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Inter-Temporal and Spatial Price Dispersion Patterns and the Well-Being of Maize Producers in Southern Tanzania

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Abstract

We revisit a methodology to gauge the short-term effect of price changes on smallholder farmer's welfare that is popular amongst policy makers and academia. Realising that farmers face substantial seasonal price volatility over the course of an agricultural year, we pay particular attention to the timing of sales and purchases. In addition we depart from the implicit assumption that all farmers scattered across rural areas face the same prices when interacting with markets. Using maize marketing during the 2007–2008 agricultural season in a sample of smallholders in Tanzania as an illustration, we find that especially poor farmers face greater losses than what a standard analysis would suggest. We also relate our methodology to factors that are likely to affect potential benefits or costs from inter-temporal and spatial price dispersion, such as means of transport, access to price information and credit.

Key words: spatial price dispersion, inter-temporal price variation, price changes, market participation, maize, Tanzania

JEL classification: O12, O13, O55

1. Introduction

The answer to the question of whether rising food prices are beneficial for the well-being of semi-subsistence farmers in developing countries crucially depends on the household's net position with respect to the commodities affected by the food price increment. If households are net sellers (defined as selling a larger quantity than is purchased over a time interval) of the product under consideration, an increase in its price will increase household income, *ceteris paribus*. The reverse holds if a household is a net buyer. This heterogeneity in market participation of the poor partly explains why some non-governmental organisations (NGOs) and international organisations have opposing views on the effects of changes in prices for farmers in low-income countries, or why their views seem to change in the light of the global food crises (Swinnen and Squicciarini, 2012; Guariso *et al.*, 2014).

Popular tools to gauge the likely effects of commodity price changes on the wealth distribution within an economy therefore rely on the concept of net benefit (or net loss), which is defined as the value of net sales. By multiplying the change in the price of a particular commodity by the net benefit of that commodity, one obtains the change to household expenditure as a result of the price change of that particular commodity for a particular household. It is customary to express net benefit as a share of total household consumption expenditure, as in Deaton (1989, 1997), resulting in the well-known net benefit ratio (NBR). This model has been used widely to assess first-order welfare effects of changes in food prices (e.g., Budd, 1993; Barrett and Dorosh, 1996; Arndt *et al.*, 2008; Benson *et al.*, 2008; Ivanic and Martin, 2008; Simler, 2010). Modest data requirements, a simple underlying model and straightforward interpretation of the results in the form of graphs have made this method also popular amongst policy makers, as compared with more advanced computable general equilibrium (CGE) alternatives.[1]

The methods referred to above are generally implemented in a fairly aggregate way, both in the time and the spatial dimension. It involves calculating each household's net position on the basis of a cross-sectional survey and then simulating welfare effects by multiplying these ratios by actual or projected changes in prices that are the same for all households regardless of the timing of sales and purchases and the location. However, throughout an agricultural year, prices vary significantly (Sahn, 1989). In addition, households may be net sellers if observed at a particular time interval (e.g., around harvest time) but become net buyers if observed at another time interval (Stephens and Barrett, 2011; Tadesse and Guttormsen, 2011). Hence, the actual welfare effects for a farmer who, for example, sells part of the harvest when prices are low and buys the same commodity back at a later point in time when prices are higher may be quite different from those found by just multiplying the average price by the net position at the end of the period.

A similar point can be made with respect to spatial price heterogeneity. As is well established, the existence of transaction costs drives a wedge between the prices at which producers sell their products and prices at which consumers buy the product. This means that the prices which the farmer faces in his or her village can be very different from price movements observed at a more aggregate level. In the light of seasonal market participation and seasonal price movements, this may mean farmers lose out twice. First, farmers will incur transaction costs when they sell to itinerant traders at the farm gate immediately post-harvest, generally at a time when prices are lowest. Second, during the lean season, many farmers need to buy food from the market at a time when prices are significantly higher. While food may be available within the village, these farmers may end up paying prices that are close to what they need to

1 The first-order effect looks at the direct effect of changed prices on expenditures and revenues of households, and it does not consider changes in quantities demanded or supplied. It may be expected the consumers of products that become more expensive may substitute these products with relatively cheaper ones. To what extent this can happen in reality is an empirical question that depends on the availability of substitutes, among others. In any case, the short-term effects provide useful benchmarks. For instance, in the event of a price increase, the first-order effects will provide the maximum welfare loss a net buyer may expect and the minimum welfare gain a net seller can expect.

pay at a central market plus the cost of transporting the goods to the village. This is so because fellow villagers know that this is the upper limit for the farmer's willingness to pay, and competition among sellers will be low as most food will have been sold immediately post-harvest. In such a scenario, the farmer incurs most of the transaction costs twice.

In this article, we propose some modest extensions to commonly used methods involving net benefits to assess the short run consequences of price changes to make it more robust to seasonal price variation and spatial price heterogeneity. We will then look at how these modifications affect the outcomes of the method with and without the modifications using data collected in the Southern Highlands of Tanzania.[2] However, we will focus the study on maize, the main food crop produced and consumed in the area. In particular, we will express the changes in the value of the net benefit of maize for each farmer due to the change in the price of maize as a share of the value of maize instead of as a share of total consumption expenditure.

Studies on the short run effect of price changes usually correlate NBRs to continuous (using non-parametric methods) or categorical (using for instance bar charts) variables to see if different groups in society are affected differently by a price increase. We therefore also relate the (extended) measures of short-term price effect to some household characteristics. We also categorise households into groups related to characteristics that are likely to affect transaction costs, such as access to a mobile phone or transport, to see if differences between methods are reflected in these different groups.

We find that an analysis that disregards price heterogeneity underestimates the short run losses resulting from the maize price evolution in 2007–2008. This is especially the case for households that are poor in terms of assets such as land ownership, livestock and education. We also find that especially vulnerable households, with higher dependency ratios, suffered during the 2007–2008 food price crisis. Finally, our analysis suggests access to non-motorised transport and higher frequency of town visits is positively correlated with farmers' ability to deal with spatial price dispersion. Access to credit from a microfinance organisation is positively related to the ability of farmers to take advantage of inter-temporal price variation. Finally, mobile phones are correlated with a farmer's capacity to exploit both inter-temporal and spatial price dispersion to their advantage.

The remainder of the article is organised as follows. The next section serves up a motivating example by describing key characteristics of the data that will be used later in the analysis. We then give a short overview of the literature. The next section describes the methods that are used to assess short run welfare effects of commodity price movements, and the extensions we propose to capture seasonal and spatial price heterogeneity. We then describe the study area and provide descriptive statistics. Section 6 presents the results of an analysis in which household characteristics are correlated with benefits or losses from changes in prices of maize and illustrates how our extensions affect the results. A final section concludes.

2. Motivation

This section serves as a motivation to extend measures that rely on the concept of net benefits or net losses associated with price changes. It is built around Figure 1. The data used to

2 The data analysis was under revision control (git). The R code as well as the data to replicate the entire analysis is available from https://bitbucket.org/bjvca/tz08_market_part_jae.git.

