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FOOD PRICE CHANGES AND POVERTY IN ZAMBIA: AN EMPIRICAL ASSESSMENT USING HOUSEHOLD MICRODATA†

FRANCESCO CARACCIOLO[1]*, DOMENICO DEPALO[2] and JOSÈ BRAMBILA MACIAS[3]
[1]*Department of Agriculture, University of Naples, Federico II, Portici, Italy*
[2]*Economic Research, Public Finance Department, Bank of Italy, Rome, Italy*
[3]*Organisation for Economic Co-operation and Development (OECD), Paris, France*

Abstract: This paper presents estimates of the welfare and poverty effects of a price increase in a major food commodity in an underdeveloped country. We use household data from a Zambian survey to estimate a demand system with which various price scenarios can be simulated for the main Zambian staple and its possible effects on different population categories. Our results show that a 50 per cent increase in maize prices could lead to an average consumption decrease of 17 per cent among Zambian households, and overall poverty could rise from 68 to 70 per cent fairly quickly at national level. Copyright © 2013 John Wiley & Sons, Ltd.

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1 INTRODUCTION

The sharp increases in farm commodity prices during the past few years have shown no sign of abating. This has fostered uncertainty regarding future market trends, prompting international institutions to raise the alarm. Focusing only on the main agricultural commodities, it may be observed that the international wheat price, constantly less than US$200/ton up to 2005, exceeded US$400 in early 2008 and was over US$320/ton in July 2012.[1] By contrast, the maize price in July 2012 reached US$320/ton, well greater than the previous historical high in June 2008 of US$275/ton.[2] Economic analysts agree that the prices of most agricultural products will

*Correspondence to: F. Caracciolo, Department of Agriculture, University of Naples, Federico II, Portici, Italy.
E-mail: francesco.caracciolo@unina.it
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[1]United States Department of Agriculture, Wheat [US No.2, Soft Red Winter Wheat, US Gulf (Tuesday)], monthly average.
[2]United States Department of Agriculture, Maize [US No.2, Yellow, U.S. Gulf (Friday)], monthly average.

remain high until 2020 and even beyond (Toye, 2009), whereas the future impact of the crude market on the demand for agricultural products and on their price also remains uncertain (Mitchell, 2008). In this scenario, the international context is in continual evolution, and forecasts remain tied to numerous global events that are changing international food markets and policies. Among the most important global factors, we should mention the global financial and economic crisis, political tension and conflicts in main oil producing countries and the slow dismantling of policies to subsidize farm incomes. As a consequence, reflections on the recent scientific debate are tied to issues concerning both allocative and productive efficiency as well as the distributional equity of resources and consumption (Peeters & Albers, 2013): Although in the Western area, the most evident effect may be distilled as the rise in the cost of living; in least developed countries (LDCs) there is a serious problem of food security insofar as the food purchasing power of millions of people is undermined (Dorward, 2011).

The importance of the price fluctuations should be viewed in the context of food expenditure in the LDCs, which accounts on average for about the two-thirds of total income. In this scenario for broad strata of the population, it is impossible to reach the minimum number of daily calories (World Bank, 2009) without a local policy intervention. Understanding the consequences of the food price crisis in developing countries, overall in terms of poverty and welfare, has become a major challenge for international organizations and academics (Masters & Shively, 2008; Piot-Lepetit & M'Barek, 2011; Caracciolo & Santeramo, 2013). Although much is known at the macrolevel, from a household perspective, it is widely held that the consequences of a food price surge can be dramatic, but the extent and magnitude of these effects have to be determined (Wodon *et al*., 2008; Aksoy & Isik-Dikmelik, 2008; Boccanfuso & Savard, 2011).

This paper presents estimates of the welfare effects of a price increase in a major food commodity in an LDC. We do this by simulating the food demand response of different groups of households to the price change, adopting a partial equilibrium framework.[3] We focus on Zambia, one of the world's 10 poorest countries, according to the World Bank's World Development Indicators. The proportion of the Zambian population living under the poverty line reached 73 per cent in 1998 and barely improved in 2006 (64 per cent) (CIA, 2013). The figure is even worse if we consider population growth (around 2 per cent annual growth during the past decade) and a considerable dependence on farming, which is vulnerable to both prolonged droughts and flash floods.

In July 2008, the Zambian Food Reserve Agency increased the price of maize from US$8 to US$14 per 50 kg bag. Maize is particularly important because it represents the key agricultural product for both producers and consumers: maize plantations cover about half of the whole farmland, and maize-based meal is Zambia's main food staple. Between January 2006 and January 2008, world maize prices doubled in nominal value. In the same period, the Zambian consumer price index for non-food items increased at a rate of 15.7 per cent on a yearly base compared with the annual food inflation rate of 3.9 per cent (CSO, 2008). Thus, in spite of a global

[3]We consider only short-term effects, adopting a partial equilibrium approach, although we recognize the usefulness of a general equilibrium analysis. A partial equilibrium framework better suits our purpose, because it analyzes the short-run household response to shocks and is more credible than long-run behaviour in a highly regulated market. The long-run impact is more difficult to assess because of the underlying assumptions on price fluctuations, government interventions and shifts in individual preferences that may transform the effort into a merely theoretical exercise, losing connection with reality.

