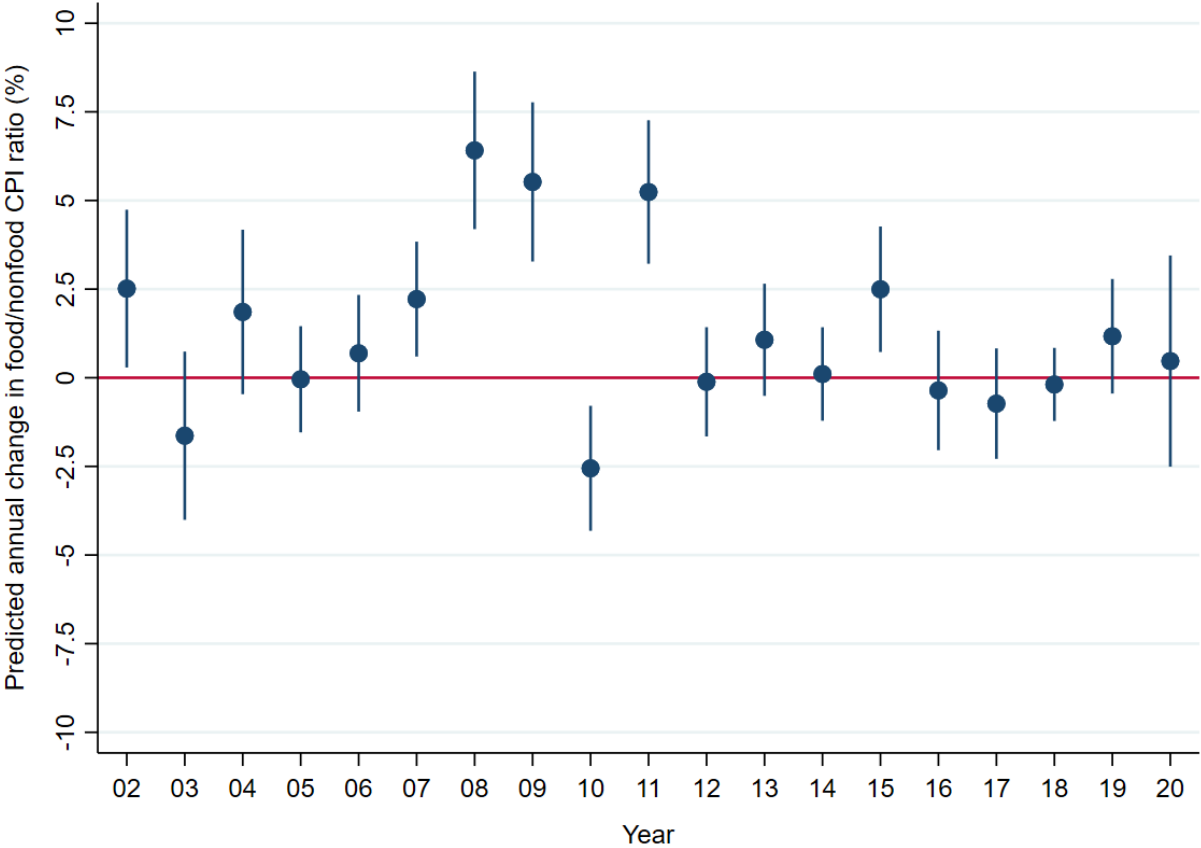
Note: Std. dev. = Standard deviation.

Sources: Poverty data is from the World Bank (2022a). Real food price changes are from the IMF (2022) and FAO (2022). GDP and urban population shares are from the World Bank (2022b).

The mean annual change in food/nonfood CPI ratio in our dataset is 0.83 percentage points with a standard deviation of 4.9 percentage points, but Figure 2 shows how much variation there was over 2002-2019 by plotting coefficients from a simple regression of percentage changes in the food/nonfood CPI ratio against binary variables for each year. The estimated coefficients measure the difference to the base year (2001). Perhaps unsurprisingly, real food price changes are zero in many years but are positive and statistically larger than zero in years of rapid growth in international food prices, although perhaps with a lag, suggesting delayed transmission. Interestingly, mean real food prices changes were statistically greater than zero in eight of the 20 years, and statistically lower than zero in just one year (2010, reflecting the lagged depression of prices in the wake of the global financial crisis). Another interesting finding from Figure 2 is that these binary indicators capturing “global” annual time effects explain 23% of the variation in real domestic food price changes. Clearly, there are many factors that influence both the timing and extent of domestic price

transmission, including policies, the tradability of a country’s basket, domestic production shocks and responses, and exchange rate movements, to name just a few.

**Figure 2. Predicted annual changes in food/nonfood CPI ratios over 2002-2019 in countries in the final dataset, with 95% confidence intervals**