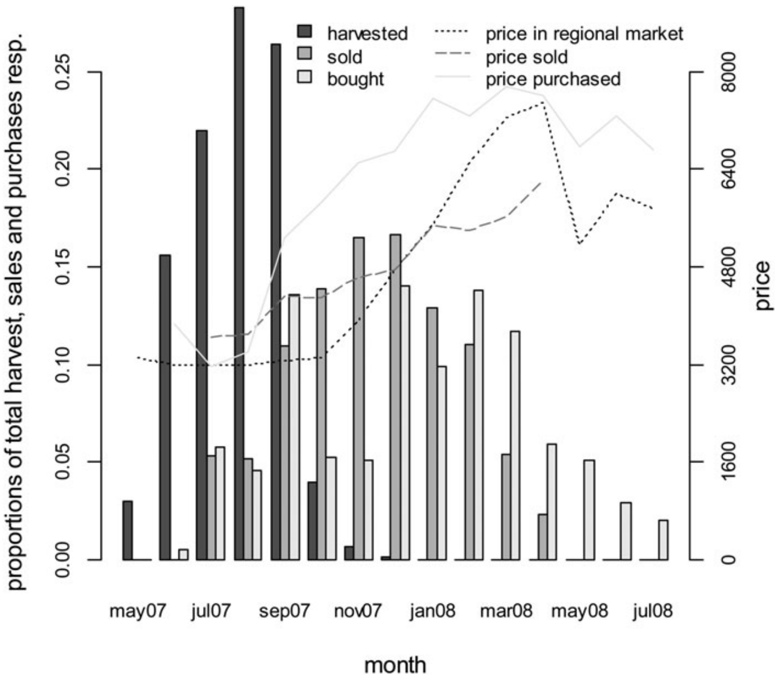

Figure 1: Maize Harvested, Sold and Bought.

produce this graph come from a household level survey done in smallholder communities in a maize growing area in the Southern Highlands of Tanzania in 2007–2008, which we will use later in the application as well. The left axis refers to the bar chart. We express amounts of maize harvested, sold and bought in each month as a percentage of the total amounts of maize harvested, sold or bought. For example, the figure shows that 100% of maize in our sample was harvested before 1 January 2008, and about 28% was harvested in August 2007. We overlay the bar chart with time series of the prices of maize. Prices are expressed in Tanzanian shillings (TZS) per *debe* (20 l; see the right axis).[3] We differentiate among three different price series. First, for each month we recorded the average price registered for a debe of maize on the market in the district capital, Mafinga, which serves as the main terminal market for the households in our sample. Second, we also calculated average prices in each month for purchases of maize as reported by the farmers. Finally, we did the same for sales of maize.

The first interesting feature shown in this figure is that amounts harvested, sold and purchased varied significantly over time. The bulk of the harvesting occurred in August 2007. At this point in time, sales also started to pick up, but farmers kept harvesting up to January 2008. The bulk of purchases by farmers happened between December 2007 and March 2008. If we look at the evolution of prices over this period, it becomes clear that

3 The exchange rate in 2008 was about TZS 1,178 to the US Dollar. We will use this exchange rate throughout this article.

large quantities of maize were sold in months when prices were relatively low while large purchases occurred when prices were relatively high.

A second observation relates to the evolution of prices over time. The graph demonstrates the substantial inter-temporal price volatility that maize farmers in the Southern Highlands of Tanzania face. In Mafinga, maize prices started to accelerate in November 2007. Prices increased by 135% between August 2007 and April 2008, the months when lowest and highest prices were recorded, respectively.[4] From May 2008 onwards, beans, the second most important crop, started to get harvested, which took some of the pressure off of maize prices. The mean price over this period was TZS 5,020 per *debe*, with a standard deviation of 1,560.

At the village level, food prices start to increase even earlier. In particular, local purchase prices started to go up from the point when harvested quantities started to decelerate in September 2007. The sharp and sudden increase is concurrent with the first peak in purchases, an increase that is probably due to some wealthier farmers/entrepreneurs buying maize from neighbours to engage in spatial or inter-temporal arbitrage. The increase between the lowest (July 2007) and highest (January 2008) prices is even higher than in Mafinga at almost 140%. Both the mean and the standard deviation of the local purchase price are also higher than in Mafinga, respectively, TZS 6,120 and TZS 1,590. On the other hand, while initially the price at which farmers sold was higher than both the central market price and the local price at which farmers bought, this quickly changed for the worse. From September 2007 onwards, as maize purchases started to pick up, the price at which farmers bought became higher than the sales price as reported by the farmers. From February onwards, farmer reported sales prices also fell below the price in Mafinga. For reported prices at which farmers sell, the maximum increase, between July 2007 and January 2008, was only 44%. While the mean over the agricultural year was slightly higher than the mean price in Mafinga, the standard deviation was only TZS 630.

A third interesting fact is that, although the village-level prices moved broadly in the same direction as the prices in Mafinga, they were by no means equal. This suggests the existence of substantial transaction costs between rural markets and the terminal market of Mafinga. But even within a village, we find large differences in the price at which farmers buy and sell. The fact that the prices at which farmers bought were higher than the terminal market price may indicate that maize flowed from Mafinga to the villages and farmers incurred the transaction cost. The fact that the average price at which maize was sold reported by the farmer was for a large part of the agricultural year between the price in Mafinga market and the purchase price may be due to transactions that took place within the village. For instance, fellow villagers may know the price in Mafinga and how much it costs to transport, and adjust their reservation price accordingly.

4 It should be noted that the magnitude of these price changes are exceptional, as the 2007–2008 agricultural season corresponds to the food price crisis. (Headey and Fan, 2008). However, substantial inter-temporal price changes are characteristics of rural agricultural-based market system. For instance, in Iringa, the closest market to Mafinga for which we have reliable price data over time, we find price increases of about 200% for the 2007–2008 agricultural year (with the lowest monthly average price recorded in July 2007 and the highest price in April 2008). In the 2008–2009 agricultural season, this range is still about 52% (with lowest prices recorded in September 2008 and highest price in February 2009).

In sum, the simple description of market participation patterns and price movements at different locations for a sample of maize farmers in Southern Tanzania throughout the agricultural year in Figure 1 suggests substantial spatial and inter-temporal price variability. A standard analysis of the net benefits or losses using aggregate price changes may therefore lead to significantly different outcomes for certain groups of people. In this study, we document how, if detailed transaction data are available, incorporating timing and location aspects into the analysis can make the workhorse model to assess the short run effect of price changes even more useful for evidence-based policy analysis.

3. Related studies

Our study looks at market participation during the 2007–2008 agricultural year for maize in Tanzania. Looking back, this period has been known as the first food price crisis. While global food prices have been increasing since 2003, there was a dramatic acceleration in 2007 and 2008. Among the factors primarily responsible for this were higher oil prices, the use of food crops for biofuel, increased meat consumption, poor harvests in certain agricultural regions, a depreciating dollar, export bans by key wheat and rice producers and underinvestment in the agricultural sector in the past (Abbot *et al*., 2008; Benson *et al*., 2008; Mitchell, 2008). From mid-2008 prices started to move downwards, but in general they remain high and volatile. In 2011, global food prices spiked again,[5] renewing interest in studies that aim to assess the welfare effects of higher global food prices, both in the short and the long run (Ivanic *et al*., 2012; Headey, 2014).

As mentioned above, we will focus on studies that assess the short run consequences of price changes on semi-subsistence farmers. In the short run, price changes only affect households through their interaction with the market. Deaton (1989, 1997) develops a straightforward model that depends on the net sales of commoditie(s) affected by price changes (divided by total consumption expenditure and referred to as the NBR) to assess the welfare effect. This model is by far the most used model to study the impact of changes in commodity prices in developing countries (Budd, 1993; Barrett and Dorosh, 1996; Arndt *et al*., 2008; Ivanic and Martin, 2008).

Probably the first study that uses the NBR methodology to assess the importance of the 2007–2008 food crisis at the micro level is that of Benson *et al*. (2008).[6] Using data from more than 7,000 Ugandan households surveyed over a 12-month period from the nationally representative 2005–2006 Uganda National Household Survey (UNHS), they determine whether households are net buyers or sellers to gauge the likely consequence of the food crisis. They find that the poor only purchase small quantities of food from the market. This fact, coupled to the fact that Ugandans have a varied diet with prominent places for traditionally non-traded crops and a poor pass-through of world to local prices, leads the researchers to conclude that the effect is likely to be small. As a follow-up to this study, Simler (2010) takes a step in the direction we propose in this study, by disaggregating by regions and individual

5 For instance, in February 2011, the Food and Agricultural Organization (FAO) food price index was at an all-time record high (236 points), while its cereal price index was at the highest level since July 2008 (FAO, 2011).

