IMPACTS OF WORLD FOOD PROGRAM LOCAL AND REGIONAL PROCUREMENT OF FOOD AID ON MARKETS, HOUSEHOLD WELFARE AND FOOD SUPPLY CHAINS IN AFRICA

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ABSTRACT

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Local and regional procurement (LRP) relative to global food aid deliveries saw a sharp increase from 8% in 2001 to a historical high of nearly 30% in 2011. Despite this growing importance, relatively little is known about the LRP impacts on local market prices, household welfare, and food supply chains, especially in countries where LRP has represented a meaningful share of marketed surplus. This dissertation addresses this knowledge gap using three self-contained but related essays.

Essay one assesses the World Food Program (WFP) LRP effects on the level and variability of market prices for maize in Uganda and Mozambique, and beans in Ethiopia. Using data spanning 2001 to 2011, we employ two complementary methodologies as a consistency check: (1) a vector autoregression (VAR) model, which is a reduced-form econometric approach; and (2) a computational model (CM), which is a structural modeling approach. Results from the VAR show average price increases brought about by LRP are statistically significant, ranging from 2% in Nampula (Mozambique) to 16% in Lira (Uganda). In all three country applications, LRP has no economically meaningful effect on price variability. When LRP is at its historical mean levels, price effects from the CM fall within the 90% confidence bounds obtained from the VAR. This suggests that the two complementary methodologies deliver consistent results.

Price increases induced by LRP purchases have welfare implications for households that buy and/or sell those commodities. In essay two, we use nationally representative household-level data to convert the estimated price increases into estimates of the corresponding household welfare effects. This is accomplished by estimating the household's willingness to accept compensation for the price increase. Due to data limitations, essay two focuses only on maize in Uganda and Mozambique. Average welfare effects in both countries are negative but fairly small in relative terms (less than 1% loss). However, 8.9% of households in Uganda and 6.9% in Mozambique experience welfare gains or losses greater than 3%. Household welfare effects vary substantially in both countries, ranging from -10% to +11% in Uganda and from -7% to +8% in Mozambique.

In addition to these price and welfare effects, the overall effects of LRP activities depend on the systemic effects that WFP is able to induce in food supply chains as the agency goes about its procurement. Essay three, therefore, employs a case study approach to complement the first two essays by investigating traders and processors responses to engagement with WFP and their perceptions of the LRP effects on food supply chains. Essay three focuses on three commodities and four countries: maize in Uganda and Mozambique, beans in Ethiopia, and high energy protein supplements (HEPS) in Ethiopia and Malawi. Two main findings stand out. First, WFP has positively influenced the "quality culture" on maize in Uganda, beans in Ethiopia, and HEPS in Ethiopia and Malawi. Second, WFP operations have spurred market entry in the Malawian and Ethiopian HEPS sectors, have facilitated greater commercial competitiveness of the Malawian HEPS and Ethiopian bean sectors, but have had limited effect on market entry in Mozambique's maize sector.

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CHAPTER 1

INTRODUCTION

The effects of food aid shipped directly from donor countries to recipient countries – referred to as transoceanic food shipment – have been extensively studied. The vast majority of the existing literature (e.g., Barrett, Mohapatra and Snyder, 1999; Bezuneh, Deaton and Zuhair, 2003; Abdulai, Barrett and Hoddinott, 2005; Gelan, 2007; Zant, 2012) focuses on the disincentive effects of transoceanic food aid shipments on food production, food consumption and commercial imports in recipient countries. Findings from this strand of the literature are mixed and appear to be case specific. For instance, Abdulai, Barrett and Hoddinott (2005) found that after controlling for endogeneity of food aid, transoceanic food shipments do not have disincentive effects on domestic food production in Ethiopia at both macroeconomic and household levels. By contrast, findings from Gelan (2007) indicate that food aid arrivals have depressing effects on domestic food production in Ethiopia. Zant (2012) found negligible effects of maize food aid received by Malawi on domestic maize production when the share of the total domestic maize demand accounted for by maize food aid was below a threshold of 10%. Above this threshold, the effects are increasingly negative and meaningful. Another extensive strand of the literature on food aid (e.g., Clay, Molla and Habtewold, 1999; Jayne *et al.*, 2001; Jayne *et al.*, 2002; Barrett and Clay, 2003; Gilligan and Hoddinott, 2007) addresses issues related to efficiency and effectiveness of food aid targeting. This literature points out that distributions of food aid to beneficiaries are generally characterized by imperfect targeting and food aid is distributed to politically connected households at the expense of the most needy households.

However, there is only a very small body of the literature on the impacts of transoceanic shipments of food aid on local markets. Mabuza *et al.* (2009) found that the distribution of maize food aid shipped directly from donor countries did not have a discernible effect on local maize prices in Swaziland. On the other hand, Tadesse and Shively (2009) estimated that the effects of food aid distribution on Ethiopian local prices for three commodities – wheat, maize and teff – are most likely to be negligible when the share of food aid in total food production is below a critical threshold of 10%. Above this threshold, food aid deliveries have increasingly dampening effects on prices. These findings are in line with those reported by Zant (2012).

Starting in the late 1990s, concerns regarding adverse effects of transoceanic shipments of food aid on the economies of recipient countries, coupled with changing agricultural policies in donor countries, made food aid agencies – including the United Nations World Food Programme (WFP) which is the World's largest agency administering multilateral food aid – move away from transoceanic shipments towards alternative modalities of food aid assistance to respond more quickly and effectively to food crises. In this regard, local and regional procurement (LRP) – the purchase of food commodities in the country or region where food aid is being distributed to targeted groups of households – became one of the predominant forms of food assistance. Data from the International Food Aid Information System (INTERFAIS) developed by WFP show that prior to 1995, LRP amounted to less than 5% of global food aid deliveries. However, this share increased sharply from 8% in 2001 to a historical high of about 30% in 2011.[1]

From an economic viewpoint, transoceanic food shipments are fundamentally different from LRP. Transoceanic shipments increase food supply in recipient countries, potentially reducing food prices. This induced price reduction has welfare implications for food consuming and producing households. Net buyers – households whose food consumption exceeds food sales – benefit from the induced price reduction because they pay lower prices for their net food purchases. Net sellers – households whose food sales exceed food consumption – are hurt because their net sales occur at lower prices. By contrast, LRP puts upward pressure on domestic food demand in procurement countries, potentially pushing food prices higher. Hence, net sellers experience welfare gains from the price increase brought about by LRP, while net buyers suffer welfare losses. The overall welfare impacts of both transoceanic food shipments and LRP depend crucially on the relative contributions of food sales and food expenditures to total household income.

[1] In addition to transoceanic shipments and LRP, Upton and Lentz (2012) provide detailed descriptions of other modalities of food assistance including prepositioned food aid, cash transfers and distribution of vouchers.

Despite the growing importance of LRP, whether and by how much LRP affects local market prices significantly remains an open empirical question. Previous work on this topic has been quite limited. For example, Walker and Wandschneider (2005), Wandschneider and Hodges (2005), and Coulter, 2007 took a case-study approach and evaluated LRP impacts in Ethiopia and Uganda. Three main findings emerge from this research. First, LRP appears to have influenced investments in the trading systems in both countries. Second, LRP contributed to improved quality awareness for traders bidding on LRP tenders. Third, in some cases, LRP may have resulted in increases in local prices.

In a recent quantitative study, Garg *et al.* (2013) employed econometric methods to estimate the impacts of the United States Department of Agriculture (USDA) LRP pilot program on local market prices in seven countries. These authors found that the effects of USDA LRP on price levels and variability are not meaningful or statistically significant. This finding is not surprising because the USDA LRP pilot programs purchased very small amounts of food relative to the size of the market in all study countries, as recognized by the authors.[2] There is an absence of empirical studies evaluating LRP effects on local markets and households in countries where LRP accounts for meaningful shares of total marketed surplus, as argued by Awokuse (2011).

This study aims to fill this knowledge gap by investigating three potential impacts of WFP LRP: (1) the effect of LRP on the level and variability of local market prices, (2) the impacts of resulting price changes on the welfare of households selling and/or consuming commodities procured by WFP, and (3) the effect of LRP purchases and related training and inspection activities on investment decisions and trading practices of traders and processors in the food system, and hence on the development of the food supply chain. The study was conducted in four countries, each with a different commodity focus: maize in Uganda; beans and locally

[2] Garg *et al.* (2013) reported that quantities transacted through USDA LRP are generally considerably smaller than volumes procured by WFP. For example, these authors documented that during the fiscal year 2011, in Kenya, USDA LRP procured, on average, about 190 metric tons (MT) of maize per month, while WFP procurement averaged about 12,000 MT per month. USDA LRP constituted less than 1% of the total market size in all seven countries studied by Garg *et al.* (2013).

produced high energy protein supplements (HEPS) in Ethiopia; maize in Mozambique; and HEPS in Malawi.

The study consists of three self-contained, but related, essays. The first essay, presented in Chapter 2, uses two complementary methodologies to estimate LRP effects on local markets: (1) a vector autoregression model (VAR) that uses data on past food aid deliveries, LRP purchase quantities, and local market price movements to empirically estimate the impact of past LRP purchases on market prices; and (2) a computational model (CM) that uses a structural economic model of local price determination, along with data on the level of LRP relative to the size of the market in which it occurs and estimated values of key parameters, such as elasticities of supply and demand, to predict effects on local market prices. The second essay, presented in Chapter 3, uses household-level data to estimate the effect of the estimated LRP-induced price increases on the economic welfare of different types of households. In the third essay (Chapter 4), we take a case study approach using interviews with a wide range of stakeholders in each study country to investigate trader and processor responses to engagement with WFP, and their perception of the effects of WFP LRP on the food supply chain. Chapter 5 summarizes and integrates cross-cutting findings from all three essays.

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CHAPTER 2

MARKET LEVEL EFFECTS OF WORLD FOOD PROGRAM LOCAL AND REGIONAL PROCUREMENT OF FOOD AID IN AFRICA

2.1 Introduction

Transoceanic shipments of food commodities directly from donor countries to recipient countries used to be the dominant modality for food aid. However, starting in the late 1990s, food assistance began to move away from traditional transoceanic shipments towards more local and regional procurement (LRP) – the purchase of food commodities in the country or region where food aid is being distributed to targeted groups of households.[3] For instance, according to data from the International Food Aid Information System (INTERFAIS) developed by the World Food Program (WFP), the share of the total volumes of global food aid deliveries accounted for by LRP increased from less than 5% prior to 1995 to 8% in 2001 to about 30% in 2011.

LRP of food aid has been shown to have at least three important advantages over transoceanic food shipments. First, LRP generates large cost savings, making it possible to feed more people in need with a given emergency response budget. Tschirley and del Castillo (2007) show that locally or regionally procured maize in Kenya, Uganda, and Zambia costs only 57% of what it would have cost to buy and ship transoceanic food commodities. These cost savings allowed 75% more food to be provided to beneficiaries for a given budget allocated to food assistance. Clay, Riley and Urey (2005) found similarly large cost savings of 61% for maize and 52% for corn-soya blend (CSB). GAO (2009) also found comparable savings.[4] Second, LRP reduces the time it takes to deliver food, increasing the timeliness of response to food crises. GAO (2009) found that, compared to an average delay of 150 days for delivery of in-kind

[3] According to Upton and Lentz (2012), food assistance instruments used by aid agencies to respond to food emergencies include transoceanic shipments, prepositioned food aid, local and regional procurement, cash transfers, and vouchers distributions. The appropriateness of one instrument over another depends on the specific recipient-country context and the overall objectives of the food assistance intervention.

[4] Lentz, Passarelli and Barrett (2013) found nearly identical savings for grains and pulses even when examining the small-scale LRP purchases of United States Non-Governmental Organizations funded under United States Department of Agriculture programs. For CSB and vegetable oil, however, they found that these small-scale transactions sometimes resulted in higher total cost, not lower.

transoceanic food aid, locally procured food took only 35 days, and regionally procured food took 41 days. Lentz, Passarelli and Barrett (2013) found LRP food commodities could be delivered in 14 fewer weeks, equivalent to a 62% reduction. Third, as argued by Tschirley and del Castillo (2007), GAO (2009), Violette *et al.* (2013) and others, LRP food commodities are generally more suited to local culture and tastes and preferences of beneficiaries, compared to donor-sourced food commodities shipped directly from developed countries. Indeed, Violette *et al.* (2013) found that in both Zambia and Guatemala, consumption of locally procured food commodities, as opposed to those sourced from the United States (US), had statistically significant and positive impacts on satisfaction levels achieved by food-aid receiving households.

Despite these advantages, very little is known about the effects of LRP on local markets and prices in the regions where LRP purchases are occurring. Early studies (Walker and Wandschneider, 2005; Wandschneider and Hodges, 2005; Coulter, 2007) used a case study approach and found that LRP had helped drive some investment in the trading systems of Uganda and Ethiopia, had driven improved quality practices for WFP transactions, and may have contributed to improved export trade of some foods in Ethiopia. Yet these studies also suggested that LRP had failed to have any appreciable effect on the broader trade and may in some instances have led to price spikes. With few years of experience to examine, these results had to be considered tentative.

More recent quantitative research (Garg *et al.*, 2013; Harou *et al.*, 2013; Lentz, Passarelli and Barrett, 2013) found that LRP had no detectable effect on local market prices or variability. However, these studies focused on small-scale LRP carried-out by US Non-Governmental Organizations (NGOs) under the US Department of Agriculture (USDA) pilot LRP programs. These pilot programs “were minuscule compared to the size of the market” (Garg *et al.*, 2013) and so it is not surprising they had no detectable effect. In this paper we focus on LRP undertaken by WFP – the World’s largest administrator of multilateral food assistance – in three African countries where LRP purchases have been high relative to the size of the marketed surplus, at least in some years. The analysis adds some new and important insights into the effects of LRP on local markets and prices and suggests that under some conditions these effects can be quite significant.

This study evaluates the effects of WFP LRP on local markets for maize in Uganda and Mozambique, and beans in Ethiopia. The study investigates the effect of LRP on the level and variability of local market prices. In addition to broadening our understanding of LRP effects on local market prices by offering new empirical evidence, the study also makes two methodological contributions. First, while we use a fairly standard structural vector autoregression (VAR) approach to estimating the effects of LRP econometrically, bootstrapping procedures are developed and used to place confidence intervals around the estimated effects on local price levels and variability. Previous applications of structural VARs to evaluate the effects of food policies (e.g. Jayne, Myers and Nyoro, 2008; Mason and Myers, 2013) have only provided point estimates, and therefore ignored the inherent sampling error associated with estimated policy effects.

Second, and perhaps more importantly, we develop and use a complementary "computational model" (CM) to validate results from the VAR. The CM is a structural simulation model that provides an alternative estimate of the LRP effect based on economic theory and best available knowledge on underlying elasticities, market shares, relative prices, trade patterns, etc. The advantages of including the complementary CM analysis are: (1) it provides an alternative estimate of the LRP effect that can be used as a consistency check on the more data-based VAR estimates; and (2) it provides an economic explanation and interpretation of the pathways through which LRP effects occur, unlike the VAR model which is generally "a-theoretic" and provides little information on *why* estimated effects occur. To our knowledge this is the first attempt to jointly apply and integrate these two potentially complementary methodologies.

This paper is structured in five sections. After this introductory section, Section two describes how study countries and commodities were chosen. It also provides brief descriptions of geographical regions, regional markets, and agricultural production and trade patterns for each country application. Section three is divided into four subsections. The first subsection outlines our structural VAR modeling approach, while the second presents the model setup and describes the data employed. Summary statistics, diagnostic tests and results are summarized in the last two subsections. We begin Section four by briefly comparing the two complementary modeling approaches (the VAR approach versus the CM). Then, we outline the mathematical derivation of the CM, followed by the description of the model setup and discussion of the results. The paper concludes in Section five with an evaluation of the robustness of results across the VAR and CM methodologies.

2.2 Country and Commodity Selection

We selected study countries and commodities based on three factors. First, the size of LRP purchases of a given commodity relative to the total estimated marketed surplus of that commodity in the relevant country. The impact of LRP on markets and, through markets, on farmers and consumers, depends critically on the size of LRP purchases relative to the total size of the market. While other factors can also intervene, effects from small purchases are likely to be small and therefore difficult to distinguish from the normal price variations seen in any market price. Second, the availability of price data of sufficiently long duration to support meaningful econometric analysis of LRP impacts on prices. With 11 years of data (2001-2011) from WFP on their LRP transactions, we looked for price series of at least monthly data that covered as much of this period as possible. Third, the absence of other factors such as large-scale government purchases that would make it difficult to isolate econometrically the effect of LRP purchases.

The five most procured commodities by WFP in Africa from 2001 to 2011 were maize, high energy protein supplements (HEPS), sorghum/millet, maize meal, and beans, accounting for 58%, 12%, 9%, 8% and 7%, respectively, of all procurement volumes.[5] Wheat is next at about 3%. The contribution of all other commodities is 1% or less. Given their relative importance, and data availability, this study focuses on the impacts of LRP purchases of maize and beans. We excluded HEPS, sorghum and millet because price data for these commodities are generally not available. We excluded wheat because WFP's wheat purchases in Ethiopia,

[5] From the product names in the WFP tender data base, we define HEPS to include biscuits, CSB, Faffa, high energy biscuits, Likuni Phala, pea-wheat blend, high energy supplements, and ready to use supplementary food.

the only African country with a meaningful wheat LRP program, have been less than 1% of the marketed surplus in the country.

Figures 2.1 and 2.2 show the mean, minimum, and maximum LRP purchases of maize and beans as a share of estimated marketed surplus of these commodities in the main African countries in which WFP operates. Data cover the period 2001-2011. LRP purchases were obtained from the WFP through their Information Network and Global System (WINGS) and estimated marketed surplus is obtained by multiplying production data from FAOSTAT by an estimate of marketed share of production. In countries where nationally representative household survey data are available (Mozambique, Zambia, Kenya, Uganda, and Malawi), we used the household surveys to compute the marketed share of production of each crop during the survey years. In other countries, estimates of marketed shares of production are obtained from Tschirley and del Castillo (2007). Marketed shares of production for each relevant country are assumed to be the constant across the sample. This seems like a reasonable assumption because representative household-level data from Mozambique and Uganda show that marketed shares do not show considerable variation across survey years.[6]

[6] Estimating LRP bean purchases as a proportion of marketed surplus is more difficult because bean production frequently takes place in very small quantities at farm level, is more frequently intercropped than maize, and tends to be less commercialized. These factors make production data for beans subject to more error than for maize.

Figure 2.1 LRP purchases of maize as share of marketed surplus, 2001-2011

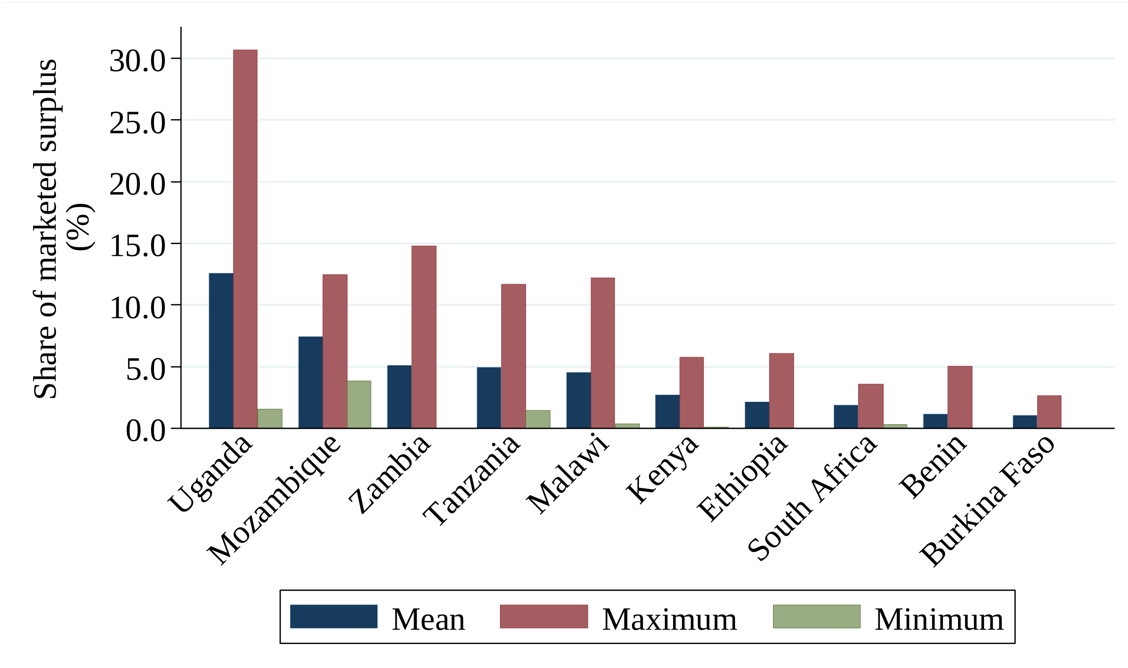
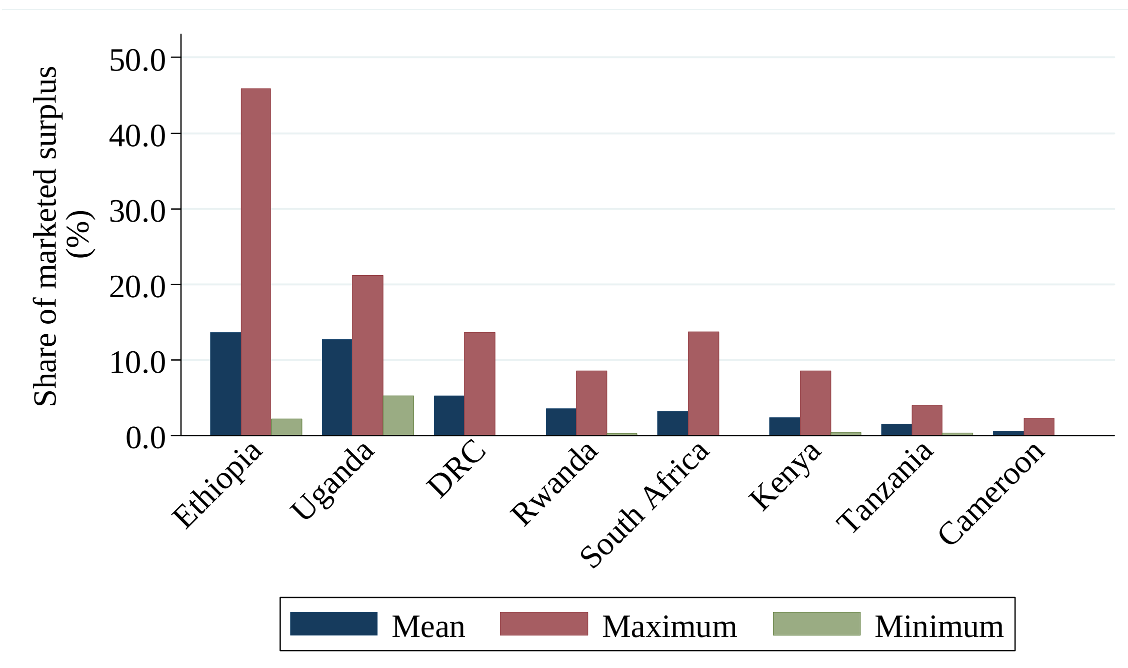


Figure 2.2 LRP purchases of bean as share of marketed surplus, 2001-2011



In order, mean LRP purchases of maize as a share of marketed surplus were highest in Uganda (14%), Mozambique (7%), Zambia (6%), Tanzania (5%), and Malawi (4%). Maximum share also matters, because it can drive large effects in years of high purchases even if there are modest effects in other years. In this regard, Uganda has by far the highest maximum share at more than 30%, followed by Zambia at 14% and then Mozambique, Tanzania, and Malawi at 11 to 12% (Figure 2.1). Figure 2.2 shows that Ethiopia has the largest LRP share of marketed surplus for beans, with mean and maximum estimated shares of 14% and 46%, respectively. Uganda follows closely at a mean of about 13% and a maximum of 21%. In all other countries, average LRP purchases of beans as a share of marketed surplus are 5% or less.

These data suggest Uganda, Mozambique, and Zambia as candidate countries for analysis of LRP purchases of maize. We excluded Zambia due to the very large market presence of the Food Reserve Agency (FRA) especially since 2006, which would make it difficult to isolate the impact of LRP.[7] Available price data for Uganda and Mozambique were sufficient to support the market modeling for maize, so these two countries were chosen for analysis. Bean purchases in Ethiopia and Uganda are sufficient to merit a focus on this commodity in those countries. However, lack of suitable price data precluded market level modeling for beans in Uganda. Therefore, we focused on beans only in Ethiopia. Before outlining our methodological approach, we provide brief descriptions of geographical regions, regional markets, and agricultural production and trade patterns for each country application. In the analysis that follows we use this information to break each country into key domestic regional markets (see sections 2.3.2 and 2.4.2).

Uganda is divided in four administrative regions: Eastern, Central, Northern and Western. Central Uganda is a maize deficit region and is dominated by the urban center of Kampala, the country's capital city and largest urban center. Eastern, Northern, and Western regions all produce a maize surplus. Kisenyi is the main wholesale maize market in Kampala. Large and medium-sized maize traders throughout the country monitor prices in Kisenyi and many of them trade there. Kisenyi is therefore the largest and most liquid market for price discovery. Masindi in the Western region, Lira in the Northern, and Mbale and Kapchorwa in

[7] Mason and Myers (2013) report that FRA expenditures accounted for about 2% and 7% of the Zambia's gross domestic product and total government expenditures in 2006 and 2007, respectively. They also document that FRA purchases as a share of smallholder maize sales in Zambia increased sharply from 16% in the 2002/03 marketing season to 86% in 2006/07.

the Eastern region are four major maize producing areas and key markets in their respective regions. These four markets are also key sources for maize flowing into Kampala and crossing the border into Kenya, South Sudan, and the Democratic Republic of the Congo (DRC).