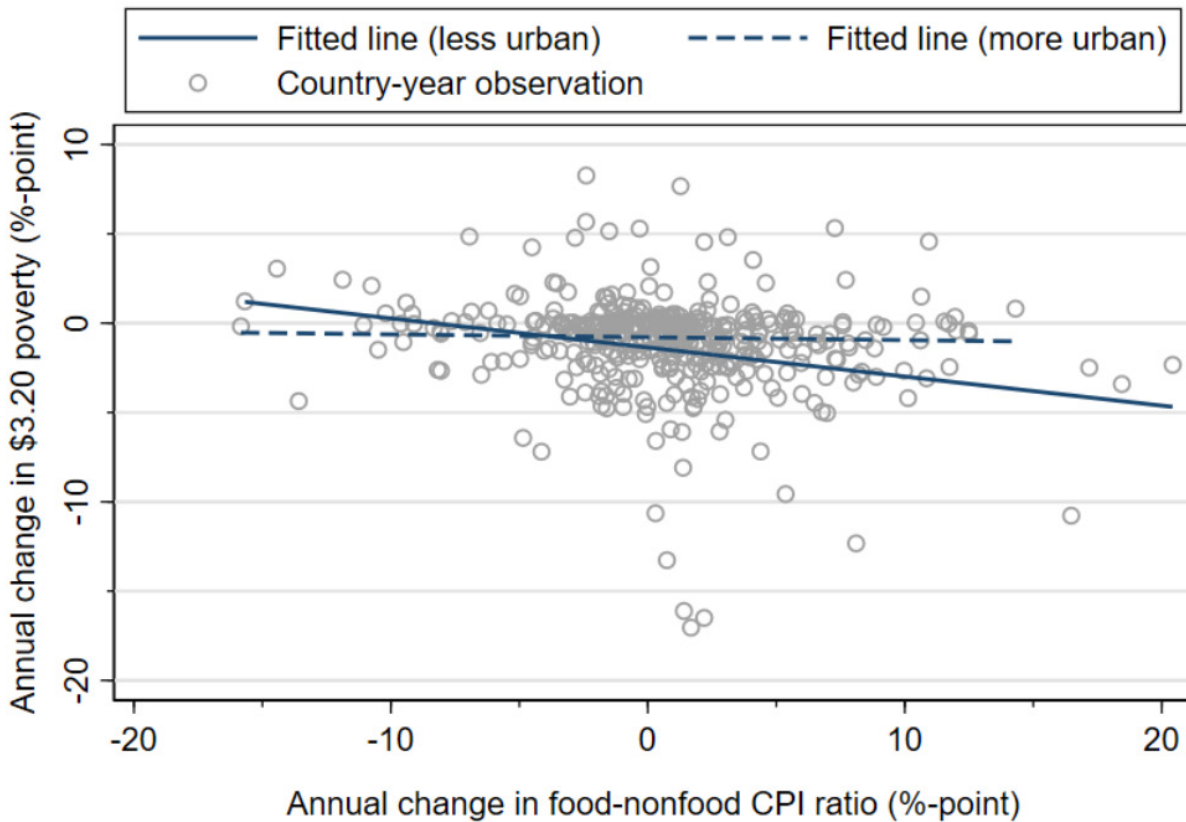


Notes: These results are derived from a simple regression of the annual change in the food/nonfood CPI ratio against binary variables for each year except 2001 (the reference year), with standard errors clustered at the country level. N=578 (32 countries).  $R^2 = 0.23$ .

Figure 3 reports a scatterplot between annual changes in poverty and changes in the food/nonfood CPI ratio to show simple bivariate association between poverty and food inflation in the short run. To provide a preliminary exploration of our hypothesis that this relationship is conditional upon a country’s urbanization level, Figure 3 reports two separate least squares regression fits: one for countries that are less urbanized (urban population share < 60%, which is the mean level of urbanization in our data; see Table 1) and one for those that are more urbanized (urban population share > 60%). Among the less urbanized countries, there is a clear negative and statistically significant ( $p < 0.01$ ) gradient between changes in poverty and changes in real food price changes. The estimated gradient is quite modest -0.16, implying that even a large

10 percentage point annual increase in the food-nonfood ratio is associated a 1.6 percentage point reduction in \$3.20 poverty headcount in the short run. The gradient becomes notably flatter for more urbanized countries ( $\beta = -0.016$ ) and is no longer statistically different from zero ( $p=0.364$ ). Of course, these results do not control for time effects and other confounders included in Equations 1-3, and it is also noticeable from Figure 3 that there is considerable variation around the fitted lines, suggesting it might be important to control for potential confounding factors and carefully explore sensitivity to outliers or other extreme values.

**Figure 3. Changes in \$3.20/day poverty against changes in real food prices with fitted linear regression lines for less urban countries (mean urbanization < 60%) and more urban countries (mean urbanization > 60%)**



Sources: See the Methods section for details on data sources. A country is defined as less urban (more urban) if its average urban population share across all survey rounds is less than 60% (more than 60%).

#### 4. Regression results

Table 2 reports our main results for the association between \$3.20 poverty headcount and food/non-food CPI ratio. Columns 1 and 2 match Equation (1), the basic linear first-differenced model. As controls for time effects, the second column includes year fixed effects. In both columns, the association between real food prices and poverty is negative and highly statistically significant, suggesting food prices increases predict reductions in poverty, on average. Both estimates are roughly similar in magnitude. In terms of interpreting that magnitude, a one (within-country) standard deviation change in the food/nonfood CPI ratio is approximately 5 percentage points. The estimate in column 2 suggests that a 5-percentage point increase in the food/nonfood CPI ratio is associated with 0.45 percentage point reduction in the \$3.20 poverty headcount.

In columns 3 and 4 we estimate equation (2), which introduces the interaction term with a country's average urban population share. The coefficient on the non-interacted food/nonfood CPI ratio is now highly significant ( $p < 0.01$ ) and negative, while the interaction term is highly significant ( $p < 0.01$ ) but positive, suggesting that the beneficial impacts of higher food prices on poverty reduction attenuate or even reverse with higher urban population shares.