6 This study refers to an earlier multi-country study (Ivanic and Martin, 2008). However, that study does not cover the climax of the crisis.

food items. He also uses more recent price data and estimates the impact on consumption poverty again. He finds that both incidence and depth of poverty increased, by 2.6 and 2.2 percentage points, respectively, higher than the effect found by Benson *et al.* (2008). The disaggregation is described as critical to the analysis, 'because of strong evidence of large regional variation of staple food prices in Uganda' (p. 3). Still, even prices of six regional markets are likely to be poor proxies for what farm households actually pay or receive at the farm gate due to high transaction cost.[7]

Apart from spatial heterogeneity, our study also states that seasonality in both commodity prices and marketing behaviour are important additional parameters when using methods that rely on the calculation of the net position of households to gauge the effect of price changes. Stephens and Barrett (2011) also look at seasonal variability in commodity marketing behaviour. More in particular, they investigate the *sell low, buy high* puzzle.[8] They argue that incomplete credit markets are to blame for this lack of inter-temporal price arbitrage. Also, a recent study by Aksoy *et al.* (2010) recognises that the buyer/seller status may change over time. However, they track the buyer/seller status using two points of a panel covering several years, while we want to specifically focus on seasonal price variation.

Wandel and Holmboe-Ottesen (1992) investigate the relationship between seasonality and well-being more directly. They look at Rukwa Region in Tanzania, a region that is a surplus grain production area similar to the one used in our application. They find that a large part of the population was found to face seasonal variations in food availability, most critically three to four months before the main harvest. They find that maize stocks are exhausted more quickly in households that participate in the market as sellers and argue that increased cash orientation may jeopardise food availability and nutritional status.

Dostie *et al.* (2002) look at seasonality in Madagascar. They find that seasonality is more pronounced in rural areas than in the capital, as urban traders appear to take advantage of shifting harvest dates in a sequence of alternative supplying regions. Seasonal malnutrition coincides with increased incidence of disease, such as malaria and diarrhoea during the rainy season, which translates into excess mortality. They discuss three typical interventions to counter this seasonality and conclude that increasing the productivity of secondary food crops (such as cassava, which is found to be counter-seasonal) would be the preferred option.

Only recently, after studies examining the dynamics of welfare using panel data found large fluctuations in consumption over relatively short periods, seasonality has been associated with poverty and well-being in a quantitative way. For instance, Dercon and Krishnan (2000) look at panel data form Ethiopia and find that, while year-to-year poverty is very similar, consumption and poverty over the course of one season varies significantly.

7 In fact, already in Deaton (1997), the study that served as the main catalyst for the current success of NBR-based models, Deaton realizes that the single price for all households in his model is not very realistic. In the light of another chapter in the same book where he underscores the importance of price heterogeneity in household survey data, he notes 'Somewhat schizophrenically in view of the analysis to come in Chapter 5, I am assuming that prices are the same for all farmers, thus ignoring regional variation in prices' (p. 183).

8 The puzzle they refer to is the fact that farmers do not seem to exploit the inter-temporal arbitrage opportunities created by predictable and recurring seasonal price movements. Instead, 'they often sell their output at low prices postharvest and buy back identical commodities several months later for prices far higher than they received postharvest' (Stephens and Barrett, 2011).

Orr *et al.* (2009) investigate if seasonality is responsible for a poverty trap mechanism whereby farmers are forced to sell their own labour during the planting season to meet consumption needs, thereby reducing the time invested in own production.

Bellmare *et al.* (2013) look at the effect of commodity price volatility as opposed to the effect of higher food prices. They find that, if governments choose to intervene in order to stabilise food prices in Ethiopia, the welfare gains from eliminating food price volatility are increasing in household income. Concluding from this that commodity price volatility is good for household well-being may be overhasty, as the intervention itself may be to blame, as the unforeseen and undesirable departures from expectation regarding commodity prices may make the effects of price volatility even worse.

In sum, studies that rely on marketed surplus to assess the consequences of price changes remain very important. However, while some studies acknowledge the importance of spatial price heterogeneity, these studies still aggregate at fairly high levels, certainly not considering the actual prices faced by the household at the farm-gate. In the meantime, higher frequency repeated measurement data on households in developing countries allow us to analyse the importance of seasonality in agriculture for well-being and poverty and determine when and to what extent it is empirically relevant. We show how these two issues can be incorporated into a widely use method for assessing the effect of price changes on well-being, if the data are available. We also show care needs to be taken when drawing conclusions from such methods if only aggregate prices are available, especially in turbulent times, such as the 2007–2008 food price crisis.

4. Method

In studies that try to assess the gains or losses of commodity price movements in the short run, net gains or losses from these price changes are often correlated to other household characteristics, to see how different types of households are affected by these price changes. This is often done using non-parametric regressions between gains or losses due to price changes (Δg) and various continuous variables, where the former is defined as[9]

$$\Delta g_i = (p_t q_i^{\mathrm{S}} - p_t q_i^{\mathrm{B}}) - (p_{t=0} q_i^{\mathrm{S}} - p_{t=0} q_i^{\mathrm{B}}), \tag{1}$$

and $p_{t=0}$ is the price for a commodity at the start of the interval over which one wants to calculate the impact and p_t is the price at the end of the period. The quantity sold of that commodity by household i is denoted as q_i^{S} and the quantity bought by q_i^{B}. In the literature, it is common to denote the welfare change as a proportion of total household wealth (y_i) defined as total consumption expenditure at the beginning of the time interval ($q_i p_{t=0}$)

$$\Delta w_i = \left(\frac{p_t - p_{t=0}}{p_{t=0}}\right) \frac{p_{t=0} q_i^{\mathrm{S}} - p_{t=0} q_i^{\mathrm{B}}}{y_i}. \tag{2}$$

In this specification, the change in wealth as measured by total consumption expenditure (Δw_i) due to a price change between $t = 0$ and t equals the percentage price change between $t = 0$ and t weighted by the difference between the share of the value of sales in total consumption

9 In more general cases where price changes of more than one commodity are modelled, it is common to also add an index for the commodity, and sum gains or losses over the different commodities.

expenditure and the share of the value of purchases in total consumption expenditure. The last term is known as the NBR since Deaton (1997).

In our application on the effects of price changes in maize in Tanzania, since we do not have consumption expenditure data for a complete set of commodities consumed by the households, we decided to express net sales as a share of the total value of maize harvested by the farmer instead of total consumption expenditure.[10] To do so, we evaluate the maize harvested by each household at the prevailing prices in Mafinga during harvest.[11] As a result, one should be aware that the conclusions should now be interpreted as proportions of the original value of maize harvested that is gained or lost through transactions under subsequent price movements.[12] We decided also to only include farmers who participated in the market.[13]

The change in denominator may seem like a major departure from a well-known concept such as the NBR. However, the focus of the article is not on the *absolute value* of the NBR and its interpretation, but on the *differences* between an NBR taking into account seasonal and spatial price heterogeneity. As such, while one may object that the absolute value of a measure of net benefit that scales by maize production will likely be higher than Deaton's (1989, 1997) original one, the relative differences between such measures that do and do not take into account seasonal and spatial price heterogeneity will be the same whichever scaling is used to calculate the ratio. If we find the NBR using the value of maize as denominator reduces by x % if one accounts for seasonal price variation (compared with the NBR using the value of maize as denominator with the average price), a comparison of a NBR using household consumption as the denominator that accounts seasonal price variation

10 The fact that net benefit is usually scaled by total consumption expenditure is due to Deaton (1989). In his data, Deaton did not have records of actual sales and purchases, but only of household consumption and production. He assumed all production in excess of consumption to be sales and all consumption in excess of production to come from purchases, implicitly using the concept of marketable surplus instead of actual net sales. Hence, the quantities produced and consumed of the commodity will appear in the equation to calculate the net benefit ratio. Dividing this by total household expenditure leads to the familiar concept of a budget share. The change in welfare judged by the percentage change in total household expenditure can then be calculated by simply multiplying the price change by the difference between the production and the consumption share of the household.