Agriculture in Mozambique is often separated into three regions: the Northern region consisting of the provinces of Niassa, Cabo Delgado, Nampula, and Zambezia; the Central region including Tete, Manica, and Sofala provinces; and the Southern region encompassing Inhambane, Gaza and Maputo provinces. Northern and Central Mozambique are maize surplus regions, while Southern Mozambique is deficit during every year. The capital city of Maputo in Southern Mozambique is the largest city and major consumption center in the country. Maputo is also a major liquid market where a lot of price discovery takes place. In the Central region, Beira is a larger city than Chimoio but is in a deficit portion of the surplus region. Chimoio is in the center of the surplus area and has historically been an important maize market. Nampula is the dominant market in Northern Mozambique.

Northern Mozambique and Tete province are important sources for maize crossing the border predominantly into Southern Malawi. Maize from the Central provinces of Manica and Sofala flows primarily to informal markets and animal feed manufacturers in Southern Mozambique (especially to Maputo). South African maize is imported by large millers in Southern Mozambique due to concerns about low quality and poor reliability of domestic supply in local markets, and the resulting maize meal is viewed as a different product in the market than meal from locally produced maize.

Ethiopia is divided into ten administrative regions: Affar; Amhara; Benishangul-Gumuz; Dire Dawa; Gambella; Harari; Oromia; Somali; Southern Nations, Nationalities and People (SNNP); and Tigray. Ethiopia grows at least three different types of bean, each of which is supplied to different domestic and international markets and is affected differently by policy. White haricot beans are almost entirely exported to international markets (Europe, Middle East and South Asia), while red haricot and horse beans are supplied to domestic and regional markets (especially Kenya, South Sudan and Djibouti). WFP has procured all three types of beans in

Ethiopia, but more recently red haricot beans dominates WFP purchases due mainly to a government policy mandate.[8]

Production of beans in Ethiopia is highly concentrated in three regions: Amhara, Oromia, and SNNP. Together these three regions account for about 95% of total bean production in the country and are key sources of beans flowing to deficit areas. All remaining administrative regions are deficit bean producers. Oromia and SNNP are very similar regions from a bean production viewpoint. Awasssa, the key bean surplus market in the SNNP region, is a more important bean surplus market than the capital city of Addis Ababa (Oromia region). Although Addis Ababa is located in a major bean producing region, high population density and urbanization create sizeable demand for beans in Addis Ababa, making it behave more like a deficit market than a surplus market. Dessie is one of the main bean surplus markets in the Amhara region. Dire Dawa (Dire Dawa region) is second only to Addis Ababa as the largest city in Ethiopia, generating a large demand for beans. Hence, Dire Dawa is viewed as the main market for price discovery.

2.3 Vector Autoregression (VAR) Model

Several econometric approaches could be used to model the impacts of LRP on markets. One possibility would be to build a structural simultaneous equation model (SEM) of supply, demand, and price determination relationships, and then estimate all parameters and LRP effects econometrically using a sample of historical data. We instead chose a reduced form vector autoregression (VAR) approach for two main reasons.

First, VAR models have proven useful when data are not available on all of the variables required to build a full structural econometric model (see, for example, Myers, Piggott and Tomek, 1990; Jayne, Myers and Nyoro, 2008; Mason and Myers, 2013). As in many developing countries, the SEM approach is impractical in our country applications because the required data are simply not available. In particular, detailed historical data *are* available on maize and bean prices from various markets, the quantity of food aid deliveries, and LRP purchases. But

[8] In 2010, the Ethiopian government mandated that the Ethiopian Commodity Exchange be the only channel through which private traders and exporters can trade white haricot beans.

consumption data, storage data, data on factor prices, and data on the prices of other competing commodities are available only sporadically or not at all.

Second, the VAR imposes fewer over-identification restrictions. The VAR estimates historical correlations between variables of interest (in our case, food aid, LRP purchases, and local prices). These historical correlations are then exploited using minimal identification restrictions to estimate the net effect of LRP purchases on local prices. By contrast, SEM requires a set of assumptions regarding the economic structure of supply and demand relationships underlying the markets when we are, in fact, often uncertain about what these relationships really are. Different assumptions can then drive very different model results, with no easy way of determining which results are preferred. This makes VAR a more attractive approach when we are faced with substantial uncertainty about the economic structure driving price determination relationships.

2.3.1 Modeling Procedures

Here we adopt the structural VAR framework used by Myers, Piggott and Tomek (1990), Jayne, Myers and Nyoro (2008), and others to analyze the effects of food price policies. Unlike these authors, and given that point estimates are subject to sampling error, we use bootstrap methods to construct confidence intervals for our point estimates of LRP price effects. See Runkle (1987) for a discussion of why constructing confidence bounds under VAR modeling is important. We estimate separate VAR models for each country application but they all have the same basic structure which will now be outlined.

Two types of variables are included in each country model. First there are WFP choice variables consisting of food aid deliveries FA_t in month t and LRP purchases LRP_t in month t. These variables are chosen by WFP on the basis of food aid needs and local food availability and prices. Second there are n local price variables $P_{1t}, P_{2t}, ..., P_{nt}$ representing prices in different local markets in month t. The relationship between the WFP choice variables and local price variables is captured with a flexible dynamic model specified as:

(2.1) $$\mathbf{D}\mathbf{x}_t = \mathbf{Q}^{\mathbf{x}}\mathbf{y}_t^{\mathbf{x}} + \sum_{i=1}^{k} \mathbf{D}_i \mathbf{x}_{t-i} + \sum_{i=0}^{k} \mathbf{G}_i \mathbf{p}_{t-i} + \mathbf{A}^{\mathbf{x}}\mathbf{u}_t^{\mathbf{x}}$$

$$\text{(2.2)} \qquad \mathbf{B}\mathbf{p}_t = \mathbf{Q}^{\mathbf{p}}\mathbf{y}_t^{\mathbf{p}} + \sum_{i=0}^{k}\mathbf{C}_i\mathbf{x}_{t-i} + \sum_{i=1}^{k}\mathbf{B}_i\mathbf{p}_{t-i} + \mathbf{A}^{\mathbf{p}}\mathbf{u}_t^{\mathbf{p}}$$

where $\mathbf{x}_t$ represents the set of WFP choice variables; $\mathbf{p}_t$ denotes the set of local market prices; $\mathbf{y}_t^{\mathbf{x}}$ and $\mathbf{y}_t^{\mathbf{p}}$ are vectors of deterministic components (e.g. a constant term and, if necessary, deterministic trend and seasonal components); $\mathbf{D}$, $\mathbf{Q}^{\mathbf{x}}$, $\mathbf{D}_i$, $\mathbf{G}_i$, $\mathbf{A}^{\mathbf{x}}$ and $\mathbf{B}$, $\mathbf{Q}^{\mathbf{p}}$, $\mathbf{C}_i$, $\mathbf{B}_i$, $\mathbf{A}^{\mathbf{p}}$ are matrices of parameters to be estimated; k is the maximum number of lags allowed; and $\mathbf{u}_t^{\mathbf{x}}$ and $\mathbf{u}_t^{\mathbf{p}}$ are vectors of mutually uncorrelated error terms representing unanticipated shocks to each variable.

We impose a Cholesky decomposition (recursive model structure) to identify structural contemporaneous interactions among variables in the system, leaving the dynamics unrestricted. This is the most extensively used identification scheme in this literature (Sims, 1980; Hamilton, 1994). In particular, we impose $\mathbf{G}_0 = \mathbf{0}$; $\mathbf{D}$ and $\mathbf{B}$ lower triangular with ones along the diagonal; and $\mathbf{A}^{\mathbf{x}}$ and $\mathbf{A}^{\mathbf{p}}$ diagonal. Since we order FA_t first this implies food aid does not respond to changes in *current* values of any variables in the system (though, of course, it remains responsive to changes in past values of all variables through the lagged terms). This seems like a reasonable assumption because food aid needs are usually determined ahead of food aid deliveries, and food aid delivery is not likely to be much influenced by current (i.e., within the delivery month) local market conditions. These restrictions also imply LRP_t responds to changes in current values of FA_t, and lagged but *not current* prices. This also seems like a reasonable assumption because it makes sense that LRP purchases respond immediately to changing food aid needs. And although LRP choices are undoubtedly sensitive to local prices, the length of the tender process is such that LRP deliveries in any month are mainly determined by past prices and have little flexibility to be changed immediately in response to current market price changes.

We then allow all prices be influenced by current as well as past food aid deliveries and LRP. This provides maximum opportunity for local prices to respond immediately to changes in WFP food aid and LRP decisions. A logical recursive ordering for the prices is to place the largest and most liquid local market first in the price ordering and other less important market prices lower in the ordering. This is because most price determination is likely to take place in the larger liquid market, with effects then filtering down to other local markets.

The recursive ordering is important because it provides identification of $\mathbf{u}_t^x$ and $\mathbf{u}_t^p$ as uncorrelated food aid, LRP, and local market price shocks. In turn, it is this identification that allows simulating the effects of alternative food aid and LRP paths on local market prices (assuming local price shocks follow their historical estimated path). Alternative recursive orderings are possible, as are more general approaches to identification that do not rely solely on a recursive structure (see Stock and Watson, 2001). However, the recursive ordering described above fits well with the structure of WFP decisions on food aid and LRP, as well as with the economics of price determination in local markets. It therefore seems like a reasonable way to achieve identification in the current application.

The recursive VAR represented by equations (2.1) and (2.2) can be estimated by applying ordinary least squares (OLS) to each equation in the system. If testing reveals some of the variables are nonstationary and cointegrated then the VAR is sometimes restricted to a vector error correction (VEC) form and estimated with maximum likelihood. Imposing VEC restrictions can lead to more efficient parameter estimates and improved statistical inference when included variables are nonstationarity and cointegrated. However, as shown by Sims, Stock and Watson (1990) and Hamilton (1994), even with nonstationary and cointegrated variables OLS estimates of the VAR form of the model will be consistent, although conventional OLS standard errors will be biased and inconsistent so standard statistical inference and hypothesis testing procedures are generally not applicable.

After the VAR has been estimated, LRP effects on local market prices are estimated by simulating the VAR over the estimation period. For the simulation, food aid is set to its actual historical value throughout the sample period. This is because we want to simulate the effect of eliminating the LRP on local market prices, but under the assumption that exactly the same amount of food aid would have been provided. In other words, when undertaking the simulation we assume that food aid would have remained at its historical values, so any reduction in LRP purchases would have been made up by additional WFP purchases outside the country, without any change in local food aid deliveries. This seems like the most sensible assumption for the simulation because we want to estimate the effect of LRP, not the effect of changing the amount of food aid delivered. Next we set LRP to zero starting at the first month in the simulation period and continuing right through the entire sample period.[9] Prior to the first month in the simulation period, however, LRP is assumed to have been at its historical level in the data. Using the estimated VAR parameters we then undertake a dynamic forecast of the local price variables, given historical food aid deliveries but no LRP, over the entire sample period.

For the simulation we use the same price shocks that were identified using the recursive ordering in the VAR (i.e., we assume that setting LRP to zero does not alter the historical market price *shocks*, although clearly there will be a response in the price levels themselves). The result is a set of counterfactual simulated local market prices that represent the estimated path that prices would have taken over the sample period if food aid deliveries had stayed the same and the markets were subject to their historical supply and demand forces, except that there had been no LRP purchases. Comparing the simulated counterfactual prices with actual historical prices highlights the estimated effect of the LRP activity over the sample period.

The VAR price impacts are statistical estimates subject to sampling error. Therefore we also computed a 90% confidence interval for the average price effects using an approach suggested by Benkwitz, Lutekpohl and Neumann (2000), and Berkowitz and Kilian (2000).

To simplify notation, our VAR model can be written more compactly as:

(2.3) $$\mathbf{z}_t = \sum_{i=0}^{p} \boldsymbol{\psi}_i \mathbf{d}_{t-i} + \boldsymbol{\varepsilon}_t$$

where $\mathbf{z}_t$ is the set of endogenous variables, $\mathbf{d}_{t-i}$ is the set of exogenous and endogenous variables, $\boldsymbol{\psi}_i$ are matrices of parameters to be estimated, and $\boldsymbol{\varepsilon}_t$ is the vector of error terms. The bootstrap procedure to construct confidence intervals consists of five steps. First, after

[9] Given that the number of lags in the VAR specification is k, the first month in the simulation period corresponds to month $k+1$.

estimation of the VAR, we compute residuals using the estimated VAR parameters: $\hat{\boldsymbol{\varepsilon}}_t = \mathbf{z}_t - \sum_{i=0}^{p} \widehat{\boldsymbol{\psi}}_i \mathbf{d}_{t-i}$. Second, from these residuals, we draw with replacement a sample of residuals, $\{\boldsymbol{\varepsilon}_t^*\}_{t=1}^{n}$, equal to the difference between the number of time periods in the sample period and the number of lags in the VAR specification. Third, using these sampled residuals and estimated VAR parameters, we recursively construct a vector of pseudo data $\mathbf{z}_t^* = \sum_{i=0}^{p} \widehat{\boldsymbol{\psi}}_i \mathbf{d}_{t-i} + \boldsymbol{\varepsilon}_t^*$ and re-estimate the VAR parameters $\boldsymbol{\psi}_i^*$ using the generated pseudo data. Fourth, we calculate the LRP effects using the simulation procedure explained above and the new set of VAR parameters $\boldsymbol{\psi}_i^*$ obtained from the pseudo data. Finally, steps one through four are repeated 1,200 times to compute a 90% confidence interval for the LRP effects using the percentile-t approach described in Efron (1979) and DiCiccio and Efron (1996).

We choose the percentile-t approach to construct the confidence bounds because the resulting confidence bounds are not dependent on distributional assumptions unlike those obtained from the normal approximation approach. When bootstrapping the confidence intervals, we drop simulated price paths that lead to negative simulated prices, which is equivalent to placing zero probability prior on negative simulated prices. Including the negative price simulations would have distorted the results because we know a priori that prices cannot be negative. As a robustness check, we also replaced negative simulated prices with minimum historical prices observed during the sample period for each country. These two simulation approaches for dealing with negative prices did not lead to major changes in the confidence bounds. This suggests that confidences bounds are not very sensitive to the two simulation approaches.

2.3.2 Model Set-Up and Data

Our applications focus on maize in Uganda and Mozambique and beans in Ethiopia. In the application to Uganda, prices from three local wholesale maize markets are included in the VAR: Kisenyi (Central region), Masindi (Western region), and Lira (Northern region). In the recursive form of the VAR we place Kisenyi first among prices, followed by Masindi and Lira. Other market prices such as Mbale and Kapchorwa could potentially have been included.

However, while some maize price data are available for Mbale market, there were too many missing observations to include this price in the VAR. And no maize price data are available for Kapchorwa. Therefore, we only included three regional market prices in the VAR, but would not expect results to be sensitive to the inclusion or exclusion of additional regional price variables because of effective regional maize price transmission in Uganda.[10]

In the application to Mozambique, prices from three domestic maize markets are included in the VAR: Maputo (Southern region), Chimoio (Central region), and Nampula (Northern region). We put Maputo and Chimoio first and second, respectively, among prices in the recursive order for the VAR. The more distant and isolated northern market of Nampula is placed last in the recursive VAR order.

In the application to Ethiopia, we focus on LRP effects on retail horse bean prices. Horse bean prices were used because price data on red and white haricot beans are not available over a sufficiently long period. WFP Ethiopia Office has provided LRP bean purchases broken down by type from July 2009 to July 2012. However, data on disaggregated WFP bean purchases by type prior to July 2009 are not available. These data limitations make it difficult to evaluate the impacts of LRP disaggregated by bean type. However, horse bean prices and aggregate LRP bean purchases are available monthly over a sufficiently large period so these are the data used in the Ethiopia beans VAR. Examining the relationship between prices for haricot beans and horse beans in Dessie over the part of the sample period where both are available suggests a strong relationship between wholesale prices of haricot beans and horse beans. Given this observed co-movement, it appears that a model based on horse bean prices only can provide a reasonable estimate of the effects of LRP aggregate bean purchases on local bean prices. Horse bean prices from three local markets are included in the Ethiopia beans VAR: Dire Dawa (Dire Dawa region), Dessie (Amhara region), and Awassa (SNNP region). Addis Ababa price is not included in the VAR because Awassa would be a better representation of a more important bean surplus market in the combined Oromia and SNNP regions than Addis Ababa would be. We place Dire Dawa first among prices in the recursive structure for the VAR. Dessie was put

[10] Market observations and examination of regional price series showing strong price co-movement suggest that regional markets in Uganda are well-integrated and price changes transmit consistently across regional markets.

before Awassa in the recursive ordering because compared to Dessie, Awassa is a more important bean surplus market.

To estimate the VAR models, we used monthly data from January 2001 through December 2011 in Uganda and Mozambique and from September 2001 through December 2011 in Ethiopia. Wholesale maize price data for Uganda were obtained from Farmgain Africa. We constructed monthly prices series for each market by averaging weekly prices. Uganda prices are reported in Ugandan Shilling per metric ton (UGX/MT). In the case of Mozambique, lack of complete wholesale market series, required that we use retail prices. We obtained retail maize prices from the Mozambique's Ministry of Agriculture Marketing Information System (SIMA). Daily prices were averaged to construct monthly price series. Mozambique prices are measured in Mozambique Metical per metric ton (MZN/MT). As in Mozambique, complete wholesale price series are not available for major bean markets in Ethiopia, so retail prices are used instead. Retail prices for horse beans are obtained from the Ethiopia Central Statistical Agency (CSA). The CSA reports monthly average retail prices, measured in Ethiopian BIRR (ETB) per quintal. We convert Ethiopia prices into ETB/MT by multiplying them by 10.

Price series included in our VAR specifications for all three study countries have missing observations. In the application to Uganda, during the entire sample period, the proportions of missing price observations in Kisenyi, Masindi and Lira are 3%, 2% and 4%, respectively. We impute missing observations using best subset regressions. This approach consists of regressing wholesale maize prices in each location on wholesale maize prices in all markets for which price data are available. Then, predicted prices from the regressions are used to fill in missing observations. In addition to the three markets included in our Uganda maize VAR specification, the following markets were included as explanatory variables in the best subset regressions: Arua, Kabale, Masaka, Mbarara, Nakawa, Owino, Soroti and Tororo. The effects of this procedure for imputing missing observations are unknown. However, as argued by Myers (2013), imputation of missing price observations using best subset regressions is likely to have little impact on the dynamic relationships between prices because the specifications of the best subset regressions do not take dynamics into account (no lags of the wholesale prices are included in the specifications).

In the case of Mozambique, 2%, 4% and 6% of the price observations in Maputo, Chimoio and Nampula, respectively, are missing over the entire sample period. To impute missing observations, the following markets are included in best subset regressions: Maputo, Manica, Chimoio, Tete, Nampula and Lichinga. In the application to Ethiopia, the proportions of missing price observations in Dire Dawa, Dessie and Awassa are 8%, 9% and 8%, respectively. In addition to these three markets, we include Asossa, Asayita, and Bahir Dar market prices in the best subset regressions.

Daily tender-level data on LRP purchases, measured in metric tons (MT), were obtained from WFP through their Information Network and Global System (WINGS). The WFP competitive tendering process involves four steps: (i) the tender is announced; (ii) suppliers submit bids; (iii) bids are reviewed and winners are chosen; and (iv) contracts are awarded and purchase orders are issued. It takes about two to three weeks from the date tenders are announced to the date purchase orders are typically issued. We aggregate the daily procurement data, measured in MT, into a monthly series by summing LRP purchases that had purchase order dates in that month.

Food aid data were provided by the International Food Aid Information System (INTERFAIS), which was developed by WFP. Food aid is reported based on the date shipments arrived in a given food aid recipient country. We aggregate food aid deliveries in each month to create a monthly food aid series, measured in MT, for maize in Uganda and Mozambique and beans in Ethiopia.

2.3.3 Summary Statistics and Preliminary Tests

Summary statistics over the sample period for the five variables included in each country VAR are reported in Table 2.1. During the sample period, WFP distributed on average 5,837 MT of maize per month and purchased an average 6,804 MT per month in Uganda. This indicates that not all LRP bought in Uganda was distributed in Uganda. Indeed, WFP procurement data show that from 2001 through 2011, 30% of the total WFP purchases of maize in Uganda were exported to other East African countries. By contrast, in Mozambique and Ethiopia, food aid deliveries exceed WFP LRP purchases. In all three country applications, the standard deviations indicate that both food aid deliveries and WFP LRP purchases fluctuated considerably over the sample period. Table 2.1 also shows that, as expected, average monthly prices are higher in deficit markets (Kisenyi in Uganda, Maputo in Mozambique and Dire Dawa in Ethiopia) than in surplus markets (Masindi and Lira in Uganda; Chimoio and Nampula in Mozambique; and Dessie and Awassa in Ethiopia) within each country. In all these markets (deficit and surplus), monthly prices also show considerable variability. Although not shown in the summary statistics, monthly prices within each country show considerable price co-movement consistent with effective spatial price transmission across regional markets.

The choice to estimate in VAR or VEC form depends on the stationarity and cointegration properties of the data. Table 2.2 contains results from augmented Dickey-Fuller and Phillips-Perron tests for nonstationarity. In the applications to Uganda and Mozambique, the evidence of unit roots is mixed, depending on which statistic is used and whether a time trend is included. In the application to Ethiopia, results support nonstationary behavior in all three price variables, but that bean food aid deliveries and LRP are stationary. As indicated by Blough (1992) and others, unit root tests are known to have low power in finite samples, suggesting that failure to reject the null hypothesis of a unit root could be a reflection of this low power rather than the presence of unit roots. Here we chose not to impose VEC restrictions and instead estimate the model as an unrestricted VAR in the levels of all variables for three reasons: (1) OLS estimation of the VAR form remains consistent under nonstationarity and cointegration; (2) the primary goal here is policy simulation not hypothesis testing, and (3) there is some value in applying consistent modeling procedures across all three country applications.

Table 2.1 Descriptive statistics for the Uganda, Mozambique and Ethiopia VAR variables

Variable	Mean	Standard deviation	Maximum	Minimum
Uganda				
Maize food aid deliveries (MT)	5,837	7,718	41,957	0
LRP maize purchases (MT)	6,804	6,957	32,251	0
Kisenyi wholesale maize price (UGX/MT)	357,092	191,248	1,307,500	103,583
Masindi wholesale maize price (UGX/MT)	311,891	186,524	1,250,000	63,750

Lira wholesale maize price (UGX/MT)	342,273	204,115	1,525,000	64,000
Mozambique				
Maize food aid deliveries (MT)	2,000	2,708	19,249	0
LRP maize purchases (MT)	1,618	2,651	15,859	0
Maputo retail maize price (MZN/MT)	7,809	3,338	13,196	2,571
Chimoio retail maize price (MZN/MT)	5,490	2,916	13,943	1,371
Nampula retail maize price (MZN/MT)	5,612	2,577	13,571	1,330
Ethiopia				
Bean food aid deliveries (MT)	4,800	8,878	44,500	0
LRP bean purchases (MT)	1,306	2,058	11,058	0
Dire Dawa retail bean price (ETB/MT)	4,904	3,280	16,000	1,433
Dessie retail bean price (ETB/MT)	3,847	2,788	13,333	767
Awassa retail bean price (ETB/MT)	4,693	3,359	16,000	1,133

Source: Authors calculations
Note: Average exchange rates from January 2001 to December 2011 are: 1,919 UGX per US dollar in Uganda, 25 MZN per US dollar in Mozambique, and 10 ETB per US dollar in Ethiopia.

Table 2.2 Nonstationarity tests for the Uganda, Mozambique and Ethiopia VAR variables

	H_o: Unit root H_1: Stationary process		H_o: Unit root H_1: Stationary process with trend	
	Approximate p-value for Z(t)		Approximate p-value for Z(t)	
	Dickey-Fuller	Phillips-Perron	Dickey-Fuller	Phillips-Perron
Uganda				
Kisenyi wholesale maize price	0.0308	0.1823	0.0003	0.0428
Masindi wholesale maize price	0.0390	0.1829	0.0006	0.0405
Lira wholesale maize price	0.0549	0.0911	0.0038	0.0063
Maize LRP quantity	0.0605	0.0000	0.2442	0.0000
Maize food aid delivery	0.0510	0.0000	0.1833	0.0000
Mozambique				
Retail maize price in Maputo	0.4222	0.5320	0.0000	0.0131
Retail maize price in Chimoio	0.0536	0.1299	0.0000	0.0021
Retail maize price in Nampula	0.0251	0.0507	0.0000	0.0013
LRP volume in Mozambique	0.0000	0.0000	0.0000	0.0000
Maize food aid delivery	0.0000	0.0000	0.0000	0.0000

Ethiopia				
Retail bean price in Dire Dawa	0.8305	0.9860	0.1266	0.8367
Retail bean price in Dessie	0.5379	0.9269	0.0604	0.6065
Retail bean price in Awassa	0.9988	0.9838	0.2965	0.8185
LRP bean purchases	0.0357	0.0000	0.1277	0.0000
Bean food aid distributions	0.0000	0.0000	0.0000	0.0000

Notes: The number of lagged price differences included in the augmented Dickey-Fuller tests varies by variable. The procedure used to choose the number of lags was to start with zero and add lags until there was no evidence of autocorrelation in the residuals from the Dickey Fuller regression.