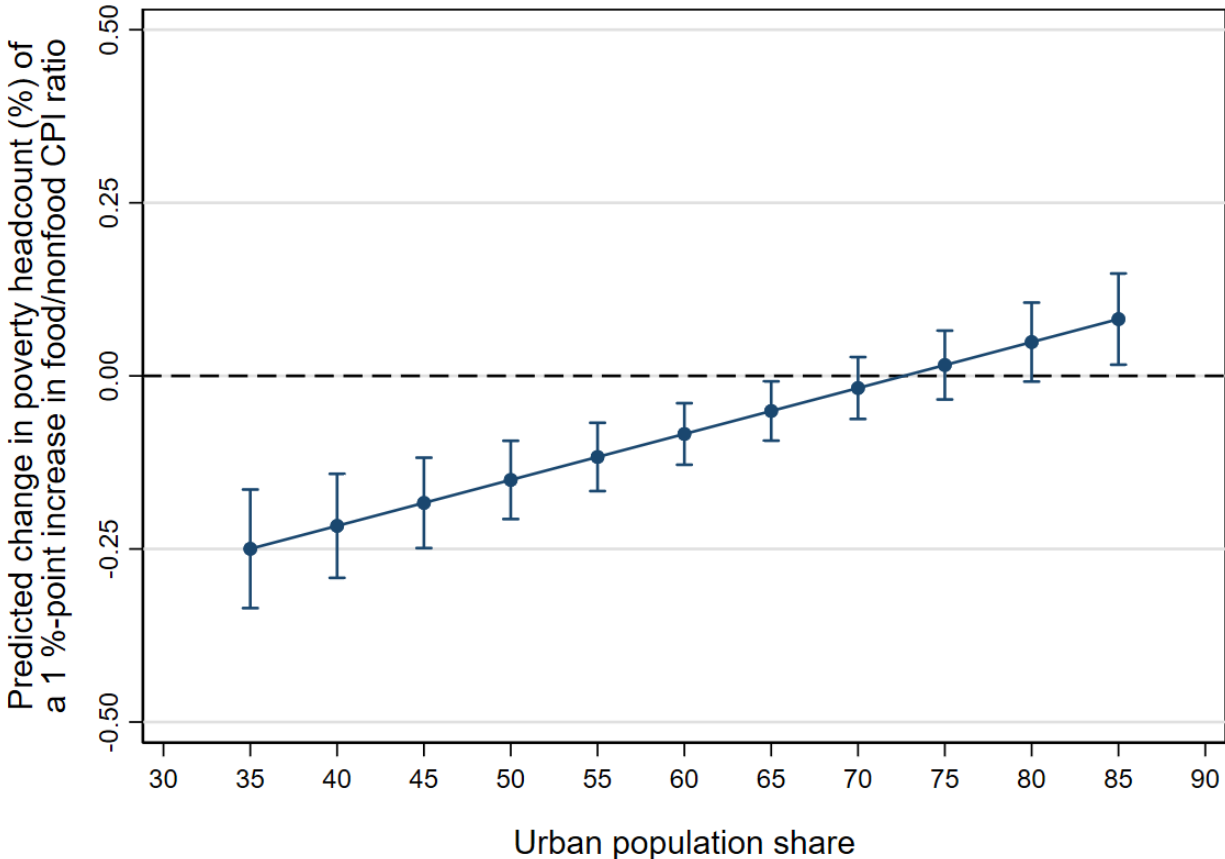
**Table 2. Associations between changes in poverty headcounts (\$3.20/day) and percentage changes in real food prices in first-differenced regressions**

	(1)	(2)	(3)	(4)
Food/nonfood CPI ratio (%)	-0.093*** (0.030)	-0.090*** (0.031)	-0.509*** (0.070)	-0.482*** (0.082)
Food/nonfood CPI ratio (%) * Urban share			0.007*** (0.001)	0.007*** (0.001)
Year fixed effects?		Yes		Yes
$R^2$	0.028	0.105	0.056	0.130
Number of observations	396	396	396	396
Number of countries	33	33	33	33

Notes: Outcome variable is poverty headcount at \$3.20/day level, measured in %. Ordinary least squares regression based on equation (1) in columns 1-2 and based on equation (2) in columns 3-4. Unit of analysis is country-year. Standard errors are clustered at the country level and reported in parentheses. Statistical significance denoted with \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Urban share variable is time-invariant and measures the mean share of urban population relative to total population over time.

How should one interpret the magnitudes of these coefficients? The solid upward-sloping line in Figure 4 represents the predicted association of a 1 percentage point increase in the food/nonfood CPI ratio on changes in poverty conditional on the urban population share (across the range present in our data), based on the coefficients reported in column 4 of Table 2. Those coefficients imply that the least urbanized countries in our dataset could expect economically and statistically significant reductions in poverty from large increases in real food prices. For example, a 5-percentage point increase in food prices is associated with a 1.25 percentage point reduction in poverty in the least urbanized countries in our dataset. Compared to the mean \$3.20 poverty headcount in the dataset (13.0 %), this translates into a 9.6 percent reduction in the poverty headcount rate. At higher levels of urbanization (at around 70%) the benefits are no longer significantly different from zero, while at the highest levels of urbanization (80-85%) it appears that higher food prices increase poverty in the short run, but only marginally.

**Figure 4. Predicted associations of a 1%-point increase in the food/nonfood CPI ratio on the change in the \$3.20/day poverty rate from first differenced regressions**



Notes: The line show the predicted association of a 1%-point increase in the food/nonfood CPI ratio on \$3.20 poverty headcount conditional on the urban population share based on the coefficients reported in Column 4 of Table 2. The vertical capped lines represent 95%-confidence intervals.

Next, we explore robustness of the main regression results reported above.

First, we examine robustness to the inclusion of potential confounding factors in Appendix Table A3. We introduce the control variables discussed at the end of Section 3 individually (columns 1 to 6) as well as together (column 7). The coefficients on the non-interacted and interacted terms remain remarkably stable and comparable to those reported in column 4 of Table 2 across the seven different specifications reported in Table A3 in the Appendix.

Second, we re-estimate the associations using the \$1.90 poverty headcount instead of the \$3.20 poverty headcount (Appendix Table A4). As before, increases in real food prices are associated with reductions in poverty headcount in the least urbanized countries and increases in highly urbanized countries (Figure A1). In the least urbanized countries, a 5-percentage point increase in the food/nonfood CPI ratio is associated with a 0.8 percentage point fall in \$1.90 poverty headcount rate.