11 One may argue that it would be better to use prices faced by the farmer in the village during harvest, especially since we point out that transaction costs are likely to result in lower seller prices in the village than in Mafinga. However, such information was again unavailable. The consequence will be that the value of the harvest is likely to be overestimated, and so the resulting ratio will be underestimated. However, as explained in more detail below, our focus is not on the levels of NBRs but on differences between different versions of the NBRs: while the choice of the prices will affect the level of the NBR, this will not affect difference we find between different versions of the NBRs (e.g., those that do take spatial price heterogeneity into account, those that do take seasonality into account, . . .)

12 We expect the effects to be higher compared with studies where total consumption expenditure is used, because we scale by the value at harvest of only maize. In most households, well-being will be higher than what is grown on their maize field only.

13 Deaton (1989) notes that in his case, adding or deleting the farmers with an NBR of zero does not influence the results. In our case, because we have a substantial share of farmers who do not participate, including them will make the lines flatter. However, it will not affect the relative position of the different lines within each graph.

will reduce by the same percentage (compared with the NBR using household consumption as denominator with the average price).

A first extension to the net-benefit approach to assessing commodity price change effects is to incorporate the fact that agricultural commodity prices are highly seasonal, and such is market participation. Therefore, we calculate the net position of the household for each sub-period (in our case each month) and evaluate it at that sup-period's change in central market price. In other words, assuming we have M periods, we now get that

$$\Delta w_i = \frac{1}{y_i}\sum_{m=0}^{M-1} \frac{p_{t=m+1} - p_{t=m}}{p_{t=m}} (p_{t=m} q^{\mathrm{S}}_{i,t=m} - p_{t=m} q^{\mathrm{B}}_{i,t=m}). \tag{3}$$

Second, Equation (2) assumes that prices at which households buy and sell goods are the same for everyone. However, we have seen that there may be substantial differences in the price depending on whether one wants to buy or sell. In addition, transaction costs are also likely to result in price differences in different locations for the same homogeneous commodity. We therefore adapt Equation (1) to use prices as reported by the households. In this case, we get

$$\Delta w_i = \frac{1}{y_i}[(p^{\mathrm{S}}_{i,t=1} q^{\mathrm{S}}_i - p^{\mathrm{B}}_{i,t=1} q^{\mathrm{B}}_i) - (p^{\mathrm{S}}_{i,t=0} q^{\mathrm{S}}_i - p^{\mathrm{B}}_{i,t=0} q^{\mathrm{B}}_i)], \tag{4}$$

which, in a form equivalent to Equation (2) gives

$$\Delta w_i = \frac{1}{y_i}\left[\frac{p^{\mathrm{S}}_{i,t} - p^{\mathrm{S}}_{i,t=0}}{p^{\mathrm{S}}_{i,t=0}} p^{\mathrm{S}}_{i,t=0} q^{\mathrm{S}}_{i,t=0} - \frac{p^{\mathrm{B}}_{i,t} - p^{\mathrm{B}}_{i,t=0}}{p^{\mathrm{B}}_{i,t=0}} p^{\mathrm{B}}_{i,t=0} q^{\mathrm{B}}_{i,t=0}\right], \tag{5}$$

where we now index the prices to indicate prices are household specific and, within each household, we allow for a different buyer ($p^{\mathrm{B}}_{i,t}$) and seller price ($p^{\mathrm{S}}_{i,t}$). Equation (5) shows how a certain increase, expressed as a percentage, in household-specific farm gate prices at which households sell contributes positively to the net benefit, while a percentage increase in household-specific retail prices as which they buy contributes negatively.

Finally, we combine the two extensions by evaluating the amounts sold or bought at reported prices received or paid by the farmer in the respective month. This is basically a combination of Equations (3) and (4)

$$\Delta w_i = \frac{1}{y_i}\sum_{m=0}^{M-1}[(p^{\mathrm{S}}_{i,t=m+1} q^{\mathrm{S}}_{i,t=m} - p^{\mathrm{B}}_{i,t=m+1} q^{\mathrm{B}}_{i,t=m}) - (p^{\mathrm{S}}_{i,t=m} q^{\mathrm{S}}_{i,t=m} - p^{\mathrm{B}}_{i,t=m} q^{\mathrm{B}}_{i,t=m})], \tag{6}$$

which can again be rewritten in terms of percentage changes in (now time and location disaggregated prices)

$$\Delta w_i = \frac{1}{y_i}\sum_{m=0}^{M-1}\left[\frac{p^{\mathrm{S}}_{i,t=m+1} - p^{\mathrm{S}}_{i,t=m}}{p^{\mathrm{S}}_{i,t=m}} p^{\mathrm{S}}_{i,t=m} q^{\mathrm{S}}_{i,t=m} - \frac{p^{\mathrm{B}}_{i,t=m+1} - p^{\mathrm{B}}_{i,t=m}}{p^{\mathrm{B}}_{i,t=m}} p^{\mathrm{B}}_{i,t=m} q^{\mathrm{B}}_{i,t=m}\right]. \tag{7}$$

The above provides four alternative ways to calculate changes in well-being as a result of price changes for semi-subsistence farmers through interactions with the market at the household level. This can then be used to calculate average gains or losses for the entire sample, or subgroups of the sample. For instance, it is likely that average gains or losses will be different for urban versus rural households. One can also plot the household level gains or losses against other continuous variables to discover relationships. For instance, it is likely that net benefit is related to the size of land operated by the household. In the remaining part of this article, we will calculate the net benefits or losses using the four alternative specifications and investigate how they differ, not only for the entire sample, but also for different groups of household. This will allow us to find out if, for instance, taking into account seasonal market participation and price movements leads to larger losses from price changes for households with less land than would be predicted by not taking into account seasonality.

5. Context and data

We interviewed 1,134 small-scale farmers on their maize production and maize-related transactions over the entire 2007–2008 agricultural year. We decided to draw our sample from the Mufindi district, which is located in Iringa region in the Southern Highlands of Tanzania. The area is known as an important maize-producing area. Mufindi is mountainous, with one of the coolest and rainiest climates in Tanzania. The district capital is Mafinga, which lies on the Tanzam Highway, an important tarmac road that runs from Dar es Salaam to Zambia and Malawi. About 70 km to the east of Mafinga along the Tanzam is the regional capital, Iringa. At about the same distance in the other direction lays Makambako, a small trading town where the railway passes.

Households living in the semiarid lowlands of Mufindi district mainly depend on semi-subsistence smallholder farming to provide for their livelihood. Most households keep small livestock to supplement their diet or for trade. Some keep small herds of cattle as savings, for milk, or for trade. Other activities include crop trade, petty trade, brick or charcoal production, seasonal labour and beer brewing. Agricultural production is primordially based on rain-fed cultivation with the use of rudimentary technology and minimal inputs. Maize is by far the most important crop, both in terms of consumption and production.

Within the district, we chose seven villages such that our sample would be representative for the district. More in particular, to reflect the geographic diversity of the region, we chose some villages in lower, dryer areas; some on the Mufindi plateau; and some in areas marked by high hills and narrow valleys. In addition, we also selected on distance to the district market (Mafinga) as well as on the quality of the road connecting the villages to this market. Within each of these villages, we sampled farmers randomly, the number of individuals proportional to the share of farmers in the village in the total sample. The villages were Ibwanzi, Ikongosi, Ipilimo, Kwatwanga, Mtambula, Mtili and Nundwe.

Each sampled household was then visited by an enumerator, who asked a series of questions related to household characteristics. A section dealt with sales and purchases of maize, asking when, how much and at what price maize was transacted.[14] The price data for Mafinga were collected at the district headquarters. District government officials record prices for a variety of products in the market on a regular basis.

