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WPS7898

Policy Research Working Paper 7898

Food Prices and Poverty

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WORLD BANK GROUP
Development Economics Vice Presidency
Operations and Strategy Team
November 2016

Policy Research Working Paper 7898

Abstract

Do higher food prices help or hinder poverty reduction? Despite much debate, existing research has almost solely relied on simulation models to address this question. In this paper World Bank poverty estimates are used to systematically test the relationship between changes in poverty and exogenous changes in real domestic food prices. The paper uncovers indicative evidence that increases in food prices are associated with reductions in poverty, not increases. A likely empirical explanation is the relatively strong agricultural supply and wage responses to food price increases, and the fact that the majority of the world's poor still heavily rely on agriculture or agriculture-related activities to earn a living.

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Produced by the Research Support Team

Food Prices and Poverty

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JEL Codes: I32; O11
Keywords: Food crisis, food prices, poverty reduction, agricultural supply response, wages

Acknowledgements: Derek Headey is a Senior Research Fellow at the Poverty, Health and Nutrition Division of The International Food Policy Research Institute (IFPRI), Washington DC, d.headey@cgiar.org**.** The author would like to thank three anonymous reviewers and the managing editor, as well as a range of colleagues for helpful comments on the paper and for insights on poverty measurement. Particular thanks go to Will Martin, Harold Alderman, Hanan Jacoby, John Hoddinott, Kathleen Beegle, Shaohua Chen, Dean Jolliffe, Walter Falcon, Rosamund Naylor, and David Lobell.

Sharp increases in international food prices in recent years have understandably raised serious concerns about potential impacts on the poor. After several decades of secular decline and relative stability, the international prices of staple grains increased sharply in 2007 and 2008 and again in 2010 and 2011 with most of this increase being passed on to domestic markets (see figure 1 and also Ivanic and Martin 2014). Such dramatic changes in the price of food could indeed have major consequences for the world's poor, who spend most of their income on food but also heavily rely on food production to earn a living.

Figure 1. Trends in international and domestic real food prices for 95 developing countries

Source: The international food price index is the real FAO (2014) food price index and the ILO (2013) domestic food price index is the cross-country median of the ratio of the food CPI to the total CPI.

The earliest simulation-based attempts to gauge the welfare impacts of higher prices invariably concluded that, in the short run, global poverty would increase sharply as the result of a *ceteris paribus* increase in food prices (Ivanic and Martin 2008; De Hoyos and Medvedev 2009).[1] Yet, over the medium term, the impacts of higher food prices on global poverty reduction are far more ambiguous. The prevailing wisdom prior to the 2008 food crisis was that low agricultural prices were retarding poverty reduction, since most of the world's poor work in agriculture or related

1. Subsequent estimates of the impact of the 2010-11 price surge suggested a further 44 million people would be thrown into poverty (Ivanic et al., 2011). A number of country studies have also found that higher food prices typically increase poverty. See Headey and Fan (2010) and Compton et al. (2011) for reviews.

sectors (Swinnen 2011). Survey-based evidence also suggested no net deterioration in self-reported food insecurity (Headey 2013; Verpoorten et al. 2013) or poverty (World Bank 2014) during the food price hikes of 2007–2008. Moreover, recent general equilibrium models for India (Jacoby 2013), Uganda (Van Campenhout et al. 2013) and a larger 31-country sample (Ivanic and Martin 2014) all find that higher agricultural prices reduce poverty in the longer run through a combination of agricultural supply and wage responses.

In this paper, we aim to further explore this question by examining the relationship between changes in food prices, agricultural production. and poverty across a large swathe of developing countries. While there is a large and related literature statistically analyzing the drivers of poverty reduction using cross-country data (Christiaensen et al. 2011; De Janvry and Sadoulet 2010; Loayza and Raddatz 2010; Ravallion et al. 2007), and within that literature a handful of papers exploring 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 empirical examination of whether higher food prices help or hinder net poverty reduction. A more empirical examination of this question is important given that simulation models are methodologically somewhat opaque because of their complexity, potentially sensitive to the assumptions and parameters that feed into the model, and silent on how quickly agricultural production and wages might respond to higher prices.[2] Hence, the empirical analysis in the present paper overcomes these deficiencies to some extent and should therefore be seen as a complement to the more structural insights afforded by simulation approaches.

The remainder of this paper is structured as follows. Section II briefly reviews existing theory and evidence on the impact of food prices on poverty and welfare. Section III discusses data and methods. Section IV tests the relationship between changes in food prices and changes in prices (both domestic and international). Section V explores likely explanations of this result, namely, agricultural supply and wage responses to higher food prices. Section VI provides some cautious interpretation of the results.

II. 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, the decisive influence on welfare outcomes is whether a household is a net consumer or net producer of food. Applications of this approach in recent years have almost invariably found that most poor households in developing countries are net consumers of food such that higher food prices are expected to increase poverty in the short run (Ivanic and Martin 2008, 2011, 2014; De Hoyos and Medvedev 2009).

Despite the consistency of this finding across different samples of countries, several critiques have emerged. First, the suitability of household surveys for accurately measuring net benefit ratios is questionable (Headey and Fan 2008, 2010; Carletto 2012). Consumption estimates typically employ short recall modules (typically from one to two weeks) that are then annualized to match up with annual recalls on agricultural production. Yet, recent World Bank research shows that both food consumption and food production estimates suffer from large biases (Beegle et al. 2012;

2. Jacoby (2013) conducts both a simulation analysis and an econometric analysis, but his econometric estimates of wage responses to higher food prices cover a five-year period and thus do not shed light on the speed of wage adjustment within that period, which is surely an important welfare concern.

Deininger et al. 2012). In Uganda, for example, Deininger et al. (2012) find that crop production might be underestimated by half due to recall biases, suggesting that standard surveys might also be underestimating net benefit ratios from higher food prices.

Other critiques focus on behavioral and market responses to higher food prices. Even if many rural people are net food consumers, their engagement in farming provides them scope to adjust production in response to higher food prices (Headey and Fan 2008, 2010). Agricultural supply responses could stem from a range of inputs, including labor, land, variable farm inputs like improved seeds or fertilizers, or longer term capital inputs such as irrigation and increased R&D. Obviously, major capital investments in R&D, irrigation, and land conversion will only induce a supply response over the longer term, but labor and other variable inputs might adjust quickly (Ivanic and Martin 2014). Land is potentially an intermediate case, depending on the availability of fallow land requiring little new investment, only more variable inputs like labor, seeds, and chemicals.

Given what we know about the diversification of activities within households, it seems likely that labor reallocation is the major mode of adjustment and the input most likely to have broader general equilibrium impacts on the demand for unskilled labor and its associated wages. To explore this more systematically, Jacoby (2016) develops a simple general equilibrium model to show that, if agriculture is a large sector, then a given agricultural supply response will result in a relatively large increase in demand for unskilled labor, which will need to be accommodated by shifting labor out of the services and manufacturing sectors. However, if the services sector is large, labor-intensive, and non-tradable (as it mostly is in poor countries), then the wage adjustment required to equilibrate labor demands across sectors will mostly need to come from the manufacturing sector and will need to be relatively large to extract sufficient labor out of that sector. Hence, the model predicts that a standard economic structure (large agricultural and services sectors) will result in an elasticity of wages with respect to food prices that is large and positive in the long run, typically close to unity (Jacoby 2013; Ivanic and Martin 2014). Much less clear, theoretically and empirically, is the speed of wage adjustments to higher food prices, though econometric estimates suggest that short-run wage elasticities vary between 0.25 and 0.69 (Ravallion 1990; Palmer-Jones 1993; Rashid 2002; Lasco et al. 2008).

In summary, the effects of higher food prices on the incomes or expenditures of the poor are complex, dynamic, and ambiguous *a priori*. Undoubtedly, higher food prices create both winners and losers. But given that the bulk of the world's poor are still predominantly rural (Ravallion et al. 2007), any sizeable agricultural supply and wage responses to higher food prices could well result in net poverty reduction over the medium term.

III. Data and Methods

This section describes in detail the data and methods used in the analysis with particular attention to some of the limitations involved.

Poverty Indicators

In this paper, we first explore these medium-term impact of higher prices on changes in national poverty rates in a sample of around 300 observations from the World Bank's (2014) POVCAL database, mostly covering the 1990s and 2000s.[3] Changes in poverty are estimated across consecutive household surveys that vary in duration (i.e., based on survey frequency). To avoid mixing very long with very short changes in poverty, we focus on observation in which the gap between consecutive surveys varies between one and five years of duration and test sensitivity to restrictions within that range. The poverty measures we focus on are changes (first differences) in the $1.25/day and $2/day headcounts, measured at 2005 international dollars. We also drop countries with very low levels of initial poverty (less than 5% in the $1.25 per day headcount) to exclude upper-middle income countries in which food is less important for both consumption and production, and to prevent the sample from being heavily overloaded with such countries.[4]

While there are many challenges in measuring comparable poverty rates across countries and over time, one particular concern with POVCAL estimates is the possibility that they suffer from biases stemming from the use of consumer price indices (CPIs) to deflate nominal estimates of household expenditure or income (or equivalently, to deflate poverty lines). Here there are two sources of bias. First, if the weights in the CPI consumption basket differ substantially from the expenditure patterns of the poor, there is a possibility of CPI bias during periods of real increases in the price of food. However, the POVCAL series used herein contains adjustments for this problem whenever food weights in the CPI were deemed to be excessively low. Moreover, a recent World Bank study of poverty in Africa in fact found evidence that CPI bias during periods of high food inflation typically works in the opposite direction: corrections for CPI bias in Africa would lead to faster poverty reduction during the recent period of rising food prices (Beegle et al. 2016).[5]

Second, when food prices increase, the poor will presumably do little to reduce the quantity of food consumed, particularly if their food expenditure is already focused on the cheapest sources of calories and if their calorie consumption is already close to minimum subsistence levels. In the extreme case, food quantities consumed might be entirely unaffected by higher prices, meaning that an increase in food prices would result in a commensurately large increase in food expenditure shares. Hence, even if the original food expenditure share used in the CPI calculation were correct prior to an increase in real food prices, it would be an underestimate of the amount the poor spend on food after an increase in real food prices. This second type of CPI bias—a classic index number problem—is likely to be smaller in magnitude than the first type of CPI bias referred to above, but both types of bias raise the concern that changes in food prices and changes in poverty could be spuriously correlated because of the way POVCAL data are calculated. It is partly for this reason that we also investigate the impacts of food price changes on FAO agricultural production statistics (see below), since the latter do not suffer from these CPI biases.