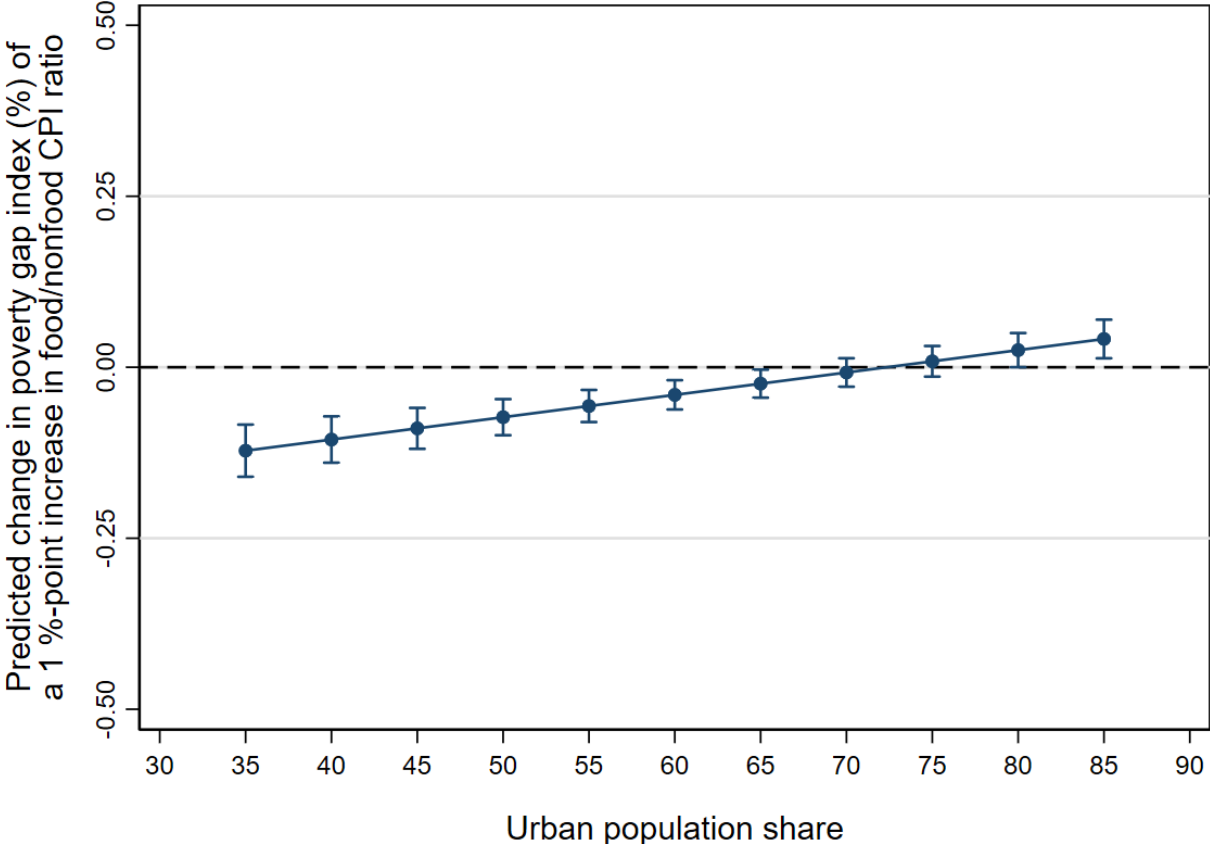
Third, we re-estimate the associations using the poverty gap index as the outcome variable instead of the poverty headcount. We do so because an increase in the poverty headcount measures the share of the population falling into poverty (the new poor) but does not tell us about the relative income effects for the existing (old) poor. Table 3 indicates that very similar coefficient patterns emerge for this depth of poverty measure: an increase in the food/non-food CPI ratio is associated with a statistically significant decrease in poverty gap index, but this is again highly conditional on urbanization. Figure 5 shows those predicted associations by the level of urbanization. At low levels of urbanization, a 5-percentage point increase in food/nonfood CPI ratio is associated with a 0.6 percentage point reduction in the poverty gap index while at higher levels of urbanization, the corresponding association is positive, predicting a roughly 0.2 percentage point increase, on average. Compared to the mean poverty gap index of 4.3 percent in our data, these associations translate into 14 % and 4.6 % reductions in poverty gaps.

**Table 3. Associations between changes in the \$3.20/day poverty gap index (%) and percentage changes in real food prices in first-differenced regressions**

	(1)	(2)	(3)	(4)
Food/nonfood CPI ratio (%)	-0.041** (0.017)	-0.043** (0.018)	-0.249*** (0.034)	-0.236*** (0.035)
Food/nonfood CPI ratio (%) * Urban share			0.004*** (0.001)	0.003*** (0.001)
Year fixed effects?		Yes		Yes
$R^2$	0.029	0.109	0.068	0.141
Number of observations	396	396	396	396
Number of countries	33	33	33	33

Notes: Outcome variable is poverty gap index at \$3.20/day level, measured in %. Ordinary least squares regression based on equation (1) in columns 1-2 and based on equation (2) in columns 3-4. Unit of analysis is country-year. Standard errors are clustered at the country level and reported in parentheses. Statistical significance denoted with \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Urban share variable is time-invariant and measures the mean share of urban population relative to total population over time.

**Figure 5. Predicted associations of a 1%-point increase in the food/nonfood CPI ratio on the change in the \$3.20/day poverty gap index (%), first-difference estimator**



Notes: The line show the predicted association of a 1%-point increase in the food/nonfood CPI ratio on \$3.20 poverty gap index (%) conditional on the urban population share based on the coefficients reported in Column 4 of Table 3. The vertical capped lines represent 95%-confidence intervals.

The fourth robustness test pertains to extreme values or outliers, which the OLS estimator can be sensitive to. As observed in Figure 3, there is considerable dispersion and potential measurement error in the World Bank’s poverty estimates. To explore sensitivity in this regard, we apply a robust regression method to the first-difference estimator (see Appendix Table A5). The robust regressor results are qualitatively similar to the least square results, although there is some modest attenuation of the coefficients after downweighing outliers.

The fifth robustness test examines whether – in our relatively small dataset of 33 countries – there is the possibility that a single country could be driving the narrative documented herein. To explore this possibility, we re-estimated column 3 in Table 2 based on Equation (2) 33 times, each time omitting one country from the dataset. Results reported in Appendix Table A6 show that coefficients on the food/nonfood

CPI ratio variable and the urban interaction term remain highly stable across these 33 regressions, indicating that a single country is not driving the results reported here.

Finally, there are variations in survey timings for individual countries, meaning that the poverty results may not strictly apply to a calendar year. We therefore experimented with adding a lagged difference of the food-nonfood CPI ratio from the previous calendar year. While the coefficients on the first-differenced variables remain similar in terms of significance and magnitude, the coefficients on the lagged-difference and its interaction are small in magnitude and mostly statistically insignificant (see Appendix Table A7).