Total maize production in our sample over the 2007–2008 agricultural year amounted to about 1,068 tons. Of this, only about 200 tons entered the market. About 61 tons of maize were bought by farmers over the entire period. Most farmers who reported sales only sold once (88%). This is remarkable, given the high seasonal variation of prices as well as the

14 This was based on recall over the last agricultural year. The precision, speed and confidence at which households were able to enumerate months, amounts sold and/or bought, prices, to whom, etc. gave us confidence the data were reasonably reliable.

high variability in amounts produced (mean 0.9 tons and a standard error of 1 ton) and sold (mean 0.17 tons and a standard error of 0.53 tons).

We find that about 35% of the farmers in our sample appear to be self-sufficient for maize. These farmers reported not a single transaction. In comparison with what is usually found in similar studies, this is very high.[15] About 31% of the households only bought maize; they reported at least one transaction. A further 27% of our households reported only selling maize. A remaining 6% reported both sales and purchases of maize.

At the aggregate level, summing over the entire sample, we find that the maize price fluctuations benefited farmers in Mufindi district. If we multiply the net position in quantities of maize of each household at the end of the agricultural year (July 2008) by the average price over this period, and then sum over all households in our sample, we obtain a figure of about TZS 36.5 million (USD 31,000). If we disaggregate net positions over the different months and evaluate them at market prices, the gains are significantly smaller: only about TZS 33.2 million (USD 28,000).

Table 1 presents summary statistics for the continuous variables we will use in the analysis in the next section. It also shows summary statistics on the net benefit (sales price times quantity sold minus purchase price times quantity bought) and the NBR (net benefit divided by the value of the harvest) for maize for each of the four versions of the net benefit measure we will use in the analysis for the entire sample. We will name then with reference to the sphere of disaggregation:

- *None*: This is the most restrictive version of net sales based measures of price effect, where there is no disaggregation over time or space. It simply subtracts quantity bought from quantity sold over the entire agricultural year and multiplies this by the percent change of the central market price in Mafinga over that entire year. This case corresponds to Equation (1) and (2). This measure forms that base of the measures used in most studies that assess the influence of commodity price movements on agricultural households in developing countries. Table 1 shows that using this measure, households gained on average about TZS 32,000 (USD 27) from the increase in maize prices. However, if we express net benefit as a share of the total harvest and then take the average, the effect is negative. This already suggests that it is especially larger farmers who benefit from higher prices.
- *Time*: In this specification, we allow for the fact that prices vary considerably in the course of the agricultural year, and farmers may also interact at different times of the year. Therefore, we now calculate the net position of the household for each month and evaluate it at the change of the central market price over that month. This case corresponds to Equation (3). Table 1 shows that the change in net benefit (as compared with the *none* case above) is marginal. However, the change in net benefit as a share of total maize harvested is much more pronounced. This suggests that it is especially smaller farmers who are disadvantaged by the seasonality in price changes.

15 For instance, Benson *et al.* (2008) find that for staple foods in Uganda two years earlier, only 14% of households had sales similar to purchases. Note that our definition is narrower than theirs, as we only consider situations where purchases are equal to sales and zero. Minten and Barrett (2008) find only 7% of households in Madagascar are self-sufficient for rice. Jayne *et al.* (2006) find that in Kenya only 8% of households do not participate in the maize market. However, these percentages are much higher in Mozambique (24%) and Zambia (39%). The authors attribute this to the fact that in these regions, cassava is the main staple.

Table 1: Summary Statistics

	Mean	Standard deviation	Minimum	Maximum
Net benefit: none	32,230	137,752	−917,400	2,036,000
Net benefit: time	31,340	156,042	−746,800	2,502,000
Net benefit: space	35,070	154,694	−1,086,000	2,272,000
Net benefit: both	29,310	150,573	−874,500	1,950,000
NB/harvest: none	−0.03	0.72	−7.54	1.36
NB/harvest: time	−0.07	0.76	−7.49	1.99
NB/harvest: space	−0.05	0.84	−8.92	1.51
NB/harvest: both	−0.12	0.92	−10.71	2.42
Local maize price sales	7,150	4,251	909	25,000
Local maize price purchases	6,813	2,297	1,714	18,000
Log value harvested per capita	10.17	0.97	7.68	14.48
Log farm size per capita	−0.35	0.71	−2.64	2.57
Log tropical livestock units per capita	−3.15	2.09	−8.39	1.57
Education (years)	5.18	3.02	0.00	13.00
Household size	5.60	2.59	1.00	22.00
Children/hhsize	0.45	0.21	0.00	0.88
Women/hhsize	0.30	0.17	0.00	1.00
(Women + children)/hhsize	0.75	0.17	0.00	1.00

- *Space*: In this case, we accommodate the fact that farmers in different locations and capacities (as buyer versus seller) face different prices. We subtract quantity bought from quantity sold over the entire agricultural year as in *none*, but now evaluate this at the change at average local prices instead of assuming farmers transact at Mafinga prices. This corresponds to Equations (4) and (5). In Table 1, we see that this specification leads to the highest average net benefit, but a net benefit that is negative and in between *none* and *time*. This suggests that spatial heterogeneity in prices works against farmers with lower maize harvests.
- *Both*: In this specification, we consider price heterogeneity in both time and space. It essentially means we use household-specific prices at which sales and purchases happened at different points in time throughout the agricultural year. This specification corresponds to Equations (6) and (7). Accounting for both spatial and inter-temporal price variability results in the lowest average net benefit and the largest net loss as a share of total maize harvest.

The four scenarios above can be interpreted in terms of differences in overall market efficiency. For instance, the *none*-case assumes that all framers transact at one and the same price, irrespective of their location. This would be a case where markets are perfectly integrated over space and transaction costs are absent. The *space*-case allows for different prices in different locations, reflecting actual market efficiency, with sluggish price adjustment between rural and urban areas and substantial transaction costs. Comparing outcomes of the *space* scenario to the *none* scenario, we thus get a sense of what the likely effects of increasing spatial market efficiency (for instance, through the construction of feeder roads) will be on NBRs.

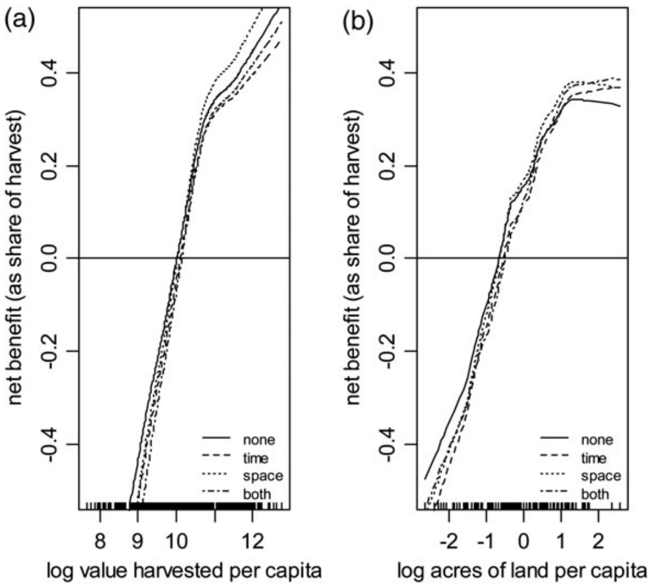

Figure 2: NBRs by Maize Harvested and Land Access.

The same holds for inter-temporal market efficiency. The *none*-case equally assumes that all framers transact at one and the same price, irrespective of when they transact. This would be a case where all price movements between the beginning and the end of the period have been levelled out. Such a case requires complete inter-temporal market efficiency. The *time* case reflects reality, where demand and supply conditions change over the course of the year and inter-temporal arbitrage is unable to completely eliminate price movements cause by these changing demand and supply conditions. Comparing outcomes of the *time* scenario with the *none* scenario, we thus get a sense of what the likely effects of increasing inter-temporal market efficiency (for instance, through the introduction of warehouse receipt systems) will be on NBRs.

We next turn to an analysis where we correlate net benefit to different household characteristics.