Various criteria are used to determine the appropriate lag length for VARs, each with their advantages and disadvantages. Information criteria, such as final prediction error (FPE), Akaike's information criterion (AIC), and Schwarz's Bayesian information criterion (SBIC) are often used, along with likelihood ratio (LR) tests for the null hypothesis that one more lag is needed. Another key criterion for adequate lag length is to ensure that none of the residuals from any equation show evidence of autocorrelation. For all three country applications, results from AIC, SBIC, FPE and LR were inconsistent with one another regarding the appropriate lag length. Some criteria suggest short lag lengths, while others indicated very long lag lengths. Because very long lag lengths can lead to over-parameterized models we used a procedure of starting with the lower lag length suggested by the information criteria and testing the residuals for autocorrelation. If statistically significant evidence of autocorrelation was found in any residual we then increased the lag length by one and repeated the procedure. When no additional autocorrelation was found that is the lag length we chose. This procedure suggested that the appropriate lag lengths were five months for the Uganda model, and three months for the Mozambique and Ethiopia models. We also did sensitivity analysis to see if the simulated LRP effects were sensitive to the choice of lag length.

Due to seasonality in agricultural production, a seasonal component is often included in commodity VAR models. In all three country applications, we expect that data, especially prices, would have a strong seasonal component because agricultural production is predominantly rain-fed. Hence, in addition to a constant term we included a seasonal component to account for seasonal patterns in prices. The seasonal component was represented as a Fourier approximation to an unknown seasonal pattern (i.e., as a linear combination of sine and cosine functions with different frequencies). This provides a very flexible representation for an underlying seasonal pattern in the VAR variables. The deterministic parts of the VAR models could also include time trends. There was mixed evidence of time trends in the data for all three country applications. However, given that the evidence is mixed, and that it has been argued that VAR policy models are best estimated without explicit time trends, we exclude time trends from the deterministic components of all three VAR models.

2.3.4 VAR Results

When estimating VAR models, some authors use untransformed prices while others use a log transformation.[11] In our models we examined both possibilities by comparing goodness of fit, measured by R squared, between these two specifications.[12] Results reported in Table 2.3 suggest that the VAR specification with price levels fits the data slightly better (i.e. delivers slightly higher R squared) for all price equations in all three country applications (Uganda, Mozambique and Ethiopia), compared with the specification with log of prices. For the remaining two equations (food aid distributions and LRP purchases) in the VAR model, the results are mixed depending on the country application. Because of these results we chose to estimate the VAR models for all three country applications using price levels rather than log of price levels.

Table 2.3 Comparison of R squared for two specifications: price levels and log of prices

	Equation				
Prices used in the VAR estimation	Food aid distributions	LRP purchases	Price one[a]	Price two[b]	Price three[c]
			Uganda		
Price levels	0.318	0.324	0.893	0.984	0.951
Log of price levels	0.282	0.252	0.868	0.978	0.929
			Mozambique		
Price levels	0.103	0.121	0.953	0.953	0.932

[11] We made log transformation of prices, but not of LRP nor of food aid distributions.

[12] For both specifications, we computed correlation coefficients between predicted and observed explanatory variable for each equation in the VAR models (prices, LRP and food aid distribution). For price equations in the specification with log transformed prices, we used predicted untransformed prices when computing the correlation coefficients. We calculated squared correlation coefficients and used them as our measure of R squared.

Log of price levels	0.141	0.136	0.951	0.947	0.929
			Ethiopia		
Price levels	0.192	0.196	0.989	0.984	0.987
Log of price levels	0.287	0.296	0.987	0.983	0.984

[a] Price one denotes prices in Kisenyi (Uganda), Maputo (Mozambique) and Dire Dawa (Ethiopia).
[b] Price two indicates prices in Masindi (Uganda), Chimoio (Mozambique) and Dessie (Ethiopia).
[c] Price three represents prices in Lira (Uganda), Nampula (Mozambique) and Awassa (Ethiopia).

Most of the estimated parameters from the VAR do not, by themselves, have an economic interpretation or individual economic significance. Therefore we do not report a full set of estimation results for all parameters in each country application.[13] However, in Tables 2.4 through 2.6 we provide model evaluation statistics for each country VAR model. Results generally support the model specifications used.

Table 2.4 Fifth-order VAR model evaluation statistics for Uganda Maize

	Equation				
Statistic	Food aid distributions	LRP purchases	Kisenyi price	Masindi price	Lira price
R^2	0.318	0.324	0.893	0.984	0.951
AR(1)	0.031	0.024	0.073	0.056	0.051
	(0.859)	(0.878)	(0.787)	(0.814)	(0.821)
AR(6)	1.284	1.666	2.543	1.461	1.676
	(0.973)	(0.948)	(0.864)	(0.962)	(0.947)
AR(12)	6.738	10.643	6.310	14.467	6.402
	(0.874)	(0.560)	(0.900)	(0.272)	(0.894)
ARCH(1)	1.690	1.401	44.513	0.322	0.051
	(0.194)	(0.236)	0.000	(0.571)	(0.822)
ARCH(6)	5.227	4.958	47.377	4.041	5.797
	(0.515)	(0.549)	0.000	(0.671)	(0.446)
ARCH(12)	7.732	12.506	47.469	16.990	11.815
	(0.806)	(0.406)	0.000	(0.150)	(0.461)
Seasonal component	0.721	2.552	4.746	14.502	1.299
	(0.697)	(0.279)	(0.093)	(0.001)	(0.522)

[13] Estimated parameters from VARs are available upon request.

Notes: AR(*i*) indicates Portmanteau (Q) statistics for testing the null of no autocorrelation against the alternative of *i*th degree autocorrelation in the residuals. ARCH(*i*) indicates Portmanteau (Q) statistics for testing the null of no autocorrelation against the alternative of *i*th degree autocorrelation in the *squared* residuals (a test for conditional heteroscedasticity). The seasonal component is a Chi-square statistic for testing the null of no seasonal component. Numbers in parentheses under statistics are associated p-values.

Table 2.5 Third-order VAR model evaluation statistics for Mozambique Maize

Statistic	Equation				
	Food aid distributions	LRP purchases	Maputo price	Chimoio price	Nampula price
R^2	0.103	0.121	0.953	0.953	0.932
AR(1)	0.004	0.163	0.013	0.019	0.016
	(0.949)	(0.687)	(0.911)	(0.889)	(0.901)
AR(6)	4.690	1.326	6.613	1.590	1.639
	(0.584)	(0.970)	(0.358)	(0.953)	(0.950)
AR(12)	10.253	7.846	11.175	14.003	7.116
	(0.594)	(0.797)	(0.514)	(0.300)	(0.850)
ARCH(1)	0.330	0.057	3.089	0.496	16.717
	(0.566)	(0.811)	(0.079)	(0.481)	0.000
ARCH(6)	9.550	0.662	5.867	3.149	20.118
	(0.145)	(0.995)	(0.438)	(0.790)	(0.003)
ARCH(12)	10.941	7.893	8.629	5.350	25.756
	(0.534)	(0.793)	(0.734)	(0.945)	(0.012)
Seasonal component	0.221	2.491	7.413	7.402	14.067
	(0.895)	(0.288)	(0.025)	(0.025)	(0.001)

Notes: AR(*i*) indicates Portmanteau (Q) statistics for testing the null of no autocorrelation against the alternative of *i*th degree autocorrelation in the residuals. ARCH(*i*) indicates Portmanteau (Q) statistics for testing the null of no autocorrelation against the alternative of *i*th degree autocorrelation in the *squared* residuals (a test for conditional heteroscedasticity). The seasonal component is a Chi-square statistic for testing the null of no seasonal component. Numbers in parentheses under statistics are associated p-values.

Table 2.6 Third-order VAR model evaluation statistics for Ethiopia beans

Statistic	Equation				
	Food aid distributions	LRP purchases	Dire Dawa price	Dessie price	Awassa price
R^2	0.192	0.196	0.989	0.984	0.987
AR(1)	0.000	0.151	0.112	0.062	0.065
	(0.993)	(0.698)	(0.738)	(0.803)	(0.799)
AR(6)	2.475	12.135	2.989	5.635	3.728
	(0.871)	(0.059)	(0.810)	(0.465)	(0.713)
AR(12)	8.591	15.514	10.872	9.048	11.454
	(0.737)	(0.215)	(0.540)	(0.699)	(0.491)
ARCH(1)	0.003	0.230	4.489	0.001	45.475
	(0.957)	(0.632)	(0.034)	(0.975)	0.000
ARCH(6)	0.599	30.070	17.827	19.588	55.103
	(0.996)	0.000	(0.007)	(0.003)	0.000
ARCH(12)	0.898	32.811	30.248	33.366	57.361
	(1.000)	(0.001)	(0.003)	(0.001)	0.000
Seasonal component	4.778	0.855	3.131	8.645	2.919
	(0.092)	(0.652)	(0.209)	(0.013)	(0.232)

Notes: AR(*i*) indicates Portmanteau (Q) statistics for testing the null of no autocorrelation against the alternative of *i*th degree autocorrelation in the residuals. ARCH(*i*) indicates Portmanteau (Q) statistics for testing the null of no autocorrelation against the alternative of *i*th degree autocorrelation in the *squared* residuals (a test for conditional heteroscedasticity). The seasonal component is a Chi-square statistic for testing the null of no seasonal component. Numbers in parentheses under statistics are associated p-values.

Table 2.7 presents simulation results for LRP effects on local markets. The simulation was undertaken by setting LRP to zero starting with the first month of the simulation period, assuming food aid deliveries and local price shocks follow their historical estimated paths. Estimated average price level effects of the WFP LRP over the historical sample period – the average percentage reduction in prices from eliminating LRP – are reported in the second through fourth columns of Table 2.7. As discussed earlier, the VAR price impacts are statistical estimates subject to sampling error. Therefore we also computed 90% confidence intervals for the average price effects using the bootstrapping procedures outlined previously. The lower and upper bounds reported in the table are the lower and upper bounds for these 90% confidence intervals, while the mean column provides the preferred estimate. Panel A of Table 2.7 reports bootstrap confidence bounds obtained when simulation paths that generate negative simulated prices are dropped, while panel B shows bootstrap confidence bounds computed when negative simulated prices are replaced with minimum historical prices observed over the sample period for each regional market.

Table 2.7 Estimated LRP effects on price levels and variability, VAR model

	Price level effects			Price variability effects		
Market	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
			PANEL A			
Uganda						
Kisenyi	12.51%	13.40%	15.74%	0.42%	1.28%	3.63%
Masindi	13.13%	13.99%	16.35%	-0.03%	0.81%	3.13%
Lira	14.65%	15.54%	17.89%	-2.15%	-1.29%	1.00%
Mozambique						
Maputo	5.32%	6.91%	8.61%	-0.54%	0.42%	2.11%
Chimoio	3.91%	5.51%	7.26%	-1.17%	-0.40%	1.44%
Nampula	0.58%	2.22%	3.93%	0.91%	1.99%	3.91%
Ethiopia						
Dire Dawa	3.57%	4.63%	6.90%	-2.23%	-1.39%	0.94%
Dessie	2.66%	3.74%	5.88%	-1.66%	-0.83%	1.57%
Awassa	4.04%	5.10%	7.36%	-2.85%	-2.04%	0.40%
			PANEL B			
Uganda						
Kisenyi	12.41%	13.40%	15.70%	-0.10%	1.28%	3.17%
Masindi	13.06%	13.99%	16.37%	-0.68%	0.81%	2.52%
Lira	14.60%	15.54%	17.94%	-2.88%	-1.29%	0.38%
Mozambique						
Maputo	5.47%	6.91%	8.73%	-1.02%	0.42%	2.19%
Chimoio	4.11%	5.51%	7.34%	-1.86%	-0.40%	1.36%
Nampula	0.78%	2.22%	4.02%	0.42%	1.99%	3.69%
Ethiopia						
Dire Dawa	3.67%	4.63%	6.94%	-3.11%	-1.39%	0.23%
Dessie	2.79%	3.74%	6.06%	-2.60%	-0.83%	0.76%
Awassa	4.14%	5.10%	7.42%	-3.80%	-2.04%	-0.47%

Notes: Price variability is measured by the coefficient of variation. Mean refers to percentage difference between historical (with LRP) and simulated (without LRP) prices. Lower and upper bounds refers, respectively, to lower and upper of bootstrapped 90% confidence interval (percentile-t) with 1,200 replications. The number of dropped observations required to generate 1,200 bootstrap replications in Uganda, Mozambique and Ethiopia are 8,446; 2,688; and 2,410; respectively. For panel A, to construct confidence bounds, we dropped simulations that generated negative prices. For panel B, to construct confidence bounds, simulated negative prices were replaced with minimum historical prices over the sample for each market.

For Uganda average maize price impacts range from about 13% in Kisenyi (deficit) to 16% in Lira (surplus). Furthermore, the upper and lower bounds for the 90% confidence interval suggests that average price impacts of LRP are statistically different from zero (Table 2.7). Average price effects for beans in Ethiopia are quite small, as expected, though statistically different from zero given that the 90% confidence interval does not contain zero. Like Uganda, there is no clear pattern between surplus and deficit areas in Ethiopia. In the case of Mozambique, estimated average maize price effects show larger effects in deficit Maputo and surplus Chimoio markets than in surplus Nampula. Upper and lower bounds for the 90% confidence intervals show that average prices effects are statistically different from zero for all three markets (Maputo, Chimoio, and Nampula) in Mozambique.

The relatively high effect in Maputo may appear surprising because no LRP purchases are made in that area of the country. But this finding is consistent with the fact that Maputo (and the Southern region in general) is a relatively small market for Mozambican maize grain. Most maize consumption in Southern Mozambique is from refined maize meal produced overwhelmingly with imported grain from South Africa. As a result, any reduction of marketable supplies in the Central region, which serves informal markets in the Southern region, is expected to have a meaningful effect on the informal market prices for locally produced maize in Maputo. We believe, however, that this effect will have limited influence on the price of the refined maize meal produced with imported grain, given the much larger size of this latter market. As a partial check on this assertion, we used SIMA retail data to compute correlation coefficients between retail maize grain across three markets in the Southern region (Maputo, Maxixe, and Xai-Xai), refined maize meal across the same markets, and between maize grain and refined maize meal *within* each of these markets. Correlations for maize grain across spatially separated markets ranged from 0.74 to 0.80, while those for maize meal across the same markets ranged from 0.54 to 0.58. In contrast, correlations between grain and meal prices, even *within* the same markets, were lower, ranging from 0.35 to 0.46. This suggests that the impact of LRP on maize grain prices in Maputo is likely to have some, but limited effect on the maize meal that most consumers eat.

The last three columns of Table 2.7 contain estimates of LRP impacts on the coefficient of variation (CV) of prices over the sample period, which is a measure of price variability. The upper and lower bound estimates again show bounds for 90% confidence intervals for the CV. The results suggest that LRP has had no statistically significant effect on price variability in any regional market, except Nampula (Mozambique). We note that for Kisenyi (Uganda) and Awassa (Ethiopia), the two simulation approaches we employed to construct confidence bounds for the CV deliver contradictory findings regarding statistical significance of the estimated parameters. For these two markets, one approach suggests that LRP effects on price variability are statistically significant, but the other approach indicates that they are not. This finding could potentially be driven by the fact that the estimated LRP effects on price variability are quite small.

Figures 2.3 through 2.5 graph actual and simulated (no LRP) prices, along with associated LRP levels, for different markets over the sample period. The LRP effect is from the VAR using the actual sample data. Graphs for all markets in any country are quite similar so we only present one market for each country. A common pattern in each graph is that LRP shows little impact on markets for several months then the effects become increasingly apparent.

As explained earlier, the no LRP prices are simulated by setting LRP to zero starting in the first month of the simulation period and keeping it at zero throughout the remainder of the simulation. Prior to the first month in the simulation period, however, LRP is assumed to have been at its historical level in the data. Therefore, the simulated effects of eliminating LRP start out small (historical and simulated prices remain relatively close) as markets adjust to the elimination of LRP. Then over a period of months as the markets adjust, and no additional LRP is forthcoming, the magnitude of price effects generally rises. We would expect that the magnitude of the price effects in any given month depends on the amount of recent LRP activity that took place, and results do reflect this general pattern. However, a one-to-one correspondence between higher LRP in any particular month and a larger price effect for that month should not necessarily be expected for two main reasons. First, the VAR simulation allows prices to adjust dynamically over time in response to both current and past changes in LRP. Second, the simulated no LRP prices reflect the effect of eliminating LRP assuming all other factors influencing prices continue to play the same role as they did historically. So some of the price effects occur in months in which underlying market conditions are quite different than in others.

Figure 2.3 Historical (with LRP) and simulated (without LRP) prices of maize in Kisenyi market, Uganda, 2001-2011

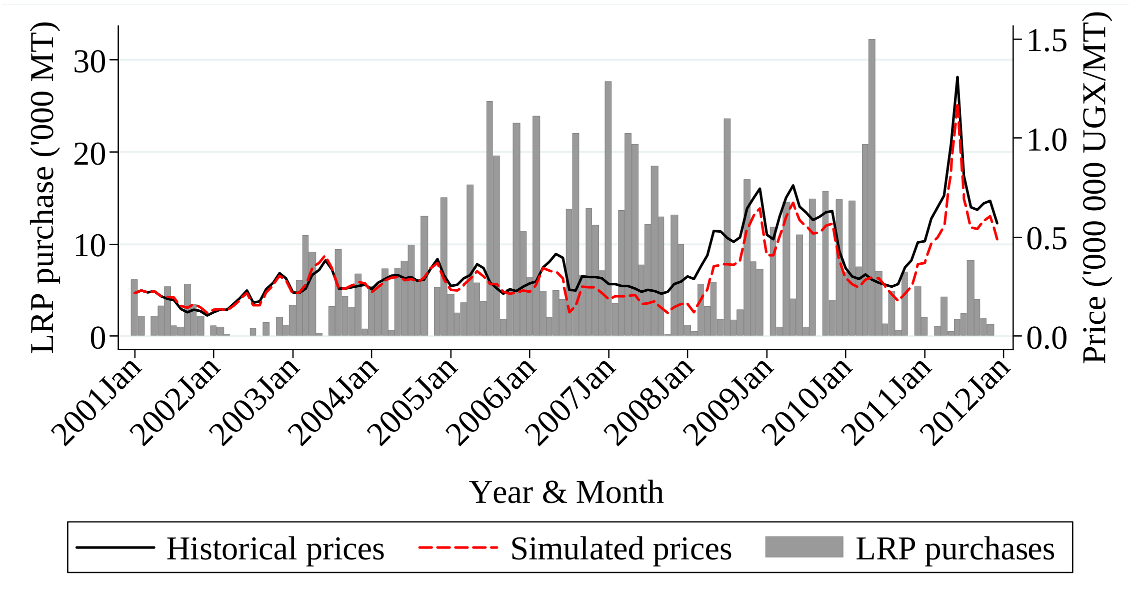


Figure 2.4 Historical (with LRP) and simulated (without LRP) prices of maize in Chimoio market, Mozambique, 2001-2011

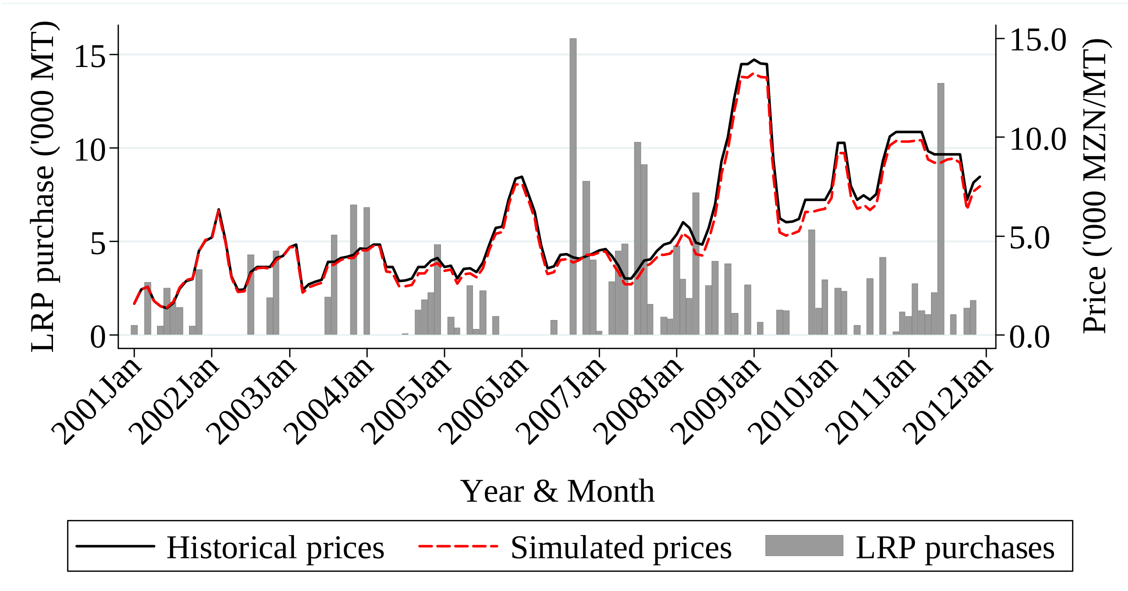
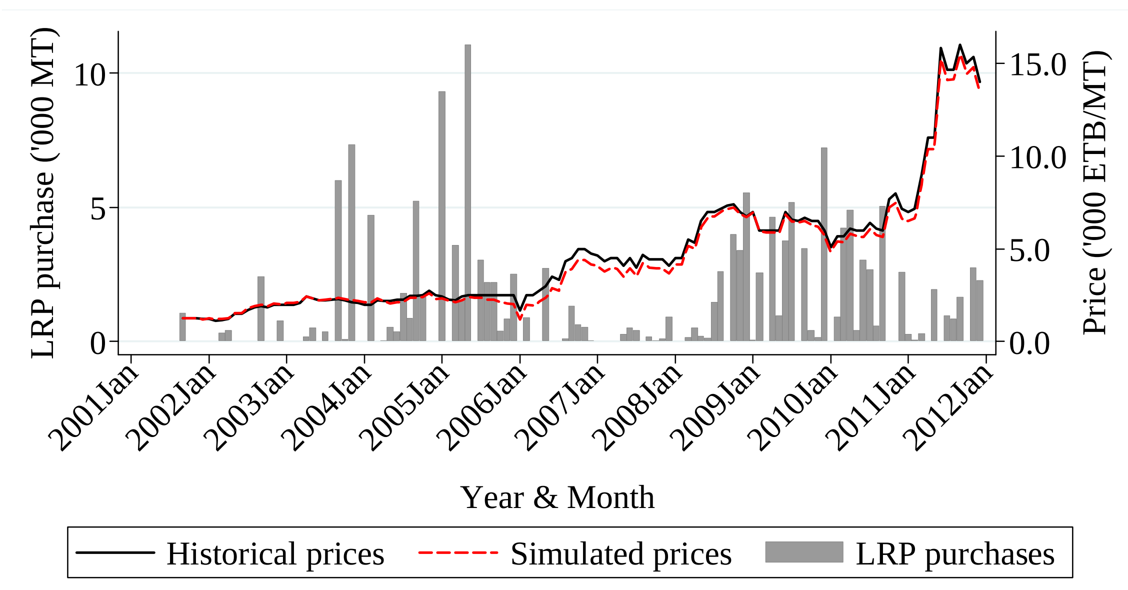


Figure 2.5 Historical (with LRP) and simulated (without LRP) prices of horse beans in Awasa market, Ethiopia, 2001-2011



We also did sensitivity analysis to see if the simulated LRP effects were sensitive to the choice of lag length. Unfortunately, in all three country applications, simulation results were sensitive to lag length (small changes in lag length often led to major changes in simulated LRP effects). Therefore, while the results we report are our preferred estimates, we acknowledge that simulation results for LRP effects on local prices appear sensitive to the choice of lag length.

Overall, the VAR analysis indicates LRP induced modest local price increases for maize in Mozambique and beans in Ethiopia, but more economically meaningful effects on maize prices in Uganda. In all cases, the 90% confidence intervals for the VAR average price effects show that the price effect is statistically significant. There is no statistically significant effect on price variability in any of the estimated VARs, except Nampula market (Mozambique). And even when there is some evidence of statistically significant effects on price variability, the magnitude of the estimated effect remains quite small. Monthly LRP price effects do vary considerably in all country applications; ranging from -13% to 58% in Uganda, from -15% to 13% in Mozambique, and from -17% to 27% in Ethiopia.[14]

2.4 Computational Model (CM)

The VAR approach discussed in the previous section is a data-based method with no explicit assumptions about how underlying markets are structured and organized. As a check on the robustness of the VAR results, we also built a computational model (CM) to predict what economic theory has to say about the likely magnitude of LRP effects. The CM complements the VAR by providing insights about the demand and supply pathways through which LRP effects occur. Unlike the VAR model, the CM takes a comparative static approach by evaluating two static equilibria – one with and one without LRP – without accounting for any dynamic adjustment path between them. The estimated effects should therefore be viewed as long-run outcomes after any dynamic adjustments between equilibria have occurred.