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upward trend, Zambian households faced almost constant maize prices thanks to the activity of the Food Reserve Agency, which successfully kept prices low during 2007 (FEWSNET, 2007).[4] However, the (artificially) steady maize prices within Zambia together with a massive increase in input costs, mainly of fuel and fertilizers, discouraged agricultural production within the country in 2008, with the side effect of potential shortage risks because of unpredictable events such as floods. Further, according to some researchers (Dorosh, Dradri, & Haggblade, 2009), the unpredictability of the Zambian government policy over the past decades has forced the exit of almost two-thirds of the major international grain trading firms present in the country. Given that poor societies allocate most of their budgets to food consumption, the importance of having stable markets and continuous access to food supplies (Ul-Haq, Nazli, & Meilke, 2008) in countries such as Zambia appears patently clear.

To evaluate the effects of a price surge on poverty and welfare, the first step requires estimation of a demand system. Having household survey data allow us to distinguish among different types of households and closely evaluate how they respond to shocks. Unfortunately, survey data are exposed to some econometric problems that in principle can affect results and conclusions; the sample selection issue arises because only a fraction of the population has positive consumption for the items under study. Because the sensitivity of results to these issues is too important to go unnoticed, we pay particular attention to sample selection throughout our study.

Estimates of welfare measures indicate that a price increase of maize will affect the rich and poor households and the urban and rural households in Zambia differently. However, by far, the greatest impact will be on the welfare of poor households. Our results suggest that a 50 per cent increase in the price of maize has a dramatic impact on the population, in terms of the number of poor households affected. This has complex policy implications for those who wish to understand how a price increase affects the population, possibly across different subgroups, and is an essential step towards the design of plans to alleviate disparity and to help the poorest strata.

The paper is organized as follows. Section 2 discusses the specification and estimation of the household food demand model. Section 3 discusses the household data and the household categories used in the empirical analysis. Section 4 evaluates welfare measures for different categories of households that are associated with the price increase of maize in Zambia. Section 5 offers some conclusions.

2 EMPIRICAL STRATEGY

This study provides welfare measures of the impact of an increase in the price of maize for different categories of households in Zambia. Estimates of a household food demand model provide own-price and cross-price elasticities of compensated demand. These estimates provide measures of household substitution responses, which are used to evaluate the welfare impacts of a price increase of maize on different categories of households in Zambia.

Several alternative economic and empirical methods have been discussed in the literature for the estimation of a food demand system (Barnett & Serletis, 2008), such as the AIDS (Deaton & Muellbauer, 1980), the EASI (Lewbel & Pendakur, 2009) and the compensated double-log model (Alston, Chalfant, & Piggott, 2002). Among them, we preferred the 'double-log' specification thanks to its well-known theoretical properties, in particular the

[4]At harvest time, the Food Reserve Agency (FRA) purchases maize, to be released later, stabilizing prices when demand exceeds private supply. Between 1995 and 2004, the quota of domestic production purchased by the FRA is estimated to have ranged from 11 to 45 per cent (Jayne, Zulu, & Nijhoff, 2006). Exports are banned unless the FRA reaches its market equilibrium objective.

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virtue of estimating the Hicksian elasticities directly, and its computational attractiveness (Alston *et al.*, 2002). We support our decision on the basis of statistical procedures (Davidson & MacKinnon, 1981).[5]

Alston *et al.* (2002) manipulate the original double-log model, including in the system the Slutsky equation in elasticity form, thus obtaining direct estimation of the Hicksian elasticities. With this manipulation, the compensated form of the double-log specification shares the right-hand side of the equation with that of the popular linear approximation AIDS (Deaton & Muellbauer, 1980). The demand equation for the *i*-th good in compensated double-log form is as follows:

$$\ln Q_i = \alpha_{i^*} + \sum_{j=1}^{I-1} \gamma_{ij} \ln \frac{P_j}{P_I} + \beta_i \ln \left[\frac{X}{P_*} \right] + u_i \qquad \forall i = 1, \ldots, I-1, \tag{1}$$

where P_j is the price of the *j*-th good, X is the total expenditure on food categories in the system, u_i is the error term, γ_{ij} are the Hicksian compensated demand own-price and cross-price elasticities and β_i are the expenditure elasticities, respectively. α_{i*} is a demand shifter augmented for a set of K demographic attributes:

$$\alpha_{i^*} = \alpha_i + \sum_{k=1}^{K} \delta_{ik} D_k \qquad \forall K; \tag{2}$$

where P_* is the Stone price index proposed by Moschini (1995), that is,

$$\ln P_* = \sum_{i=1}^{I} \varpi_i \ln P_i, \tag{3}$$

with ϖ_i as the mean of the budget share.

The demand system must satisfy homogeneity and symmetry conditions. The former restriction is imposed by including the prices relative to the *I-1-th* price (Alston *et al.*, 2002), the latter through

$$\gamma_{ij} = \gamma_{ji} \quad \forall i, j = 1, \ldots, I-1. \tag{4}$$

We consider a consumer multi-stage budgeting process that implies home food consumption as weakly separable from the demands of other non-food goods (Akbay, Boz, & Chern, 2007).[6] This hypothesis justifies also the exclusion of other non-food-goods expenditure, on which information is limited in our data.