## 5. Discussion

The 21<sup>st</sup> century has seen a reversal of the secular decline in real food prices observed towards the end of the 20<sup>th</sup> century; a reversal accompanied by increased food price volatility and “food crises”, which have also translated in increases in real food prices at the national level in LMICs. However, while international food price spikes clearly create a variety of problems for food importers, international food aid, and potentially for the urban poor if price transmission is high, previous research has shown that higher domestic food prices tend to be poverty-*reducing* in aggregate over the medium term in LMICs, both in cross-country econometric research<sup>24</sup> and in retrospective country case studies.<sup>25-28</sup>

Here we tried to address the valid concern that the short run (annual) impacts of food price increases *could* be much more adverse than the medium run impacts, especially for net food consumers in urban areas. Consistent with the intuition of urban populations being net food consumers and rural populations having many food producers, we find that the predicted impacts of increasing real food prices on the \$3.20/day poverty headcounts and gap measures are highly conditional upon a country’s urban population share. However, the results imply that an increase in food prices still reduces poverty, albeit marginally, in most countries in our dataset over the annual “short term”. This finding is also highly robust to a different poverty line (\$1.90/day), to a different estimator (the robust regressor), to the inclusion of different control variables (including annual economic growth), and to dropping individual countries from the sample. It also likely stems from the fact that the majority of the world’s \$3.20/day poor are still rural, with a World Bank study<sup>5</sup> estimating that 75% of the \$3.20/day poor and 80% of the \$1.90/day poor living in rural areas in 2013.

Despite the robustness of our core finding, there are several limitations to our analysis. First, we are compelled to use national-level poverty data and look at differential associations on rural and urban populations in a very indirect fashion. It is unfortunate that the World Bank does not report separate rural and urban poverty estimates for all countries. Doing so would not only facilitate more granular research on this issue and many others of global importance; it would also improve monitoring of subnational poverty

and targeting of anti-poverty interventions. Another limitation is the lack of high frequency survey data in low income countries whose vulnerability to shocks surely warrants much more investment in higher frequency welfare surveillance.<sup>37</sup>

Second, we find a robust conditional association between changes in poverty and changes in food prices, but this should be thought of a “stylized fact” rather than a causal relationship. It is encouraging that many structural models lead to broadly similar predictions on the differential impacts of higher food prices in rural and urban areas, although our results are arguably consistent with the contention that household surveys systematically underestimate food production by rural households, thereby misclassifying some households as net food consumers. It may also be that our “short run” annual timeframe is still long enough to allow farm households to increase food output and profits, with knock-on effects on rural wages.

Finally, our results may only offer limited insights into the outcomes of the 2021-2022 food crisis. In contrast to 2007-08, most LMICs in 2022 are in an especially weak fiscal position to deal with food, fuel and fertilizer inflation in the wake of the COVID-19 pandemic.<sup>30</sup> Indeed, it may be that the strong agricultural supply responses observed in LMICs in the wake of the 2007-08<sup>24</sup> crisis will not easily be replicated because of the more limited fiscal capacity of LMIC governments to facilitate a strong supply response, and due to exceptionally tight fertilizer supplies.

Bearing those limitations in mind, the current study builds on previous econometric and modelling research and illustrates the urbanization conditionality of the relationship between changes in poverty and changes in food prices in a broad swathe of MICs. Our key results are likely indicative of the fact that the bulk of the world’s poor – even in middle income countries – may still be predominantly rural and still frequently engaged in farming or related activities, and that rural economies as a whole remain highly sensitive to positive or negative perturbations in the agricultural sector.

## References

- 1 Fukase, E. & Martin, W. Economic growth, convergence, and world food demand and supply. *World Development* **132**, 104954, doi:<https://doi.org/10.1016/j.worlddev.2020.104954> (2020).
- 2 Vos, R. G., Joseph W.; Hernandez, Manuel A.; and Laborde Debucquet, David. 2022. COVID-19 and food inflation scares. In COVID-19 and global food security: Two years later, eds. John McDermott and Johan Swinnen. Part Two: Agricultural Production and Value Chains, Chapter 10, Pp. 64-72. [https://doi.org/10.2499/9780896294226\\_10](https://doi.org/10.2499/9780896294226_10). in *COVID-19 and global food security: Two years later* (eds John McDermott & Johan Swinnen) Ch. 10, 64-72 (2022).
- 3 Weersink, A. & von Massow, M. in *The Conversation UK* (ed Jo Adetunji) (London, UK, 2022).
- 4 Baltzer, K. International to domestic price transmission in fourteen developing countries during the 2007–8 food crisis. *Food Price Policy in an Era of Market Instability: A Political Economy Analysis*, 21 (2014).
- 5 Castaneda Aguilar, R. A. *et al.* *Who are the poor in the developing world?* (Policy Research Working Paper Series No. 7784. (World Bank Group, Washington DC, 2016).
- 6 Deaton, A. Rice prices and income distribution in Thailand: a non-parametric analysis. *Economic Journal* **99**, 1-37. (1989).
- 7 FAO. FAO Food Price Index Database, Food and Agriculture Organisation, [www.fao.org/worldfoodsituation/FoodPricesIndex/en/](http://www.fao.org/worldfoodsituation/FoodPricesIndex/en/) (2022).
- 8 IMF. International Commodity Price Database, The International Monetary Fund, <https://www.imf.org/en/Research/commodity-prices> (2022).
- 9 World-Bank. World Development Indicators Online, The World Bank, <http://devdata.worldbank.org/dataonline/> (2022).
- 10 FAO. FAOSTAT Consumer Price Indices, Food and Agriculture Organization, <https://www.fao.org/faostat/en/> (2021).
- 11 Arndt, C., Benfica, R., Maximiano, N., Nucifora, A. M. D. & Thurlow, J. T. Higher fuel and food prices: impacts and responses for Mozambique. *Agricultural Economics* **39**, 497–511 (2008).
- 12 Benson, T. An assessment of the likely impact on Ugandan households of rising global food prices: A secondary data analysis. *Agricultural Economics* **39**, 513-524 (2008).
- 13 Cudjoe, G., Breisinger, C. & Diao, X. *Local impacts of a global crisis: Food price transmission and poverty impacts in Ghana* (IFPRI discussion paper no. 842. (International Food Policy Research Institute (IFPRI), Washington, DC., 2008).
- 14 Zezza, A. *et al.* *The Impact of Rising Food Prices on the Poor*. (Rome, 2008).
- 15 Ivanic, M. & Martin, W. Implications of Higher Global Food Prices for Poverty in Low-Income Countries. *Agricultural Economics* **39(s1)**, pages 405-416, 405-416 (2008).
- 16 de Hoyos, R. & Medvedev, D. *Poverty Effects of Higher Food Prices: A Global Perspective*. (The World Bank, Washington DC, 2009).
- 17 Valero-Gil, J. N. & Valero, M. The effects of rising food prices on poverty in Mexico. *Agricultural Economics* **39**, 485-496, doi:<https://doi.org/10.1111/j.1574-0862.2008.00354.x> (2008).
- 18 Warr, P. World food prices and poverty incidence in a food exporting country: a multihousehold general equilibrium analysis for Thailand. *Agricultural Economics* **39**, 525-537 (2008).