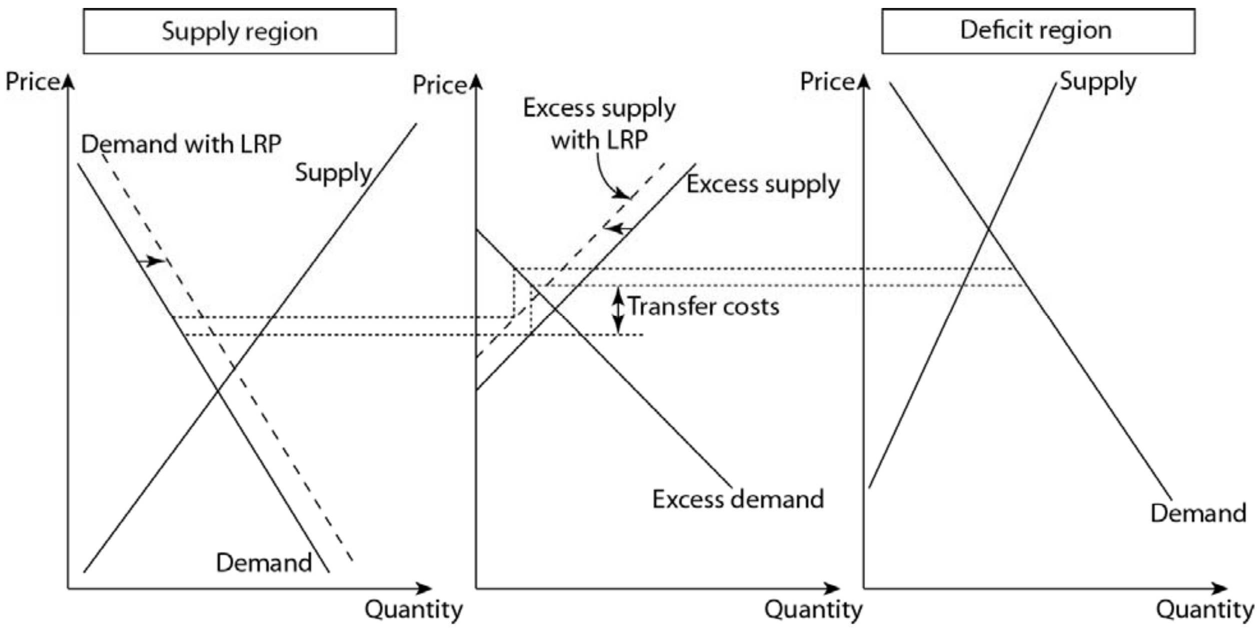
[14] Although we report the range of monthly LRP effects across markets within each country application, the variation in individual markets is substantial and follows patterns similar to that reported here for each country.

The CM is a mathematical representation of supply, demand, and price determination in spatially connected markets based on parameters that use best available knowledge on the size and organization of relevant markets. Our CM assumes that all markets are competitive and well-integrated, so estimated LRP effects transmit readily across regional markets. The VAR model makes no such assumptions about market competitiveness and/or market integration. Once the CM has been specified, key parameters including supply and demand elasticities, shares of marketed surplus, and price ratios are quantified using existing econometric elasticity estimates and current knowledge of the size and workings of markets in each country studied. The final step is to use the model, along with relevant parameter estimates, to quantify the effect of LRP purchases on outcomes of interest in local markets, which may include price levels, the supply of marketed surplus, and the amount of marketed surplus being consumed by households.

A simple graphical analysis of a country with two regions and no imports or exports provides intuition for the CM. In Figure 2.6 food staple supply and demand responses to price for the first region, assumed to be in surplus, are shown in the left panel while supply and demand for the second region, assumed to be in deficit, are shown in the right panel. The middle panel shows equilibrium occurs when excess supply in the surplus region equals excess demand in the deficit region.

The equilibrium price in each region must differ by the cost of transferring the commodity from the surplus region to the deficit region (see the transfer cost differential in the middle panel of Figure 2.6). The solid lines in the figure show the initial equilibrium without LRP purchases. The dashed demand curve in the left panel shows that if LRP purchases take place in the surplus region they shift that demand curve to the right (i.e., LRP becomes an additional source of demand). This shift in demand then shifts the excess supply curve from the surplus region to the left (see the dashed line in the middle panel). The new equilibrium features higher prices in both regions, increased marketed supply in both regions, and decreased consumption out of the marketed surplus in both regions. The decrease in consumption out of the marketed surplus occurs because LRP withdraws a certain amount of the commodity from normal market channels, putting upward pressure on prices and downward pressure on consumption from market purchases.

Figure 2.6 Graph of effects of LRP on local markets



Of course, the LRP purchases are then distributed either domestically or in other countries in the region as food aid. However, the food aid will, in principle, be provided to those in dire need who do not have effective demand at prevailing prices. Therefore these food aid distributions will have little, if any, effect on prices and quantities purchased through normal market channels.[15] The magnitude of these various effects will depend on the price responsiveness of supply and demand in the two regions (i.e., elasticities of supply and demand), the size of transfer costs, and the magnitude of LRP purchases relative to the size of the market. Exports and imports of the commodity can also be incorporated, as shown in the mathematical derivation.

[15] We realize that food aid targeting in practice is frequently imperfect but abstract from that here because any effects on market prices from food aid crowding out effective demand are likely to be small. This view is consistent with findings from Jayne *et al.* (2001) indicating that the probability of receiving food aid in rural Ethiopia was greater for poorer households compared to wealthier households in spite of the empirical evidence of imperfect targeting.

2.4.1 Mathematical Derivation

Suppose there are n regions in a country and supply and demand in each region are represented by:

(2.4) $$S_i = f_i\left(P_i\right) \qquad \text{for } i = 1, 2, \ldots, n \qquad \text{(Supply)}$$

(2.5) $$D_i = g_i\left(P_i\right) \qquad \text{for } i = 1, 2, \ldots, n \qquad \text{(Demand)}$$

where S_i is quantity of marketed supply in region i, D_i is quantity of consumption purchases in region i, P_i is market price in region i, and f_i and g_i are regional supply and demand functions. Supply and demand may depend on other factors besides own price, for example input prices and prices of other competing outputs on the supply side and income and the price of other consumption goods on the demand side. We do not show these other factors explicitly because we keep them constant in the analysis that follows.

We define region 1 with price P_1 to be the reference market for the commodity. The reference market is usually the most important and liquid market in the country where the majority of the price discovery takes place. Then for all other regions connected to the reference market through trade, spatial market equilibrium requires:

(2.6) $$P_i = P_1 - C_i \qquad \text{for } i = 2, 3, \ldots, n \qquad \text{(Spatial Price Relationship)}$$

where C_i is the cost of transferring the commodity from region i to the reference market (or, if negative, the cost of transferring the commodity from the reference market to market i). If there is imperfect price transmission between markets we could assume a relatively high transfer cost or, at the limit, no trade between regions.

We also allow for exports to or imports from neighboring countries. Net export demand is specified as:

(2.7) $$X = h\left(P_1\right) \qquad \text{(Net Export Demand)}$$

where X is net exports from the country (imports if negative) and h is a net export demand function. As in the case of the domestic regional supply and demand functions, this net export demand function may depend on other variables besides own price in the reference market (e.g., price in the neighboring country) but in the analysis that follows we keep these other variables constant and so do not include them explicitly in the equation.

The model is closed with a market clearing condition that requires total consumption purchases in all regions of the country, plus net exports, plus LRP purchases, to equal total marketed surplus in all regions:

(2.8) $$\sum_{i=1}^{n} D_i + X + LRP = \sum_{i=1}^{n} S_i \qquad \text{(Market Clearing)}$$

If a region or set of regions is autarkic then its prices will be determined completely by the equilibration of supply and demand in that region or group of regions. In this case there will be separate equilibrium conditions of the form (2.8) for each autarkic region or group of regions, and LRP purchases must be allocated among the regions or groups (see the discussion of the Mozambique case below).

To compute comparative static effects of a change in LRP on local market variables of interest we apply total differentiation to the model, holding transfer costs C_i and other supply and demand shift variables constant. Totally differentiating the supply and demand functions gives:

(2.9) $$d\ln S_i = \alpha_i d\ln P_i \qquad \text{for } i = 1, 2, ..., n$$

(2.10) $$d\ln D_i = \beta_i d\ln P_i \qquad \text{for } i = 1, 2, ..., n$$

where the α_i and β_i are regional supply and demand elasticities, respectively. Similarly, totally differentiating the spatial price relationships (2.6) we get:

(2.11) $$d\ln P_i = r_i d\ln P_1 \qquad \text{for } i = 2, 3, ..., n$$

where r_i is the ratio of price in the reference region (region one) to the price in region i. Total differentiation of the net export demand function (2.7) leads to:

(2.12) $$d\ln X = \gamma d\ln P_1$$

where γ is the export demand elasticity with respect to the reference region price. Finally, totally differentiating the market clearing condition (2.8), holding transfer costs constant,[16] leads to:

(2.13)
$$\sum_{i=1}^{n} s_i^d d\ln D_i + s^x d\ln X + s^{LRP} d\ln LRP = \sum_{i=1}^{n} s_i^s d\ln S_i$$

where s_i^d is the share of each region's consumption purchases as a proportion of total country-wide marketed surplus, s^x is the share of exports (imports if negative) as a proportion of total country-wide marketed surplus, s^{LRP} is the share of LRP purchases as a proportion of total country-wide marketed surplus, and s_i^s is each regions share of marketed surplus as a proportion of total country-wide marketed surplus. Adding up requires:

(2.14)
$$\sum_{i=1}^{n} s_i^d + s^x + s^{LRP} = \sum_{i=1}^{n} s_i^s = 1$$

Equations (2.9) through (2.13) constitute a set of simultaneous equations that can be solved to derive the proportional effect of a change in LRP on prices, supply of marketed surplus, and consumption of marketed surplus, all by region. The results, which can be computed recursively, are:

(2.15)
$$\frac{d\ln P_i}{d\ln LRP} = \frac{r_i s^{LRP}}{\sum_{i=1}^{n} s_i^s \alpha_i r_i - \sum_{i=1}^{n} s_i^d \beta_i r_i - s^x \gamma}$$

(2.16)
$$\frac{d\ln S_i}{d\ln LRP} = \alpha_i \frac{d\ln P_i}{d\ln LRP}$$

(2.17)
$$\frac{d\ln D_i}{d\ln LRP} = \beta_i \frac{d\ln P_i}{d\ln LRP}$$

Given parameter values for supply and demand elasticities, shares of marketed surplus, and regional price ratios, equations (2.15) through (2.17) can be used to estimate the comparative static effects of a change in LRP on local markets.

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[16] This assumes implicitly that changes in LRP have no effect on the cost of transferring the commodity between regions. If more LRP were to reduce (increase) transfer costs then LRP would have the additional effect of reducing (increasing) price differences between regions.

2.4.2 Computational Model Set-Up, Data and Results

There will always be some uncertainty about the magnitude of key parameters in the CM. Therefore, we first estimate a "base case" using best estimates of these parameters to generate preferred estimates of the impact of LRP. We then use sensitivity analysis to vary these parameters within a range of reasonable values, thus establishing a reasonable range for the impacts of LRP under different market conditions. All results are presented as the average percent decline in prices predicted from eliminating LRP, using a base level of LRP that is consistent with historical LRP purchases in each country.

To implement the CM we break each of the three countries into regions based on their surplus or deficit situation and patterns of trade. In Uganda, available data did not allow a meaningful distinction between Western and Northern regions, so we group these two together, giving a total of three regions: deficit Central, surplus Eastern, and surplus Western *plus* Northern. Ugandan maize surplus flows primarily to Kampala, Kenya, South Sudan and, to lesser degree, DRC. Therefore, in addition to domestic maize consumption, we account for maize exports.

We also separate Mozambique into three regions: surplus Northern, surplus Central, and deficit Southern. These three regions can be viewed as two market segments: a Northern segment, which lies entirely north of the Zambezi River, consists of the Northern region alone, and a Southern segment consisting of the Central and Southern regions, south of the Zambezi River. Prior to August 2009, there was no bridge over the Zambezi River in Eastern Mozambique, which isolated Northern maize markets from those in the Central and Southern parts of the country. So to investigate the historical effect of LRP we assume maize markets in the Northern region are segmented from markets in the Central and Southern regions. The Northern region is modeled as a separate market segment (but integrated with Southern Malawi via exports) while the Central and Southern regions form a separate Southern segment with integration between the two sub-regions (but not with the Northern region). This characterization is based on market observations and market information system data showing regular flows of maize from the production zones in the Central region to markets in Southern Mozambique, particularly into Maputo. Note that Mozambique exports and imports maize regularly. Large volumes of maize are imported into Maputo by millers from South Africa at the same time that maize flows across the border to Southern Malawi from Northern Mozambique. Hence, we account for maize imports in the Southern region and maize exports in the Northern region.

In the application to Ethiopia, Oromia and SNNP are similar enough from a bean production and marketing viewpoint to be grouped as one aggregate surplus region, which we call Oromia-SNNP region. The other surplus region in our model is Amhara. All remaining administrative regions are grouped as one aggregate deficit region. We account for bean exports because Ethiopian beans are exported primarily to Kenya, South Sudan and Djibouti.

Our CM requires a set of values for key model parameters such as demand and supply elasticities, shares of marketed surplus, and price ratios. Table 2.8 presents the base case parameters used for each country, organized nationally and by region. In the application to Uganda, based on estimates from the literature (Chhibber, 1989; Karanja, Renkow and Crawford, 2003; Ulimwengu and Ramadan, 2009) complemented with prior knowledge of the country and its maize markets, base regional supply and demand elasticities for maize are set at 0.7 and -0.8, respectively. The marketed surplus supply of maize in Uganda is expected to be more price responsive than in many African countries because of widespread mixed cropping which presents opportunities for switching to and from competing crops. A demand elasticity of -0.8 might seem too elastic for a staple food like maize in an African country. However, Ugandans have a diversified diet and can switch to and from other staple foods such as matooke, cassava, sweet potato, beans, and rice in response to higher or lower maize prices. Because results may be sensitive to supply and demand elasticity assumptions, we also investigate the sensitivity of results to alternative elasticity assumptions over the range from 0.5 to 0.9 on the supply side and -0.6 to -1.0 on the demand side.

We could not find any existing empirical estimates of the maize export demand elasticity facing Uganda. However, since the main importing countries of Kenya and South Sudan have limited alternative sources of surplus maize to buy in the region, and domestic maize demand in these countries is likely to be more inelastic than domestic demand in Uganda, the export demand elasticity facing Uganda is likely to be more inelastic than domestic demand. We therefore use a base export demand elasticity estimate of -0.24. Because the share of exports in total marketed surplus is relatively small, reasonable changes in the magnitude of the export demand elasticity have little impact on the estimated effects of LRP on local markets. Therefore we do not report any sensitivity results to changes in the export demand elasticity.

Base estimates for the shares of marketed surplus for Uganda were estimated from household-level data. We estimated maize consumption purchases (maize grain and maize meal equivalent) using data from the Uganda National Panel Survey (UNPS) 2009/10. The UNPS 2009/10, conducted by the Uganda Bureau of Statistics (UBOS), is a nationally representative survey during which 3,123 households were interviewed. Maize sales, also obtained from the UNPS 2009/10, are used as our estimate of marketed supply. Marketed surplus and consumption data is disaggregated by region. An estimate of total Ugandan maize exports is obtained from various annual Statistical Abstracts published by UBOS and aggregate LRP purchases in Uganda were provided by WFP through WINGS. Maize export and WFP procurement data span the period 2001 through 2011.

Table 2.8 Base case parameters for the computational models: maize in Uganda and Mozambique, beans in Ethiopia

Parameter	Uganda	Mozambique: Northern	Mozambique: Central & Southern	Ethiopia
National				
Share of LRP relative to total marketed surplus	0.14	0.04	0.11	0.03
Share of net exports relative to total marketed surplus	0.15	0.17	-0.79	0.02
Price elasticity of net export demand	-0.24	-0.24	0.00	-0.24

	Uganda			**Mozambique**			**Ethiopia**		
Regional	Central (Deficit)	Northwest (Surplus)	Eastern (Surplus)	Northern (Surplus)	Central (Surplus)	Southern (Deficit)	Oromia + SNNP (Surplus)	Amhara (Surplus)	All Other Regions (Deficit)
Price elasticity of supply	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6
Price elasticity of demand	-0.8	-0.8	-0.8	-0.6	-0.6	-0.6	-0.6	-0.6	-0.6
Ratio of reference region price to prices in other regions	1.00	1.09	1.02	1.00	1.42	1.00	1.13	1.30	1.00
Regional purchases relative to total marketed surplus	0.33	0.27	0.11	0.79	0.72	0.96	0.57	0.36	0.02
Regional sales relative to total marketed surplus	0.36	0.43	0.21	1.00	0.94	0.06	0.57	0.39	0.04

Note: Shares of LRP, net exports, and imports in total market supplies are based on historical annual average data from 2001 to 2011. Shares of marketed surplus sold by region relative to total country-wide marketed surplus sum to one. Shares of consumption by region relative to total market supplies, plus share of LRP relative to total market surplus, plus share of net maize exports relative to total market supplies sum to one (see the adding up constraints in Equation (2.14) in Section 2.4.1).

To compute regional shares of marketed surplus in Uganda we took the regional sales data and divided by the aggregate sales across the country. To compute the purchased consumption shares as a proportion of total marketed surplus we obtained a consistent estimate of total purchases by adding maize consumption purchases across regions, estimated from the household data, and then adding in exports and LRP. Each component (regional purchases, exports, and LRP) was then expressed as a share of the total. This procedure ensured that the adding up restrictions in equation (2.14) in Section 2.4.1 hold for the estimated shares. The effects of LRP on local markets are likely to be most sensitive to the share of LRP in total marketed surplus. Therefore we conduct sensitivity analysis with respect to this parameter, over the range from 2% to 25%, which represents the range of annual maize LRP shares of marketed surplus observed in Uganda over the period 2001 to 2011. The base estimate of 14% is the mean of the LRP share over this period.

We compute estimates of price ratios using monthly maize prices obtained from Farmgain Africa. Covering the period January 2001 through December 2011, monthly maize prices are measured in UGX/MT. We use prices for Kisenyi market in Kampala (Central Region) as the reference price. We then computed the ratio of average prices in Kisenyi to average price in other regional markets (Masindi and Lira in the Northern *plus* Western Region, and Soroti in the Eastern Region) over the sample period and used the results as estimates of the base price ratios shown in Table 2.8. We did not conduct sensitivity analysis with respect to price ratios for two reasons: (1) price ratios are relatively stable, and (2) changing them will mainly influence LRP effects on regional price differences, not on the price level in the reference market.

In the application to Mozambique, base regional supply and demand elasticities for maize are set at 0.6 and -0.6, respectively, based on previous studies (Chhibber, 1989; Karanja, Renkow and Crawford, 2003; Zant, 2012) along with prior knowledge of the country and its maize markets. Maize supply (demand) is expected to be less elastic in Mozambique than in Uganda due to wider crop (dietary) diversity in Uganda. We investigated sensitivity to a range of regional supply and demand elasticities ranging from 0.4 to 0.8 on the supply side and -0.4 to -0.8 on the demand side.

We need two net export demand elasticities for Mozambique. First, there are maize exports from Northern Mozambique to Southern Malawi. We could not find econometric estimates of the Malawi demand elasticity for Northern Mozambique maize exports. However, based on similar arguments used when specifying the demand for maize exports from Uganda, we set a base value of -0.24 for this parameter. Results for LRP effects on local markets are not very sensitive to the value of this parameter because the share of maize exports in total marketed surplus from the Northern region is relatively small. Second, there is the Southern Mozambique demand for South African maize imports. We set the price elasticity of Southern Mozambique demand for South African maize imports to zero. This is a reasonable assumption because: (1) the market for the refined South African maize meal is differentiated from meal from locally produced maize, and (2) the demand for the refined South African maize is very inflexible.

Base estimates for the shares of marketed surplus parameters for Mozambique presented in Table 2.8 were computed from household-level data. Regional sales of marketed surplus are computed from the National Agricultural Survey (TIA) 2008. The TIA 2008 is a nationally representative survey administrated by the Mozambique Ministry of Agriculture. A total of 5,975 households were interviewed during the TIA 2008. In the Northern market segment there is only one region so the share of marketed surplus produced by the region is by definition one. For the southern market segment the shares of the Central and Southern regions were calculated as the regional proportions of total sales of marketed surplus in both regions combined.

We estimate maize consumption purchases (maize grain and maize meal equivalent) in Mozambique using data from the Household Budget Survey (IOF) 2008/09. With a sample of 10,832 households, the IOF 2008/09 is a nationally representative survey conducted by the Mozambique National Institute of Statistics (INE). To compute the consumption shares we take our estimate of total household consumption purchases and add LRP purchases and exports (subtract imports). This provides an estimate of total consumption out of the marketed surplus. To ensure that the adding up restrictions hold, the base proportions for regional consumption purchases, LRP, and exports are then calculated as a proportion of the total.

Annual data on Mozambique's maize (informal) exports, measured in MT, were gathered from the Famine Early Warming Systems (FEWSNET), while annual data on South African maize imports, measured in MT, to Mozambique were obtained from the South Africa Grain Information Service (SAGIS). FEWSNET maize export data cover the period 2005 to 2011 and SAGIS maize import data span the period 2004 through 2011.[17] LRP purchase data from January 2001 to December 2011 were provided by WINGS. As in the application to Uganda, we undertake sensitivity analysis on the LRP share of total marketed surplus. Maize LRP shares of marketed surplus in Mozambique over the period 2001 to 2011 ranged from 0.05 to 0.18 in the Southern region and 0.02 to 0.07 in the Northern region. We therefore use these historical LRP shares to evaluate how sensitive results are to the size of LRP relative to size of the market. The base estimates of 0.11 in the Southern Region and 0.04 in the Northern Region are the means of the LRP shares over this period.

To compute price ratios for Mozambique we obtain retail maize prices spanning the period January 2001 through December 2011 from the Mozambique's Ministry of Agriculture Marketing Information System (SIMA). Prices are measured in MZN/MT. We use average prices for Maputo and Chimoio in the southern market segment to compute price ratios using Maputo as the reference market. For the northern market segment, we use Nampula as the reference market.

In the application to Ethiopia, we assume base regional supply elasticities of 0.6 and demand elasticities of -0.6. These elasticities are based on estimates from the literature (e.g. Chhibber, 1989; Tefera, Demeke and Rashid, 2012; Zant, 2012) as well as prior knowledge of the country and its markets. Beans are not a major food staple in Ethiopia and only accounted for 6% of total cultivated area in the 2011/2012 agricultural season (CSA, 2012). It can be expected that marketed bean surplus in Ethiopia would be less responsive to price changes than marketed maize surplus in Uganda because many farmers in Uganda produce maize as a cash crop while beans are predominantly grown for self-consumption in Ethiopia. Also, given

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[17] See sagis.org.za and click on Historical Database for import data. FEWSNET export data come from the Southern African Informal Cross Border Food Trade Monitoring System, which are reported non-systematically in various FEWSNET publications. See fewsnet.net/Pages/default.aspx.

that diets are considerably more diversified in Uganda than in Ethiopia, we would expect that demand for beans in Ethiopia will be more inelastic than demand for maize in Uganda. As in the other two country applications, we also investigated sensitivity of the results to a range of supply and demand elasticities ranging from 0.4 to 0.8 on the supply side and -0.4 to -0.8 on the demand side.

We could not find any empirical estimates of the bean export demand elasticity facing Ethiopia. Similar to the case of maize in Uganda, however, we would argue that bean export demand from Ethiopia is more price inelastic than local demand, leading us to use a base export demand elasticity estimate of -0.24. But because the share of bean exports in total marketed surplus across the country is relatively small, results are not very sensitive to alternative reasonable values for this parameter.

Share parameters were estimated from a variety of sources. Annual data on volumes of Ethiopian beans, measured in MT, exported to Kenya, South Sudan and Djibouti are obtained from the Ethiopia's Central Statistical Agency (CSA). Export data covers the period from 2004 to 2009. Aggregate LRP purchases of beans in Ethiopia during the period 2001 to 2011 are gathered from WINGS.

Regional supply and demand shares of total marketed surplus were estimated from household-level data. Bean production is estimated from the Agricultural Sample Survey (ASS) 2011/12 administered by CSA. The ASS 2011/12 covered a total of 45,575 households. Based on Ferris and Kaganzi (2008), we assume 30% of bean production is sold in the market. Production multiplied by marketed shares gives marketed surplus. Regional marketed surplus data are then divided by total marketed surplus to get the share of marketed surplus supply coming from each region. Regional bean consumption purchases, used as estimates of domestic purchases from marketed surplus, are estimated from Household Income, Consumption and Expenditure Survey (HICES) 2004/05 conducted by CSA. The HICES 2004/05 is a nationally representative survey during which 21,600 households were interviewed. To ensure that the adding up restrictions hold, we use the procedure outlined for maize in Uganda to compute shares of regional purchases, exports and LRP. We conduct sensitivity analysis with respect to the share of LRP in total marketed surplus, over the range from 1% to 8%, which represents the range of annual bean LRP shares of marketed surplus observed in Ethiopia over the period 2001 to 2011. The base estimate of 3% is the mean of the LRP share over this period.

We use monthly retail prices for horse beans, obtained from the CSA, to compute price ratios in Ethiopia. Monthly prices, measured in ETB/MT, cover the period September 2001 through December 2011. Annual average prices for Dire Dawa (aggregate Deficit Region), Addis Ababa (Oromia-SNNP Region) and Dessie (Amhara Region) are used to compute price ratios and Dire Dawa was chosen as the reference market.

CM results on the percentage price reduction from eliminating LRP, assuming the base case parameter values in Table 2.8, are presented in the second column of Table 2.9. The base case shares of LRP relative to total marketed surplus (14% for maize in Uganda, 7% for maize in Mozambique, and 3% for beans in Ethiopia) are the historical mean for these shares.[18] The third and fourth columns of Table 2.9 show how sensitive the price effects are if we decrease the LRP shares to their historical lows over the data period (2%, 3%, and 1%, respectively), and increase them to their historical highs (25%, 13%, and 8%, respectively). We find that, at historical mean LRP levels, price impacts were about 11 to 12% in Uganda, between about 4% and 8% in Mozambique, and around 3% in Ethiopia. Impacts fall to about 1% in Uganda, 2 to 3% in Mozambique, and below 1% in Ethiopia when LRP is at its historical low, and rise to about 20% in Uganda, 6 to 13% in Mozambique, and 6 to 8% in Ethiopia with LRP at its historical high. As expected, we find little difference in effects across regions in each country.