As for estimation, a demand system poses several methodological problems when cross-section data on consumption are used. The issue of censoring arises because only a subset of households has positive consumption for the *i*-th good during the selected observation period. Because of the seminal papers by Gronau (1974) and Heckman (1979), the importance of censoring has been recognized not only as a statistical problem but also as an economic issue. If we were to focus only on the positive quantity decision to estimate a consumption equation, we would probably estimate a significant effect on the *level* of consumption for those covariates that instead affect the *probability* of positive consumption:

[5]In order to choose between the double-log model and the linear approximation of the AIDS model, we performed the Davidson and MacKinnon (1981) test. On the basis of the result (available from the authors upon request), we found that there is no statistical evidence that one model performs better than the other.
[6]The incomplete demand system of LaFrance (1995) can overcome the weak separability assumption in the structure of consumer preferences. However, this assumption seems reasonable in a country such as Zambia where food expenditure averages about 80 per cent of the overall household budget.

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more formally, estimates would be inconsistent. In fact, simple procedures fix the problem by treating it as a specification error. The solution to this problem is provided by Heckman (1979), who suggests an estimation procedure with two separate stages. In the first stage, a model is estimated for the probability of non-censoring or the decision to 'take part in the market', whereas the second stage concerns consumption, including all the observations and solving the sample 'selection error' through a correction of the omitted variable type.

Here, we consider a slightly more complicated approach because we have a system of equations. The natural extension is proposed by Heien and Wessells (1990) again in two steps, where from the first step we obtain the inverse Mills' ratio, added as a covariate in the second step to correct for the selection bias. Because of the work of Heien and Wessells, several empirical procedures for censored data have been developed such as those suggested by Golan, Perloff, and Shen (2001), Perali and Chavas (2000) and Shonkwiler and Yen (1999).

Starting from Equation (1), Shonkwiler and Yen (1999) modelled zero-food consumption for a demand system as follows:

$$\ln Q_i^* = Q_i(\mathbf{p}, m; \mathbf{\Gamma}_i)\Phi(\mathbf{z\theta}_i) + \lambda_i \phi(\mathbf{z\theta}_i) + e_i \quad \forall i = 1, \ldots, I-1 \tag{5}$$

and

$$e_i = u_i + Q_i(\mathbf{p}, m; \mathbf{\Gamma}_i)\left[\left[\mathbf{\Phi}(\mathbf{z\theta}_i) - \mathbf{\Phi}\left(\mathbf{z}\hat{\mathbf{\theta}}_i\right)\right]\right] + \lambda_i\left[\phi_i(\mathbf{z\theta}_i) - \phi\left(\mathbf{z}\hat{\mathbf{\theta}}_i\right)\right] \quad \forall i = 1, \ldots, I-1 \tag{6}$$

where Γ_i is a vector containing system demand parameters, $\mathbf{z}$ is a vector of exogenous variables, θ_i is a conformable vector of parameters and $\phi\left(\mathbf{z}\hat{\mathbf{\theta}}_i\right)$ and $\phi\left(\mathbf{z}\hat{\mathbf{\theta}}_i\right)$ are the probability density function and the cumulative distribution function, respectively. Estimation of Equation (5) can be performed in two steps; where in the first step, the maximum-likelihood Probit estimates of $\phi\left(\mathbf{z}\hat{\mathbf{\theta}}_i\right)$ and $\phi\left(\mathbf{z}\hat{\mathbf{\theta}}_i\right)$ are obtained using Equation (7):

$$\mathrm{y_i}^* = (\mathbf{z\theta}_\mathrm{i} + \mathrm{v_i}) \quad \forall i = 1, \ldots, I-1 \tag{7}$$

with v_i as the random errors and

$$y_i = \begin{cases} 1 & if \quad y_i^* > 0 \\ 0 & if \quad y_i^* \leq 0 \end{cases} \quad \forall i = 1, \ldots, I-1 \tag{8}$$

and then estimating Γ_i and λ_i in the augmented system where

$$\ln Q_\mathrm{i}^* = \mathrm{y_i} \; ln \; Q_\mathrm{i} \quad \forall i = 1, \ldots, I-1 \tag{9}$$

Equation (1) therefore becomes the following:

$$y_i \ln Q_i = \left\{ \alpha_{i*} + \sum_{j=1}^{I-1} \gamma_{ij} \ln \frac{P_j}{P_I} + \beta_i \ln \left[\frac{X}{P_*} \right] \right\} \phi(\mathbf{z\theta}_i) + \lambda_i \phi(\mathbf{z\theta}_i) + e_i \quad \forall i = 1, \ldots, I-1\,. \tag{10}$$

To estimate a system of I equations, the nonlinear feasible generalized least squares method was employed. The standard errors would be incorrect because they do not account for the additional variability introduced by the two-step nature of the estimation process. Thus, the covariance matrix should be adjusted (Murphy & Topel, 1985) or standard errors should be bootstrapped (Green, Hahn, & Rocke, 1987). Following Sam and Zheng (2010), we preferred the second approach.

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3 HOUSEHOLD DATA

In the analysis, we used the Zambia Living Conditions Monitoring Survey IV 2004–2005 issued by the Central Statistics Office (CSO, 2005) of Zambia. The total sample comprises 11 763 households and 61 455 individuals, and, using a set of weights, is representative of the Zambian population (1 910 740 households and 9 547 290 individuals).