Food Price Indicators

The explanatory variable of interest in all our regressions is the change in real food prices, measured as the ratio of the food CPI to the total CPI. Relative to other indicators of relative food price changes, this series seemed to have little signs of substantial measurement error (though we

3. The median endyear of changes in poverty in this sample is 2002.

4. Without this restriction, around one-third of observations would be derived from Eastern Europe and Central Asia and another third from Latin America and the Caribbean.

5. Personal communications with the researchers managing the POVCAL database confirmed that CPI adjustments were made for approximately 20 countries for which the weight on food products was deemed to be excessively low. For Africa, the aforementioned World Bank study used the assumption that differences in the food budget share among demographically similar households with the same level of consumption at different points in time would indicate the CPI's mismeasurement of the true cost of living. Strikingly, the official CPIs seem to have overestimated changes in the cost of living for the poor in 13 of the 16 countries examined.

dropped several hyperinflation observations, such as Zimbabwe), and was available for a large range of developing countries.[6] However, since domestic price movements might be endogenous with respect to poverty (see below), we use an international price index to identify exogenous externally driven variation in domestic prices. To do so we construct an international price index with country-specific weights based on consumption (calorie) patterns for nine commodities for which international prices were available. This has the effect of creating an international price series that has cross-country as well as time series variation. For example, rice accounts for around 70 percent of caloric intake in Bangladesh, so international rice prices receive a very high weight in Bangladesh's index, while wheat, maize, sorghum, and so on get very low weights. This approach helps minimize the weak instrument problem stemming from the fact that international price transmission may be highly variable across countries for a variety of reasons.

Agricultural Indicators

In section V, we chiefly focus on agricultural production indicators to test for agricultural supply response and to circumvent some of the issues with the POVCAL data raised above. These indicators are mostly sourced from the FAO (2004). This set includes value-added measures of all agricultural production as well as food and crop production components. Growth in crop production can also be decomposed into increases in production per hectare and increases in land area harvested, often referred to as the intensive and extensive margins, respectively. We also examine another common indicator of the intensive margins: cereal yields.

Descriptive Statistics

Table 1 shows some summary statistics for some of our key indicators, all of which are measured as annualized changes or percentage changes across consecutive surveys. The statistics are broken up by regions to illustrate one other serious limitation of POVCAL data, namely, that it is overpopulated with countries from Latin America (approximately half the sample), while there are only about 50 observations (i.e., first differences in poverty) each for sub-Saharan Africa and Asia (South and East Asia combined). Eastern Europe and Central Asia contain around 40 observations (and are also somewhat overrepresented relative to their population sizes), while the Middle East and Africa contains only a handful of observations for Tunisia and Morocco only. Average changes in $1.25/day poverty over these observations are highest for East Asia (-2.2 points), as expected, followed by Eastern Europe and Central Asia (-1.6), sub-Saharan Africa (-1.5) and South Asia (-1.2). Mean changes in food prices are positive in all regions but substantially larger in Asia and sub-Saharan Africa.

Table 1. Summary statistics for key variables

6 .We investigated a number of different series, including the FAO series on producer prices and an index based on GDP deflators. However, results reported in appendix S1 suggest that these two series are measured with much more error than the consumer price index series. Both series are weakly correlated with international prices, for example. It also seems conceptually less suitable to focus on producer prices, since even producers also make substantial purchases of food.

	East Asia & Pacific (N=35)	South Asia (N=19)	Sub-Saharan Africa (N=52)
Annual change in \$1.25/day poverty rate (% points per year)	-2.2	-1.2	-1.5
Annual change in \$2/day poverty rate (% points per year)	-2.3	-1.2	-0.9
Annual percentage change in domestic food prices (% per year)	0.6	0.7	0.6
Annual percentage change in food production (% per year)	4.4	3.3	4.0
	Europe & Central Asia (N=41)	Latin America & Caribbean (N=157)	Middle East & North Africa (N=4)
Annual change in \$1.25/day poverty rate (% points per year)	-1.6	-0.5	-0.4
Annual change in \$2/day poverty rate (% points per year)	-1.7	-0.7	0.0
Annual percentage change in domestic food prices (% per year)	0.2	0.4	0.0
Annual percentage change in food production (% per year)	0.9	3.5	4.2

Source: Author's estimates from World Bank (2013) poverty data and ILO (2013) food price data.

Methods

For systematically testing the relationship between poverty and food prices, we use both least squares regressions and instrumental variables (IV) approach. In the least squares approach the first difference in the poverty headcount (P)[7] is regressed against the first difference in the log of domestic food prices (p^d) and series of time dummies (T), with v denoting the error term:

$$(1)\quad dP_{i,t} = \beta . d \ln p^d_{i,t} + T + v_{i,t}$$

One concern with equation (1) is that changes in food prices might be correlated with the error term because of omitted variables. The 1998 Indonesian financial crisis, for example, increased

7. First differences is preferable to percentage differences for two reasons. First, poverty headcounts are already measured in percentage terms, and taking percentage changes of very small values produces results that are arguably counterintuitive. For example, an increase in the poverty rate from 1% to 3% in one country and 30% to 32% in another country should arguably be regarded as equivalent. In contrast, the two changes are very different in percentage terms: 200% in the first case, and 6.67% in the second case. See Deaton (2006) for a discussion of this problem in the context of mortality rates. A second problem is that taking percentage changes can sometimes produce outliers.

food prices (through a large exchange rate devaluation), but also increased unemployment and reduced investment, and, therefore, likely affected poverty by other routes. In this example, an omitted variable (a financial crisis) induces a potentially spurious positive relationship between food prices and poverty, but one can also articulate biases in the other direction (e.g., expansionary monetary or fiscal policies), such that it is difficult to say in which direction OLS coefficients might be biased.

To address this concern we use a relatively simple instrumental variables strategy implemented with the two-step instrumental variables general method of moments (IV-GMM), using an optimal weighting matrix. The identification strategy rests upon the exogeneity of the international food price index (described above), which is assumed to only influence national poverty rates through its effect on domestic food prices. Hence, the IV-GMM approach results in an equation similar in structure to (1), but in which we use domestic price changes predicted by international price changes.

In addition to these basic least squares and IV-GMM approaches, we engage in several robustness tests. First, IV approaches can sometimes be sensitive to the choice of estimator. While results from standard IV and LIML estimators are also very similar (available on request), in our appendix we also report results for the Arellano and Bond (1991) dynamic panel estimator, in which lagged poverty rates are introduced.

Second, we conduct robustness tests to gauge whether the introduction of potentially confounding factors to the model has any influence on our core results. For example, increases in food prices might be strongly associated with increases in non-food commodities, so we control for changes in the overall terms of trade but also overall inflation, monetary expansion, exchange rate movements, changes in trade and foreign investment ratios, and non-agricultural growth rates.

Third, we test robustness of results to splitting up the sample by region and by time periods. The former is implemented to test whether any particular region might be driving the result, while the latter is done to test whether the effects of food prices were systematically different in the 2000s, a period of heightened international price volatility. We also extensively tested for interactions between changes in food prices and other structural indicators of interest (such as indicators of the size of agriculture in total GDP or total employment and the magnitude of initial poverty rates), to see whether there is observable heterogeneity in the effects of food price changes on national poverty (results available upon request).

Lastly, we also investigate whether changes in food prices influence agricultural production and input use and unskilled wages. For the agricultural production regressions, we adopt the same form as equation (1) and its IV-GMM analog, but we replace poverty rates with various measures of agricultural output or input use. We also exploit the availability of monthly data on rural and urban wages in Bangladesh to test whether rice prices differentially influence rural and urban labor markets, using both auto-distributed lag (ADL) models and vector error correction models (VECM). These results are reported in section V.

IV. ESTIMATING THE NET POVERTY IMPACTS OF INCREASES IN FOOD PRICES

This section presents some core results on the associations between changes in poverty headcounts and changes in real food prices, followed by a description of their robustness to different methodological variations.

Core Results

Table 2 reports regressions of changes in the \$1.25/day and \$2/day poverty headcounts against percentage changes in food prices using OLS and the IV GMM. For both regressors the standard errors are clustered at the country level, and, though not reported, both models include time dummies to control for generic international economic trends.

The most striking feature of regressions 1 through 4 in table 2 is that all the coefficients are negative and significant at the 5% level or higher, implying that increases in real food prices tend to reduce poverty rates at both the \$1.25/day and \$2/day poverty lines. The magnitude of the estimated coefficients is similar across the two poverty lines but very different across estimators. Specifically, the IV GMM estimates are several times larger than the robust regression estimates, suggesting that the OLS estimates might be biased upwards, perhaps because increases in domestic food prices are often driven by negative domestic shocks such as droughts or broader economic crises.[8]

Even so, the IV GMM point estimates also need to be interpreted cautiously. While the exclusion assumption is supported by the hypothesis tests in the bottom of table 2, the Kleibergen-Paap rk Wald F statistic suggests that our instrument (international food prices) is relatively weak, which is to be expected since international price transmission into domestic markets is quite variable and since the basket of nine international prices is not always relevant to domestic consumption and production patterns.[9] Consistent with a weak instrument problem, the standard errors on the IV GMM coefficient estimates are relatively large. This suggests we should be cautious in attaching too much importance to an economic interpretation of the magnitudes of these coefficients. Bearing that caveat in mind, the six percent food price increase in the median country from 2005 to 2008 would predict a 1.76 percentage point decline in \$1.25 poverty in the average country based on the least squares regression result and a 4.9 point decline based on the IV GMM result.