Table 2.9 Base case and sensitivity analysis for estimated effects of LRP on price levels for maize in Uganda and Mozambique, beans in Ethiopia

Variable and Region	Base Case (Historical mean LRP)[1]	Historical low LRP[2]	Historical high LRP[3]
	-------------------	% impact	-------------------

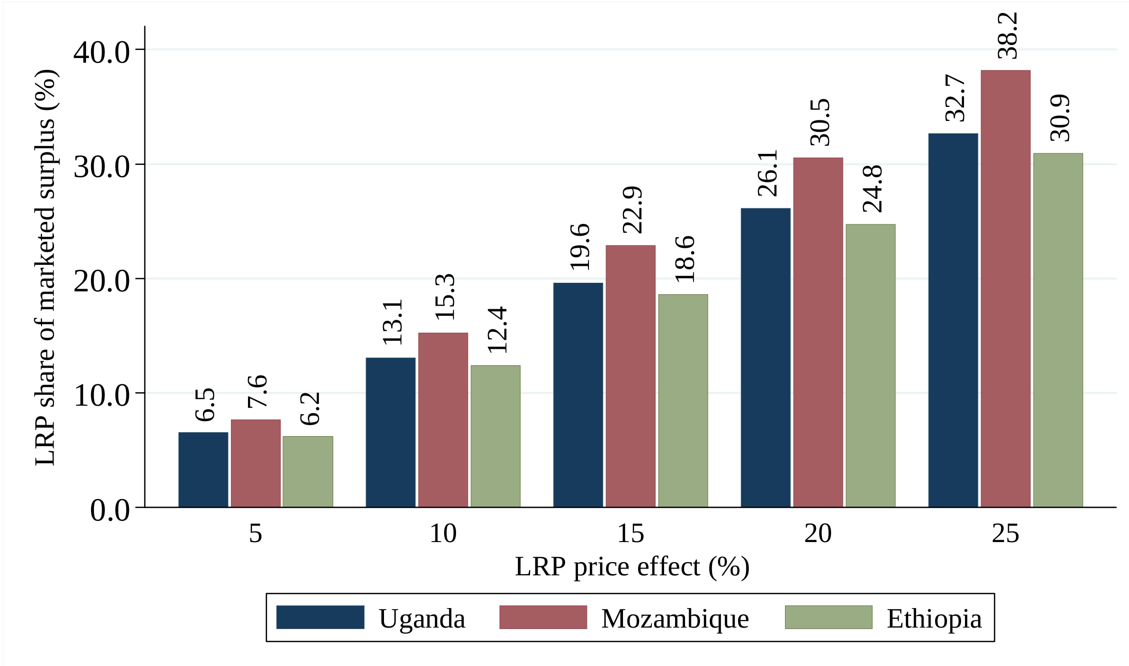
[18] Due to modeling requirements, the method for computing marketed surplus in this section differs from the approach we initially used in selecting study countries (described in Section 2.2). These two approaches thus provide a robustness check for our estimates. In the case of maize in Uganda and Mozambique, the two approaches generated similar results for LRP's share of the market: 14% versus 12.5% in Uganda, and 7% in Mozambique for each approach. For beans in Ethiopia, however, the two approaches generated very different results: 14% versus 3%. Our interviews in Ethiopia strongly suggested that 14% was a significant over-estimate of the LRP share. VAR analysis (showing small price effects) suggested the same. We believe the 3% figure used in this section to be the best estimate of WFP's share of Ethiopia's bean market.

Uganda			
1 Central	10.7%	1.1%	19.8%
2 Eastern	10.9%	1.2%	20.1%
3 Northern + Western	11.7%	1.2%	21.6%
National Average	11.1%	1.2%	20.5%
Mozambique			
1 Northern	3.6%	1.5%	6.4%
2 Central	7.5%	3.1%	13.2%
3 Southern	5.3%	2.2%	9.3%
National Average	5.5%	2.2%	9.7%
Ethiopia			
1 Oromia + SNNP	2.8%	0.5%	6.6%
2 Amhara	3.2%	0.5%	7.6%
3 Deficit regions	2.4%	0.4%	5.9%
National Average	2.8%	0.5%	6.7%

[1] 14% Uganda, 7% Mozambique, 3% Ethiopia; [2] 2% Uganda, 3% Mozambique, 1% Ethiopia; [3] 25% Uganda, 13% Mozambique, 8% Ethiopia

Table 2.9 suggests that LRP price effects and LRP share of marketed surplus are positively associated. To gain additional insights on the relationship between LRP effects and LRP share of marketed surplus, we use the CM to simulate what level of LRP purchases relative to marketed surplus would have led to a given LRP price effect. This exercise helps us identify thresholds of LRP purchases as a proportion of marketed surplus beyond which the corresponding LRP price effects become significant in each country application, especially in Mozambique and Ethiopia. Findings are plotted in Figure 2.7. This figure reinforces that LRP as a share of marketed surplus and LRP price effects are positively related in all country applications. Although LRP price effects are estimated to be modest when LRP is at its historical mean in Mozambique and Ethiopia (see Table 2.9), Figure 2.7 illustrates that significant LRP purchases relative to marketed surplus (above 15% in Mozambique and above 12% in Ethiopia) are associated with meaningful LRP price effects (greater than 10%).

Figure 2.7 Relationship between LRP price effect and LRP share of marketed surplus



We also conducted sensitivity analysis on how changing assumptions about supply and demand elasticities influence the estimated LRP price effects (Table 2.10). For these estimates we assume the share of LRP relative to total marketed surplus remains at its base level (historical average). As expected, the inelastic supply and demand scenario gives the largest impact: about 15 to 16% in Uganda compared to 11 to 12% in the base case, about 5 to 11% in Mozambique compared to 4 to 8% in the base case, and 4 to 5% in Ethiopia compared to about 3% in the base case. The elastic supply and demand scenario gives the lowest estimated impact, consistently 20 to 25% below the base case scenario. The intermediate cases of inelastic (elastic) demand and elastic (inelastic) supply deliver results that are not meaningfully different from the base elasticities.

Table 2.10 Sensitivty of LRP effects to changes in supply and demand elasticities

Variable	Scenario

	Inelastic Supply and Demand[1]	Inelastic Supply, Elastic Demand	Base Elasticities[3]	Elastic Supply, Inelastic Demand	Elastic Supply and Demand[2]
	----------------------------	----------------------------	% effect	----------------------------	----------------------------
Uganda					
Central Region	14.5%	11.2%	10.7%	10.2%	8.5%
Eastern Region	14.8%	11.4%	10.9%	10.4%	8.6%
Northwestern Region	15.8%	12.2%	11.7%	11.2%	9.3%
National Average	15.0%	11.6%	11.1%	10.6%	8.8%
Mozambique					
Northern Region	5.3%	3.7%	3.6%	3.5%	2.7%
Central Region	11.3%	7.1%	7.5%	8.0%	5.6%
Southern Region	7.9%	5.0%	5.3%	5.6%	4.0%
National Average	8.2%	5.3%	5.5%	5.7%	4.1%
Ethiopia					
Oromia + SNNP	4.1%	2.8%	2.8%	3.3%	2.1%
Amhara	4.7%	3.2%	3.2%	3.8%	2.4%
Deficit regions	3.7%	2.5%	2.4%	2.9%	1.8%
National Average	4.2%	2.8%	2.8%	3.3%	2.1%

Notes: [1] Inelastic supply and demand: 0.5 and -0.6 in Uganda; 0.4 and -0.4 in Mozambique and Ethiopia;[2] Elastic supply & demand: 0.9 and -1.0 in Uganda; 0.8 and -0.8 in Mozambique and Ethiopia; [3] Base elasticities: 0.7 and -0.8 in Uganda; 0.6 and -0.6 in Mozambique and Ethiopia.

Overall, the CM analysis indicates that, under preferred market parameter estimates and average historical LRP levels, price effects on maize in Mozambique and beans in Ethiopia are modest. Under the most extreme cases – inelastic supply and demand and historically high LRP, which are not shown in the tables, effects average about 14% in Mozambique and 10% in Ethiopia. While these are meaningful figures, they are likely to occur only if supply and demand are much more inelastic than we believe, and only then in the few periods when the LRP share of total marketed surplus is at historically high levels. In Uganda, on the other hand, even the base case scenario delivers economically meaningful estimated price changes of 11 to 12%, rising to 20% under the highest observed LRP, and beyond that if we assume that supply and demand are more inelastic than the base case.

In all three country applications, the results from the CM are quite consistent with mean average price effects obtained from the VAR. For instance, in the application to Uganda, the average price effects obtained from the VAR – ranging from 13% in Kisenyi to 16% in Lira –

compare to the base case range of 11 to 12% from the CM and are consistent with our inelastic supply and demand scenario under historical average LRP from the CM (see Tables 2.7, 2.9 and 2.10). Furthermore, in all three study countries, CM results under preferred elasticity estimates and historical average LRP share of marketed surplus (i.e., the base case in Table 2.9) lie within the 90% confidence interval from the average VAR results (i.e. second and fourth columns in Table 2.7). These results show that major conclusions regarding the extent to which WFP LRP has raised local market prices are robust to our two alternative modeling approaches.

2.5 Conclusions

LRP is playing an increasingly important role in food aid. Yet, relatively little is known about the effects of LRP on local market prices, especially in countries where LRP represents a meaningful share of the marketed surplus. This paper adds to knowledge by broadening our understanding of the LRP effects on local markets and prices in countries where LRP is important relative to marketed surplus. The paper also makes two methodological contributions. First, unlike previous studies that use structural VARs to evaluate the effects of food policies, we develop a bootstrapping procedure to construct confidence intervals around estimated LRP effects on local market prices to account for sampling error. Second, although VAR models and a CM approach have been used separately to investigate the effects of food and other policies, to our knowledge this is the first attempt to use these two complementary methodologies together as a consistency/robustness check.

Using data from January 2001 through December 2011 in Uganda and Mozambique and from September 2001 through December 2011 in Ethiopia, this paper provides empirical evidence on how LRP activities are affecting local maize prices in Uganda and Mozambique and local beans prices in Ethiopia. Results from the VAR reveal that, with the exception of Uganda, the average LRP effects on local prices are statistically significant but modest in size. LRP purchases are estimated to have increased average local market prices by 13 to 16% in Uganda, compared to 2 to 7% in Mozambique and 4 to 5% in Ethiopia. In all three countries, LRP interventions had no meaningful effect on price variability. Because we chose countries with the highest LRP as a share of marketed surplus for this study, it is likely that LRP price effects in other African countries will be lower. Overall, the results from the CM are consistent with those from the VAR as price effects estimated from the CM at the historical mean LRP levels (base case) lie within the 90% confidence bounds obtained from the VAR. Results from the CM suggest that LRP price impacts are most sensitive to LRP as a share of marketed surplus, as expected. Our findings also indicate that supply and demand elasticities can have an important impact on the magnitude of the LRP effects on local market prices.

Even though WFP LRP effects on local market maize prices in Mozambique and bean prices in Ethiopia were estimated to be modest on average, effects were substantial in particular years when the recent history of LRP purchases were especially high. Furthermore, even average effects for maize prices in Uganda are estimated to be quite substantial. This suggests that WFP does need to pay attention to possible local market price increases when their LRP purchases become significant relative to the size of the marketed surplus (greater than 13%, 15%, and 12% in Uganda, Mozambique, and Ethiopia, respectively). In situations where these price increases are significant, this could have important implications for both the prices WFP is paying for their LRP, and for the welfare of food aid recipients and non-recipients alike. Detailed calculations of the effects of these price increases on household welfare are left until essay two of the dissertation. However, we expect that net sellers will benefit from price increases brought about by LRP purchases and net buyers will be hurt.

In situations where price effects are modest the overall effect of LRP will depend on the systemic effects that WFP is able to induce in the supply chain as it goes about its procurement. WFP LRP activities can potentially contribute to improved quality practices, investments aimed at improving quality, gains in operational efficiencies resulting from large-scale LRP transactions at known prices traders can bid, and consequently increased local traders' ability to enter quality-stringent export markets. These effects could potentially lead to transformational changes in food systems, contributing to overall development of countries where WFP procures food commodities and are the subject of essay three of the dissertation.

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CHAPTER 3

HOUSEHOLD WELFARE EFFECTS OF LOCAL PRICE INCREASES INDUCED BY WORLD FOOD PROGRAM LOCAL AND REGIONAL PROCUREMENT IN AFRICA

3.1 Introduction

Prior to 1995, local and regional procurement (LRP) – the purchase of food commodities in the country or region where food aid is being distributed to targeted groups of households – accounted for less than 5% of total global food aid deliveries. But from 2001 to 2011, LRP experienced a sharp upward trend, reaching its historical high of about 30% in 2011. Despite this increasingly important role played by LRP as an instrument for sourcing food aid, relatively little is known about the LRP impacts on local market prices and resulting welfare effects on households participating in those markets.[19]

A study by Garg *et al.* (2013) evaluated the impacts of the United States Department of Agriculture (USDA) LRP pilot programs on local market prices in seven countries and found that USDA LRP did not have statistically significant effects on price levels or variability. This finding is not surprising because the USDA LRP pilot programs, accounting for less than 1% of the size of the market, were very small in all seven study countries, as recognized by the authors.[20] Essay one of this dissertation reports on a comprehensive investigation into the United Nations World Food Program (WFP) LRP effects on local market prices in three countries where WFP LRP purchases were much larger relative to the size of the marketed surplus. Results suggest that WFP LRP in these countries had statistically significant effects on price levels in all three countries, and that average price increases were in the order of 3% to 16%. On the other hand, the impacts of WFP LRP on price variability were not statistically significant, except in Nampula (Mozambique) where they were statistically significant but still quite small.

When LRP purchases increase local market prices of LRP commodities there will be a corresponding effect on the welfare of households that buy and/or sell those commodities. The purpose of this paper is to take the LRP-induced local price changes estimated in the

[19] Figures reported here are computed from data from the International Food Aid Information System developed by the United Nations World Food Program.
[20] Garg *et al.* (2013) define the size of the market as difference between production and net exports.

previous chapter and convert them into estimates of resulting changes in household welfare. Starting with the pioneering work of Deaton (1989), the literature on welfare effects of commodity price changes is extensive and growing, especially after the spike in global food prices in 2008 (Friedman and Levinsohn, 2002; Mghenyi, Myers and Jayne, 2011; Vu and Glewwe, 2011; Azzam and Rettab, 2012; Ferreira *et al.*, 2013). Yet we are not aware of any empirical study that assesses how price changes brought about by LRP affect household welfare.

This paper addresses this issue by focusing on LRP welfare effects for one commodity and two countries where LRP has been a meaningful share of marketed surplus: maize in Uganda and Mozambique.[21] Maize income and expenditure shares are among the key determinants of the welfare effects of price increases. Uganda and Mozambique, therefore, make an interesting contrast because the importance of maize in food consumption and total household income are quite different in each country. Maize is the dominant staple food in Mozambique where the share of total household income accounted for by maize expenditures averages 12%. By contract, maize is only one of the many staple foods in Uganda where the grain represents on average 6% of total household income and households have more diversified diets. The average share of total household income that comes from maize is 12% in Mozambique, compared to 5% in Uganda. Possibilities for switching to and from crops competing with maize are also greater in Uganda than in Mozambique.

A study by Levinsohn and McMillan (2007) uses an approach similar to ours to investigate the welfare effects of wheat food aid deliveries in Ethiopia. However, our approach differs from Levinsohn and McMillan in at least two ways. First, in contrast to Levinsohn and McMillan who investigated the welfare effect induced by a supply shifter (food aid deliveries), we assess the welfare effects induced by a demand shifter (LRP). Second, unlike the measure used by Levinsohn and McMillan, our welfare measure takes into account second-order effects where households may respond to price increases by adjusting their production and consumption

[21] Essay one also estimated LRP impacts on local bean prices in Ethiopia. However, lack of suitable nationally representative household survey data prevented us from assessing the household welfare impacts stemming from bean price increases induced by LRP purchases in Ethiopia.

decisions. Accounting for these adjustments should result in better estimates especially if supply and demand are highly responsive to price changes, as argued by Mghenyi, Myers and Jayne (2011) and Vu and Glewwe (2011). A limitation of our study is that we only examine the welfare effects of the LRP price effect, excluding the welfare effect of the food aid deliveries themselves.

LRP maize purchases put upward pressure on local demand for maize, reducing the amount of marketed maize surplus available through normal market channels for household consumption in the surplus region of the country where LRP takes place. Consequently, local market maize prices rise in both surplus and deficit regions of the country.[22] Different types of households may experience the welfare effects of increased maize prices very differently because households are heterogeneous. Household maize market position – whether a household is autarkic, a net seller or net buyer – is a key factor determining whether a household is better off or worse off with the LRP-induced maize price increase. Net sellers are expected to gain while net buyers lose. This paper therefore uses household-level data to provide insights on how household welfare effects stemming from LRP-induced maize price increases differ across region, across household market position, and across households with different income levels. Results provide information on how the welfare effects are distributed throughout the population of households in each country application. This makes our results of interest to food aid agencies in particular and policy makers in general because it is important to determine who would benefit and be hurt from the induced maize price increase.

The remainder of the paper is structured as follows. Our conceptual framework is described in Section two. Section three outlines the welfare measure used, while Section four discusses the model setup and describes the data used to operationalize the welfare measure. Summary statistics for key factors used in the calculation of our welfare measure and the corresponding results are presented in Section five. A nonparametric regression approach used

[22] LRP maize purchases are distributed as food aid to targeted households. We recognize that food aid distribution is usually characterized by imperfect targeting, but we abstract from this issue here because any effects on market prices from food aid crowding out effective demand are likely to be small. This view is consistent with findings by Jayne *et al.* (2001) indicating that the probability of receiving food aid in rural Ethiopia was greater for poorer households compared to wealthier households in spite of the empirical evidence of imperfect targeting.

to investigate the relationship between welfare effects and household income, and the corresponding results, is also discussed in Section five. Section six closes with concluding remarks.

3.2 Conceptual framework

Our conceptual framework is based on the agricultural household model outlined by Singh, Squire and Strauss (1986), and Taylor and Adelman (2003); among others. Let $U_i(S_i)$ denote a twice continuously differentiable and strictly quasi-concave utility function for household i where S_i represents consumption of a food commodity. The utility function may also depend on consumption of several other commodities consumed by households. However, we do not show these other commodities explicitly because they are held constant in the analysis that follows. We assume that household i is both consumer and producer of the food commodity. The household solves the following utility maximization problem:

(3.1)
$$\max_{S_i} U_i\left(S_i\right)$$
$$\text{subject to} \quad p_i S_i \leq y_i + \pi_i\left(p_i\right)$$

where p_i represents price of the food commodity; y_i is other income (excluding income from production of the food commodity); $\pi_i(p_i) = p_i F_i[K_i(p_i)] - r_i K_i(p_i)$ denotes profits from production of the food commodity; $F_i(\cdot)$ represents production function for the food commodity; $K_i(\cdot)$ denotes profit-maximizing choices of productive assets (e.g. land) employed in the production of the food commodity; and r_i represents prices of productive assets.[23] We note that total household income, $y_i + \pi_i(p_i)$, is endogenous in the agricultural household model because it depends on household profit-maximizing production decisions resulting from changes in prices of the food commodity. Solving the utility maximization problem yields household demand for the food commodity:

(3.2)
$$S_i = S_i\left[p_i; y_i + \pi_i\left(p_i\right)\right]$$

[23] In addition to price of the food commodity, the profit function and demand functions for productive asset also depend on the prices of productive assets. However, we do not explicitly show the prices of the productive assets in these functions because they are kept constant in the analysis that follows.

Differentiating equation (3.2) with respect to price of the food commodity yields

(3.3)
$$\frac{dS_i}{dp_i} = \frac{\partial S_i}{\partial p_i} + \frac{\partial S_i}{\partial \pi_i}\frac{d\pi_i}{dp_i}$$

From this last expression, two channels through which changes in the price of the food commodity affect demand for the commodity can be identified. First, households adjust their consumption – the first right-hand term in equation (3.3) – in response to changes in the food commodity price (consumption effect). Second, consumption is further changed – the second right-hand term in equation (3.3) – because commodity price changes also affect household profits from the commodity (profit effect). Suppose that WFP LRP purchases increase price of the food commodity. Consumer demand theory predicts that consumption of the commodity whose price increased should decline, assuming that the commodity in question is a normal good. This indicates that the first term on the right hand side of (3.3) is negative. On the other hand, production theory predicts that household should increase supply (production) of the food commodity whose price increased, leading to higher household profits and consequently higher household total income. This in turn leads to increase in the consumption of the food commodity, suggesting that the second term is positive. Hence, the aggregate effect of the price increase on the demand for the commodity depends on whether or not the consumption effect outweighs the profit effect.

Substituting the demand function for the food commodity into the utility function gives the following indirect utility function

(3.4)
$$U_i\left[S_i\left(p_i; y_i + \pi_i(p_i)\right)\right] \equiv V_i[p_i; y_i + \pi_i(p_i)]$$

We use the indirect utility function to derive our household welfare measure stemming from an increase in the price of the food commodity. The household welfare measure we estimate is the household's willingness to accept compensation for the price increase. More precisely, we estimate proportional compensating variation, which is the percentage reduction in a household's income that would have to be made after the price increase to make them as well off as they were before the increase (see, for example, Friedman and Levinsohn, 2002; Mghenyi, Myers and Jayne, 2011). If the compensating reduction in income is positive (income has to be taken away to make the household as well off as before) then the price increase improved the household's welfare. Similarly, if the compensating reduction in income is negative (income has to be provided to make the household as well off as before) then the price increase reduced the household's welfare. Hence, positive values of our welfare measure indicate a household's welfare was improved by the price increase and negative values indicate welfare was reduced. Proportional rather than actual compensating variation is used (i.e. the compensating payment is expressed as a proportion of base income) because this gives a more intuitive measure of *relative* welfare change that is not sensitive to the currency used to measure income and prices.

3.3 Estimation of Household Welfare Effects

Consider the indirect utility function for household i, $V_i[p_i; y_i + \pi_i(p_i)]$, as an ordinal measure of household utility given commodity price p_i and assuming the household makes utility maximizing consumption choices and profit maximizing production choices. The household is implicitly assumed to sell all of its commodity production at price p_i and to buy back its consumption choice at that same price. Therefore, $\pi_i(\cdot)$ represents the value of all production (whether own-consumed or not).

A proportional compensating variation measure of the welfare effect of a change in the household's price from p_i^0 to p_i^1 is defined implicitly by an m that satisfies:

(3.5) $$V\left[p^0; y + \pi\left(p^0\right)\right] \equiv V\left\{p^1; (1-m)\left[y + \pi\left(p^1\right)\right]\right\}$$

where we have dropped the i subscript to simplify notation. By definition, m is the proportional reduction in income that would have to be made after the price change to make the household as well off as it was before the change. It has been shown (e.g., Deaton, 1989; Kim, 1997) that m is a theoretically consistent cardinal money metric measure of welfare change for binary comparisons (e.g., with and without the price change).

Following Mghenyi, Myers and Jayne (2011), and others, we take a second-order Taylor series approximation of the left-hand side of (3.5) around $(p^0, m) = (p^1, 0)$ to get:

(3.6) $$V\left(p^1\right)+\left[V_p+V_y\pi_p\right]\left(p^0-p^1\right)+\frac{1}{2}\left\{V_{pp}+2V_{py}\pi_p+V_{yy}\left(\pi_p\right)^2+V_y\pi_{pp}\right\}\left(p^0-p^1\right)^2$$

where subscripts denote derivatives with respect to the subscripted variable evaluated at the post-change price p^1. Similarly, defining $y^1 = y+\pi(p^1)$ and taking a second-order Taylor approximation of the right-hand side of (3.5) at $m=0$ gives:

(3.7) $$V\left(p^1\right)-V_y y^1 m+V_{yy}\left(y^1\right)^2 m^2$$

The term in m^2 is of higher order and can be ignored in the context of a second-order approximation. After imposing this restriction, using Roy's identity and Hotelling's lemma, making some simplifying assumptions, and equating (3.6) and (3.7), it has been shown (see Newbery and Stiglitz, 1981; Myers, 2006; Mghenyi, Myers and Jayne, 2011) that solving for m gives:

(3.8) $$m \approx \left(s^s-s^d\right)\lambda-\frac{1}{2}\left[s^s\xi^{sp}-s^d\xi^{dp}\right]\lambda^2+\frac{1}{2}\left\{\left(R-\xi^{dy}\right)\left[\left(s^d\right)^2-2s^d s^s\right]+\left(s^s\right)^2 R\right\}\lambda^2$$

where s^s is the share of maize production in total income; s^d is the share of maize consumption expenditures; $\lambda=\left(p^1-p^0\right)/p^1$ is the change in price expressed as a proportion of the post-change price; ξ^{sp} is the price elasticity of supply; ξ^{dp} is the price elasticity of demand; ξ^{dy} is the income elasticity of demand; and R is the coefficient of relative risk aversion. The first term in (3.8) is the standard first-order welfare effect (no allowance for production or consumption responses), while remaining terms capture the second-order welfare effects (additional welfare change due to supply and demand responses).