Living Conditions Monitoring Survey IV includes household food and non-food purchases, household cash and non-cash income and a set of other household socio-economic characteristics. At a personal level, it reports detailed information on education, nutrition and health condition, labour market participation and access to facilities, among other things. After dropping observations for which there were inconsistencies or missing data, a total of 11 167 households (slightly less than 95 per cent of the starting sample) were used in the econometric analysis. The missing data are mainly because of observations regarding education (302 observations) and employment status (240; in 77 cases both education and employment status are missing); 54 cases do not consume anything and so were dropped.

The collection of the data is left to the households. They maintained fortnightly diaries of their daily expenses, distinguishing cash expenditure from self-consumption and gifts. The information about food consumption refers to the last 2 weeks. The surveys were conducted during various seasons of the year so that the sample reflects different seasonal food consumption patterns within an entire year, even though the food expenditures for any given household are specific to the time at which the interview was conducted. Food is classified in 29 main items, recorded in Kwacha, the Zambian currency. Because there are several different units for maize (although about 50 per cent of the information is in 20-litre tins), we first converted everything to prices per kilogramme, taking advantage of a conversion table provided by the Zambian Food Security Research Project. Following the guidelines in Deaton and Zaidi (2002) when the prices were missing or unavailable because the households did not consume the listed commodity, we replaced unobserved values with the median reported by households in the same area of the same province. This procedure gave us quantities for nine homogeneous categories in the same measurement unit, which we conventionally take as kilogrammes (kg). The categories are maize, cassava, other cereals, potato, meat and fish, fruit and vegetables, eggs and milk, beans and pulses and other foods.

We take advantage of the information contained in the questionnaire to build *ad hoc* household categories in order to assess the impact of the maize price surge more precisely. In particular, we divided the households into different categories according to three dimensions: their poverty condition, their living area and whether they were net buyers or net sellers of maize. The resulting categories are the following: (i) poor urban households; (ii) poor rural maize buyers; (iii) poor rural maize sellers; (iv) non-poor urban households; (v) non-poor rural households that are maize buyers; and (vi) non-poor rural households that are maize sellers.

A critical issue with this distinction is the identification of poor individuals. Following the existing literature, a household is defined poor if its food expenditure (extrapolated on a per-adult equivalent basis) is below the food poverty line calculated by the National Food and Nutrition Commission of Zambia and reported by the official report of the Living Conditions Monitoring Survey IV (CSO, 2005). This line is based on the cost of a Basic Needs Basket (food and non-food inclusive) required to maintain

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Table 1. Share of households by province

	Poor			Non-poor			
	Urban	Rural		Urban	Rural		
Province		Maize buyers	Maize sellers		Maize buyers	Maize sellers	Total
Central	0.29	0.32	0.14	0.16	0.06	0.03	1.00
Copperbelt	0.44	0.10	0.05	0.38	0.03	0.01	1.00
Eastern	0.20	0.46	0.15	0.10	0.06	0.02	1.00
Luapula	0.31	0.39	0.13	0.11	0.05	0.02	1.00
Lusaka	0.36	0.05	0.03	0.54	0.01	0.01	1.00
Northern	0.21	0.44	0.18	0.09	0.07	0.01	1.00
North western	0.27	0.31	0.18	0.18	0.05	0.01	1.00
Southern	0.22	0.36	0.12	0.21	0.08	0.02	1.00
Western	0.20	0.38	0.20	0.15	0.05	0.01	1.00

the essential needs for an average Zambian family (Deaton & Zaidi, 2002) and is set to K111 747 per adult equivalent per month.[7]

In Table 1, we report the share of households by province and category. Important differences are observed between urban and rural households. About 68 per cent of all households are in the poor category, which is consistent with the official documentation, even though there are important exceptions. In particular, in the province of the Copperbelt and Lusaka, the share of poor households is lower than the overall average, whereas the Northern Province lies somewhat between these regions and the poorest, with poor households accounting for about 83 per cent. The substantial income difference between rural and urban areas is largely reflected in the sample distribution by provinces.

Poor and non-poor households differ in many respects. Striking difference is observed in the average hectares of cultivated land conditional on being a maize buyer or seller. Indeed, being the main staple, maize certainly reflects on the size of cultivated land. Maize sellers in general have the largest share of cultivated land, with the north western concentrating the highest shares, followed closely by eastern and central. Of course, systematic and substantial differences arise because the non-poor have more cultivated land, in some cases even twice as much (Table 2).

We conclude this section with the food expenditure shares by household type (Table 3). The highest expenditure share is for maize and meat independently of household type. Cereals and processed foods are more expensive goods that are maize substitutes and are consumed by non-poor households and in urban areas. Finally, consumption of cassava is higher in rural areas, although it represents the smallest share for urban households, independently of being poor or non-poor. This argument introduces the next section in which we consider substitution between goods, which we specifically address for the analysis of food price impacts.

4 RESULTS

In this section, we estimate a demand system to obtain the Hicksian demand elasticities, and then, we proceed to simulate price shocks and to evaluate the consequences that these could

[7]We acknowledge that this measure suffers from many drawbacks, the main one being the unknown allocation of the money within the family. Hence, we take this as given in our data.