8. OLS estimates reported in appendix S2 are also significant and negative but somewhat smaller than the robust regression estimates.

9. In appendix table S2.4, we explore whether the instrument is stronger in a sample of more recent poverty observations in which there was more variability in international food prices, restricting the sample to 200.

Table 2. Estimating the effect of percentage changes in domestic food prices on changes in the $1.25/day and $2/day poverty headcounts in robust and IV GMM models

Regression Number	1	2	3	4
Poverty line for headcount measure	$1.25/day	$1.25/day	$2/day	$2/day
Estimator	OLS	IV GMM	OLS	IV GMM
Change in log of domestic food prices	-19.27**	-81.67**	-17.65***	-71.87**
	(9.24)	(40.10)	(7.48)	(36.09)
N	302	300	313	310
<u>Tests</u>				
Kleibergen-Paap rk Wald F statistic		12.20		13.68
Kleibergen-Paap rk LM statistic		0.01		0.01
Stock-Wright LM statistic		0.04		0.04

Source: Author's estimates from World Bank (2013) poverty data and ILO (2013) food price data.

Notes: See text for definitions of the variables. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors clustered at the country level are reported in parentheses. For the IV GMM, errors are clustered at the country level and the excluded instrument is the change in international prices (see section III for details). All regressions control for time dummies. The null hypothesis of the Hausman tests is that the variable under consideration can be treated as exogenous. The Kleibergen-Paap rk Wald F statistic measures weak instruments, with critical values varying between 5.53 and 16.38, suggesting that the regressions above may suffer from a weak instrument problem. The null hypothesis of the Kleibergen-Paap rk LM statistic is that the equation is underidentified. The null hypothesis of the Stock-Wright LM test has the null hypothesis that the coefficient on the change in real food prices is equal to zero and overidentifying restrictions are valid.

Robustness Tests

Qualitatively, the results reported in table 2 are largely quite robust to important variations in data and methods, which are reported in appendix S2. Table S2.1 reports the specifications from table 2 after using a robust regressor instead of ordinary least squares. The robust regressor yields slightly larger and more precise coefficients relative to OLS, suggesting that the latter are somewhat influenced by outliers. Tables S2.2 and S2.3 report Arellano-Bond dynamic GMM regression models with lagged poverty rates as an additional dependent variable. The dynamic GMM results are closer to the OLS results than to the IV GMM. Table S2.4 restricts the sample to observations in which the last survey year used is 2002 onwards to examine whether the results are robust to the more recent period of international price variability. The results in table S2.4 suggest that they are. Table S2.5 looks at sample restrictions in which we exclude each major region one at a time. Though these are weak tests of parameter heterogeneity across regions, there is some suggestion that higher food prices are more beneficial in Latin America and sub-Saharan Africa. Table S2.6 imposes increasingly tight restrictions on the permitted gap between successive surveys, moving from one-year to five-year intervals (as in table 2) to 1–4 year, 1–3 year and 1–2 year intervals. We do indeed see some evidence that the coefficients reduce in size over these shorter intervals, although it is unclear as to whether these weaker effects in the 1–2 year sample stem from dynamic processes or changes in sample composition, given that very few low income countries conduct household survey at high frequency (i.e., 1–2 year gaps).[10] Finally, tables S2.7 and S2.8 add various additional control variables to the least squares and IV-GMM models respectively, namely, changes in the total CPI, a country's terms of trade, money supply, foreign investment, trade ratio, and non-agricultural GDP. The core results remain highly robust in the presence of such controls, though the IV-GMM results are sensitive to the addition of non-agricultural growth rates to the model (though the coefficient remains relatively large). In general, then, the results in table 2 are quite robust to different samples, different estimators and different specifications.

V. Supply and Wage Responses to Higher Food Prices

In this section, we explore two important mechanisms that may explain why changes in food prices seem to be negatively associated with changes in the poverty: agricultural supply responses to higher prices and wage responses stemming from increased demand for labor in the agricultural sector. Different literatures have argued that there is substantial evidence that poverty reduction is linked to both stronger agricultural growth (Christiaensen, Demery, and Kühl 2011) and higher unskilled wages (Deaton and Dreze 2002). Hence, econometric evidence of a systematic effect on production and wages would go a long way to explaining the effects observed in the previous section.

Agricultural Supply Responses to Higher Food Prices

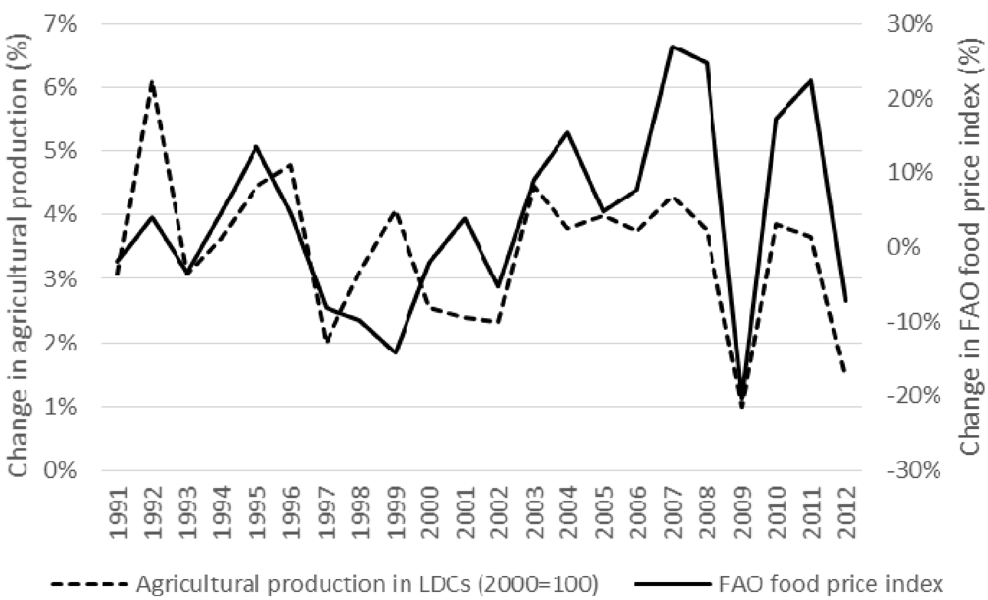
Figure 2 shows annual changes in the international food price index and annual changes in net agricultural production in less developed countries from 1991 to 2012 (note that the two series are measured on different axes and hence different scales). Strikingly, even this highly aggregated production series demonstrates some signs of supply response in developing countries, especially from 2003 onwards when international prices first started to trend upwards. In 2008, the aggregate supply response was weak, but the price crash in late 2008 and early 2009 coincided with slower growth in production followed by a strong rebound in 2010–11 as prices again increased.[11] Figure S3.1 in appendix S3 shows analogous graphs for major developing regions and some of the larger countries. Most strikingly, production in South America and India has moved very closely with international prices in the past decade. In contrast, strong production growth in China and Southeast Asia preceded international price increases, and, therefore, seems less likely to be a

10. In the full one- to five-year sample, low income countries comprise 17.5% of the sample, but, in the one- to two-year sample, they comprise just 8.6%.

11. A caveat here is that the timing of production in the FAO series is actually somewhat heterogeneous across countries and does not necessarily follow the conventional calendar. It may be that production responds to higher food prices with some lag.

specific response to rising international prices.[12] Africa looks like an intermediate case with some positive trends prior to 2007–2008 and a further acceleration in the wake of international price increases. In Nigeria, Africa's largest country, agricultural production seems very closely connected to international price movements.

Figure 2. Annual changes in international food prices and agricultural production in less developed countries (LDCs)



Source: Author's estimates from FAOSTAT (2013) data.

Table 3 more formally tests supply response in the POVCAL sample by regressing changes in various aggregated agricultural production indicators against exogenous changes in real domestic food prices using the IV GMM model.[13] Regressions 1 to 3 respectively estimate the response elasticities for total agricultural production, total food production and total crop production. The point estimates of these elasticities are all significant at the 1% level and progressively increase from 1.76 to 2.48 to 2.96, respectively. In regressions 4, 5, and 6, we explore the extent to which this growth comes from the extensive margin or the intensive margin, though we note that any

12. Many Asian countries use price supports for agriculture, of course, and very actively insulate rice markets in particular, so low price transmission is a likely explanation for weaker linkages in Asia (Dawe 2008).

13. The workhouse supply response model derived by Nerlove (1958) depicts supply responding to expected price changes, which are a function of lagged price changes. In these very aggregated data in which different seasons are aggregated into calendar years, it isn't immediately obvious whether lags should be included or not, but in practice lagging one year makes no material difference to the results (available on request), so we model supply responses to approximately contemporaneous price changes. Note also that appendix S3 reports least squares results linking domestic prices to changes in agricultural production. These estimates tend to be insignificantly different from zero, but unsurprisingly so since changes in agricultural production can obviously affect food prices rather than vice versa.

systematic errors in estimating land area could bias all of these results. Regression 4 estimates an elasticity of crop production per hectare of 0.95, though this estimate is highly insignificant. The elasticity of crop area harvested is 1.90 and statistically significant, however, which perhaps that the extensive margin is important for generating supply response. However, in regression 6 we also find a large and highly significant coefficient on cereal yields (2.41), suggesting that cereals production, at least, might respond on the intensive, as well as extensive, margin.

Clearly, all the supply response elasticities in table 3 are highly significant, but how large are they in economic magnitudes? From 2005 to 2008 the domestic food price index rose by six percent, which would predict a 10.6 percent increase in agricultural output based on the coefficient of 1.76 reported in regression 1 of table 3. This in itself is a sizeable effect, but higher prices will also have a direct effect on farm revenue in addition to any supply response. Assuming that farmers receive the full six percent increase in real food prices, the total effect on farm revenue in this example would be an increase of about 17 percent. While the data do not permit us to estimate potential increases in input costs (and hence farm profits or net farm income), it nevertheless seems likely that higher output prices are associated with higher farm incomes, which the literature tells us should, in turn, produce quite strong poverty reduction effects (Christiaensen, Demery, and Kühl 2011).[14]

In appendix table S3.1, we report a series of robustness tests of the crop production response to higher food prices by again imposing sample restrictions. As was the case with the poverty results, we again find suggestive evidence that supply responses are stronger in Latin America and sub-Saharan Africa and weaker in Asian countries. This result seems consistent with differences in land endowments across regions. Indeed, we find weaker supply responses in a sample that excludes more land abundant countries. Consistent with the poverty evidence and with the aggregate supply response observed in figure 2, we find substantially stronger supply responses in a more recent sample of poverty observations (2003 to 2011), during which time there was more variability in international prices. Finally, we find evidence that this supply response exists even in the relatively short run; restricting the sample to poverty differences 1–3 years in duration leaves the point estimate materially unchanged.