6. Results

We start by seeing if the capital within a household is correlated to gains or losses from price changes during the 2007–2008 agricultural year in the Southern Highlands of Tanzania. Figure 2 shows two panels. The first panel plots out the net benefit as a share of total maize production against the log of the value of the amount of maize harvested per household member. The second plots the same against the log of acres of land per capita, while the third looks at correlation with tropical livestock units (TLU) per capita.[16]

16 The concept of TLU, developed by the FAO, provides a convenient method for quantifying a wide range of different livestock types and sizes in a standardized manner. In our calculation of TLU, a bull/cow gets a weight of 0.5, a pig gets a weight of 0.2, a goat/sheep gets a weight of 0.1 and a chicken gets a weight of 0.01.

Each panel in Figure 2 shows four non-parametric regression lines,[17] corresponding to the different assumptions made when calculating the net position of the farmer, and given appropriate names in the previous section. The solid line is the most restrictive one, which we referred to as the case where no disaggregation takes place (*none*). The dashed line disaggregates the net position over time but still assumes local farmers buy and sell at central market prices. We called this the *time* case. Next, the dotted line in Figure 2 shows the cumulated net position, but this time we multiply by the percent change of the average local price. This line corresponds to the *space* measure. Finally, the dash-dot line represents the least restricted scenario, the *both* case, essentially combining *space* and *time*.

The non-parametric regression lines in Figure 2, as well as those that will follow in Figures 3–5, are limited in that they do not provide confidence bands and as such cannot be used to evaluate if differences between scenarios are statistically significant. Unfortunately, adding confidence bands would make the graphs unreadable. However, we have made an alternative set of figures available as an Supplementary Material, Appendix that shows non-parametric regressions with 5% confidence intervals for two scenarios (instead of the four) using colours. In particular, we compare the most restrictive scenario where no allowance is made for inter-temporal and spatial price variation (the *none* case), to the broadest case that considers both price heterogeneity in time and space (the *both* case). Each of the Figures 2–5 reported in this article has a corresponding figure in the Supplementary Material, Appendix.

The first panel, (a), in Figure 2 shows the correlation between the logarithm of the value of the maize harvest per capita and the net benefit as a share of total maize harvested. We learn that the households at the bottom end of the distribution are likely to be hurt more by high food prices. For instance, for households that harvest little maize per capita, say less than ten on the log scale (which is equivalent to TZS 22,000 or USD 19), the net benefit becomes negative. The amounts are substantial: for a household that harvests about TZS 8,000 per capita—corresponding to about nine on the log scale or USD 6.5—the loss is equivalent to more than 40% of the value of maize harvested. For households at the upper end of the distribution, those that harvest more than TZS 170,000 per capita—corresponding to about twelve on the log scale or USD 145—the net benefit appears to level out at about 40% of the value of maize harvested. It is also interesting to note that the *none* case is always higher than the other scenarios for farmers who lose from higher food prices. For instance, for households with a total harvest value of about TSZ 13,000 (USD 11), the loss as a share of total maize harvest is about 13 percentage points higher when one considers both inter-temporal and spatial price heterogeneity (a reduction from about −0.21 to −0.34 and the difference is significant at a 5% significance level). The one exception is when we use the *space* case. For farmers who are net sellers of maize, the gains are higher in this scenario, as the local price for maize sales is higher than the market price. However, in this range, the differences are not statistically significant. In sum, especially for the poorest farmers in terms of maize production, the losses incurred increase substantially when one considers local prices and allows for differences in timing of maize transactions.

17 More in particular, we use locally weighted polynomial regression as implemented by the R lowess function (Cleveland, 1981). The reason why we deviate from standard practice to use a kernel average smoother is that locally weighted regressions are better at estimating functions at the boundaries. Because we are especially interested in the effect for the poorest and the richest, we believe locally weighted regressions are more useful.

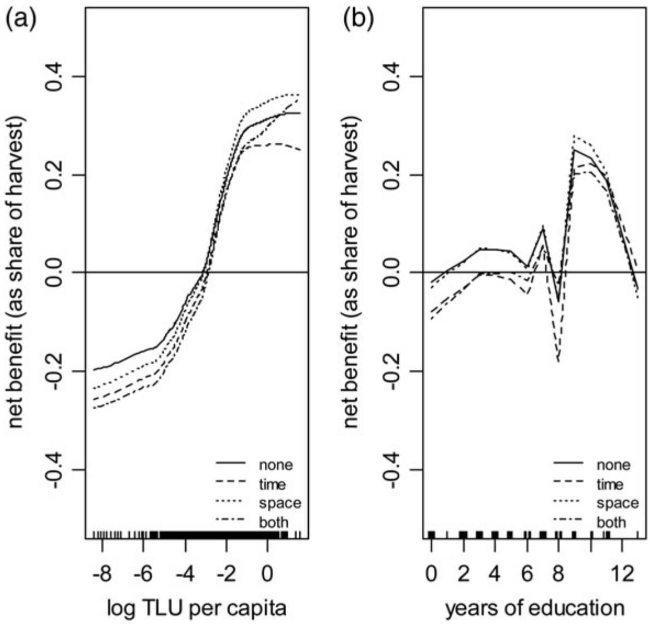

Figure 3: NBRs by Livestock and Education.

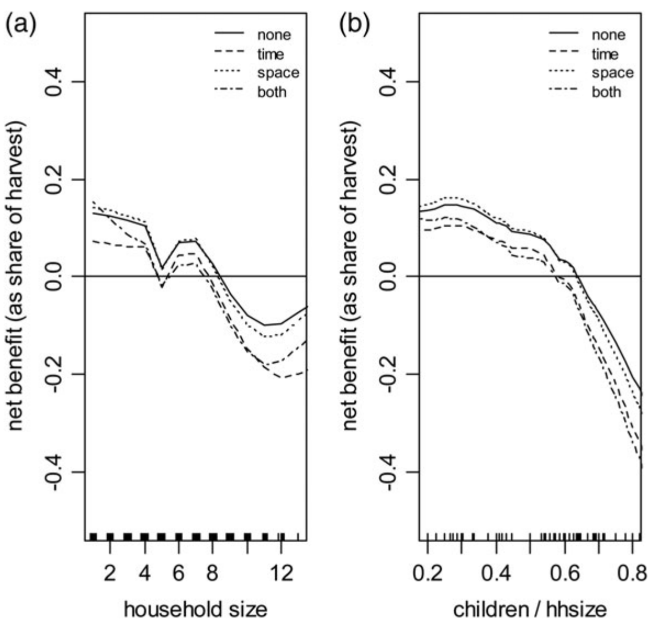

Figure 4: NBR by Household Size and Percentage of Children.

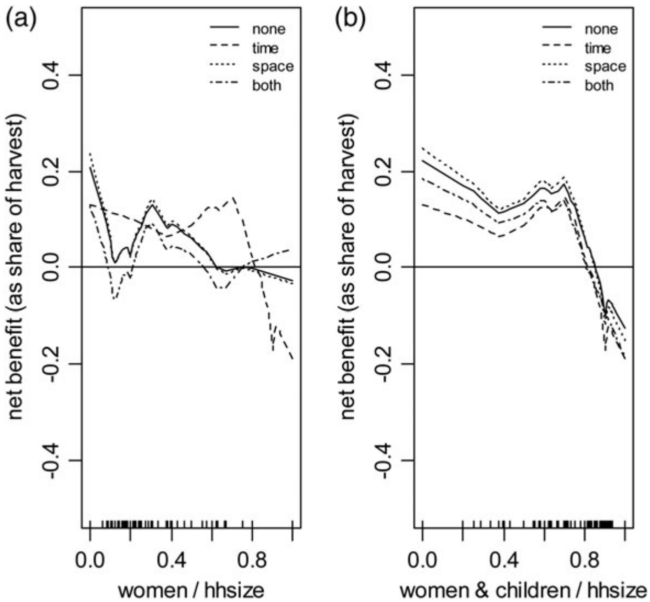

Figure 5: NBR by Percentage of Women and Percentage of Women and Children.