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Table 2. Average hectare of cultivated land by province

	Poor			Non-poor		
	Urban	Rural		Urban	Rural	
Province		Maize buyers	Maize sellers		Maize buyers	Maize sellers
Central	3.69	12.97	22.09	3.43	14.30	50.37
Copperbelt	3.93	17.64	33.12	6.50	7.75	21.81
Eastern	6.01	12.99	12.75	6.16	18.62	31.49
Luapula	4.27	8.27	10.78	2.64	8.50	11.74
Lusaka	1.25	4.31	12.39	1.10	11.31	83.47
Northern	17.94	9.96	16.57	5.42	11.24	38.38
North western	8.17	15.81	20.60	6.61	8.64	28.48
Southern	2.05	12.34	19.58	2.74	7.34	11.98
Western	4.20	10.02	9.50	2.53	10.54	9.78

have on households' welfare. Our strategy is in three steps. First, we obtain a benchmark; second, we shock the price to obtain the forecasts, and third, we provide a set of welfare measures that enable us to analyze the welfare impact.

In order to obtain the Hicksian demand elasticities, we estimated the censored double-log demand system (Equation (10)).[8] The variables and parameters used in the model are summarized in Table 4, whereas the results are shown in Table 5 (the own-price elasticities are printed in bold). The overall goodness of fit of the estimated sample is good, given the cross-section characteristics of our estimation, presenting R^2 values between 0.28 (potato) and 0.73 (meat and fish). Parameters λ are statistically significant, supporting the idea that correction for sample selection bias is necessary. It is worth remembering that the price parameter estimates represent directly the Hicksian demand elasticities. All own-price compensated demand elasticities for food categories are negative and strongly significant. The demands for meat, cereals, beans and fruit and vegetables are relatively more sensitive to price changes than staple foods such as maize, cassava and potato.

Compensated cross-price elasticities are generally small in magnitude but in all cases significantly different from zero, at the 5 per cent confidence level. According to these results, cassava and cereals are substitute goods for maize, whereas potatoes can be considered as a complement good of maize. The relationship of complementarity and substitutability between food categories allows us to simulate the overall change in consumption pattern as a consequence of a price shock. Notwithstanding a wide variation in the results, the estimated expenditure elasticities are significantly different from zero for all the food categories: as expected, meat and cassava present the highest and lowest compensated expenditure elasticities, , respectively.

Demographic attributes included in the model also influence demand. The reference category in all estimates is a household of five individuals (two of them are employed and one is a child), headed by a 42-year-old male with an average level of education and a resident in Lusaka Province. The effect of demographic characteristics of households is generally small, albeit with a few exceptions: the province of residence influences demand more than other variables, which present different impacts across food categories. Further considerations can

[8]As exclusion restriction, we rely on the household distance from food markets, information that ensures the consistency of point estimates for two reasons. The first is econometric and simply requires that the distance from the food market affects the propensity to consume but not the quantity consumed, and this is a reasonable assumption that is usually made in the literature. The second virtue of the variable is the high rate of response.

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Table 3. Food expenditure shares by household type

	Poor			Non-poor		
	Urban	Rural		Urban	Rural	
Good		Maize buyers	Maize sellers		Maize buyers	Maize sellers
Maize	0.09	0.28	0.31	0.04	0.22	0.22
Cassava	0.01	0.10	0.08	0.00	0.05	0.05
Cereals	0.12	0.06	0.09	0.16	0.09	0.09
Potato	0.06	0.04	0.04	0.04	0.03	0.04
Meat and fish	0.28	0.20	0.19	0.33	0.27	0.27
Fruit and vegetable	0.17	0.13	0.13	0.13	0.09	0.09
Egg and milk	0.05	0.03	0.03	0.09	0.04	0.05
Beans	0.07	0.09	0.07	0.05	0.08	0.08
Other	0.05	0.01	0.01	0.03	0.02	0.02
Processed	0.10	0.06	0.05	0.13	0.11	0.09
Total	1.00	1.00	1.00	1.00	1.00	1.00

be drawn; that is, less price-sensitive foods such as maize and cassava are consumed in the poorest regions; in the same provinces, meat, eggs and milk are consumed less. A higher level of education reduces the consumption of staple food; by contrast, maize consume is increased if the household is a maize seller.

In the second step, we shocked the price of maize. In 2008, the price of maize in Zambia increased from US$ 8 to about US$14. Thus, in order to be as close as possible to actual shocks, we decided to simulate a series of shocks ranging from 10 to 50 per cent price increases. We shock the original prices to determine the impact of an increase in the price of good i on the consumed quantity not only of good i itself (own elasticity) but also on quantities of other items (cross-elasticities), with direct impact on poverty in general. By comparing outcomes before and after the shock, we can construct some indicators of interest. This exercise allows us to identify the short-run impact of a shock, leaving individuals' preferences as they were just before the shock took place.[9]

Table 6 shows the effects of price shocks on household food consumption. The maize price boom scenario implies a huge reduction in maize consumption across household categories, whereas consumption is shifted to another food group. At first glance, it seems strange that consumption of some staples such as meat and fish or fruit and vegetables increases. However, it must be pointed out that food groups, for example, meat and fish, comprise a wide variety of products, which are not necessarily only red meat or high-end fish products. They include several cheap types of meat, which are readily available to Zambian consumers at lower prices.[10]

Furthermore, an increase in maize prices does not have significant effects on cassava consumption, which remains fairly stable through the different shocks, whereas beans and potatoes increase slightly and cereals and meat carry the largest weight. Most

[9]In Section 1, we emphasized that in a highly regulated market, price fluctuations and government intervention are so hard to predict that a potential drawback is the loss of connection with the real world. Finally, the link between the long and short term is the speed at which preferences adapt. We leave these as open issues for future research because the data at hand are not suited to this goal.
[10]One example would be dried foods such as Kapenta (sardines), which are relatively cheap and can substitute more expensive items.