We highlight a few key features of the approach. First, to compute the welfare effects we assume that LRP increases local market prices for LRP commodities but has no effect on wage rates or the local market prices of other commodities. In this sense our approach is partial equilibrium. However, the additional general equilibrium effects (which would take possible changes in wage rates and other commodity prices into account) are likely to be small in our country applications because there is limited substitution between major food staples and other commodities, and because wage rates are determined by many other factors besides the prices of a single staple food. So the partial equilibrium welfare measure used here should give a good approximation to the total welfare effect of the price increase. Findings from Ivanic and Martin (2008) support this assertion.[24]

Second, our welfare measure allows for the fact that households consume own-produced food by including the value of own consumption and own production in the calculation of expenditure and income shares. It is important to account for consumption of own-produced food because this is an important activity among many of the households in the study countries. Household-level data we use in our applications show that consumption from own production constitutes, on average, about 15% and 40% of annual household maize consumption in Uganda and Mozambique, respectively. The data also show that about 25% and 45% of households consume maize from own production in Uganda and Mozambique, respectively.

Third, our measure focuses on the effects of a price increase and takes no account of the welfare effects of changes in price variability or risk. It has been shown that changes in price variability and risk can have significant welfare effects (e.g., Barrett and Dorosh, 1996; Bellemare, Barrett and Just, 2013). However, as indicated in the introduction, WFP LRP purchases had no statistically significant effect on maize price variability in our country applications, and therefore presumably no significant effect on price risk. Therefore, we can appropriately focus on price level effects and assume any additional welfare change due to a change in price variability or risk is negligible.

Fourth, our welfare measure takes account of second-order effects where households may change their production and consumption decisions in response to the LRP-induced price change. Many existing studies of household welfare effects of price changes (e.g. Barrett and Dorosh, 1996; Levinsohn and McMillan, 2007; Valero-Gil and Valero, 2008; Ivanic, Martin and Zaman, 2012; Fujii, 2013) assume no production or consumption response to the price change

[24] These authors estimated the impact of soaring global food prices on poverty in nine low-income countries using household-level data and found that a 10% increase in maize prices resulted, on average, in a 0.1 percentage points increase in poverty – in both rural and urban areas – with and without the induced wage impact on unskilled labor. In each of the nine low-income countries, there is no change in the magnitude or the sign of the estimated effects of the higher maize price on poverty when the induced wage impacts are accounted for.

(i.e., they estimate first-order effects only) but including second-order effects should lead to better estimates, especially if production and consumption respond significantly to changes in price.

3.4 Welfare Estimation Set-Up and Data

Given its relative importance in WFP LRP purchases, the focus of this paper is on maize in Africa. The two most important African countries in terms of the average share of LRP maize purchases in total marketed surplus over the period 2001 to 2011 are Uganda at 14% and Mozambique at 7%.[25] Given this relative importance, we focus on maize in Uganda and Mozambique.

The most critical determinants of the welfare effects of a maize price increase are the size of the maize price increase, the share of total household income that comes from maize, and the share of total expenditures devoted to maize. The size of the maize price increases were estimated in the previous chapter of this dissertation. For the income and expenditure calculations for Uganda we use data from the Uganda National Panel Survey (UNPS) 2009/2010 conducted by the Uganda Bureau of Statistics (UBOS) to compute household-level estimates of these shares. The UNPS 2009/2010 is a nationally representative survey during which 3,123 households were interviewed, of which 73% reside in rural areas. Our measure of total household income consists of crop income (total value of crop production), livestock income (gross value of sales of livestock and livestock products), income from formal and informal labor employment of household members, revenues from medium-to-small enterprises operated by household members, and remittances and pensions received by household members. We use median district-level maize prices, estimated from the household data, to value maize production and consumption. We estimate expenditure on maize by adding expenditures on purchases from the market and implicit expenditures on consumption from own production. To compute the maize income and expenditure shares, we took income from maize production and total expenditure on maize and divided by total household income.

[25] Details on how the share of LRP purchases in total marketed surplus is estimated are presented in essay one of this dissertation that deals with the LRP effects on local market prices.

For Mozambique, our estimates of the share of household expenditures on maize and the share of total income from maize production are drawn from household-level data from the Household Budget Survey (IOF) 2008/09. The IOF 2008/09 is a nationally representative survey administrated by the Mozambique National Institute of Statistics (INE). A total of 10,832 households were interviewed during the IOF 2008/09. The share of the sample accounted for by rural households was 53%. Given that IOF 2008/09 is an expenditure survey that does not collect household income, we use total household expenditure as our estimate of total household income. Total household expenditure is comprised of four components: consumption of food, non-food, durable goods and housing. As in the case of Uganda, we compute maize expenditures by multiplying the quantity of maize consumed by each household by the median district-level maize price. Maize expenditure consists of expenditures on maize consumed by the household whether purchased or from own production. Median district-level maize prices are computed from the household-level data. We estimate income from maize production by multiplying maize production by median district-level maize price. Maize income and expenditure shares are calculated as the ratio of income from maize production and expenditure on maize to total household expenditure, respectively.

Essay one of this dissertation estimates the WFP LRP effects on local prices using two complementary methodologies: vector autoregression (VAR) and a computational model (CM). The essay develops a CM to stimulate the long-run effects of WFP LRP purchases on prices over the period 2001 to 2011. The CM is a structural simulation model that takes a comparative static approach to compare two equilibria – one with and one without LRP. The CM price effects are simulated under three hypothetical scenarios: (1) base case corresponding to historical mean LRP share of marketed surplus (14% in Uganda and 7% in Mozambique); (2) historical high LRP corresponding to the highest LRP share (25% in Uganda and 13% in Mozambique); and (3) historical low LRP corresponding to the lowest LRP share (2% in Uganda and 3% in Mozambique). Here we take the estimated CM price effects obtained from the base case and convert them into resulting effects on household welfare. Given that findings from essay one show that the magnitude of price effects are sensitive to the size of LRP relative to marketed surplus, we also undertake sensitivity analysis using the estimated CM price effects from the historical high and low LRP scenarios.

To account for dynamic adjustment between the equilibria, essay one complements the CM with VAR models as a consistency check. For the VAR estimates we use a bootstrapping procedure to construct confidence intervals around estimated mean price effects to account for sampling error. Unlike the CM, VAR is a “reduced-form” approach that makes no assumptions about the underlying market structure. Therefore, we could have alternatively taken the VAR mean estimates of price effects to undertake our welfare analysis and used the 90% confidence intervals for the mean VAR estimates for sensitivity analysis. However, the mean estimated price effects from the VAR are similar to the CM base results so base welfare change estimates would be little different under the two methods for estimating the price change. Furthermore, the upper and lower bounds for the estimated CM price effects (under historical high and low LRP) encompass a wider range for the price effects than the 90% confidence interval from the VAR. Therefore, using the CM model price effect estimates to operationalize the welfare calculations allowed for a greater range of sensitivity analysis.

Results from the CM reported in essay one of this dissertation show that estimates of LRP-induced maize price increases vary slightly by region throughout each country application. Hence, when computing the welfare effects we also allow the price change to vary across regions. We assume the market level price effects of LRP transmit fully to changes in prices at the household level (the percentage increase in household prices is the same as the percentage increase in market prices). This assumption fits well for maize in Uganda where evidence suggests excellent price transmission from markets to farmers. There is more uncertainty about price transmission from markets to farmers in Mozambique, particularly prior to 2009 when there was no bridge over the Zambezi River, creating a natural trade barrier between markets in Northern Mozambique and those in the Central and Southern parts of the country. However, we also did sensitivity analysis on the size of the price effect to illustrate how welfare effects may differ if household prices increase by smaller or larger proportions than market prices. Results show estimated household welfare effects are sensitive to the magnitude of the price effect, dropping when price effects are smaller and increasing when price effects are larger.

Other data required to estimate the household welfare change includes: (1) elasticities of household supply and demand for maize; and (2) a measure of the household's relative risk aversion. Estimates of supply and demand elasticities for maize are set at 0.7 and -0.8, respectively, in Uganda and at 0.6 and -0.6, respectively, in Mozambique. These choices are based on estimates from the literature along with prior knowledge of the countries and their maize markets (Chhibber, 1989; Karanja, Renkow and Crawford, 2003; Ulimwengu and Ramadan, 2009; Zant, 2012). These are reasonable demand and supply assumptions because wider crop and dietary diversities in Uganda make supply and demand more responsive to price changes in Uganda compared to Mozambique.

We could not find any empirical estimates of the maize income elasticity of demand for our country applications. Following the approach of Mghenyi, Myers and Jayne (2011) in the neighboring country of Kenya, we set the base value of income elasticity of demand for maize at 0.40 in our application to Uganda. Given that Kenya and Mozambique are similar in many ways with regard to maize consumption, income elasticity of maize demand is also set at 0.4 in our application to Mozambique. For both Uganda and Mozambique, supply elasticities, demand elasticities and maize income elasticities of demand are assumed to be the same across all households within each country. Although these elasticities could show some variation across geographical regions in each country application, we could not find estimates disaggregated by regions to account for regional variations. However, we expect that accounting for these regional variations would not have any discernible effects on the magnitude of the welfare effects because sensitivity analysis shows that estimated welfare effects are not very sensitive to a reasonable range of values for the supply and demand elasticities.

Finally, we need estimates of the coefficient of relative risk aversion. Estimates for developing countries are rare in the literature. Myers (1989) generated point estimates of between 1.6 and 3.1 for U.S. farmers. Hansen and Singleton (1983) estimated values ranging from 0.0 to 2.0 for U.S. consumers. Therefore, we set the base parameter of relative risk aversion at one for both Uganda and Mozambique. Mghenyi, Myers and Jayne (2011) and Bellemare, Barrett and Just (2013) argue that a value of one is reasonable and use the same value in their studies. Like supply and demand elasticities, the coefficient of relative risk aversion is assumed to be the same across all households in each study country. Sensitivity analysis for both Uganda and Mozambique revealed that estimated welfare effects in each country application change very little under a wide range of alternative assumptions about supply elasticities, demand elasticities and household risk aversion, so results are not sensitive to these assumptions.[26] This suggests that varying these parameters across regions within each country application would have negligible effects on the magnitude of the estimated welfare effects.

3.5 Summary Statistics and Welfare Results

The distribution of effects across regions is of interest and maize market position is a key factor determining whether households are better off or worse off from the maize price increase. Table 3.1 shows the distribution of households in each country data set broken down by regional location and maize market position. Northern Mozambique has the highest proportion of total households in the Mozambique sample (54%) while Northwest Uganda has the highest proportion of households in the Uganda sample (46%). At the national level in both Mozambique and Uganda about 24% of households are autarkic, implying that LRP-induced maize price increases will have no impacts on the welfare of about one fourth of households in both countries. However, the proportion of autarkic households does vary across regions, ranging from about 17% in Central Mozambique to 40% in Southern Mozambique. There are also significant proportions of households in each region that are either sellers or net sellers (expected to gain from the price increase), and either buyers or net buyers (expected to lose). The regions with the largest proportion of households that only buy or are net buyers are Central Mozambique (54%) and Eastern Uganda (51%). Central Mozambique and Central Uganda are the regions with the largest proportion of households that only sell or are net sellers (30% and 36%, respectively).

Table 3.1 Distribution of households by region and maize marketing position in Mozambique and Uganda

Region	Percentage	Maize market position (%)

[26] Results of the sensitivity analysis are available upon request.

of households	Autarky	Buy only	Buy and sell (net buyer)	Sell only	Sell and buy (net seller)
Mozambique						
Northern	53.7%	19.7%	21.3%	31.9%	12.5%	14.6%
Central	22.8%	16.6%	8.6%	44.9%	16.7%	13.2%
Southern	23.5%	39.7%	16.3%	17.1%	20.7%	6.2%
National	100.0%	23.7%	17.2%	31.4%	15.4%	12.3%
Uganda						
Eastern	32.8%	22.8%	35.9%	14.9%	10.3%	16.1%
Central	21.2%	17.1%	12.4%	34.8%	18.3%	17.5%
Northwest	46.0%	26.3%	21.7%	16.7%	24.8%	10.4%
National	100.0%	23.2%	24.4%	20.0%	18.6%	13.8%

Source: Author calculations based on IOF 2008 for Mozambique and UNPS 2009 for Uganda.

Because welfare effects depend critically on maize income and expenditure shares, we report mean shares across households for the national population, by region, by maize market position, by income tercile, and for urban and rural households (see Table 3.2). A number of insights from the table stand out. First, maize accounts for, on average over the national sample, a much higher proportion of household income and expenditure in Mozambique than in Uganda (12% versus 5% for income share, 16% versus 6% for expenditure share). Relative to other regions, Central Mozambique and Eastern Uganda are the most dependent on maize in their respective countries. The heavier reliance on maize as a food staple in Mozambique means that, for a given percentage price increase and market position, we should expect welfare effects to be larger in Mozambique than in Uganda.

Table 3.2 Income and expenditures shares for maize in Mozambique and Uganda

	Average maize income shares		Average maize expenditure shares	
	Mozambique 2008	Uganda 2009	Mozambique 2008	Uganda 2009
Region				
Eastern (Uganda), Central (Mozambique)	23.05%	6.48%	28.37%	9.65%
Central (Uganda), North (Mozambique)	10.94%	5.20%	14.59%	5.70%
Northwest (Uganda), South (Mozambique)	5.33%	4.20%	5.41%	4.02%
National	12.38%	5.01%	15.58%	5.76%
Maize market position				
Autarky	0.00%	0.00%	0.00%	0.00%
Buy only	0.00%	0.00%	12.53%	8.69%
Buy and sell (net buyer)	13.37%	4.47%	34.39%	14.80%

Sell only	21.21%	11.06%	0.00%	0.00%
Sell and buy (net seller)	39.92%	14.93%	21.32%	4.98%
Income category: national				
Lowest tercile	13.38%	6.88%	12.30%	10.98%
Middle tercile	12.31%	4.93%	19.20%	4.86%
Highest tercile	11.06%	3.37%	15.61%	1.77%
Income category: urban				
Lowest tercile	6.23%	1.23%	10.18%	11.75%
Middle tercile	5.48%	1.00%	11.52%	3.56%
Highest tercile	3.14%	1.10%	5.25%	0.83%
Total	4.71%	1.10%	8.55%	4.03%
Income category: rural				
Lowest tercile	15.20%	7.64%	12.84%	10.88%
Middle tercile	14.78%	5.58%	21.97%	5.08%
Highest tercile	17.50%	4.11%	24.03%	2.08%
Total	15.53%	5.82%	18.46%	6.12%

Source: Author calculations based on IOF 2008 for Mozambique and UNPS 2009 for Uganda

Second, for both Mozambique and Uganda average income and expenditure shares across the national sample are similar, but expenditure shares are slightly higher than income shares (16% expenditure versus 12% income for Mozambique and 6% expenditure versus 5% income for Uganda). This suggests that average welfare effects across the sample should be close to zero but slightly negative in both countries. Third, households that only buy maize, or are net buyers, have the smallest maize income shares and highest maize expenditure shares, while those that only sell or are net sellers have the highest maize income shares and lowest maize expenditure shares. This pattern holds across both countries and is important because the greater the difference between income and expenditure shares the greater and more positive the welfare effects of a price increase will be.

Fourth, in Uganda, maize income and expenditure shares are on average highest for low income households and lowest for high income households (see Table 3.2). Maize expenditure shares in Uganda average 11% for the poorest one third of households but only around 1% for the richest one third. Similarly, income shares average 7% for the poorest one third but only 3% for the richest one third. This pattern repeats when households are separated into urban and rural, though the actual size of the income shares for maize are much higher in rural than urban areas. In Mozambique, low income urban households also have higher maize income and expenditure shares than high income urban households. For rural households, however, income shares show no discernible pattern across different income terciles, while maize expenditure shares rise as income increases. This is likely due to the differing mix of staple foods found in rural and urban areas of Mozambique. Cassava is widely produced in rural areas and is cheaper than maize, rice is not widely produced, and wheat not at all. In contrast, while cassava can be found in urban areas it is not nearly as commonly available as maize meal. Imported rice, bread made from imported wheat, and other staples are also far more readily available in urban areas than in rural areas. As a result, maize becomes the preferred staple as incomes rise in rural areas and households move away from cassava, while it becomes the least preferred staple in urban areas because households have access to the rice, bread, and other staples which displace coarse grains as incomes rise.

Fifth, urban households have maize expenditure shares that are on average higher relative to maize income shares than rural households. This pattern is to be expected, holds across both countries, and suggests that negative welfare effects of a maize price increase are likely, on average, to fall more heavily on urban households than rural households.

As indicated earlier, LRP-induced price effects used in this paper are obtained from the CM outlined in essay one of this dissertation. Findings show that when LRP share of marketed surplus is at its historical mean in each country during the period 2001 through 2011, the impact of LRP maize purchases on local maize prices amounted to a 10.7% increase for Central Uganda; 10.9% for Eastern Uganda; 11.7% for Northwestern Uganda; 5.3% for Southern Mozambique; 7.5% for Central Mozambique; and 5.3% for Northern Mozambique. These are the estimates of price effects we used as our base case. However, we also do sensitivity analysis to investigate the welfare effects of larger price increases (consistent with historically high levels of LRP) and smaller price increases (consistent with historically low levels of LRP). Maize price increases on average by about 20% in Uganda and 10% in Mozambique when LRP relative to marketed surplus is at its historical high in each country, while the average maize price increase drops to nearly 1% in Uganda and 2% in Mozambique with LRP at its historical low.

Summary statistics (mean, median, minimum, and maximum values across all households) for estimated welfare effects are shown in Table 3.3 for each country and by region. The top panel shows estimates for the effect of a price change corresponding to the historical mean level of LRP in each country between 2001 and 2011. The middle and bottom panels then show how sensitive the welfare effects are to changes in the size of the price increase (corresponding to historically high and low levels of LRP). Results show that a maize price increase corresponding to historical mean LRP results, on average across all households, in a 0.18% and 0.12% loss in household welfare in Mozambique and Uganda, respectively. The average welfare loss drops to 0.07% in Mozambique and 0.01% in Uganda for a lower price increase, and increases to 0.34% in Mozambique and 0.28% in Uganda for a higher price increase. All of these average household proportional welfare effects are quite small.

Table 3.3 Estimated welfare effects of LRP-induced maize price increases for Mozambique and Uganda

	Mozambique (2008)				Uganda (2009)			
Region	Mean	Median	Minimum	Maximum	Mean	Median	Minimum	Maximum
				-------------------- % effect -----------------				
				Historical mean LRP[1]				
Eastern (Uganda), Central (Mozambique)	-0.45%	-0.39%	-6.71%	7.61%	-0.40%	0.00%	-10.27%	7.71%
Central (Uganda), North (Mozambique)	-0.14%	-0.06%	-3.21%	3.63%	-0.09%	0.00%	-9.00%	10.80%
Northwest (Uganda), South (Mozambique)	-0.01%	0.00%	-3.75%	5.36%	-0.01%	0.00%	-9.62%	10.74%
National	-0.18%	0.00%	-6.71%	7.61%	-0.12%	0.00%	-10.27%	10.80%
				Historical high LRP[2]				
Eastern (Uganda), Central (Mozambique)	-0.86%	-0.72%	-11.84%	13.55%	-0.83%	0.00%	-19.19%	14.22%
Central (Uganda), North (Mozambique)	-0.26%	-0.10%	-5.72%	6.48%	-0.22%	-0.01%	-16.87%	20.24%
Northwest (Uganda), South (Mozambique)	-0.03%	0.00%	-6.62%	9.47%	-0.07%	0.00%	-18.04%	20.02%
National	-0.34%	0.00%	-11.84%	13.55%	-0.28%	0.00%	-19.19%	20.24%
				Historical low LRP[3]				
Eastern (Uganda), Central (Mozambique)	-0.17%	-0.15%	-2.77%	3.12%	-0.04%	0.00%	-1.12%	0.85%
Central (Uganda), North (Mozambique)	-0.06%	-0.02%	-1.34%	1.50%	-0.01%	0.00%	-0.91%	1.09%
Northwest (Uganda), South (Mozambique)	0.00%	0.00%	-1.55%	2.21%	0.00%	0.00%	-0.97%	1.09%
National	-0.07%	0.00%	-2.77%	3.12%	-0.01%	0.00%	-1.12%	1.09%

Source: Author calculations based on IOF 2008 for Mozambique and UNPS 2009 for Uganda

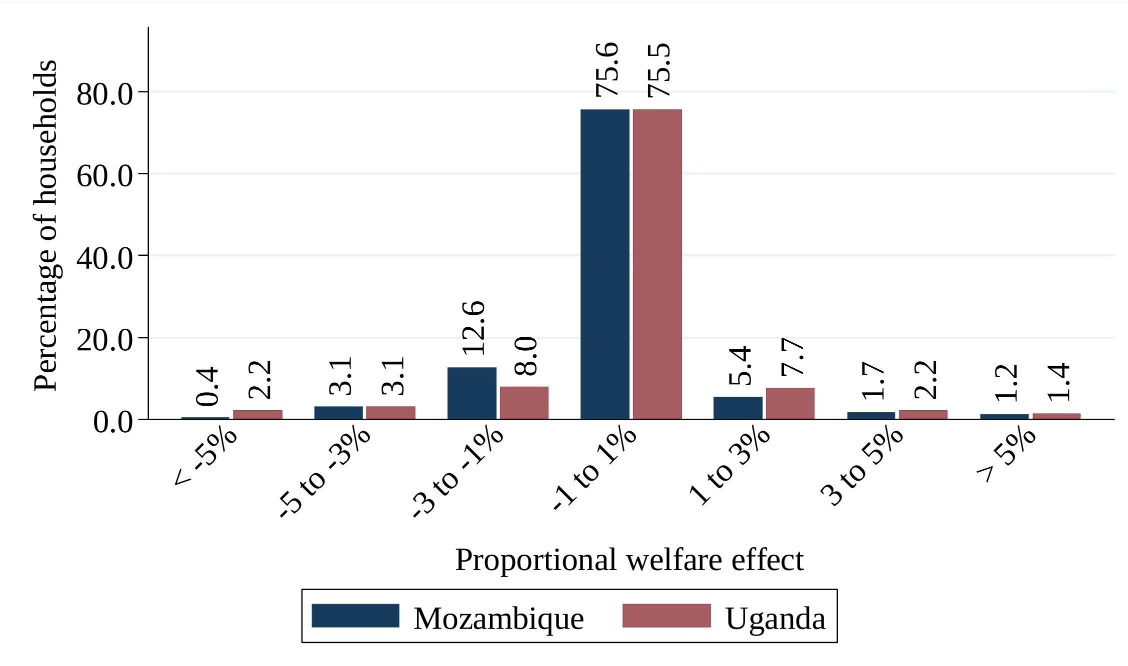
[1] 14% Uganda, 7% Mozambique; [2] 25% Uganda, 13% Mozambique; [3] 2% Uganda, 3% Mozambique.

Even though the mean LRP-induced price increase is estimated to be larger in Uganda than Mozambique (national averages of about 11% compared to 6%) the average household welfare loss is slightly higher in Mozambique than Uganda. This occurs because maize is a more dominant food staple in Mozambique while Ugandan diets and production possibilities are more diverse. This means Mozambique households generally have higher maize expenditure shares than Ugandan households which results in higher welfare effects for a given proportional price increase (see Table 3.2).

The distribution of average welfare effects across regions follows patterns that are consistent with the pattern of income and expenditure shares reported in Table 3.2. In particular, average welfare effects are more negative in regions with lower average maize income shares and higher average expenditure shares. At the national level, median welfare effects are approximately zero in both countries, indicating that half the households lose from the price increase and half gain. Regional results show some variation in medians but they are close to zero in all regions.

Although the mean and median welfare effects in Table 3.3 are small, maximum and minimum values show quite a large range in estimated welfare effects across different households. A clearer picture of the distribution of effects across the sample emerges from a graph of the frequency distributions of the welfare effects for each country under base level price increases (see Figure 3.1). The majority of households (around 76% for both Mozambique and Uganda) are little affected by the maize price increase (gain or loss of less than 1%). However, there are a significant number of households that experience moderate welfare gains and losses (5% of households in Mozambique and 8% in Uganda experience gains of 1% to 3% while 13% in Mozambique and 8% in Uganda experience losses of that magnitude). There are also a very small proportion of households that experience major welfare gains or losses (greater than 5%). The large gainers are households that have very high maize income shares and low expenditure shares while the large losers are households with very high maize expenditure shares and low income shares.

Figure 3.1 Distribution of household welfare effects of LRP-induced maize price increases for Mozambique and Uganda



Additional insight into who gains and loses is provided in Table 3.4, which shows average welfare effects broken down by household maize market position, income ranking, and rural/urban location. Effects in the table are estimated using base LRP-induced price increases for each country. As expected, autarkic households are not affected by the price increase and buyer and net buyer households are hurt the most while seller and net seller households benefit the most.

Results by income category show that in Uganda the average welfare effect across the poorest one third of households is a 0.51% loss, while the richest one third experience an average 0.16% gain. In Mozambique the pattern is reversed with the poorest one third experiencing an average 0.13% gain while the richest one third have an average 0.33% loss. The different welfare effects across income categories in the two countries is explained by earlier results on income and expenditure shares – expenditure shares on maize tend not to decline with increases in income in Mozambique, especially in rural areas (see Table 3.2).