- 19 Haq, Z. u., Nazli, H. & Meilke, K. Implications of high food prices for poverty in Pakistan. *Agricultural Economics* **39**, 477-484, doi:<https://doi.org/10.1111/j.1574-0862.2008.00353.x> (2008).
- 20 Aksoy, M. A. & Isik-Dikmelik, A. Are Low Food Prices Pro-Poor? Net Food Buyers and Sellers in Low-Income Countries. (The World Bank, Washington DC, 2008).
- 21 Swinnen, J. The Right Price of Food. *Development Policy Review* **29**, 667-688 (2011).
- 22 Jacoby, H. G. Food prices, wages and welfare in rural India. *Economic Inquiry* **54**, 159-176, doi:10.1111/ecin.12237 (2016).
- 23 Van Campenhout, B., Pauw, K. & Minot, N. The impact of food price shocks in Uganda: first-order effects versus general-equilibrium consequences. *European Review of Agricultural Economics* **45**, 783-807, doi:10.1093/erae/jby013 (2018).
- 24 Headey, D. Food Prices and Poverty. *The World Bank Economic Review*, lhw064-lhw064, doi:10.1093/wber/lhw064 (2016).
- 25 World-Bank. Where Have All the Poor Gone? Cambodia Poverty Assessment 2013. (World Bank, Washington, DC, 2013).
- 26 World-Bank. Ethiopia Poverty Assessment 2014 (World Bank, Washington, DC, 2015).
- 27 World-Bank. The Uganda Poverty Assessment Report 2016 : Farms, Cities and Good Fortune - Assessing Poverty Reduction in Uganda from 2006 to 2013 (World Bank, Washington, DC, 2016).
- 28 Ahmed, F., Gimenez-Duarte, L., Jolliffe, D. M. & Sharif, I. A. Bangladesh - Poverty assessment : assessing a decade of progress in reducing poverty, 2000-2010. (The World Bank, Washington DC, 2013).
- 29 Headey, D. & Martin, W. J. Food Prices, Poverty, and Food Security. *Annual Review of Resource Economics* **8**, 329-351, doi:doi:10.1146/annurev-resource-100815-095303 (2016).
- 30 Headey, D. & Hirvonen, K. in *The Conversation UK* (ed Jo Adetunji) (London, UK, 2022).
- 31 World-Bank. Poverty and Inequality Platform, The World Bank, <https://pip.worldbank.org/home>> (2022).
- 32 IMF. IMF Consumer Price Index Database, <https://data.imf.org/?sk=4FFB52B2-3653-409A-B471-D47B46D904B5&sId=1485878855236>> (2022).
- 33 Mahrt, K., Herforth, A., Robinson, S., Arndt, C. & Headey, D. Nutrition as a Basic Need: A new method for utility-consistent and nutritionally adequate food poverty lines (Washington DC, 2022).
- 34 Hirvonen, K., Bai, Y., Headey, D. & Masters, W. A. Affordability of the EAT-Lancet reference diet: a global analysis. *The Lancet Global Health* **8**, e59-e66, doi:10.1016/S2214-109X(19)30447-4 (2020).
- 35 Herforth, A. *et al.* Cost and affordability of healthy diets across and within countries. (Rome, 2020).
- 36 FAO, IFAD, UNICEF, WFP & WHO. *The State of Food Security and Nutrition in the World 2022: Repurposing food and agricultural policies to make healthy diets more affordable.* (FAO, IFAD, UNICEF, WFP and WHO, 2020).
- 37 Headey, D. & Barrett, C. B. Opinion: Measuring development resilience in the world's poorest countries. *Proceedings of the National Academy of Sciences* **112**, 11423-11425, doi:10.1073/pnas.1512215112 (2015).

## Appendix

**Table A1. Composition of the dataset**

Country	N	Years	Mean poverty rate, \$3.20/day	Mean GDP per capita	World Bank income status
Albania	3	2015-2017	8.6	4,098	Upper middle
Armenia	18	2002-2019	16.2	3,093	Upper middle
Azerbaijan	3	2002-2004	0.5	1,917	Upper middle
Belarus	18	2002-2019	1.8	5,162	Upper middle
Bolivia	8	2012-2019	11.9	3,054	Lower middle
Brazil	8	2012-2019	8.5	8,813	Upper middle
Bulgaria	10	2009-2018	4.3	6,938	Upper middle
China	6	2011-2016	13.0	7,311	Upper middle
Colombia	11	2009-2019	14.3	5,860	Upper middle
Costa Rica	19	2001-2019	5.8	10,271	Upper middle
Dominican Republic	19	2001-2019	11.0	5,863	Upper middle
Ecuador	16	2004-2019	14.8	5,576	Upper middle
El Salvador	18	2001-2019	16.6	3,446	Lower middle
Georgia	19	2001-2019	25.6	3,194	Upper middle
Honduras	18	2002-2019	33.9	2,154	Lower middle
Indonesia	19	2001-2019	45.3	2,783	Upper middle
Iran, Islamic Rep	5	2014-2018	3.1	5,249	Upper middle
Kazakhstan	17	2002-2018	5.7	8,857	Upper middle
Kosovo	8	2010-2017	6.8	3,307	Upper middle
Kyrgyz Republic	18	2001-2019	28.0	989	Lower middle
Mexico	2	2005-2006	14.5	9,010	Upper middle
Moldova	5	2014-2018	1.1	2,934	Lower middle
Mongolia	2	2011-2012	5.3	3,182	Lower middle
Montenegro	9	2006-2014	1.1	5,990	Upper middle
North Macedonia	8	2011-2018	11.0	4,768	Upper middle
Paraguay	18	2002-2019	11.7	4,762	Upper middle
Peru	19	2001-2019	18.2	5,090	Upper middle
Russian Federation	18	2001-2018	2.4	8,360	Upper middle
Serbia	8	2003-2010	2.0	4,702	Upper middle
Thailand	13	2007-2019	1.5	5,613	Upper middle
Turkey	17	2003-2019	4.9	9,457	Upper middle
Ukraine	14	2006-2019	0.4	2,359	Lower middle
West Bank and Gaza	2	2010-2011	3.1	3,028	Lower middle
<b>Total</b>	<b>396</b>				

Source: See main text for sources.