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Table 4. Description of variables and parameters

Parameter	Variable	Mean	Standard deviation
α_i	Intercept		
$\gamma_{i,\text{Maize}}$	Price of maize (ZMK/kg)	712.53	146.46
$\gamma_{i,\text{Cassava}}$	Price of cassava (ZMK/kg)	100.58	31.41
$\gamma_{i,\text{Cereals}}$	Price of cereals(ZMK/kg)	2 851.88	1360.12
$\gamma_{i,\text{Potato}}$	Price of potato (ZMK/kg)	1 140.05	872.14
$\gamma_{i,\text{Meat\&Fish}}$	Price of meat and fish (ZMK/kg)	3 177.27	3 040.69
$\gamma_{i,\text{Fruit\&Veg}\cdot}$	Price of fruit and vegetables (ZMK/kg)	2 280.10	1 551.06
$\gamma_{i,\text{Egg\&Milk}}$	Price of egg and milk (ZMK/kg)	1 695.82	1 356.66
$\gamma_{i,\text{Beans}}$	Price of beans (ZMK/kg)	1 322.72	542.43
β_i	Total family food expenditure (ZMK)	354 376	281 773
$\delta_{i,\text{Household size}}$	Number of family members	4.99	2.77
$\delta_{i,\text{Female}}$	1 if Head of household is female	0.21	NA
$\delta_{i,\text{Age squared}\cdot}$	Age of household head^2	1 959.38	1 384.50
$\delta_{i,\text{Age}}$	Age of household head	41.81	14.53
$\delta_{i,\text{N.children}}$	Number of children	1.41	1.58
$\delta_{i,\text{N.employed}}$	Number of employed	1.76	0.75
$\delta_{i,\text{Central}}$	1 if the family resides central province	0.10	NA
$\delta_{i,\text{Copperbelt}}$	1 if the family resides in the Copperbelt Province	0.15	NA
$\delta_{i,\text{East}}$	1 if the family resides in the east province	0.14	NA
$\delta_{i,\text{Luapula}}$	1 if the family resides in the Luapula Province	0.08	NA
$\delta_{i,\text{North}}$	1 if the family resides in the north province	0.13	NA
$\delta_{i,\text{North West}}$	1 if the family resides in the north west province	0.06	NA
$\delta_{i,\text{South}}$	1 if the family resides in the south province	0.12	NA
$\delta_{i,\text{West}}$	1 if the family resides in the west province	0.08	NA
$\delta_{i,\text{HH education}}$	Household head education level (1 primary; 2 secondary; 3 upper)	1.09	0.46
$\delta_{i,\text{Maize\_sellers}}$	1 if the household is maize net seller	0.14	NA
λ_{i}	Probability density function		

ZMK, Zambian Kwache; NA, not applicable.
During the survey period the exchange rate averaged 4750ZMK per US dollar.

important for this paper, we are in the position to provide a welfare impact on the simulated price increase in the third step of our strategy.

In terms of welfare, price shocks affect households differently depending on their endowments and preferences. Therefore, the money measure of the resultant welfare effect is evaluated by calculating the compensating variation per each *h*-household (CV^h) measured as a second-order Taylor series expansion approximation (Friedman & Levinsohn, 2002):

$$\Delta \ln CV^h \approx \sum_{i=1}^{I} w_i^h \Delta \ln p_i^h + \frac{1}{2} \sum_{i=1}^{I} \sum_{j=1}^{J} w_i^h \gamma_{i,j} \Delta \ln p_i^h \Delta \ln p_j^h. \tag{11}$$

The compensating variation represents the amount of money required to compensate the household after a price change occurs and such that the household keeps the same level of utility as before the change in price. Thus, in order to understand these effects better, we take the poverty line as given. After the shock, individuals face a new poverty line. This poverty line is individual-specific and is obtained by adding the amount of the compensating variation for each individual (Equation (11)) to the original poverty line.

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Table 5. Demand system parameter estimation