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14. One possibility to consider is that public policies partially explain this strong supply response. In response to higher food prices, governments might increase subsidies (decrease taxes) to agriculture. There is some evidence of this, such as a number of governments resorting to larger input subsidies. A paucity of data on these parameters prevents us from exploring this issue further, however.

Table 3. Instrumental variable (IV GMM) regressions of the agricultural supply response to changes in instrumented domestic food prices changes

Regression number	1	2	3
Dependent variable (growth rates)	Agricultural production	Food production	Crop production
Estimator	IV GMM	IV GMM	IV GMM
Change in log of domestic food prices	1.76**	2.48**	2.86***
	(0.76)	(0.97)	(1.11)
N	300	300	300
Tests			
Kleibergen-Paap rk Wald F statistic	12.20	12.20	12.20
Kleibergen-Paap rk LM statistic	0.01	0.01	0.01
Stock-Wright LM statistic	0.00	0.01	0.21
Regression number	4	5	6
Dependent variable (growth rates)	Crop production per hectare	Crop area harvested	Cereal yields
Estimator	IV GMM	IV GMM	IV GMM
Change in log of domestic food prices	0.95	1.90**	2.41**
	(0.84)	(0.87)	(1.19)
N	300	300	300
Tests			
Kleibergen-Paap rk Wald F statistic	12.20	12.20	10.82
Kleibergen-Paap rk LM statistic	0.01	0.01	0.01
Stock-Wright LM statistic	0.02	0.01	0.09

Source: Author's estimates from World Bank (2013) poverty data and ILO (2013) food price data.

Notes: See text for definitions of the variables. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Standard errors clustered at the country level are reported in parentheses. The excluded instrument is the change in international prices (see section III for details). All regressions control for time dummies. The Kleibergen-Paap rk Wald F statistic measures weak instruments, with critical values varying between 5.53 and 16.38, suggesting that the regressions above may suffer from a weak instrument problem. The null hypothesis of the Kleibergen-Paap rk LM statistic is that the equation is underidentified. The null hypothesis of the Stock-Wright LM test has the null hypothesis that the coefficient on the change in real food prices is equal to zero and overidentifying restrictions are valid.

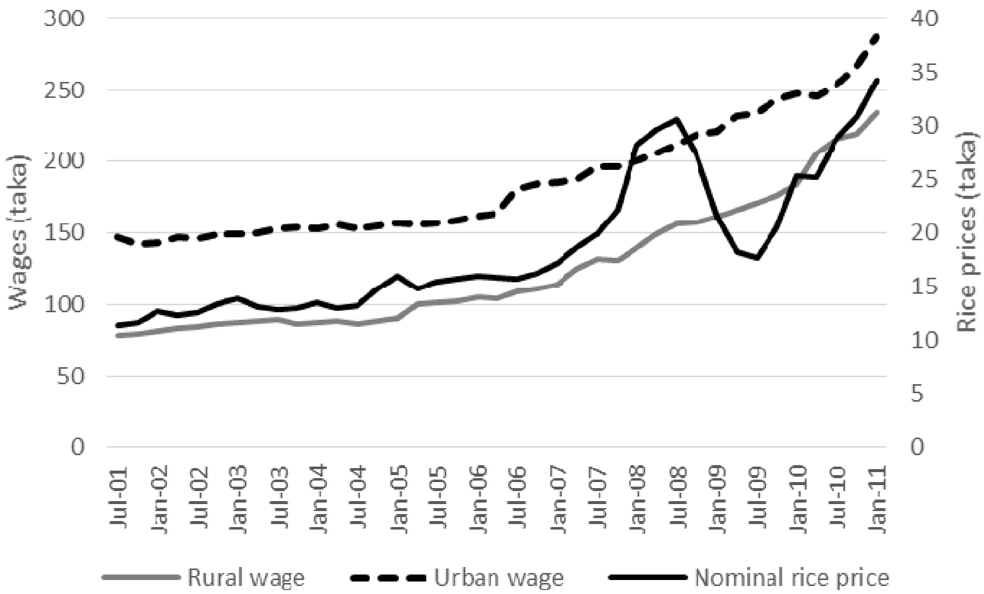
Wage Responses to Higher Food Prices

In principle, the indicator of agricultural GDP used in table 3 includes farm wage incomes as part of value added. However, higher food prices might also result in increases in non-farm wages. Yet, as we noted in section II, only a small empirical literature has focused on these issues. Rarely has this literature used sufficiently high frequency data to accurately inform the question of how long it takes for wages to react to food price increases, and only one paper has examined the responses of urban wages to higher food prices (Headey et al. 2011). We therefore revisit short-run adjustment issues using high frequency data on rural and urban wage indices for Bangladesh from 2001 to 2011.[15] Although the data are monthly, the noise in the data prompts us to aggregate the data into quarters, which also more closely approximates Bangladesh's different agricultural seasons (*aman, aus, boro*). Our expectation was that labor demand and supply may be less likely to respond in the current season but may respond more substantially in subsequent seasons as planting decisions constitute an important behavioral response to higher food prices.

Figure 3 shows trends in these nominal rural and urban wage indices along with the nominal producer price of rice, which is easily the most important crop in Bangladesh. Nominal rice prices roughly doubled from July 2006 to July 2008 in close accordance with international prices. Nominal rural and urban wages also increased, but rural wages increased much faster than urban wages. Indeed, from July 2006 to January 2011, the ratio of rural to urban wages increased rapidly from 59 percent to 82 percent. This suggests two important conclusions. First, rural and urban wages (and hence labor markets) may not be very closely integrated in the short term. Second, it is plausible that higher food prices were the leading factor behind the declining rural-urban wage gap, though there are other possible explanations such as accelerated out-migration from rural areas (Zhang et al. 2013).

15. The rural wage index places most of its weight on the agricultural wage series for Bangladesh while the urban series includes wages for construction, masons, carpenters, plumbers, painters, electricians, and brick-breaking.

Figure 3. Rice prices and rural and urban wages in Bangladesh, 2001-2011

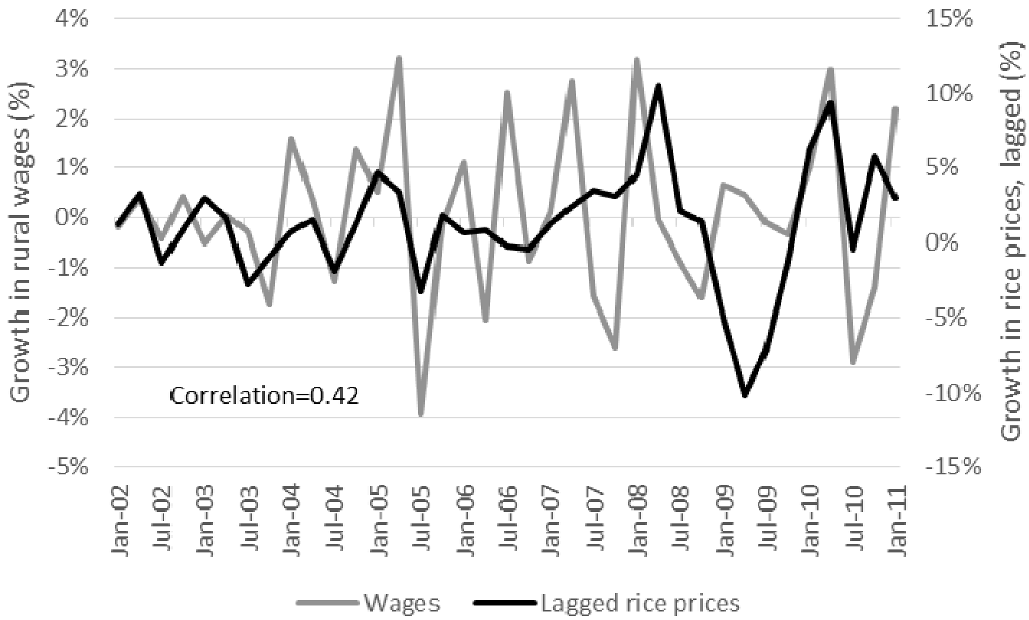


Source: Author's estimates from Bangladesh Bureau of Statistics (BBS 2014).

To explore the relationship between food prices and wages more rigorously, we first conducted a graphical analysis of growth rates in wages and rice prices before deriving wage-food price elasticities in a vector error correction model (VECM). Both the graphical analysis in figure 4 and the VECM reveal a statistically significant short-run elasticity between wages and the one quarter lag of rice prices of 0.14 and a long-run elasticity of 1.11. For urban wages, we also find evidence of long-run cointegration (an elasticity of 0.78), but a short-run elasticity that is highly insignificant and close to zero (-0.02). The short-run results for rural and urban wages are also robust to various robustness tests,[16] though the OLS auto distributed lag (ADL) model with a second lag of rice price changes also yields a significant coefficient of 0.08 and an elasticity on the first lag of rice prices of 0.11. This suggests that a 100 percent increase in rice prices would increase wages by almost 20 percent over two-quarters.

16. If we run a VECM with food prices and both rural and urban wages, we derive the same rural wage-rice price elasticity of 0.14 and again derive an insignificant urban wage-food price elasticity. An OLS regression of growth rates of rural wages against lagged growth rates in rice prices and wages (with a time trend) also yields an almost identical short-run rural wage-food price elasticity (0.13) and insignificant elasticities for urban wages.