**Table A2. Summary statistics for the control variables used in the analysis**

<b>Variable</b>	<b>N</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
GDP per capita (US\$)	396	5,164.0	2,668.1	742	12,735
Broad money (% GDP)	386	8.3	0.6	6.1	9.4
Exchange rate index (LCU/US\$) (2011=100)	394	121.5	55.0	36.0	420.5
Food production index (2014-16=100)	385	92.4	15.5	48.6	156.2
Battle-related deaths per 10,000 people	396	72.5	286.8	1.0	4,378.0
Net barter terms of trade index (2000=100)	379	117.9	30.5	67.3	223.5

Notes: Broad money is the sum of currency outside banks. Std. Dev. = Standard Deviation. LCU = Local currency unit. All data are from the World Bank's World Development Indicators.

**Table A3. Associations between changes in poverty headcounts (\$3.20/day) and percentage changes in real food prices in first-differenced regressions with time-varying controls**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Food/nonfood CPI ratio (%)	-0.419*** (0.070)	-0.488*** (0.078)	-0.483*** (0.082)	-0.463*** (0.078)	-0.482*** (0.082)	-0.469*** (0.079)	-0.411*** (0.069)
Food/nonfood CPI ratio* Urban share	0.006*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.006*** (0.001)	0.007*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
(log) GDP per capita (US\$)	-20.282*** (5.362)						-22.241*** (5.748)
Broad money (% GDP)		-0.027 (0.039)					-0.045 (0.050)
Exchange rate index (LCU/US\$)			0.000 (0.003)				-0.001 (0.002)
Food production index				-0.008 (0.017)			0.011 (0.014)
(log) Battle-related deaths					-0.173 (0.121)		-0.180 (0.123)
Net barter terms of trade index						-0.006 (0.006)	-0.003 (0.008)
Year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$R^2$	0.179	0.132	0.129	0.130	0.134	0.131	0.192
Number of observations	396	393	394	383	396	379	370
Number of countries	33	33	32	32	33	31	30

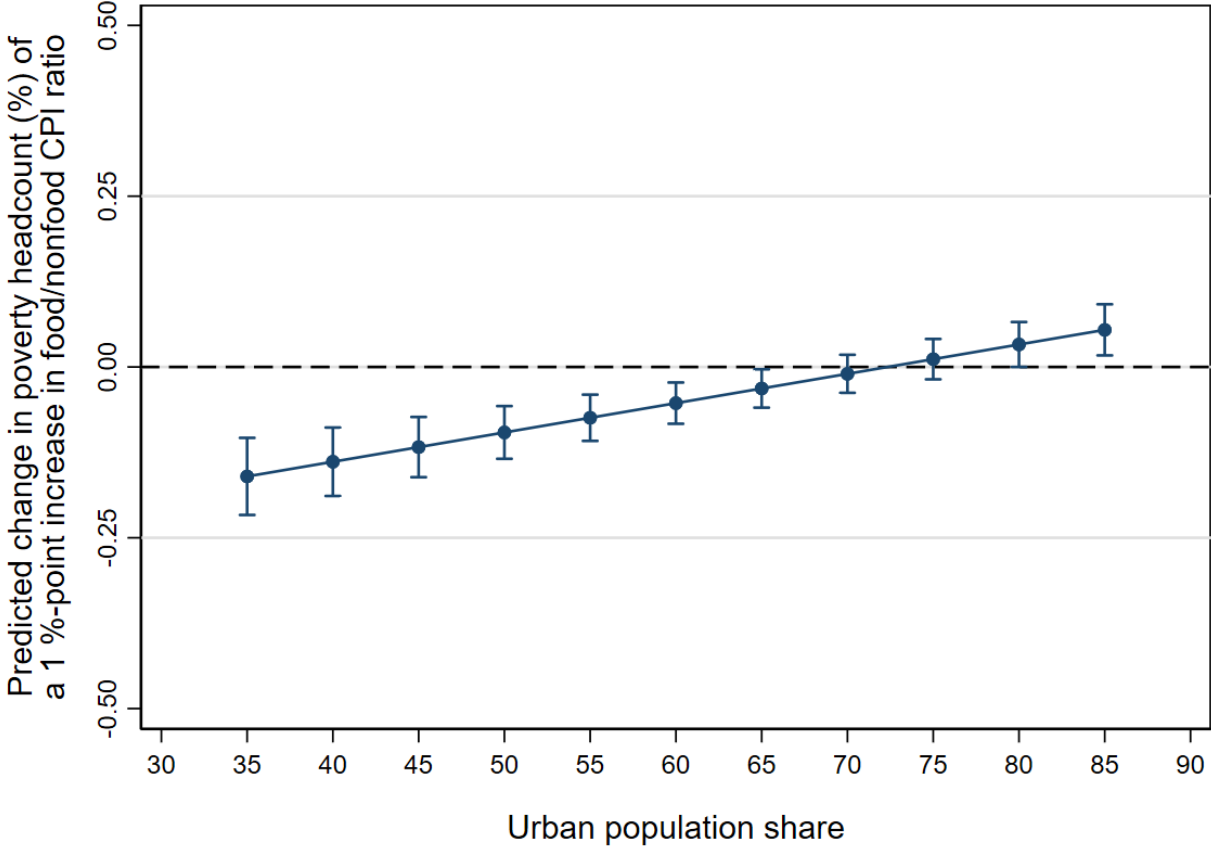
Notes: Outcome variable is poverty headcount at \$3.20/day level, measured in %. Ordinary least squares regression based on equation (3). Unit of analysis is country-year. Standard errors are clustered at the country level and reported in parentheses. Statistical significance denoted with \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Urban share variable is time-invariant and measures the mean share of urban population relative to total population over time.