	Eq.Maize	Eq.Cassava	Eq.Cereals	Eq.Potato	Eq.Meat&Fish	Eq.Fruit&Veg	Eq.Egg&Milk	Eq.Beans
α_i	−1.685***	−3.355***	−1.844***	−2.017***	−1.025***	−0.216***	−1.199***	−1.261***
$\gamma_{i,\text{Maize}}$	−**0.459*****							
$\gamma_{i,\text{Cassava}}$	0.031***	−**0.284*****						
$\gamma_{i,\text{Cereals}}$	0.143***	−0.024***	−**0.621*****					
$\gamma_{i,\text{Potato}}$	−0.096***	0.017*	0.119***	−**0.379*****				
$\gamma_{i,\text{Meat\&Fish}}$	0.112***	0.064***	0.083***	0.042***	−**0.698*****			
$\gamma_{i,\text{Fruit\&Veg}\cdot}$	0.135***	0.029***	0.080***	0.082***	0.127***	−**0.750*****		
$\gamma_{i,\text{Egg\&Milk}}$	0.044***	0.058***	0.086***	0.100***	0.075***	0.074***	−**0.664*****	
$\gamma_{i,\text{Beans}}$	0.079***	0.065***	0.084***	0.087***	0.053***	0.087***	0.093***	−**0.731*****
β_i	0.547***	0.400***	0.943***	0.544***	0.966***	0.645***	0.753***	0.673***
λ_i	−1.607***	0.301***	0.530***	0.120***	0.142***	0.067***	0.001	0.001
$\delta_{i,\text{Household size}}$	0.013	−0.027***	−0.028***	0.005	−0.008**	0.008*	−0.020***	0.009
$\delta_{i,\text{Female}}$	0.099**	0.067**	0.001	0.131***	−0.127***	0.008	0.036	0.001
$\delta_{i,\text{Age squared}\cdot}$	0.001	0.000**	−0.000**	0.001	−0.000***	0.001	0.001	0.001
$\delta_{i,\text{Age}}$	0.006***	0.001	0.001	0.001	0.001	0.001*	−0.002**	0.001
$\delta_{i,\text{N.children}}$	0.017	0.018	0.021	0.044**	0.001	0.001	0.021	0.001
$\delta_{i,\text{N.employed}}$	0.072***	0.053***	−0.044***	0.029	−0.034***	−0.029***	0.027**	−0.031***
$\delta_{i,\text{Central}}$	1.808***	0.567***	0.001	0.338***	−0.067*	−0.143***	−0.203***	0.094*
$\delta_{i,\text{Copperbelt}}$	0.263***	0.583***	0.173***	0.466***	0.001	0.117***	−0.207***	0.123***
$\delta_{i,\text{East}}$	1.871***	0.544***	0.001	0.024	−0.063*	0.003	−0.292***	0.327***
$\delta_{i,\text{Luapula}}$	0.781***	3.044***	−0.504***	0.437***	−0.142***	−0.520***	−0.512***	0.463***
$\delta_{i,\text{North}}$	0.859***	1.871***	0.414***	−0.218***	−0.128***	−0.270***	−0.366***	0.644***
$\delta_{i,\text{North West}}$	1.421***	1.641***	−0.740***	1.089***	−0.101**	0.001	−0.380***	0.478***
$\delta_{i,\text{South}}$	1.712***	0.666***	0.05	−0.146*	−0.131***	0.001	−0.210***	0.151***
$\delta_{i,\text{West}}$	1.901***	1.175***	−0.199***	−0.346***	0.025	−0.152***	−0.826***	−0.385***
$\delta_{i,\text{HH education}}$	−0.031***	−0.038***	0.034***	0.001	0.007***	0.011***	0.025***	−0.011***
$\delta_{i,\text{Maize\_sellers}}$	0.383***	0.047	−0.235***	0.081	−0.054**	0.001	0.068**	0.079**
R^2	0.481	0.466	0.439	0.277	0.729	0.682	0.547	0.630

*$p < 0.10$. **$p < 0.05$. ***$p < 0.01$.

Table 6. Price shock simulation, consumption quantity (kg) and percentage variation

Shock	Maize	Cassava	Cereals	Potato	Meat and fish	Fruit and vegetable	Egg and milk	Beans
Bench	145.9	42.6	62.4	36.0	18.4	29.2	15.0	20.5
0.1	136.9	42.3	64.0	36.4	18.7	29.2	15.0	20.6
0.2	126.3	41.9	66.2	36.8	19.1	29.4	15.1	20.8
0.5	104.8	41.5	70.6	37.5	19.9	29.9	15.5	21.5
Percentage variation								
0.1	−6.2	−0.8	2.6	1.2	1.8	0.1	0.2	0.5
0.2	−7.7	−0.9	3.4	1.2	1.8	0.5	0.2	1.2
0.5	−17.0	−0.9	6.6	1.9	4.1	1.8	2.9	3.1

We use this new poverty line to assess the impact of a price shock on welfare by using some poverty measures. In this study, we refer to three indicators:

(1) The 'headcount ratio' (HCR);
(2) The 'poverty gap' (PG) index.
(3) The Sen (1976, 1997) poverty index.[11]

The HCR is the percentage of the population living below the poverty line; the PG is the mean income shortfall with respect to the poverty line, expressed as a percentage of the poverty line (households above the poverty line are not considered):

$$PG = \frac{1}{G}\sum_{g=1}^{G}\left(\frac{p-y_g}{p}\right) \tag{12}$$

where G is the total population of poor, p is the poverty line and y_g is the income of poor household g.