Figure 4. Quarterly changes in rural wages and lagged changes in rice prices (%), Bangladesh 2001-2011



Source: Author's estimates from Bangladesh Bureau of Statistics (BBS 2014).

Table 4. VECM estimates for rural and urban wage models

Regression Number	1	2
Wage series included	Rural wages	Urban wages
Number of observations	37	37
R-squared: wage regression	0.58	0.45
R-squared: rice price regression	0.51	0.48
Short run coefficients:		
Wage regression		
Cointegration term, lag 1	-0.005 (0.035)	-0.04 (0.04)
Rural wages, lag 1	0.15 (0.159)	0.10 (0.17)
Rice prices, lag 1	0.14** (0.058)	-0.02 (0.05)
Rice price regression		
Cointegration term, lag 1	0.33*** (0.035)	0.38 (0.11)
Rural wages, lag 1	0.15 (0.159)	-0.31 (0.54)
Rice prices, lag 1	0.135 (0.058)	0.63*** (0.114)
Cointegrating relationship		
Wages	1	1
Rice prices	-1.11*** (0.13)	-0.78***
Constant	-1.56	-2.92

Source: Author's estimates from Bangladesh Bureau of Statistics (BBS 2014).

Notes: See text for definitions of the variables. *, **, and *** indicate significance at the 10%, 5% and 1% levels respectively.

These results should be interpreted with some caution—certainly they are still relatively imprecise and almost certainly lack broader external validity—but they have several important implications. First, the conclusion that the long-run rural wage-rice price elasticity is approximately equal to unity is similar to the conclusions of Jacoby (2013) for India, Lasco et al. (2008) for Bangladesh, and Ivanic and Martin (2014) for a broader range of countries. Second, the short-run food price elasticity is quite low (0.14 to 0.19), though our use of higher frequency data reveals that the response is relatively quick: wages start to change in the next quarter. Third, consistent with Headey et al.'s (2011) results for Ethiopia, urban wages might adjust to higher food prices quite strongly in the long run but they show no substantial adjustment in the short run. This further suggests that rural and urban labor markets may be quite weakly integrated, perhaps because of low levels of short-term mobility between rural and urban areas.[17] In summary, wage adjustments seem to provide some compensation for rural laborers—and relatively quickly at that—but it would appear that agricultural supply responses are likely to be the main explanation of the poverty-reducing effects of higher food prices.

17. This is in contrast to the assumption in Ivanic and Martin's (2014) model, in which rural and urban labor markets are perfectly integrated.

VI. Conclusions

When international food prices first rose sharply in 2007 and 2008 there was understandable concern that higher prices constituted a grave risk for the world's poor. While there was much debate about the true extent of these risks, extensive evidence on the relationship between food prices and poverty is only now emerging (Ivanic and Martin 2014; Jacoby 2016). Consistent with recent simulation exercises for subsets of developing countries, this paper finds that increases in international food prices typically predict reductions in national poverty rates in a large sample of developing countries over periods of one to five years.

This core result is subject to two important caveats. First, the magnitudes of these associations are much larger in IV-GMM regressions than in OLS and dynamic panel GMM regressions, but the IV-GMM regressions potentially suffer from a weak instruments problem and certainly suffer from imprecision. Second, in section III we noted that the POVCAL data utilize CPIs to deflate their income and expenditure series, and it is quite possible that these CPIs series understate true increases in the cost of living for the poor during food price increases. While the World Bank has taken some steps to address this problem, these potential biases warrant further investigation.

Bearing these caveats in mind, a negative relationship between changes in food prices and changes in poverty could stem from three factors. First, the most recent estimates suggest that around three-quarters of the world's poor are still rural (Ravallion et al. 2007) and are therefore either directly dependent on farm income or on non-farm incomes that are likely to be strongly influenced by agricultural production decisions, particularly the demand for labor. Second, we find that higher food prices appear to have produced a positive, large, and relatively quick agricultural supply response in developing countries. Third, there are some indications from Bangladeshi data that wage increases provide compensation for rural wage earners relatively quickly, though there is no evidence that urban workers benefit from any wage response except perhaps in the long run.

These findings potentially point to some important implications. Most importantly, they suggest that international food price movements might be important drivers of national and global poverty trends as well as rural-urban inequality within countries. The data at hand should not be used to draw conclusions on the contributions of higher food prices to global poverty trends, but it is notable that poverty reduction over 2005-2012—a period of relatively high international food prices—was relatively rapid in the developing world. More recently (2013 to early 2016), food prices have plummeted. Time will tell, but the evidence in this paper suggests that declining food prices could have adverse implications for many of the world's poor by suppressing their most important sources of income: agricultural production and rural wages.

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Supplementary Appendix (for online publication only)

<u>Contents</u>

Appendix S1. Alternative price indices

Food prices can be measured in different ways. The analysis in this paper uses the consumer food price index relative to the total price index to measure changes in real food prices. Alternative aggregated price indices include the FAO producer price index for all agricultural commodities or all cereals, or the agricultural GDP deflator. All three indices uses production data to weight the indices, and all are deflated using the total GDP deflator to capture real price changes. All are also available for a reasonably large array of countries, although the FAO producer price indices are only available after 1990, and are not available for all countries. These series are also widely regarded as being prone to substantial measurement error, and the same is likely true of the agricultural GDP deflator, since national accounting systems are quite poor in many African countries in particular. Finally, international price indices were also available to us. We constructed country-specific indices of international prices based on weighting prices for nine food staples by domestic consumption patterns, as measured by the share of calories obtained from each of these food items. Since international prices are exogenous, we use this price series as an instrument in most of our regressions.

Table A1 shows a correlation matrix of these various price indices, all measured in real terms using either the total CPI or the total GDP deflator to convert the nominal indices into real price indices. Strikingly, the correlation between the domestic price indicators is often quite weak. The correlation between the real consumer food price index and the agricultural GDP deflator is moderately strong (0.47), but the FAO agricultural and cereal price indices are quite weakly correlated with both consumer prices and the agricultural GDP deflator, suggesting these FAO series may include substantial measurement error. Perhaps most pertinent – at least in terms of our instrumentation strategy – is that it is the consumer food price index which shares the strongest correlation with the two international prices indices (0.31-0.34). This suggests that consumer food price indices are quite sensitive to international prices relative to the other indices.

Table S1.1 Correlations between different domestic and international price indices

	Consumer food price index	Producer agricultural price index	Producer cereal price index	Agricultural GDP deflator	International food price index	International grain price index
Consumer food price index	1.00					
Producer agricultural price index	0.08	1.00				
Producer cereal price index	0.08	0.69	1.00			
Agricultural GDP deflator	0.47	0.27	0.25	1.00		
International food price index	0.32	0.23	0.16	0.28	1.00	
International grain price index	0.35	0.24	0.21	0.28	0.77	1.00

Source: Authors' estimated from various sources, described in the text.

Notes: All indices are measured in real terms, relative to general prices.

Appendix S2. Robustness tests for the poverty-food price regressions

Table S2.1 Re-estimating the core results with the robust regressor

Regression Number	2	4
Estimator	Robust	Robust
	$1.25/day poverty	$2/day poverty
Change in log of domestic food prices	-29.34***	-21.69***
	(6.02)	(6.56)
R-squared	0.12	0.07
N	302	313

Source: Author's estimates.

Notes: See text for definitions of the variables. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Regressions are estimated using the *rreg* command in STATA.

Table S2.2 Arellano-Bond dynamic GMM regressions of the $1.25/day poverty headcount against food prices under different survey gaps

Regression Number	1	2	3
Length of gap between surveys	1-5 years	1-4 years	1-3 years
Change in log of domestic food prices	-18.77**	-25.04***	-24.21***
	(7.69)	(8.08)	(6.93)
Initial poverty level (%)	0.72***	0.66***	0.52***
	(0.06)	(0.09)	(0.10)
Times dummies included?	Yes	Yes	Yes
<u>Tests</u>			
Arellano-Bond autocorrelation p-value	0.21	0.18	0.06
Sargan over-identification p-value	0.99	0.99	0.90
No. of observations	308	278	253
No. of countries	60	48	46
No. of instruments	97	97	97

Source: Author's estimates.

Notes: See text for definitions of the variables. Time dummies are included in all regressions. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Robust standard errors are reported in parentheses. The null hypothesis of the overidentification test is that the instruments are uncorrelated with the error term. Arellano-Bond autocorrelation test is for the second lag of the first differenced error.

Table S2.3 Arellano-Bond dynamic GMM regressions of the $2/day poverty headcount against food prices under different survey gaps

Regression Number	1	2	3
Length of gap between surveys	1-5 years	1-4 years	1-3 years
Change in log of domestic food prices	-23.06**	-29.79***	-30.65***
	(9.60)	(10.9)	(11.77)
Initial poverty level (%)	0.78***	0.70***	0.60***
	(0.06)	(0.08)	(0.09)
Times dummies included?	Yes	Yes	Yes
Tests			
Arellano-Bond autocorrelation p-value	0.13	0.15	0.10
Sargan over-identification p-value	0.97	0.96	0.65
No. of observations	319	288	262
No. of countries	70	57	54
No. of instruments	97	97	97

Source: Author's estimates.

Notes: See text for definitions of the variables. Time dummies are included in all regressions. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Robust standard errors are reported in parentheses. The null hypothesis of the overidentification test is that the instruments are uncorrelated with the error term. Arellano-Bond autocorrelation test is for the second lag of the first differenced error.

Table S2.4 $1.25/day and $2/day OLS and IV GMM results after restricting the sample to more recent poverty observations (ending in 2003 or later)

Regression Number	1	2	3	4
Poverty line for headcount measure	**$1.25/day**	**$1.25/day**	**$2/day**	**$2/day**
Estimator	**OLS**	**IV GMM**	**OLS**	**IV GMM**
Change in log of domestic food prices	-22.12	-89.13**	-13.72	-60.18**
	(13.56)	(37.39)	(9.67)	(26.87)
N	145	144	153	151
<u>Tests</u>				
Kleibergen-Paap rk Wald F statistic		17.81		19.5
Kleibergen-Paap rk LM statistic		0.01		0.02
Stock-Wright LM statistic		0.03		0.04

Source: Author's estimates.