In panel (b), we consider land access as asset. As in panel (a), we take logs after controlling for household size. We again find an upward-sloping pattern of the net benefits, but this time it is slightly less steep. For households that have only about 0.13 acres of land per capita, the loss is also equivalent to about 40% of the value of maize harvested. While, as in the previous panel, the least restrictive way to calculate net benefit as a share of total maize harvest (*both*) shows larger losses when farmers are net buyers, we now observe that the restrictive measure (*none*) underestimates the gains for net sellers. Put differently, our analysis suggests that rising food prices will increase inequality more than what is suggested by studies that only look at aggregated marketing behaviour and prices. However, the differences between the different scenarios are not significant at a 5% level.

Panel (a) in Figure 3 assesses assets in terms of livestock holdings. One self-insurance strategy often observed in the face of a covariate shock like a food price crisis is to use savings as a buffer stock (Deaton, 1991). Livestock may be an obvious asset to use for this purpose, because it has a positive return (Verpoorten, 2009). We aggregate livestock assets in TLUs. For a household of average size (5.6 members), the net benefit scaled by the maize harvest become positive at about TLU 0.6. This is interesting, as a value lower than this would be typical for a household that only has small animals such as chicken and goats. We see that especially for households at the lower end of the TLU distribution, net benefit measures that aggregate prices (*none*) underestimate the losses due to price changes compared with less aggregate measures, although the differences with other scenarios are not statistically significant. For instance, for a typical family with about TLU 0.4 (which would mean something like one pig, one goat and ten chicken), the maize price change would reduce the value of the maize harvest by about 13% if one does not take into account price disaggregation (*none*).

This loss would amount to about 21% if one takes both price differences over time and space into account.

In the second panel of Figure 3 we also look at the correlation between years of schooling and the net benefit as a percentage of total maize harvest. While the pattern is not monotonous, farmers with no education seem to lose out from the 2007 to 2008 maize price increase. For the least restrictive case (*both*), the loss amounts on average to about 10% of total maize harvested. A standard analysis that relies on aggregate prices (*none*) would predict slight gains for households with a head that has at least some education. When prices are disaggregated by time (*time* and *both*), there are only gains for household heads that have completed grade 7. Unfortunately, again, none of these differences are statistically significant.

It is argued that the welfare effect of increasing food prices may differ across members within the household. Although the degree varies across countries and regions and by household characteristics (Quisumbing, 2003, p. 118), often children and women are most at risk. We can get a sense of this effect by looking at household demographics. If we find that it is particularly households with relatively more women, children or both that have lower benefit ratios, this should alert us that the consequences of rising food prices may be particularly bad for some.

In Figures 4 and 5, we plot net benefit as a share of total maize production against different measures of dependency. In the first panel (a) of Figure 4, we simply correlate net benefit with total household size. It is clear that the effect of high prices becomes negative if households exceed seven members. As in Figure 2, we plot four non-parametric regression lines corresponding to our four cases. Also here, we see that the aggregated case (*none*) seriously underestimates the negative effect on large households. The influence in terms of the share of total maize produced almost doubles at around a household size of eleven if one allows for disaggregation of sales and purchases over the agricultural year and accounts for price differences between rural areas and trade centres.

The second panel of Figure 4, (b), plots benefit ratios against the share of children within total household size. This can be thought of as a child dependency ratio.[18] When more than 60% of the household members are children, we see that the effect of a maize price increase becomes negative. Also here, we see that the method that aggregates prices in both space and time (*none*) underestimates this negative influence as compared with more flexible specifications. Households with less than 60% children, on average, benefit from a price increase, but the effects are overestimated by the baseline scenario (*none*). Unfortunately, confidence intervals suggest that differences between the scenarios are not significant.

The first panel of Figure 5, (a), plots benefit ratios against the share of women within total household size. This gives us an idea of whether households with relatively more female members are more or less likely to benefit from the increase in maize prices during the 2007–2008 agricultural year. While the pattern is much more erratic than in previous figure, there seems to be a slight downward trend, indicating falling benefits from a price rise as the number of women as a share of total household size increases. More importantly, the aggregate case again seems to overestimate the gains and underestimate the losses, but the difference with disaggregated cases is not significant. The second panel of Figure 5, (b), combines the latter two assessments. In sum, these results suggest that households with a high

18 In fact, child dependency ratios are defined as the ratio of the number of children over the active members within the household, which can become larger than one.

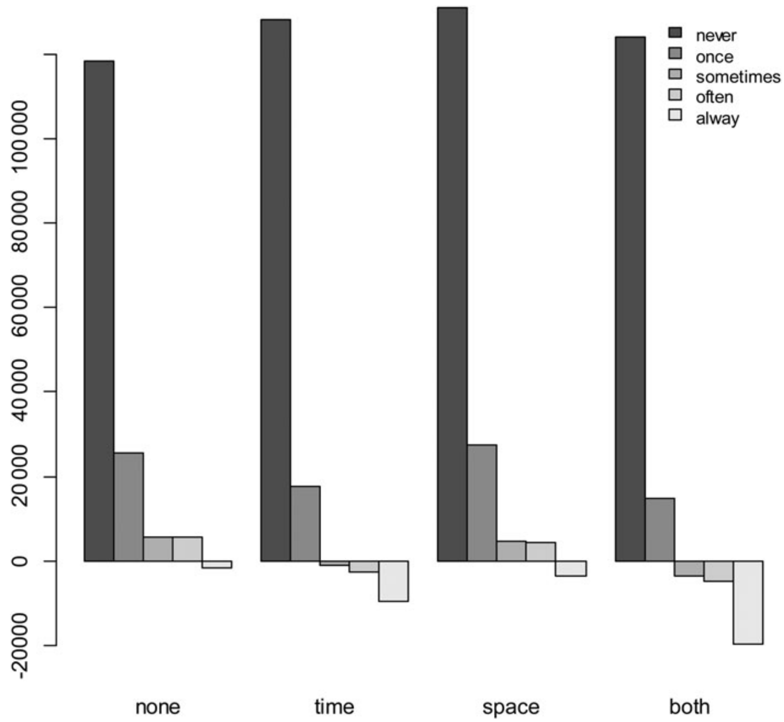

Figure 6: Average Gain or Loss by Food Insecurity Category.

share of women and children are likely to be hurt most by a maize price increase. Again, differences are not significant.

We now have a look at average losses and gains grouped by a qualitative variable. Figure 6 categorises households into different groups depending on their reported food security status. There were five possible answers to the question on how often the household experienced food problems over the last agricultural year, ranging from *never* to *always*. We see that for households never experiencing food problems, about 260, the average gain from market participation is large and positive. These farmers seem to gain most from exploiting the price difference between their location and the terminal market (i.e., the case referred to as *space*). This loss of potential benefits becomes much larger for farmers reporting to have experienced food problems once during the last year. When farmers report to have been 'sometimes food insecure', the benefit turns into a loss once interpersonal price variability and marketing are incorporated into the analysis, suggesting that most of this loss stems from seasonal price variation (i.e., sell low, buy high or both).