Table 3.4 Estimated LRP household welfare effects by maize marketing position, income ranking, and rural/urban location for Mozambique and Uganda

	Mozambique (2008)				Uganda (2009)			
	Mean	Median	Minimum	Maximum	Mean	Median	Minimum	Maximum
				--------------------- % effect ------------------				
Maize market position								
Autarky	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Buy only	-0.57%	-0.34%	-6.38%	0.00%	-1.01%	-0.36%	-10.23%	0.00%
Buy and sell (net buyer)	-1.21%	-0.81%	-6.71%	0.00%	-1.22%	-0.57%	-10.27%	4.77%
Sell only	1.21%	0.38%	0.00%	7.61%	1.22%	0.50%	0.00%	10.61%
Sell and buy (net seller)	0.91%	0.41%	-0.11%	7.42%	1.03%	0.61%	-0.31%	10.80%
Income category: national								
Lowest tercile	0.13%	0.00%	-5.27%	7.61%	-0.51%	0.00%	-10.27%	7.94%
Middle tercile	-0.41%	-0.12%	-6.38%	7.61%	-0.03%	0.00%	-7.00%	10.74%
Highest tercile	-0.33%	0.00%	-6.71%	6.72%	0.16%	0.00%	-7.60%	10.80%
Income category: urban								
Lowest tercile	-0.16%	0.00%	-4.91%	7.61%	-1.21%	-0.16%	-10.23%	2.16%
Middle tercile	-0.33%	-0.04%	-5.42%	7.42%	-0.30%	-0.21%	-7.00%	2.75%
Highest tercile	-0.13%	0.00%	-4.97%	5.93%	0.02%	-0.01%	-1.44%	5.57%
Total	-0.20%	0.00%	-5.42%	7.61%	-0.34%	-0.04%	-10.23%	5.57%
Income category: rural								
Lowest tercile	0.21%	0.00%	-5.27%	7.61%	-0.42%	0.00%	-10.27%	7.94%
Middle tercile	-0.44%	-0.15%	-6.38%	7.61%	0.02%	0.00%	-6.31%	10.74%
Highest tercile	-0.50%	-0.12%	-6.71%	6.72%	0.21%	0.00%	-7.60%	10.80%
Total	-0.17%	-0.02%	-6.71%	7.61%	-0.07%	0.00%	-10.27%	10.80%

Source: Author calculations based on IOF 2008 for Mozambique and UNPS 2009 for Uganda

While these average effects do change across income categories they remain small (less than plus or minus 1%) in every income category, and maximum and minimum values across categories continue to show a wide range of welfare effects (see Table 3.4). More detail on the distribution of welfare effects across each income category are shown in Figures 3.2 (Uganda) and 3.3 (Mozambique). In Uganda the poorest one third of households has a larger proportion experiencing higher welfare losses (greater than 1%) compared to middle and high income households. However, the poorest one third also has a higher proportion of households that experience higher welfare gains (greater than 1%). The distribution of welfare effects is therefore less peaked and more spread out for the poorest one third of households compared to middle and high income households. The richest one third of households has a very peaked distribution with most members (90%) experiencing small welfare changes (between plus and minus 1%). In Mozambique the welfare distributions are very similar across income categories, indicating that the welfare effects are not distributed disproportionally across poorer households compared to richer households (see Figure 3.3).

Figure 3.2 Distribution of household welfare effects of LRP-induced maize price increases in Uganda across different income categories

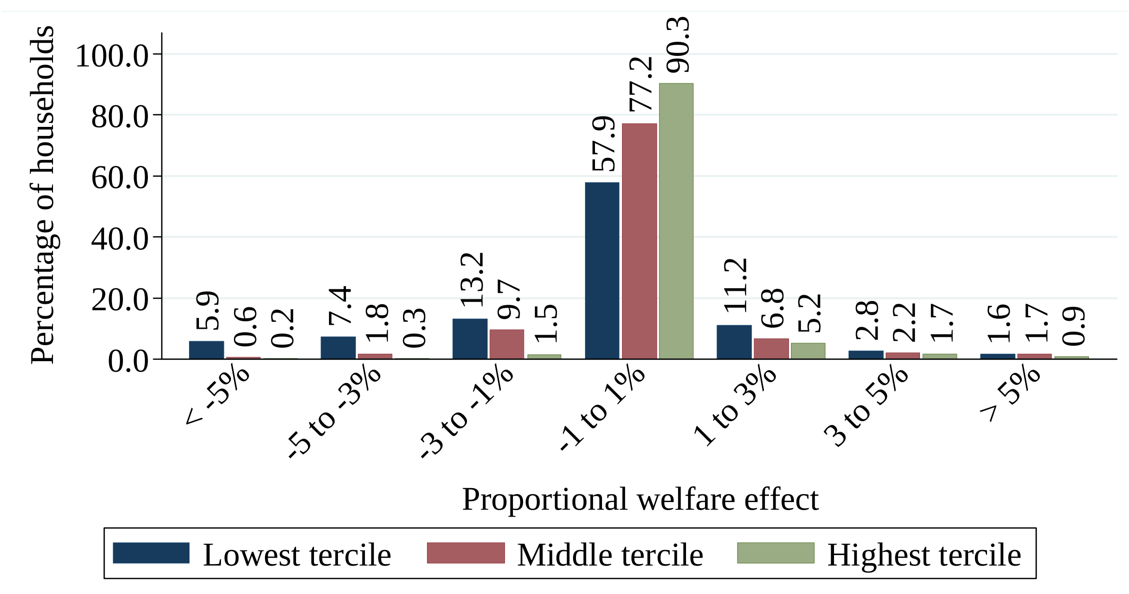
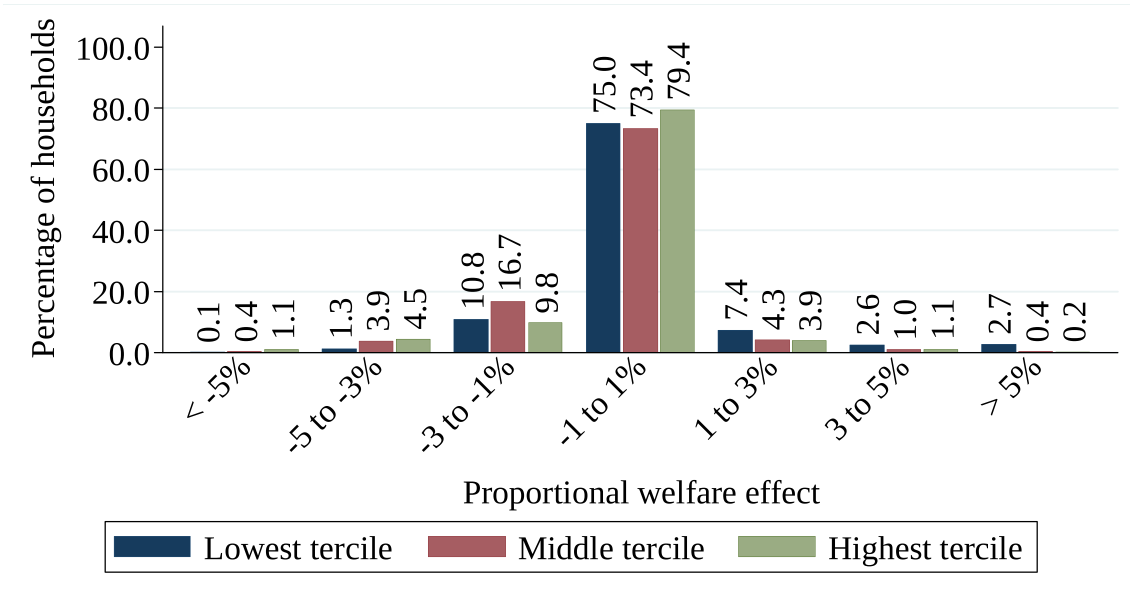


Figure 3.3 Distribution of household welfare effects of LRP-induced maize price increases in Mozambique across different income categories



Results for urban and rural households in Table 3.4 show that urban households in Uganda are more likely to experience greater welfare losses than rural households (an average 0.34% loss versus a 0.07% loss). Urban households also experience higher average losses than rural households in Mozambique (0.20% versus 0.17%). As expected, there continue to be a wide range of effects across different households within the urban and rural categories (see the maximum and minimum values for urban and rural households in Table 3.4).

To gain additional insights on who gains and loses from the maize price increases brought about by LRP maize purchases, following Deaton (1989), Barrett and Dorosh (1996) and others, we use nonparametric regression to explore the relationship between proportional welfare effects and per adult equivalent total household income. The advantage of this technique over parametric approaches is that no assumptions about functional forms are made, letting the data "speak for themselves". This is of particular importance when functional forms are unknown, which is the case in our applications. The Nadaraya (1964) and Watson (1964) estimator is the most extensively used smoothing approach in the literature on nonparametric regression analysis. However, we instead employ Kernel-weighted local polynomial smoothing, which involves regressing the welfare effect on a polynomial of per adult equivalent total household income through locally weighted least squares. We made this choice because it has been shown that local polynomial smoothers have higher asymptotic efficiency compared to the Nadaraya-Watson estimator (see Fan, 1992; Ruppert and Wand, 1994). The model we estimate is specified as

$$m_i = f\left(x_i\right) + u_i \tag{3.9}$$

where m_i denotes the welfare effect of the LRP-induced maize price increase on household i; x_i represents per adult equivalent total household income; u_i is mutually independent and identically distributed error term satisfying $E\left(u_i \mid x_i = x\right) = 0$ and $Var\left(u_i \mid x_i = x\right) = \sigma^2\left(x\right)$; and $f(\cdot)$ and $\sigma^2(\cdot)$ are, respectively, unknown mean and variance functions to be estimated. Local polynomial smoothing regression consists of estimating local approximations of $f(x) = E[y_i \mid x_i = x]$ and $\sigma^2(x) = Var[y_i \mid x_i = x]$ using p^{th} order polynomials of the form $(x_i - x)^p$ in the neighborhood of x. Assuming that the unknown conditional mean function, $f(x)$, is twice differentiable, as outlined in Hardle and Linton (1994), the local polynomial estimator for this conditional mean function solves the following locally weighted least squares problem:

$$\sum_{i=1}^{n} K_h\left(x - x_i\right)\left\{m_i - \beta_0 - \beta_1\left(x_i - x\right) - \ldots - \beta_p \frac{\left(x_i - x\right)^p}{p!}\right\}^2 \tag{3.10}$$

where $\beta_0, \beta_1, ..., \beta_p$ are unknown parameters to be estimated and $K_h(x_i - x)$ is a weighting kernel function. The estimated conditional mean function is given by $\widehat{f}(x) = \widehat{\beta}_0$, while $\widehat{\beta}_1$ through $\widehat{\beta}_p$ are estimates of the derivatives of $f(x)$. In our applications to Uganda and Mozambique, we chose a polynomial of order three to be used for the smoothing because it provided a reasonable fit for the data. Also, for both Uganda and Mozambique, given that it has been shown that the Epanechnikov kernel function is the most efficient in minimizing the mean integrated squared error, we employed the Epanechnikov kernel function specified as

$$K_h(x - x_i) = \frac{3}{4\sqrt{5}h}\left[1 - \frac{1}{5}\left(\frac{x_i - x}{h}\right)^2\right] \times I\left(\left|\frac{x_i - x}{h}\right| \le \sqrt{5}\right) \quad (3.11)$$

where h is the bandwidth that determines the degree of smoothness of $f(x)$ and $I(\cdot)$ is an indicator function taking the value of one when its argument is true and zero otherwise. In our applications to Uganda and Mozambique, we chose the bandwidth using the data-dependent rule of thumb (ROT) method because it delivers asymptotically optimal bandwidths that minimize the conditional mean integrated squared error.

In addition to household income, other household-specific characteristics such as gender of household head, education of household head, value of farm assets, etc could potentially help explain variation in the proportional welfare effects. However, we do not include these household-specific characteristics in our model specification because results (not reported here) from semi-parametric analysis – whereby the nonparametric component contains only household income – revealed that they do not have a statistically significant relationship with the proportional welfare.

Nonparametric regression curves showing the relationship between the proportional welfare effect and per adult equivalent annual household income, broken down by region and urban/rural location, are plotted in Figures 3.4 and 3.5 for Uganda and Figures 3.6 and 3.7 for Mozambique. These figures suggest that the relationship between the proportional welfare effect and total household income varies across regions in both Uganda and Mozambique. In the application to Uganda, regression curves for all three regions (Figure 3.4) suggest that for low and middle income households, proportional welfare effects and household income generally have a U-shaped relationship. Proportional welfare effects appear to be monotonically decreasing (increasing) with income for low (middle) income households. For high income households, the regression curve is upward slopping in the Eastern region and flattens out around zero in the other two regions (Central and Northwestern). The pattern for the Uganda full sample is similar to that for the Northwestern region.

To gain additional insights about what drives these patterns, we explore the relationships between maize income and expenditure shares with per adult equivalent annual household income using the same nonparametric techniques described above. Results from these nonparametric regressions – not reported here – show that predicted conditional mean maize income shares exceed expenditure shares among low income households, while the opposite is found for middle income household. This is consistent with patterns seen in Figure 3.4. The findings also indicate that predicted conditional income and expenditure shares are on average small and the difference between them are negligible for households in the top of income distribution. This pattern can be attributed to higher reliance on nonagricultural income among high income households.

Figure 3.4 Second-order welfare effect by region: Uganda

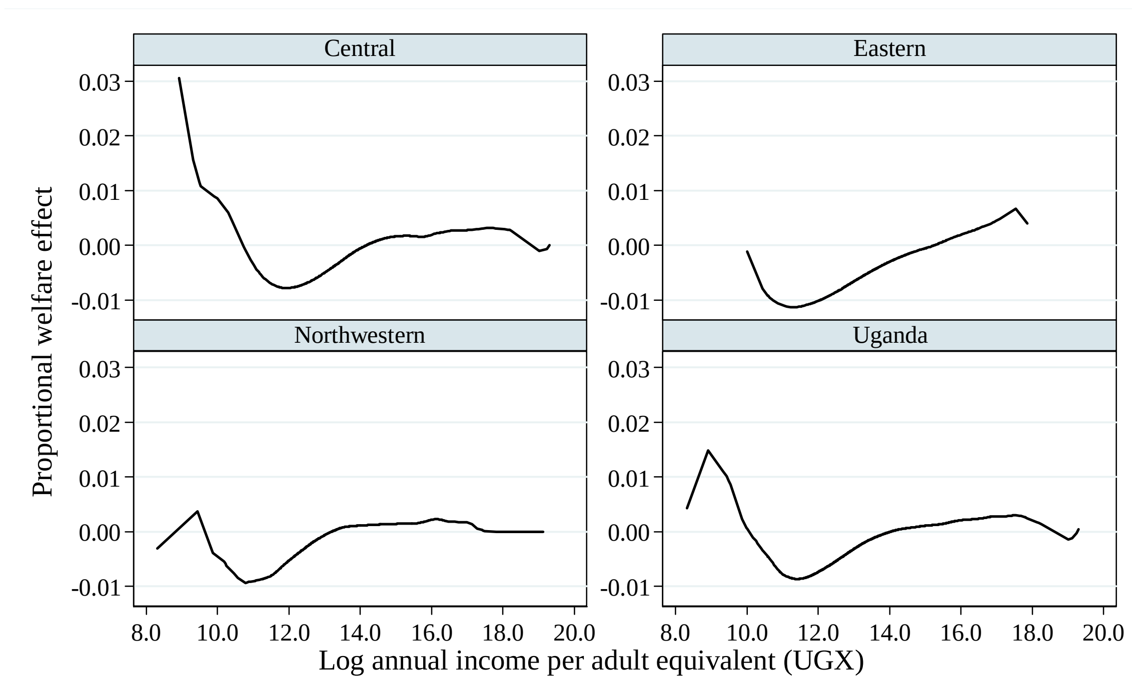


Figure 3.5 Second-order welfare effect by urban/rural location: Uganda

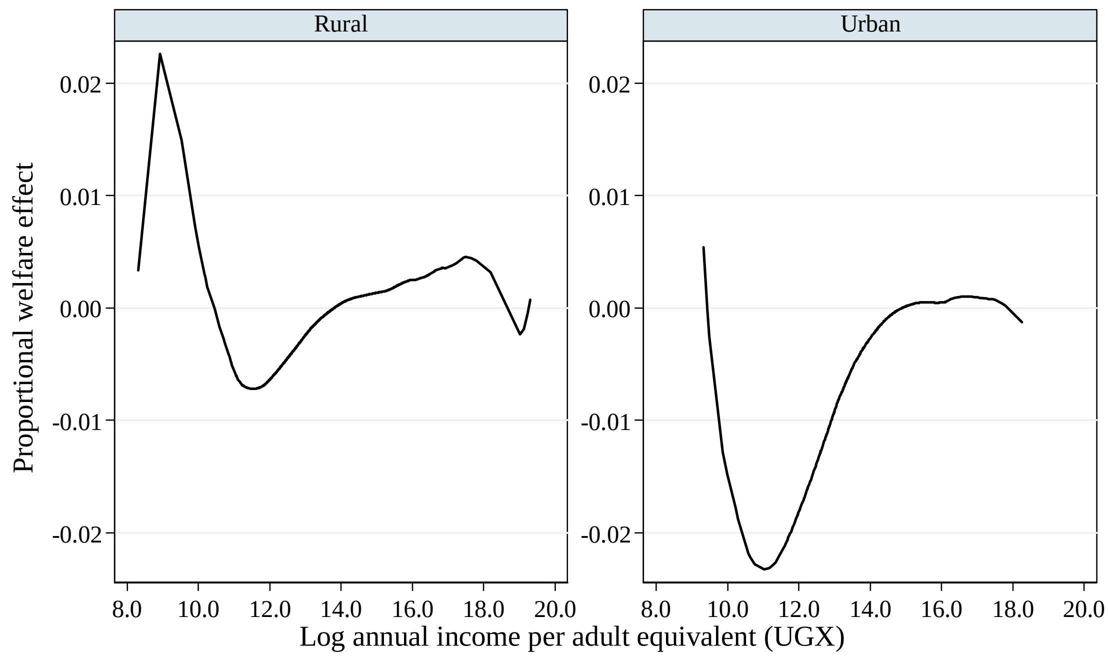


Figure 3.6 Second-order welfare effect by region: Mozambique

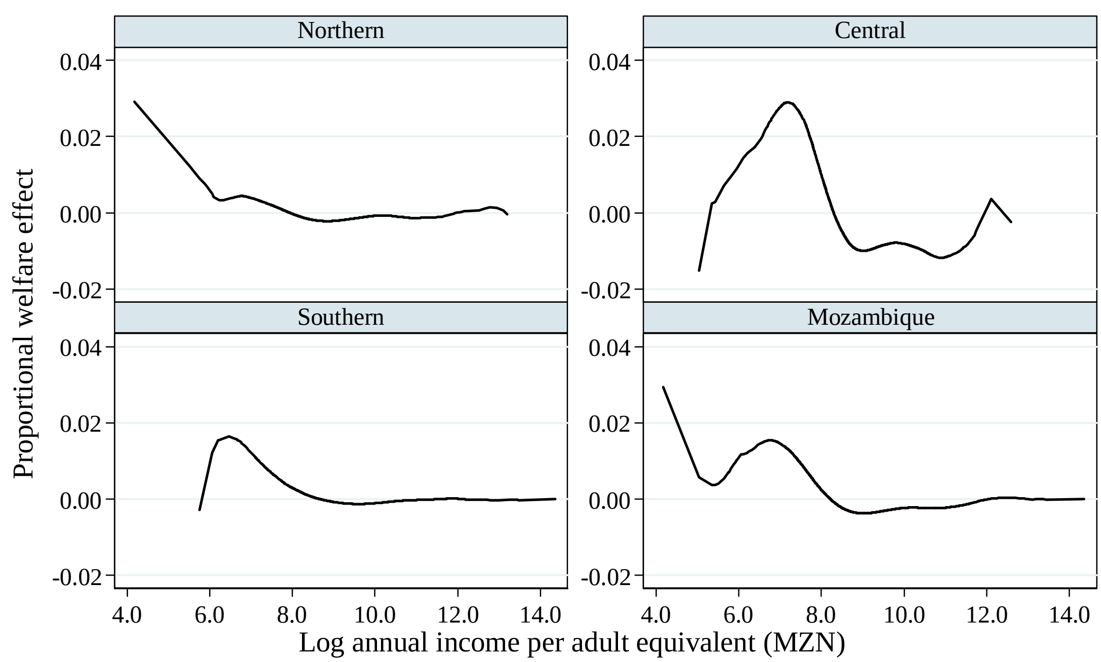


Figure 3.7 Second-order welfare effect by urban/rural location: Mozambique

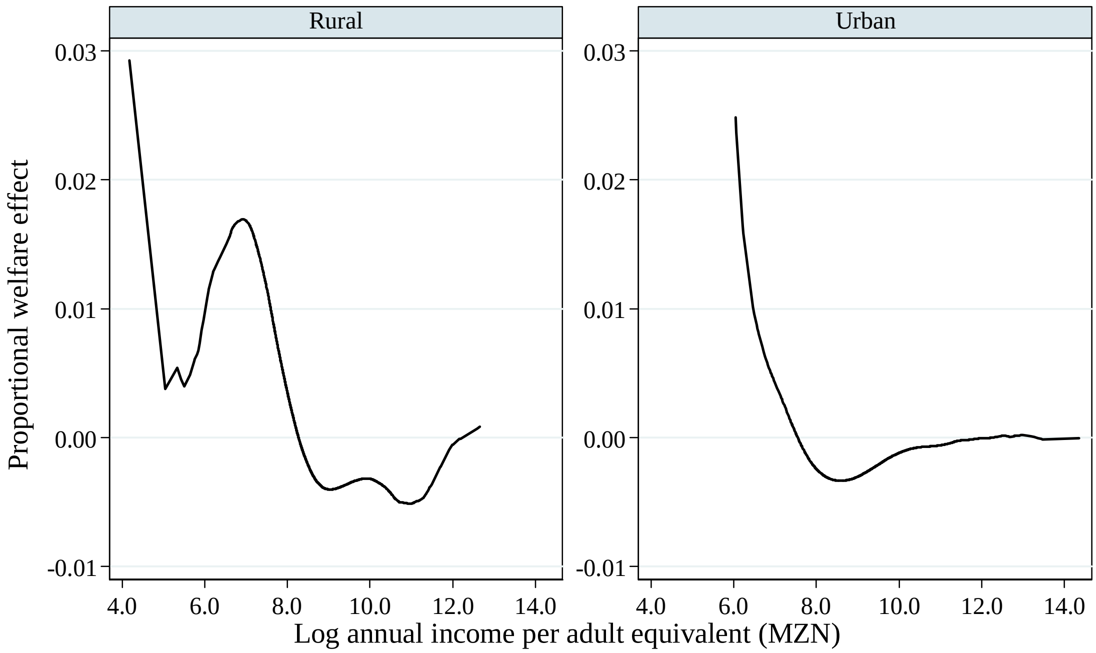


Figure 3.5 shows that the relationship between proportional welfare effects and household income is U-shaped in urban Uganda; while there is no clear pattern in rural Uganda. Figures 3.4 and 3.5 suggest that households with per adult equivalent log annual income in the range of 10 to 12 UGX suffer the highest welfare loss from maize price increases. This is because the difference between average maize expenditure and income shares is largest among households in this income category, compared to lower and higher income households.

In the application to Mozambique (Figure 3.6), regression curves suggest that for low and middle income households, proportional welfare effects and income appears to have an inverse U-shaped relationship in Central and Southern Mozambique; while the relationship is monotonically decreasing in Northern Mozambique. Results from nonparametric regressions of income and expenditure shares on per adult equivalent income – not shown here – reveal that the gap between predicted conditional maize income and expenditure shares widens as income rises for households with very low income residing in Central and Southern regions, then the difference between these shares narrows as income continues to increase. This explains the relationship between proportional welfare effects and incomes for low and middle income households in Central and Southern Mozambique. The pattern of proportional welfare effects observed in Northern Mozambique is attributed to greater importance of maize consumption relative to maize income as incomes rise among low and middle income households.

For high income households in Mozambique, proportional welfare effects are not meaningfully different from zero in all three regions (Northern, Central and Southern). For the full sample, the proportional welfare effects fluctuate with no discernible pattern as income increases among households at the bottom and middle of income distribution; while proportional welfare effects are essentially zero among high income households. In rural Mozambique, proportional welfare effects fluctuate with no clear pattern as income grows; while the effects are monotonically decreasing (increasing) for low (middle) income households in urban Mozambique (Figure 3.7). This occurs because urban households rely more on nonagricultural income and have relatively smaller maize expenditure shares of income as income grows.

3.6 Conclusions

We used nationally-representative household-level data to assess the household welfare effects of WFP LRP-induced maize price increases in Uganda and Mozambique, focusing on variation across regional location, household maize market position, household income categories and urban/rural location. Results should be of interest to food aid agencies and policy makers for at least two reasons. First, in both Uganda and Mozambique, LRP maize purchase accounted for meaningful average shares of marketed surplus during 2001 to 2011, leading to meaningful increases in local market maize prices. Second, households rely more on maize for income and for consumption in Mozambique than in Uganda, allowing for meaningful comparisons of welfare effects across the two countries.

Our findings indicate that there is a large group of households in Mozambique and Uganda whose welfare is little affected by any reasonable estimate of LRP-induced maize price increases. Average welfare effects are less than a 1% loss for maize in both countries, and about three-quarters of all households experience impacts between 1% and -1%. Furthermore, in both countries about as many households gain as lose from any maize price increase. However, there are still small proportions of households that experience greater welfare gains and greater losses. In Uganda, 8.9% of households are estimated to experience welfare gains or losses greater than 3%, while in Mozambique 6.9% experience such effects. The households who gain more are net sellers whose income share from maize is high relative to their expenditure share. More of these households tend to be located in rural areas. The households that lose more are net buyers whose expenditure share on maize is high relative to their income share. More of these households tend to be located in urban areas.