Notes: The sample consists of observations in which the last poverty observation is in 2003 or thereafter. See text for definitions of the variables. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Standard errors clustered at the country level are reported in parentheses. For the IV GMM, errors are clustered at the country level and the excluded instrument is the change in international prices (see Section 3 for details). All regressions control for time dummies. The null hypothesis of the Hausman tests is that the variable under consideration can be treated as exogenous. The Kleibergen-Paap rk Wald F statistic measures weak instruments, with critical values varying between 5.53 and 16.38, suggesting that the regressions above may suffer from a weak instrument problem. The null hypothesis of the Kleibergen-Paap rk LM statistic is that the equation is underidentified. The null hypothesis of the Stock-Wright LM test has the null hypothesis that the coefficient on the change in real food prices is equal to zero and overidentifying restrictions are valid.

Table S2.5 OLS and IV-GMM regression results for the $1.25/day poverty headcount after removing one major region at a time

Excluded region	**Latin America & Caribbean**	**Eastern Europe & Central Asia**	**Asia**	**Sub-Saharan Africa**
Estimator	**OLS**	**OLS**	**OLS**	**OLS**
Change in log of domestic food prices	-14.64*	-16.90*	-21.62**	-13.62*
	(8.23)	(9.75)	(10.71)	(7.71)
Estimator	**IV-GMM**	**IV-GMM**	**IV-GMM**	**IV-GMM**
Change in log of domestic food prices	-41.92	-85.56*	-81.6	-59.08*
	(48.26)	(46.74)	(53.65)	(34.32)
N	246	266	249	250

Source: Author's estimates.

Notes: See text for definitions of the variables. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively, and # indicates marginal insignificance at the 10% level. Standard errors clustered at the country level are reported in parentheses. All regressions control for time dummies. For the IV GMM, errors are clustered at the country level and the excluded instrument is the change in international prices (see Section 3 for details). IV-GMM hypothesis tests are available upon requests. In general, weak instruments remain a concern in all IV-GMM regressions.

Table S2.6 Estimating the effects of percentage changes in domestic food prices on changes in the $1.25/day poverty headcount for different gaps between successive poverty observations

		Robust regression results	
Regression Number	**1**	**2**	**3**
Gap between successive poverty observations	**1-4 years**	**1-3 years**	**1-2 years**
Change in log of domestic food prices	-22.36***	-21.59***	-10.85
	(5.95)	(6.45)	(8.04)
Number of observations	273	248	198
Observations from low income countries (%)	15.23%	11.27%	8.65%
		IV-GMM results	
Regression Number	**4**	**5**	**6**
Gap between successive poverty observations	**1-4 years**	**1-3 years**	**1-2 years**
Change in log of domestic food prices	-50.02	-63.79	6.70
	(37.84)	(45.76)	(40.20)
Number of observations	273	248	198
Observations from low income countries (%)	15.23%	11.27%	8.65%

Source: Author's estimates.

Notes: See text for definitions of the variables. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Standard errors are reported in parentheses. The robust regressor corresponds to the *rreg* command in STATA™. For the IV GMM, errors are clustered at the country level. Specification tests for the IV-GMM results are omitted for the sake of brevity, but are similar to those reported in Table 2, with weak instruments being a potential problem.

Table S2.7 Adding control variables to the least squares regression model for $1.25/day poverty headcounts

Regression No.	1	2	3	4
Control added (% change)	None	Exchange rate	Terms of trade	Trade/GDP
Change in domestic food prices	-19.27**	-19.92**	-19.58*	-18.01*
	(9.24)	(9.56)	(10.86)	(9.52)
Change in control variable		1.328	-4.048	-1.69
		(2.02)	(2.97)	(3.22)
N	300	297	251	300
Regression No.	5	6	7	8
Controls added	FDI/GDP	M2/GDP	Total CPI	Non-agricultural GDP
Change in domestic food prices	-23.15***	-18.08*	-19.54**	-17.63*
	(8.482)	(9.60)	(9.36)	(9.69)
Change in control variable	-0.57	-6.05**	0.87	-16.69***
	(0.82)	(2.51)	(1.03)	(3.39)
N	300	284	300	236

Source: Author's estimates.

Notes: See text for definitions of the variables. All right hand side variables are measured as percentage changes. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively, and # indicates marginal insignificance at the 10% level. Standard errors clustered at the country level are reported in parentheses. All regressions control for time dummies.

Table S2.8 Adding control variables to the IV-GMM model for changes in $1.25/day poverty headcounts

Regression No.	1	2	3	4
Control added (% change)	None	Exchange rate	Terms of trade	Trade/GDP
Change in domestic food prices	-81.67**	-83.91*	-84.48**	-96.98*
	(40.10)	(43.02)	(40.67)	(55.61)
Change in control variable		2.2	-2.95	5.58
		(2.98)	(3.20)	(6.08)
N	300	297	251	300
Regression No.	5	6	7	8
Controls added	FDI/GDP	M2/GDP	Total CPI	Non-agricultural GDP
Change in domestic food prices	-82.57**	-74.84	-84.68**	-30.16
	(40.74)	(45.54)	(39.54)	(33.32)
Change in control variable	-1.00	-5.93**	1.28	-16.46***
	(1.06)	(2.64)	(1.18)	(3.60)
N	298	284	300	296

Source: Author's estimates.

Notes: See text for definitions of the variables. All right hand side variables are measured as percentage changes. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively, and # indicates marginal insignificance at the 10% level. Standard errors clustered at the country level are reported in parentheses. All regressions control for time dummies. For the IV GMM, errors are clustered at the country level and the excluded instrument is the change in international prices (see Section 3 for details). IV-GMM hypothesis tests are available upon requests. In general, weak instruments remain a concern in all IV-GMM regressions.

Appendix S3. Additional results on supply and wage responses

Figure S3.1 International prices and production indices in major countries and regions, 2000-2012

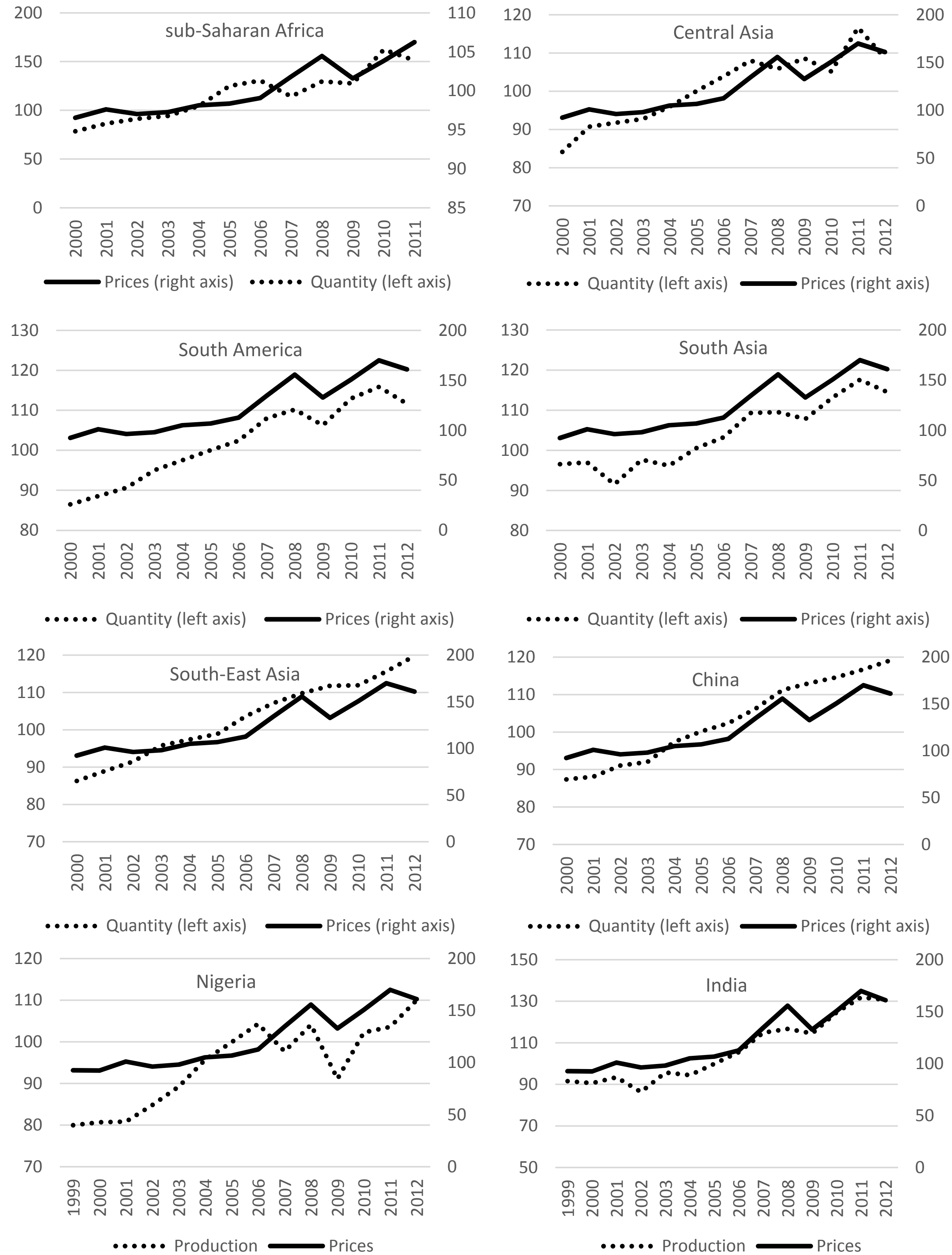

Table S3.1 Testing the sensitivity of growth in crop production to international prices under various sample restrictions (IV GMM)

Regression Number	1	2	3	4	5	6	7	8
Sample restrictions	None	No Latin America	No Eastern Europe & Central Asia	No sub-Saharan Africa	No Asia	No land abundant countries[a]	No observations before 2003	No survey gaps longer than 3 years
<u>Sample restrictions</u>								
Change in domestic food prices	2.86***	2.25*	2.70**	1.44**	3.97**	2.16*	3.15***	2.63**
	(1.11)	(1.36)	(1.17)	(0.68)	(1.90)	(1.10)	(1.06)	(1.17)
N	300	244	264	248	249	246	144	248

Source: Author's estimates.