Figure 7 presents average net gains or losses by a selection of other categorical variables. For instance, one factor that will affect a farmer's potential to exploit spatial and temporal price variation to his advantage is his access to transport. We therefore grouped the households into three categories: those that own no means of transport, those that own at least one bicycle or an ox and a cart (non-motorised) and those that own a car (sedan, pickup or truck). Panel (a) of Figure 7 gives mean net benefits or losses from the increase in maize

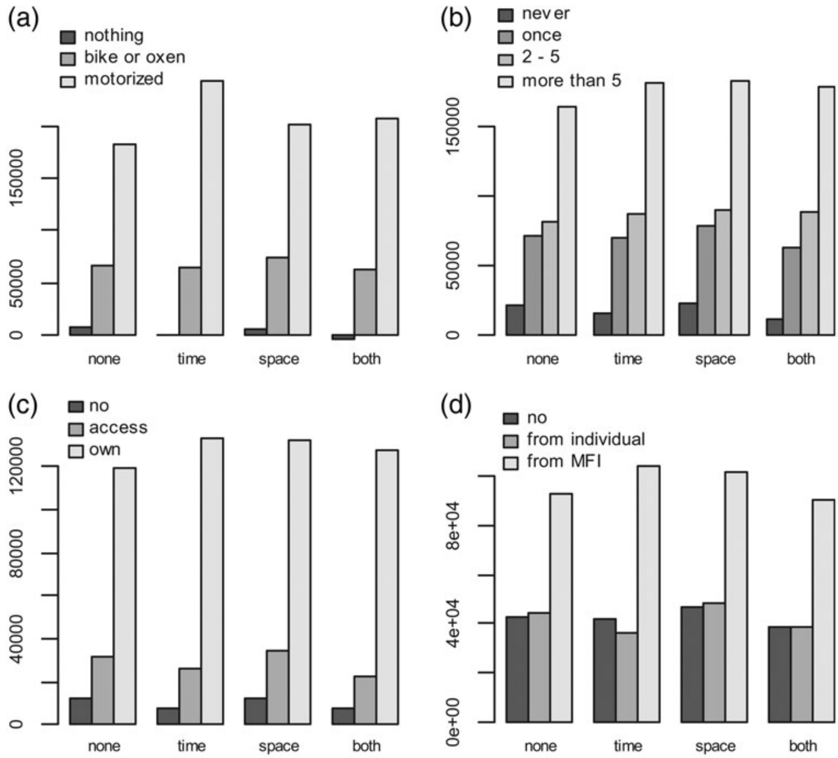

Figure 7: Average Gain or Loss by Selected Categorical Variables.

prices for the four different ways of calculating the first-order effect. For those who have no other option than to walk, it seems that the average loss should be mainly attributed to their inability to sell, buy or both sell and buy at the right time. Those who have motorised transport win most from the maize price changes over time. We would have expected to see a larger increase in spatial arbitrage here. It seems that spatial arbitrage is not so much driven by motorised transport. In fact, the group that reports possessing an ox and cart or bicycle seems to profit from spatial price dispersion, but the effect is small.

Information, and especially price information, is also an important factor that will affect losses or benefits from price changes over time and space. We correlate net benefits with two proxies: the number of visits to a town (categorised) and mobile telephone access (no telephone, access to a telephone and ownership of a telephone). Panel (b) shows that every household wins on average, but the gains increase with the number of trips made to town during the last month. We see that, more than motorised transport, visits to town are correlated to household's ability to exploit spatial price heterogeneity, but again, the differences are small. Panel (c) suggests that mobile phone access and ownership is correlated with increased returns to maize price changes, with access to communication suggesting to a better ability to engage in spatial arbitrage and ownership correlated to increased inter-temporal price arbitrage.

Finally, access to credit may also be important, especially for inter-temporal arbitrage. Panel (d) divides the farmers into those who received no loan, those who received a loan from another individual and those who received a loan from a microfinance institution (MFI). Here, the data suggest that indeed, households that have access to loans from a MFI are also the ones that are able to turn inter-temporal price movements to their advantage.

In sum, our findings suggest that an analysis that disregards price heterogeneity underestimates the short run losses resulting from maize price increases such as those experienced during the 2007–2008 food price crisis. This is especially the case for households that are poor in terms of assets such as land ownership and education. Our analysis also suggests that especially vulnerable households, with higher dependency ratios, are likely to suffer from adverse price movements, and that conventional methods that rely on net benefit underestimate these losses. Finally, we find that access to non-motorised transport and higher frequency of town visits is positively correlated with farmers' ability to better deal with spatial price dispersion. Access to credit from a microfinance organisation is also positively correlated with farmers' capability to deal with inter-temporal price variation. Finally, mobile phones are positively related to one's capacity to exploit both inter-temporal and spatial price dispersion.

7. Conclusion, significance and policy recommendations

Recent price hikes in basic commodities have reignited interest in simple tools that can be used by for instance governments, donor agencies and NGOs to analyse distributional consequences. Many of these tools rely on the idea that semi-subsistence farm households are affected mainly through their interaction with the market, as both sellers and buyers. As such, commodity price changes are multiplied by each household's net sales to (or purchases in) the market. Often, these methods work with prices that are the same, irrespective of when or where those sales and purchases were done. This article attempted to point out the consequences of such aggregation and suggests simple extensions allow for different prices and marketing behaviour over space (integration) and over time (seasonality).

We do this by looking at how the evolution of maize prices during the 2007–2008 food crisis affected a sample of semi-subsistence farmers in a maize-producing area in the Southern Highlands of Tanzania throughout the agricultural year. Unlike other studies that try to assess the effect of price changes, we pay specific attention to the timing of households' sales and purchases over time. In addition, we depart from the implicit assumption made in most studies that rural households face the same prices as the prices prevailing at more aggregate levels (regional, national).

We find that poorer households lost substantially from the evolution of maize prices during the 2007–2008 agricultural year. More important, we find that studies that do not properly account for seasonal price variability and differences between terminal market prices and local prices tend to underestimate the negative first-order effect of rising food prices. We also find that larger households tend to benefit less from price changes than smaller ones. Especially households with lots of children and few adults experienced sizable costs due to the increased maize prices during the 2007–2008 crisis. Because women and children are likely to be most at risk from adverse price shocks, this indicates substantial problems in terms of food and nutrient intake that are not reflected in household-level analysis.

While this article is limited in geographical scope and only looks at first-order effects, we feel it is nevertheless important. Recently, food prices have been reported to be on the rise again, reaching levels reminiscent of the 2007–2008 crisis. Therefore, studies that aim to assess the consequences of these price crises continue to remain relevant. This study underlines that it is important to look beyond the average effects, as some households will gain from higher food prices and some will lose from them.

With respect to the narrow geographical focus of this study, we strongly feel that the points made in this article are relevant in other areas as well. There is no reason to believe that the reported large seasonal price variations do not occur in other regions. Indeed, Sahn (1989) reports that regular, sharp seasonal price fluctuations are a common characteristic in many developing countries. Likewise, the existence of substantial transaction costs is characteristic of agricultural-based societies with poor infrastructure, lack of commercial credit and the virtual absence of insurance, leading to spatial price variability for otherwise homogeneous commodities.

Another concern may be the fact that we only study first-order effects. It does not incorporate the demand or supply response from household. In other words, it assumes households do not alter consumption or supply of commodities in the light of a price change. While the importance of such effects is an empirical issue, especially poor people may not have many degrees of freedom with respect to behavioural adjustments to a price increase. Substitution options for the poor are relatively limited (the poor will already spend the bulk of their budget on the cheapest commodities) and their nutrient intake is often so low that reducing consumption even more is not an option. In addition, one could argue that the effects would be less dramatic in the long run due to the increase in the price elasticity of the wage rate to the price of staples (Ravallion, 1990). However, Rashid (2002) argues that this elasticity is low. Even more, Christiaensen and Demery (2007) also estimate the second-round effects of a price change on agricultural productivity. They find that this effect is negligible and conclude that higher food prices are likely to increase poverty, even after taking wage and productivity adjustments into account.

As these sharp seasonal price fluctuations seem to be a regularity, credit would seem to have a key role to play here. Although we do not observe the *sell low, buy high* strategy very often, it is striking that most households sell at a price that is very low compared with what they could get in a not-so-distant future. More research is needed to find out where investment can generate most benefits. For instance, what is the role of on farm storage? Is there scope for a public private cooperation to increase storage facilities? Or would extension on post-harvest practices be more rewarding? What is the importance of distress sales? If so, given the substantial forgone benefits, it may make sense for MFI to approve more loans. Until this happens, governments should make a priority of social safety nets to safeguard national intake of the poor in periods of sharp increases in commodity prices.

Supplementary material

Supplementary material available at *JAFECO* online.

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