**Table A4. Associations between changes in the \$1.90/day poverty gap index (%) and percentage changes in real food prices in first-differenced regressions**

	(1)	(2)	(3)	(4)
Food/nonfood CPI ratio (%)	-0.051** (0.023)	-0.057** (0.025)	-0.327*** (0.053)	-0.310*** (0.052)
Food/nonfood CPI ratio (%) * Urban share			0.005*** (0.001)	0.004*** (0.001)
Year fixed effects?		Yes		Yes
$R^2$	0.027	0.110	0.066	0.142
Number of observations	396	396	396	396
Number of countries	33	33	33	33

Notes: Outcome variable is poverty gap index at \$1.90/day level, measured in %. Ordinary least squares regression based on equation (1) in columns 1-2 and based on equation (2) in columns 3-4. Unit of analysis is country-year. Standard errors are clustered at the country level and reported in parentheses. Statistical significance denoted with \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Urban share variable is time-invariant and measures the mean share of urban population relative to total population over time.

**Figure A1. Predicted associations of a 1%-point increase in the food/nonfood CPI ratio on the change in the \$1.90/day poverty rate from first differenced regressions**



Notes: The line show the predicted association of a 1%-point increase in the food/nonfood CPI ratio on \$1.90 poverty headcount conditional on the urban population share based on the coefficients reported in Column 4 of Table A4. The vertical capped lines represent 95%-confidence intervals.

**Table A5. Associations between changes in poverty headcounts (\$3.20/day) and percentage changes in real food prices in first-differenced models estimated with the robust regressor to downweigh outliers**

	(1)	(2)	(3)	(4)
Food/nonfood CPI ratio (%)	-0.072*** (0.017)	-0.067*** (0.018)	-0.396*** (0.072)	-0.363*** (0.073)
Food/nonfood CPI ratio (%) * Urban share			0.005*** (0.001)	0.005*** (0.001)
Year fixed effects?		Yes		Yes
$R^2$	0.044	0.161	0.110	0.213
Number of observations	396	396	396	396
Number of countries	33	33	33	33

Notes: Outcome variable is poverty headcount at \$3.20/day level, measured in %. Robust regression based on equation (1) in columns 1-2 and based on equation (2) in columns 3-4. Unit of analysis is country-year. Robust regression standard errors reported in parentheses. Statistical significance denoted with \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Urban share variable is time-invariant and measures the mean share of urban population relative to total population over time. Regression is implemented using the *rreg* command in Stata v17<sup>TM</sup>.

**Table A6. Re-estimating column 3 in Table 2 by omitting one country at a time from the dataset**

Country omitted:	Coefficient, Food/nonfood CPI ratio (%)	Coefficient, Food/nonfood CPI ratio (%) * Urban share	N	R <sup>2</sup>
Albania	-0.510***	0.007***	393	0.053
Armenia	-0.509***	0.007***	378	0.062
Azerbaijan	-0.502***	0.007***	393	0.059
Bulgaria	-0.513***	0.007***	386	0.056
Belarus	-0.522***	0.007***	378	0.057
Bolivia	-0.509***	0.007***	388	0.056
Brazil	-0.512***	0.007***	388	0.056
China	-0.491***	0.007***	390	0.053
Colombia	-0.515***	0.007***	385	0.056
Costa Rica	-0.495***	0.007***	377	0.056
Dominican Republic	-0.492***	0.007***	377	0.058
Ecuador	-0.509***	0.007***	380	0.057
Georgia	-0.520***	0.007***	377	0.064
Honduras	-0.480***	0.007***	378	0.049
Indonesia	-0.488***	0.007***	377	0.055
Iran	-0.499***	0.007***	391	0.056
Kazakhstan	-0.508***	0.007***	379	0.063
Kyrgyz Republic	-0.568***	0.008***	378	0.033
Moldova	-0.514***	0.007***	391	0.057
Mexico	-0.510***	0.007***	394	0.056
North Macedonia	-0.509***	0.007***	388	0.056
Montenegro	-0.509***	0.007***	387	0.056
Mongolia	-0.510***	0.007***	394	0.056
Peru	-0.517***	0.007***	377	0.058
Paraguay	-0.513***	0.007***	378	0.061
West Bank and Gaza	-0.510***	0.007***	394	0.056
Russian Federation	-0.504***	0.007***	378	0.056
El Salvador	-0.508***	0.007***	378	0.058
Serbia	-0.514***	0.007***	388	0.055
Thailand	-0.554***	0.008***	383	0.062
Turkey	-0.512***	0.007***	379	0.056
Ukraine	-0.510***	0.007***	382	0.055
Kosovo	-0.496***	0.007***	388	0.053

Notes: Outcome variable is poverty headcount at \$3.20/day level, measured in %. Ordinary least squares regression based on equation (2). Unit of analysis is country-year. Standard errors are clustered at the country level and reported in parentheses. Statistical significance denoted with \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table A7. Associations between changes in poverty headcounts (\$3.20/day) and percentage changes in real food prices in first-differenced regressions augmented with lagged changes in real food prices**

	(1)	(2)	(3)	(4)
<b>First differences:</b>				
Food/nonfood CPI ratio (%)	-0.103** (0.047)	-0.125*** (0.044)	-0.607*** (0.142)	-0.598*** (0.125)
Food/nonfood CPI ratio (%)* Urban share			0.008*** (0.002)	0.008*** (0.002)
<b>Lagged differences:</b>				
Food/nonfood CPI ratio (%)	0.027 (0.020)	0.054** (0.021)	0.097 (0.100)	0.120* (0.064)
Food/nonfood CPI ratio (%)* Urban share			-0.001 (0.002)	-0.001 (0.001)
Year fixed effects?		Yes		Yes
$R^2$	0.020	0.130	0.054	0.158
Number of observations	364	364	364	364
Number of countries	33	33	33	33

Notes: Outcome variable is poverty headcount at \$3.20/day level, measured in %. Ordinary least squares regression based on equation (1) in columns 1-2 and based on equation (2) in columns 3-4, appended with lagged differences of food/nonfood CPI ratio. Unit of analysis is country-year. Standard errors are clustered at the country level and reported in parentheses. Statistical significance denoted with \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Urban share variable is time-invariant and measures the mean share of urban population relative to total population over time.

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