The Sen Index considers simultaneously both the HCR and the PG while taking into account the underlying distribution throughout the Gini coefficient of the income distribution of the poor. The higher the percentage/index, the worse the poverty outcome:[12]

$$\text{Sen} = HCR[PG + (1 - PG)\ \text{Gini}]. \tag{13}$$

In Table 7, we present these measures by shocks. In this simulation, we artificially impose 10, 20 and 50 per cent increases in the price of maize and evaluate the effects on poverty for the total sample, for urban and rural households, and we also take into account that some households are net maize sellers and others are net maize buyers. Hence, any shift in maize prices certainly has a different effect on their overall welfare. For simplicity, we assume that maize sellers' gains would suddenly increase by an amount equal to the shock.[13]

[11]It should also be recognized that these measures are just some out of many possible indicators. In particular, most recent developments aim to understand the relative importance attached to the different dimensions.
[12]It is important to highlight the advantages and disadvantages of each measure. The HCR although simple and readable, it does not truly grasp the real dimension of poverty. For example, if a poor person gets poorer, the HCR is not able to capture this change. This is somehow improved with the PG index that includes the poor person's income and the poverty line. However, this index does not allow to compare those who are better off versus those who are worse off. Therefore, Sen derived a measure that implicitly considers the HCR and PG simultaneously, while taking into account the underlying distribution throughout the Gini coefficient of the income distribution of the poor. This is far from perfect but allows for a more comprehensive analysis of poverty.
[13]This is a short-term assumption and certainly overestimates the positive effect on maize sellers. Nevertheless, the overall scenario does not change very much.

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Table 7. Poverty measures

Shock	Poor	HCR	PGR	Sen
Bench	7594	68.00	35.49	45.09
0.1	7655	68.49	35.95	45.66
0.2	7696	68.88	36.41	46.22
0.5	7842	70.14	37.90	47.91
Rural				
Bench.	4241	86.39	52.05	63.07
0.5	4351	88.66	55.68	66.93
Urban				
Bench	3353	53.58	22.50	29.62
0.5	3484	55.64	23.95	31.43
Net maize buyers				
Bench	5981	64.86	32.64	41.73
0.5	6206	67.30	35.19	44.57
Net maize sellers				
Bench	1613	82.89	48.96	60.30
0.5	1604	82.34	48.51	59.87

HCR, headcount ratio; PGR, poverty gap ratio.

We start with the analysis of the benchmark model. In this scenario, about 68 per cent of households (7594 out of 11 167) fall below the poverty line, as can be seen using the HCR. The PG is about 35 per cent as a proportion to the poverty line, whereas the Sen Index, in the last column, is around 45 per cent. This index is designed to capture poverty incidence, intensity and inequality. With the price of maize increasing progressively, the share of the poor in the population ranges from 68 per cent to more than 70 per cent. In the same way, the proportion of the poor who become even poorer worsens as the PG ratio increases from 35.5 to 37.9 per cent. To obtain as much information as possible, we jointly consider this information in the Sen Index, and the picture is even blacker as the index increases more than proportionately. Focusing only on the Sen Index, it may be seen that a maize price increase has more detrimental effects for rural areas. This could be explained by the possible opposite effects between net sellers and net buyers, thus increasing inequality, one of the dimensions captured by the Sen index. Looking specifically at net maize buyers and net maize sellers, we can see that while net buyers suffer the most from shifts in maize prices, which is in line with expectations, net sellers benefit marginally from maize price surges moving from 60.3 to 59.9 per cent of the Sen Index. When analyzing the effects by area of residence, we note that while urban households experience a net welfare loss because of the increase in the maize price (moving the Sen index from 29.6 to 31.4), we may also observe a net loss of overall welfare even in rural areas (from 63.1 to 66.9). This might be explained by the fact that, although all the net maize-sellers reside in rural areas, the majority of households in these areas are net maize buyers (Table 1).

Indeed, we observe that the increases in the maize price are matched by a detrimental distributional impact between the country's rich and poor households. This difference may be attributed to the fact that amongst net maize producers, there is a prevalence of wealthy households, whereas poor household production seems to be mainly subsistence-oriented. This provides some insight into the underlying distribution of income and thus should be closely investigated by policy makers and researchers as they are informative about the impacts of higher food prices on poverty.

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5 CONCLUSIONS

In this study, we provided a methodological framework to simulate the possible effects that a sharp increase in food prices could have on welfare and poverty in a developing country. We took into special consideration the reliability of our estimates, thus taking into account and correcting for households with zero consumption of certain goods and making efforts to calculate our own elasticities rather than plugging them exogenously from standard studies. The proposed approach is a straightforward extension of existing methodologies and provides a simple but powerful tool for the evaluation of a price surge on welfare, at least in the short run.

Applied to the Zambian case, our method shows that a price surge in maize, the main staple for Zambian producers, has an overall adverse effect for the majority of households. In general, households drastically reduce maize consumption, with the urban poor being the most affected, having fewer opportunities to substitute their staples. Furthermore, we show that different price increases lead inexorably to detrimental shifts from households falling below the poverty line. From this perspective, in the Zambian case, there is a little, albeit not decisive, evidence in favour of state market regulation of prices in order to protect the more vulnerable parts of the population.

Nevertheless, at the same time, the regulation of prices and markets could be responsible for making Zambian households more vulnerable to global price shifts, because the markets are totally dependent on government reserves (monetary and food stocks): if, for some reasons, the government reaches its limit and is unable to keep prices at their current levels, the shocks could be amplified because Zambian households have no defence, at least in the short run, to face the surge. Further, heavily regulated markets as in the Zambian case usually reduce efficiency, leave more room for corruption and dissuade investment.

From our viewpoint, for future research, more efforts should be devoted to estimating the long-run effects, bringing together economic theory and the institutional framework, paying attention to the reliability of estimates. In this paper, we took a short step in this direction.

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