Notes: See text for definitions of the variables. a. Land abundant countries are defined as those where harvested area per agricultural capita exceeds 2 hectares, which corresponds to the 90th percentile. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively, and # indicates marginal insignificance at the 10% level. Standard errors clustered at the country level are reported in parentheses. For the IV GMM, errors are clustered at the country level and the excluded instrument is the change in international prices (see Section 3 for details). All regressions control for time dummies. Hypothesis tests are not reported for the sake of brevity, but weak instruments are a problem in some samples. Details available upon request.

Table S3.2 Least squares regressions of the agricultural supply response to changes in domestic food prices changes

Regression number	1	2	3
Dependent variable (growth rates)	**Agricultural production**	**Food production**	**Crop production**
Change in log of domestic food prices	0.02	0.06	0.17
	(0.08)	(0.09)	(0.11)
N	300	302	302
Regression number	**4**	**5**	**6**
Dependent variable (growth rates)	**Crop production per hectare**	**Crop area harvested**	**Cereal Yields**
Change in log of domestic food prices	0.03	0.22**	0.01
	(0.12)	(0.10)	(0.14)
N	302	302	301

Source: Author's estimates.

Notes: See text for definitions of the variables. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Standard errors clustered at the country level are reported in parenthesis. All regressions control for time dummies.

Appendix S4. Time series estimates of wage responses to rice price increases in Bangladesh

Dickey-Fuller tests were first used to confirm that all of the series were I(0), as Figure C2 suggests. We then tested for lag order selection and lag pre-selection for the VECM. The results favored one lag length, although we also tested sensitivity to an additional lag. VECM results are reported in the main text and OLS-ADL results are reported in Table D2.

Table S4.1 Dickey-Fuller test for unit roots (McKinnon approximate p-values)

	Levels	First differences
Rice prices, log	0.95	0.01***
Rural wages, log	0.99	0.00***
Urban wages, log	0.99	0.02**

Table S4.2 OLS auto distributed lag (ADL) estimates for changes in rural and urban wages as a function of changes in rice prices

	1 Rural wages	2 Rural wages	3 Urban wages	4 Urban wages
Change in rice prices, lag 1	0.13*** (0.04)	0.11*** (0.04)	-0.01 (0.04)	-0.03 (0.05)
Change in rice prices, lag 2		0.08* (0.05)		0.03 (0.06)
Change in rural wage, lag 1	-0.02 (0.08)	-0.09 (0.10)	-0.09 (0.15)	-0.16 (0.21)
Change in rural wage, lag 2		-0.33** (0.13)		0.01 (0.10)
Change in urban wage, lag 1	-0.26 (0.17)	-0.24 (0.14)	-0.10 (0.10)	-0.11 (0.13)
Change in urban wage, lag 2		0.17 (0.15)		-0.20* (0.12)
Time trend	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
R-squared	0.36	0.50	0.21	0.24
N	37	36	37	36

Source: Author's estimates.

Notes: See text for definitions of the variables. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Appendix S5. Characteristics of the POVCAL sample

Table S5.1 List of poverty changes from the World Bank (2013) used in the statistical analysis

Country	Observation	Change in $1.25/day poverty	Change in $2/day poverty	Change in real food prices (%)
Armenia	1999-2001	1.81	1.91	-3.70%
Armenia	2001-2002	-4.87	-4.03	1.12%
Armenia	2002-2003	-4.34	-3.4	2.02%
Armenia	2003-2004	-3.2	-11.44	3.25%
Armenia	2004-2005	-3.45	-8.48	0.19%
Bangladesh	1986-1989	11.42	3.42	-1.74%
Bangladesh	1989-1992	3.53	2.34	-0.91%
Bangladesh	1992-1996	-9.31	-7.59	-0.20%
Bangladesh	1996-2000	-2.32	-1.17	2.80%
Bangladesh	2000-2005	-8.12	-4.2	0.87%
Bangladesh	2005-2010	-7.22	-3.9	6.01%
Belize	1994-1996	0.73	3.22	-0.21%
Belize	1996-1997	2.79	4.25	0.69%
Belize	1997-1998	-1.14	-1.94	-0.09%
Belize	1998-1999	0.9	-3.97	-0.49%
Bolivia	1993-1999	14.82	12.32	-2.76%
Bolivia	1999-2000	3.57	4.26	-2.35%
Bolivia	2000-2001	-5.46	-6.26	-0.98%
Bolivia	2001-2002	0.57	1.36	-1.76%
Bolivia	2002-2006	-5.8	-7.61	3.32%
Bolivia	2006-2007	-3.15	-1.01	4.55%
Bolivia	2007-2008	2.55	0.61	-5.65%
Brazil	1993-1996	-4.65	-7.24	13.74%
Brazil	1996-1997	-0.07	-0.05	-5.80%
Brazil	1997-1998	-1.29	-1.03	-0.38%
Brazil	1998-1999	0.35	0.76	-1.38%
Brazil	1999-2001	0.44	0.41	-1.91%
Brazil	2001-2002	-1.26	-2.24	1.12%
Brazil	2002-2003	0.65	1.07	4.92%
Brazil	2003-2004	-1.44	-1.93	-2.43%
Brazil	2004-2005	-1.25	-2.16	-3.54%
Brazil	2005-2006	-0.88	-2.02	-4.00%
Brazil	2006-2007	-0.51	-1.18	3.03%

Brazil	2007-2008	-1.12	-2.12	6.98%
Brazil	2008-2009	0.13	-0.32	0.87%
Burkina Faso	1998-2003	-13.49	-6.57	-9.69%
Cambodia	2007-2008	-9.48	-7.03	7.82%
Cambodia	2008-2009	-4.15	-3.77	-5.04%
Chile	1990-1992	-2.32	-4.66	5.48%
China	1996-1999	-0.74	-3.54	-3.47%
China	1999-2002	-7.27	-10.27	9.24%
China	2002-2005	-12.11	-14.27	16.57%
China	2005-2008	-3.19	-7.01	1.41%
China	2008-2009	-1.26	-2.54	3.62%
Colombia	1996-1999	3.18	4.79	-5.33%
Colombia	1999-2000	1.67	4.72	-0.44%
Colombia	2000-2001	1.33	-0.31	0.00%
Colombia	2001-2002	1.08	1.11	1.63%
Colombia	2002-2003	-0.65	0.1	0.13%
Colombia	2003-2004	-0.63	-0.99	-0.17%
Colombia	2004-2005	-6.27	-7.99	0.91%
Colombia	2005-2006	-1.67	-2.95	1.11%
Colombia	2006-2007	-2.2	-2.94	2.20%
Colombia	2007-2008	2.48	3.17	3.84%
Colombia	2008-2009	-1.65	-2.36	-0.48%
Colombia	2009-2010	-1.51	-2.72	-1.29%
Costa Rica	1995-1996	1.01	1.59	-2.29%
Costa Rica	1996-1997	-1.72	-2.77	-0.52%
Costa Rica	1997-1998	-1.08	-1.84	3.35%
Costa Rica	1998-2000	1.31	2.26	-3.25%
Costa Rica	2000-2001	0.49	0.72	0.23%
Costa Rica	2001-2002	0.01	-0.35	0.93%
Costa Rica	2002-2003	-0.23	-0.68	0.58%
Costa Rica	2003-2004	-0.52	-0.54	2.02%
Costa Rica	2004-2005	-1.37	-1.44	2.36%
Cote d'Ivoire	1986-1988	9.65	10.45	9.65%
Cote d'Ivoire	1988-1993	4.03	8.31	-0.17%
Cote d'Ivoire	1993-1995	3.3	4.43	0.18%
Cote d'Ivoire	1995-1998	2.97	1.3	-3.01%
Cote d'Ivoire	1998-2002	-0.72	-2.33	-4.03%

Dominican Republic	1989-1992	-7.5	-12.49	4.60%
Dominican Republic	1992-2001	-0.93	-3.9	-11.60%
Dominican Republic	2001-2003	2.9	4.99	-1.51%
Dominican Republic	2003-2004	1.5	4.47	11.65%
Dominican Republic	2004-2005	-1.99	-5.12	-5.53%
Dominican Republic	2005-2006	-1.91	-3.08	-3.23%
Ecuador	1999-2003	-11.75	-15.47	-1.85%
Ecuador	2003-2005	-3.04	-4.85	-1.14%
Ecuador	2005-2006	-2.99	-5.08	2.36%
Ecuador	2006-2007	1.09	0.96	0.85%
Ecuador	2007-2008	-0.78	-1.43	7.86%
Ecuador	2008-2009	-0.07	0.39	0.64%
Ecuador	2009-2010	-1.77	-2.95	1.25%
El Salvador	1991-1995	-7.14	-9.73	-5.24%
El Salvador	1995-1996	1.54	2.12	4.23%
El Salvador	1996-1998	5.88	4.86	-1.26%
El Salvador	1998-1999	-3.57	-3.74	-2.02%
El Salvador	1999-2001	0.59	0.42	-1.02%
El Salvador	2001-2002	0.35	0.48	-0.08%
El Salvador	2002-2003	-1.45	-1.72	-0.12%
El Salvador	2003-2004	-1.81	-2.67	1.76%
El Salvador	2004-2005	0.08	1.18	1.44%
El Salvador	2005-2006	-6.25	-6.76	-1.00%
El Salvador	2006-2007	1.26	-0.28	1.62%
El Salvador	2007-2008	-1.14	0.66	4.57%
El Salvador	2008-2009	3.53	2.91	-4.87%
Ethiopia	2000-2005	-16.62	-9.09	21.58%
Georgia	1998-1999	10.06	16.11	-0.50%
Georgia	1999-2000	1.38	2.28	-2.63%
Georgia	2000-2001	0.24	1.92	1.81%
Georgia	2001-2002	-3.8	-6.57	1.86%
Georgia	2002-2003	1.92	2.73	2.17%
Georgia	2003-2005	-1.67	-3.14	6.56%
Georgia	2005-2006	-0.4	0.08	2.35%
Georgia	2006-2007	-0.39	1.26	0.45%
Georgia	2007-2008	0.08	-2.64	1.12%
Ghana	1989-1992	1.7	-0.04	-5.08%

Guatemala	1989-2000	-27.22	-30.15	-8.23%
Guatemala	2000-2002	13.87	14.44	4.74%
Guatemala	2002-2003	-3.19	-5.17	0.15%
Guatemala	2003-2004	1.87	4.6	2.49%
Guatemala	2004-2006	-10.9	-12.87	4.37%
Guinea	1994-2007	-20.47	-12.33	24.88%
Honduras	1990-1991	-13.87	-11.23	6.95%
Honduras	1991-1992	-5.71	-7.37	-2.55%
Honduras	1992-1993	-3.83	-3.23	1.90%
Honduras	1993-1994	12.39	12.76	4.45%
Honduras	1994-1995	-8.57	-9.9	-0.79%
Honduras	1995-1996	4.1	3.93	0.65%
Honduras	1996-1997	-10.81	-12.48	-0.27%
Honduras	1997-1998	4.91	1.76	-1.76%
Honduras	1998-1999	-0.09	1.28	-3.34%
Honduras	1999-2001	-7.45	-9.6	-4.94%
Honduras	2001-2002	10.18	10.91	-3.62%
Honduras	2002-2003	-2.01	-1.24	-3.70%
Honduras	2003-2004	-0.88	-1.09	-1.32%
Honduras	2004-2005	1.17	0.56	1.25%
Honduras	2005-2006	-3.59	-4.88	-1.05%
Honduras	2006-2007	-6.59	-5.32	3.57%
Honduras	2007-2008	5.1	2.8	6.77%
Honduras	2008-2009	-3.44	-2.6	-2.34%
India	1983-1988	-1.92	-1.02	-0.53%
India	1988-2010	-20.91	-15.34	1.08%
Indonesia	1987-1990	-13.89	-6.71	5.76%
Indonesia	1990-1993	0.13	0	-3.54%
Indonesia	1993-1996	-11.02	-7.74	7.30%
Indonesia	1996-2002	-14.07	-10.29	14.14%
Indonesia	2002-2005	-7.87	-13.18	-6.70%
Indonesia	2005-2008	1.2	0.61	13.18%
Indonesia	2008-2010	-4.58	-8.21	6.81%
Kazakhstan	2002-2003	-2.03	-4.3	0.49%
Kenya	1994-1997	-8.93	-10.92	-0.42%
Kyrgyz Republic	1998-2002	2.19	5.84	0.47%
Kyrgyz Republic	2002-2004	-19.81	-27.83	-1.11%

Kyrgyz Republic	2004-2005	8.72	7.11	0.86%
Kyrgyz Republic	2005-2006	-17	-13.9	3.06%
Kyrgyz Republic	2006-2007	-4.04	-2.77	6.66%
Kyrgyz Republic	2007-2009	4.33	-7.3	-0.85%
Kyrgyz Republic	2009-2010	0.47	1.19	6.48%
Kyrgyz Republic	2010-2011	-1.67	-1.33	1.81%
Lao PDR	1997-2002	-5.36	-3.14	-8.59%
Latvia	2002-2003	0.36	1.37	-0.19%
Macedonia, FYR	2000-2010	-3.68	-2.4	-0.24%
Madagascar	1997-1999	10.28	3.87	1.86%
Madagascar	1999-2001	-5.98	-4.44	-3.06%
Madagascar	2001-2005	-8.51	0.72	17.48%
Madagascar	2005-2010	13.46	3.2	-12.43%
Mali	2006-2010	-1	1.52	7.78%
Mauritania	1996-2000	-2.24	-4.09	0.49%
Mauritania	2000-2004	4.25	8.4	5.64%
Mauritania	2004-2008	-1.98	-4.88	5.89%
Mexico	1994-1998	6.05	7.59	7.53%
Mexico	1998-2002	-5.69	-8.55	-5.38%
Mexico	2002-2005	-1.12	-1.73	3.68%
Mexico	2005-2006	-1.41	-2.63	0.02%
Moldova	1998-1999	11.77	14.78	-4.68%
Moldova	1999-2001	-12.52	-12.73	4.81%
Moldova	2001-2002	-8.98	-13.33	-0.90%
Moldova	2002-2003	-10.73	-13.17	1.64%
Moldova	2003-2004	1.38	1.08	0.24%
Moldova	2004-2005	-6.13	-17.36	-1.76%
Mongolia	1998-2002	0	0	-9.00%
Niger	1994-2008	-34.55	-16.81	0.85%
Nigeria	1996-2011	-14.14	-8.17	-7.77%
Pakistan	1991-1999	-35.66	-22.19	4.07%
Pakistan	1999-2002	6.82	7.45	-2.52%
Pakistan	2002-2005	-13.28	-13.78	3.45%

Pakistan	2005-2006	-0.01	0.69	0.56%
Pakistan	2006-2008	-1.54	-0.83	9.24%
Panama	1991-1995	-5.2	-6.17	1.36%
Panama	1995-1997	-1.1	-1.21	-1.19%
Panama	1997-2001	0.77	2.41	-2.90%
Panama	2001-2002	-4.36	-3.7	0.50%
Panama	2002-2003	-0.46	-1.02	-2.24%
Panama	2003-2004	-0.7	-1.05	2.29%
Panama	2004-2005	-0.34	-0.88	2.43%
Panama	2005-2006	0.67	0.83	-1.16%
Panama	2006-2009	-4.28	-3.41	11.87%
Panama	2009-2010	0.67	-0.57	-0.60%
Paraguay	1998-1999	1.16	0.91	-3.43%
Paraguay	1999-2001	-3.12	-2.84	-3.75%
Paraguay	2001-2002	4.69	8.43	-0.22%
Paraguay	2002-2003	-5.04	-6.44	6.56%
Paraguay	2003-2004	-2.6	-3.92	2.96%
Paraguay	2004-2005	-0.93	-2.78	-1.36%
Paraguay	2005-2006	3.72	5.94	5.60%
Paraguay	2006-2007	-2.15	-4.55	7.80%
Paraguay	2007-2008	-3.18	-2.3	5.09%
Paraguay	2008-2009	1.97	0.6	-2.02%
Paraguay	2009-2010	-0.4	-0.78	3.70%
Peru	1998-1999	1.48	1.82	-3.59%
Peru	1999-2000	-3.4	-4	-2.85%
Peru	2000-2001	2.07	3.44	-1.47%
Peru	2001-2002	-2.07	-3.24	-0.49%
Peru	2002-2003	-2.92	-2.1	-1.42%
Peru	2003-2004	-2.13	-3.31	1.75%
Peru	2004-2005	1.19	1.63	-0.62%
Peru	2005-2006	-1.36	-2.62	0.41%
Peru	2006-2007	0.75	0.46	0.75%
Peru	2007-2008	-1.74	-3.33	3.16%
Peru	2008-2009	-0.66	-0.79	1.20%
Peru	2009-2010	-0.63	-1.26	1.03%
Philippines	1988-1991	0.2	-1.48	-3.16%
Philippines	1991-1994	-2.57	-2.77	-3.71%
Philippines	1994-1997	-6.5	-8.77	-0.16%
Philippines	1997-2000	0.84	1.01	-4.31%

Philippines	2000-2003	-0.46	-1.04	-3.81%
Philippines	2003-2006	0.63	1.25	-1.54%
Philippines	2006-2009	-4.2	-3.55	6.38%
Senegal	1994-2005	-20.14	-18.93	1.43%
South Africa	1995-2000	4.77	3.06	0.84%
South Africa	2000-2009	-12.43	-11.6	19.39%
Sri Lanka	1996-2007	-9.28	-17.36	2.46%
Sri Lanka	2007-2010	-2.93	-5.31	6.68%
Tajikistan	2004-2007	-6.11	-12.87	3.73%
Tajikistan	2007-2009	-8.1	-9.17	4.16%
Thailand	1990-1992	-2.95	-7.22	1.60%
Thailand	1992-1994	-4.49	-9.46	0.62%
Tunisia	1990-1995	0.61	1.35	-0.36%
Tunisia	1995-2000	-3.93	-7.49	1.31%
Uganda	1992-1996	-5.62	-2.74	-6.23%
Uganda	1996-1999	-3.9	-3.34	7.38%
Uganda	1999-2002	-3.12	-2.83	-10.98%
Uganda	2002-2006	-5.84	-4.34	14.78%
Uganda	2006-2009	-13.52	-10.45	14.22%
Venezuela, RB	1992-1998	5.48	10.56	-11.23%
Venezuela, RB	1998-1999	1.53	2.52	-5.49%
Venezuela, RB	1999-2001	-1.84	-2.29	-4.68%
Venezuela, RB	2001-2002	6.28	8.4	4.68%
Venezuela, RB	2002-2003	3.21	5.38	5.08%
Venezuela, RB	2003-2004	-3.18	-5.22	9.90%
Venezuela, RB	2004-2005	-2.44	-7.44	4.42%
Venezuela, RB	2005-2006	-6.81	-8.96	5.67%
Vietnam	1998-2002	-9.6	-9.63	-0.15%
Vietnam	2002-2004	-11.8	-11.89	1.82%
Vietnam	2004-2006	-6.83	-8.91	2.25%
Vietnam	2006-2008	-4.57	-4.72	14.14%
Zambia	1998-2003	8.93	10.38	-1.56%
Zambia	2003-2004	-0.31	-3.62	-1.37%
Zambia	2004-2006	4.22	1.1	-3.55%
Zambia	2006-2010	5.94	4.15	-6.01%

Figure S5.1 Histogram of the duration of gaps between POVCAL surveys