In Mozambique the distribution of welfare gains and losses is similar across different income categories (as many low income as high income households benefit and are harmed), so there is no clear tendency for lower income households to be affected disproportionately by maize price increases brought about by WFP LRP purchases. By contrast, in Uganda, the distribution of welfare gains and losses suggests that higher welfare losses tend to be more concentrated among low income households due to these households' greater reliance on maize for their consumption. Focusing on the bottom third of the income distribution in that country, over 13% had estimated losses of greater than 3%, and nearly 6% had losses greater than 5%. Given that Uganda and Mozambique are countries with the largest LRP share of marketed surplus for maize, we expect that both positive and negative welfare effects will be smaller in countries with lower levels of LRP relative to marketed surplus.

Our findings from Essay two indicate that supply and demand elasticities can have an important impact on the magnitude of the LRP effects on local market prices: LRP price effects are smaller with elastic demand and supply, compared to inelastic demand and supply. Hence, supply and demand elasticities also affect welfare effects brought about by LRP-induced price increases. This might suggest that in order to not impose excessive LRP-induced welfare costs on households, LRP purchases relative to marketed surplus should be higher in multiple-staple markets (relatively elastic demand and supply) than in single-staple markets (relatively inelastic demand and supply). However, operationalization of this procurement option by food aid agencies might be challenging because food aid commodities are procured through a tender process with active participation of private traders. This makes it difficult for food aid agencies to ensure that winners of tenders concentrate their procurement on multiple-staple markets because private traders have no incentives to do so when prices in multiple-staple markets are not attractive to profitably delivery of commodities to food aid agencies.

Although the average welfare effects of maize price increases brought about by WFP LRP purchases are fairly small, our findings reveal that welfare gains and losses are substantial among some households. This suggests that WFP should be conscious of the household welfare effects (gains and losses) stemming from price increases induced by WFP LRP purchases, especially in years during which the purchases are substantial relative to marketed surplus. When price effects are generally modest and welfare effects are small for the vast majority of households, then the overall effect of WFP LRP depends on the systemic effects on the food systems that WFP is able to induce by the way in which it goes about its procurement. The induced systemic effects could lead to transformational changes in food supply chains in countries where WFP operates, helping those countries develop their economies. Analysis of such systemic effects is the subject of essay three of the dissertation.

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CHAPTER 4:

IMPACTS OF WORLD FOOD PROGRAM LOCAL AND REGIONAL PROCUREMENT ON THE FOOD SUPPLY CHAIN: CASE STUDIES IN UGANDA, MOZAMBIQUE, ETHIOPIA AND MALAWI

4.1 Introduction

Well into the 1990s, transoceanic food shipments from donor countries to recipient countries had been the dominant way of delivering food assistance. However, the importance of alternative modalities of food assistance has been rapidly growing since the late 1990s as food aid agencies strive to respond more quickly and effectively to food emergencies.[27] For example, data from the United Nations World Food Program (WFP) International Food Aid Information System (INTERFAIS) show that local and regional procurement (LRP) – the purchase of food commodities in the country or region where food aid is being distributed to targeted groups of households – is playing an increasingly important role, with its share of the worldwide total food aid deliveries rising from 5% prior to 1995 to 8% in 2001 and about 30% in 2011.

The choice of LRP over transoceanic shipment is usually based on at least three factors. First, as shown by Clay, Riley and Urey (2005); Tschirley and del Castillo (2007); and GAO (2009), the use of LRP as opposed to transoceanic shipments reduces considerably the costs of delivering food aid, with average cost savings ranging from 39% to 48% depending on the commodity being procured. This indicates the same budget can be used to provide more food aid to beneficiaries. Second, GAO (2009); and Lentz, Passarelli and Barrett (2013) estimated that LRP generally shortens the time it takes to deliver food aid, improving the timeliness of response to food crises with average time savings ranging from 14 to 16 weeks. Third, Tschirley and del Castillo (2007), GAO (2009), Violette *et al.* (2013), and others highlight that households that receive food aid are usually more satisfied with the food commodities they receive when these originated through LRP compared to transoceanic shipment. Findings from Violette *et al.* (2013) indicate that consumption of locally procured food commodities rather than those

[27] Modalities of food assistance include transoceanic shipments, prepositioned food aid, local and regional procurement, cash transfers and voucher distributions. See Upton and Lentz (2012) for characterization of each modality.

shipped from the United States (US) resulted in statistically significantly higher levels of satisfaction among food aid beneficiaries in Zambia and Guatemala.

These are important benefits of LRP. Yet, relatively little is known about the impacts of LRP activities on the markets and food supply chains of countries where LRP takes place. Essay one of this dissertation assessed the effects of WFP LRP on local prices for maize in Uganda and Mozambique and beans in Ethiopia. Findings showed that average price effects of WFP LRP ranged from about 3% to 16% and that the impacts on price variability are negligible. Essay two of the dissertation took these estimated WFP LRP price effects and converted them into corresponding household welfare effects. Results revealed that the household welfare effects of maize price increases induced by WFP LRP purchases in Uganda and Mozambique are on average very small, but that they are meaningfully large for some households.

In addition to these price and welfare effects, the overall effects of WFP LRP activities depend on the systemic effects that WFP is able to induce in food supply chains as it goes about its procurement. This paper complements the previous studies by assessing whether WFP LRP is an effective tool to drive positive *systemic* changes in African markets. More specifically, the paper investigates five related issues: (1) whether WFP LRP contributed to knowledge, practices, and investments of traders and farmers concerning quality; (2) whether WFP LRP led, where relevant, to greater competition among firms in the sectors where WFP operates; (3) whether WFP LRP helped traders be more competitive in the commercial (and especially the regional) market; (4) whether the seasonal pattern of WFP LRP purchases has increased or moderated what are typically very large seasonal price movements; and (5) whether WFP pays "market prices" when procuring commodities.

The paper adds to knowledge on the LRP effects on the food supply chain by focusing on four countries and three commodities where WFP LRP has been a meaningful share of the marketed surplus: maize in Uganda and Mozambique, beans in Ethiopia, and high energy protein supplements (HEPS) in Ethiopia and Malawi.[28] The paper employs a case study

[28] We define HEPS to include biscuits, corn-soya blend (CSB), Faffa, high energy biscuits, Likuni Phala, pea-wheat blend, high energy supplements, and ready to use supplementary food. Among these, only pea wheat blend was not found originating from our two HEPS study countries. Faffa and CSB accounted for 92% of all observations,

approach in an attempt to answer the five aforementioned questions. We interviewed a wide range of stakeholders in each country to investigate trader and processor responses to engagement with WFP and their perception of the WFP LRP effects on the food supply chain in which they operate. Additional insights are generated from analysis of WFP procurement data to gain a better understanding of the structure of the WFP procurement of each commodity in each country application.

We are not the first to use a case study approach to look at similar issues. Walker and Wandschneider (2005); Wandschneider and Hodges (2005); and Coulter (2007) also employed case study approaches to assess the developmental impacts of LRP in Ethiopia and Uganda. Their findings suggest that LRP had helped drive some investment in the trading systems in both countries, had driven improved quality practices for WFP transactions, and may have contributed to improved export trade of some food commodities in Ethiopia. Yet they also suggested that LRP had failed to have any appreciable effect on the broader trade within each country and may in some instances have led to spikes in local market prices. These case studies are at least seven years old and occurred prior to the peak in WFP LRP that lasted from 2008 to 2010.[29] Hence, we contribute to a better understanding of the LRP effects on the food supply chain by providing new evidence using more recent quantitative and qualitative data.

The paper proceeds as follows. Section two reviews our criteria for country and commodity selection. Section three characterizes trends and patterns in procurement volumes, while Section four describes what we learned from interviews focusing on issues related to knowledge, practices and investments of traders and farmers concerning quality. Section five briefly analyzes trends in the seasonality of LRP purchases of maize. Regional and local market pricing performance is discussed in Section six. Section seven closes with a summary of key cross-cutting findings.

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with Likuni Phala listed for 5.8%. We understand that Faffa and Likuni Phala are brand names and that products listed as these may sometimes have been comparable products produced by other companies.

[29] This statement is based on quantities and values adjusted for the very large purchases that took place in Iraq between 2003 and 2005.

4.2 Country and Commodity Selection

We use three main criteria to select countries and commodities. First, the size of LRP purchases as a share of the total estimated marketed surplus in the relevant country. Second, data availability to support meaningful analysis of LRP impacts on the food supply chain. Third, the absence of other factors such as large-scale government purchases that would make it difficult to isolate the effect of LRP. Commodities with the highest shares of total volumes procured by WFP in Africa from 2001 to 2011 are maize (58%), HEPS (12%), sorghum/millet (9%), maize meal (8%), and beans (7%). Shares of all other commodities are 1% or less. Given their relative importance, this paper focuses on maize, HEPS, and beans. We excluded sorghum/millet due to lack of suitable data.

The volume of LRP purchases as a share of total marketed surplus is a key factor driving the effects of LRP on local markets and food supply chains. Among the main African countries in which WFP procures maize, Uganda and Mozambique are the countries with the highest average LRP shares of estimated maize marketed surplus from 2001 to 2011, at 14% and 7%, respectively. Zambia follows closely at an average share of 6%.[30] Maximum shares are also important because significant effects can arise in years during which large LRP purchases occurred. Uganda at 30% and Zambia at 14% rank first and second, respectively, in terms of maximum share; followed in order by Mozambique, Tanzania and Malawi with maximum shares between 11% and 12%. Given its relative importance, we analyze procurement of maize in Uganda and Mozambique. We excluded Zambia because of very large government purchases of maize through the Food Reserve Agency (FRA) especially since 2006.

Ranking of African countries based on LRP share of marketed beans surplus from 2001 to 2011 shows Ethiopia and Uganda essentially tied with averages of 14% and 13%, respectively. LRP purchases of beans account on average for 5% or less of beans production in all other countries. With regard to maximum share, Ethiopia clearly stands out at 46%, followed by Uganda at 21%. This suggests comparable average importance of LRP purchases of beans in

[30] Details on how the share of LRP purchases in total marketed surplus is estimated are presented in essay one of this dissertation.

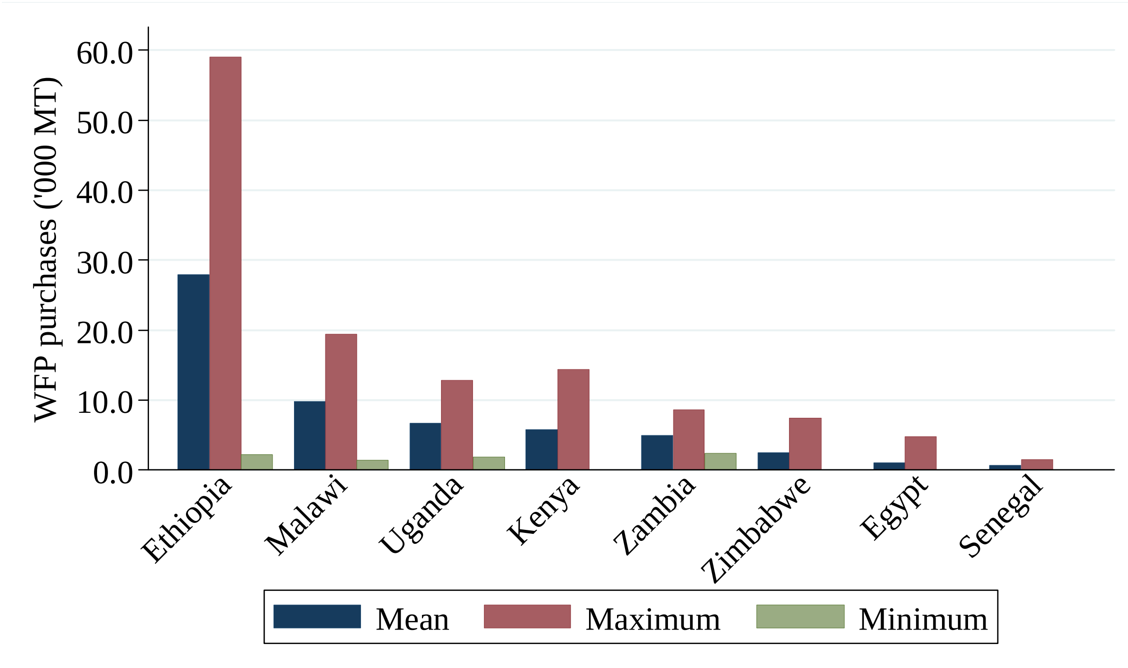
Ethiopia and Uganda but with a much higher maximum in Ethiopia. Our analysis focuses on Ethiopia.

For HEPS, we focus on annual metric tons (MT) rather than market share because these products have only an incipient hold in the commercial market and WFP is therefore likely to be nearly the entire market for these products in most countries. Ethiopia clearly stands out with an average annual purchase of about 28,000 MT and a maximum of nearly 60,000 MT (Figure 4.1). Malawi is next at an average of nearly 10,000 MT and per capita purchases of HEPS similar to those in Ethiopia, suggesting roughly comparable importance relative to broader markets. Average yearly purchases in all other countries are 7,000 MT or lower, and are also lower on a per capita basis than in Ethiopia and Malawi. We chose Ethiopia and Malawi, the top two countries in total and per capita purchases of HEPS.

We visited Uganda during July, 2012, conducting interviews in Kampala (capital city) in Central region, Mbale and Kapchorwa in Eastern, Lira in Northern, and Masindi in Western. We interviewed a wide range of stakeholders in the private and public sectors, including small farmers, farmer associations, local traders and small-scale maize processors, large traders participating in WFP LRP tenders, and selected public sector officials.

Two visits were conducted to Mozambique, in September, 2012 and again in May, 2013, to interview farmer associations, and small- and large-scale traders in Central and Northern Mozambique. We also interviewed public officials and other stakeholders in Maputo (capital city). During the field visit to Ethiopia in September 2012, we interviewed HEPS manufacturers operating in Addis Ababa (capital city) and a wide range of stakeholders in the bean sector operating in Addis Ababa, Adama, Awassa, and their surrounding areas. We visited Malawi (Lilongwe and Blantyre) in April 2013 to interview HEPS manufacturers and other stakeholders active in the maize and soybean markets including poultry feed manufacturers.

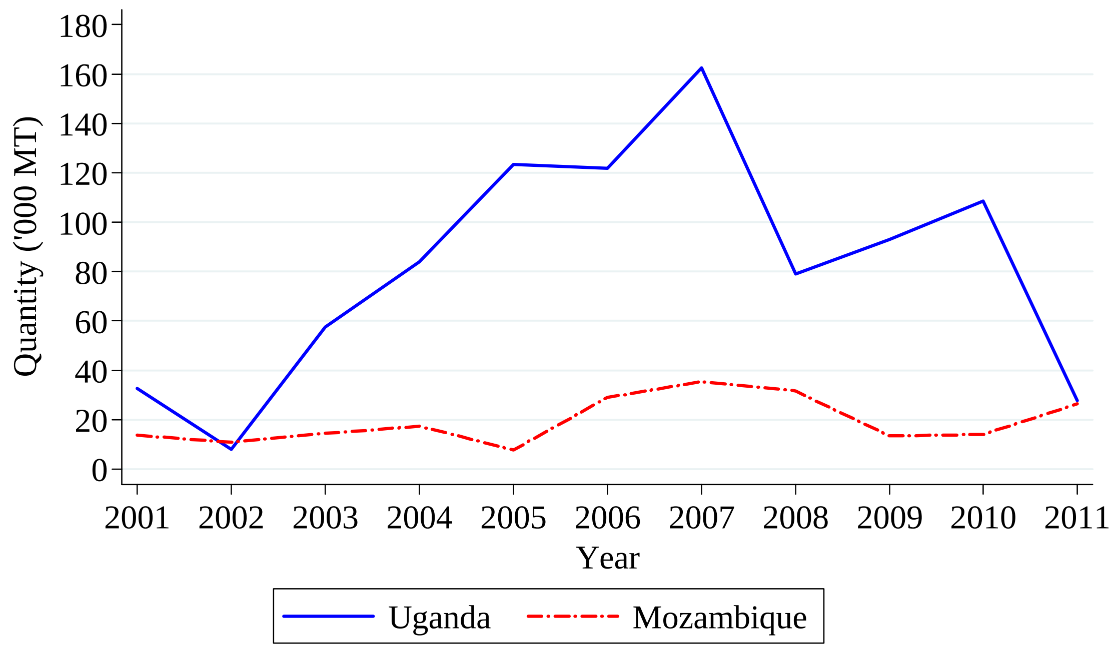
Figure 4.1 Annual average LRP purchases of HEPS from 2001 to 2011



4.3 LRP Trends and Patterns

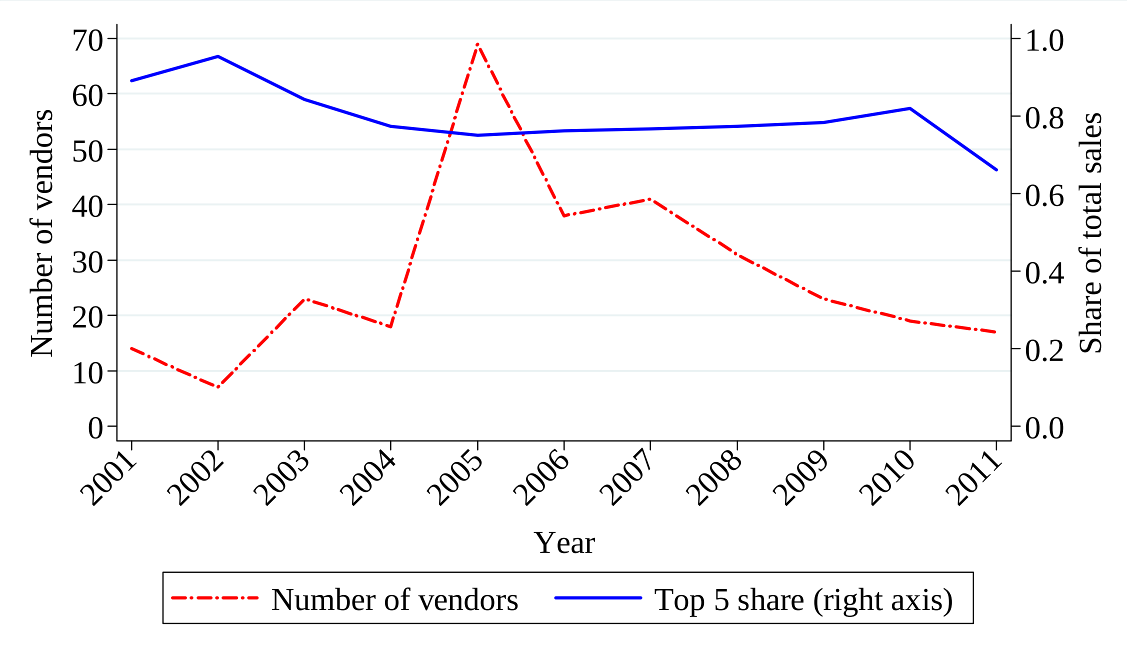
Uganda and Mozambique present large differences in the way that LRP has developed. Figures 4.2 through 4.6 present basic information on the levels, structure, and flows of locally procured maize in each country. Uganda is well known as the country where LRP first scaled-up to levels capable of having major impacts on local markets. This is seen clearly in the dramatic rise of LRP from less than 10,000 MT in 2002 to over 160,000 MT in 2007 (Figure 4.2). During the same period, Mozambique's procurement fluctuated below 20,000 MT through 2005 before rising sharply to nearly 29,000 MT in 2006 and over 35,000 MT in 2007. Since then, procurement in Mozambique has declined slightly while in Uganda it has dropped sharply.

Figure 4.2 WFP LRP purchases of maize in Uganda and Mozambique, 2001 - 2011



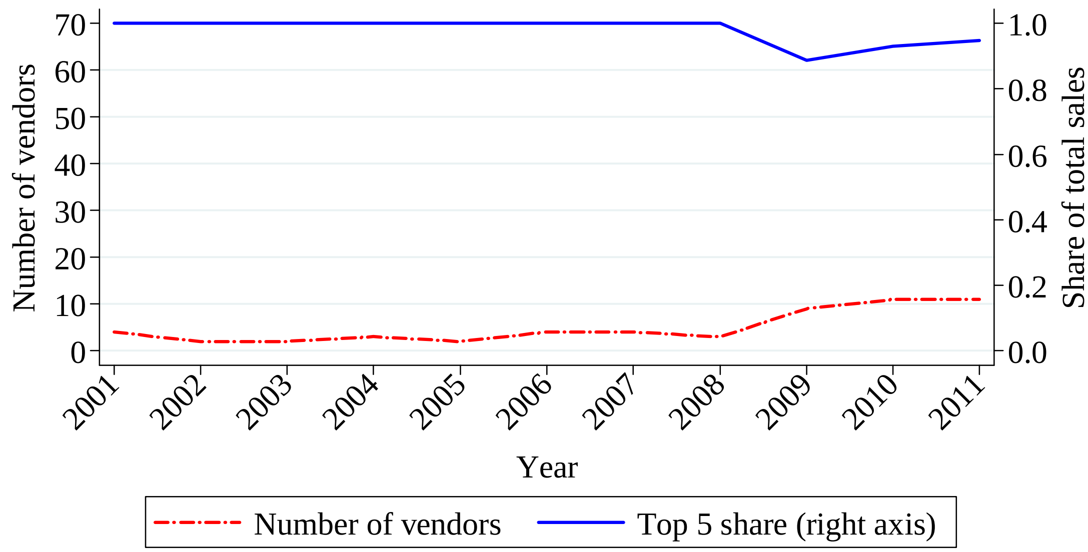
The concentration of sales, measured by the number of vendors and share of the top five vendors in LRP sales, also differs dramatically across the two countries (Figures 4.3 and 4.4). Uganda has never had fewer than seven vendors per year and averaged 27 annually over the period 2001 to 2011, while Mozambique has never had *more* than 11 and averaged five per year. Uganda's top five vendors during any year never accounted for more than 95% of sales and averaged 80%, while Mozambique's top five accounted for *all* sales every year until 2008 and averaged 98% of sales. In fact, two vendors accounted to all sales to WFP in Mozambique during every year from 2002 to 2005 and again in 2008. The structure of sales to WFP in Mozambique mirrored structural characteristics in the country's broader maize trade. Up until the early 2000s, the two vendors – one operating in Northern Mozambique and the other in Central Mozambique – were the only large-scale buyers of domestically produced maize, leaving each without any large competitor in their region. However, starting late in the 2007 marketing season, a considerable number of new and much larger buyers entered the market.

Figure 4.3 Number of vendors and share of top 5 in maize sales to WFP in Uganda, 2001-2011



Uganda received much less maize food aid procured outside its borders than did Mozambique and sent more of its locally procured food outside its borders. Local procurement within Uganda accounted for an average of 97% (and never less than 88% during any year) of all the procured maize food aid from any origin distributed within the country during 2001 to 2011 (Figure 4.5). In contrast, purchases within Mozambique accounted for only 59% of its locally distributed procured food aid from any origin, and its yearly share fluctuated widely. WFP in Uganda exported 30% of its locally procured food over the period compared to 18% for Mozambique (Figure 4.6).

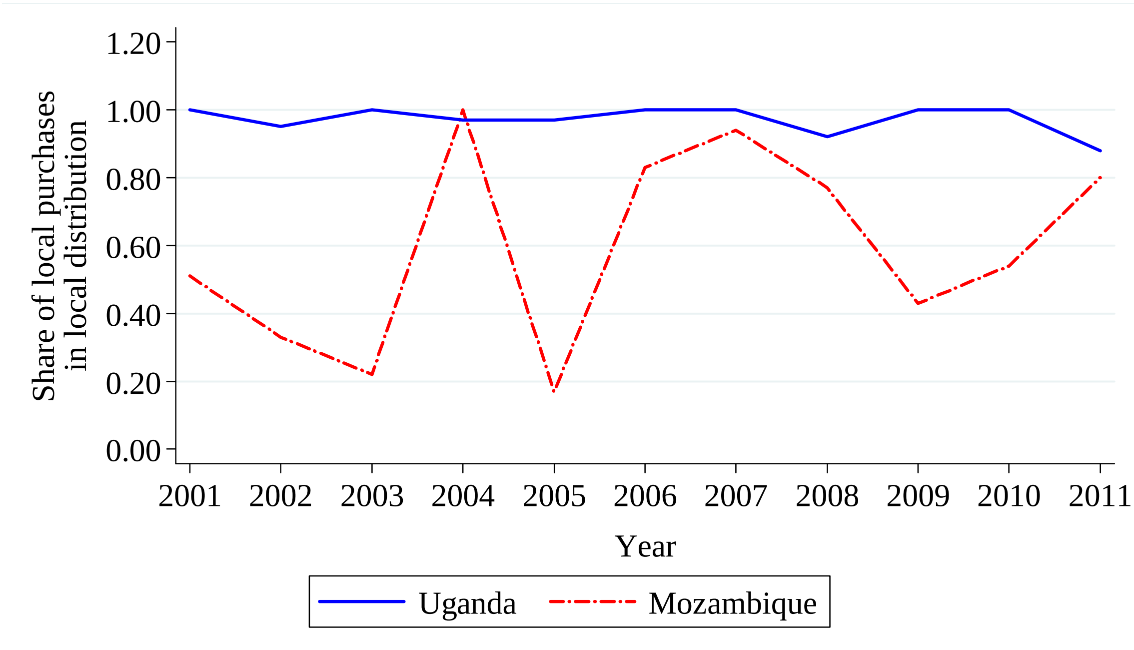
Figure 4.4 Number of vendors and share of top 5 in maize sales to WFP in Mozambique, 2001-2011



Notes: only two (2) vendors sold during 2002-2005 and 2008

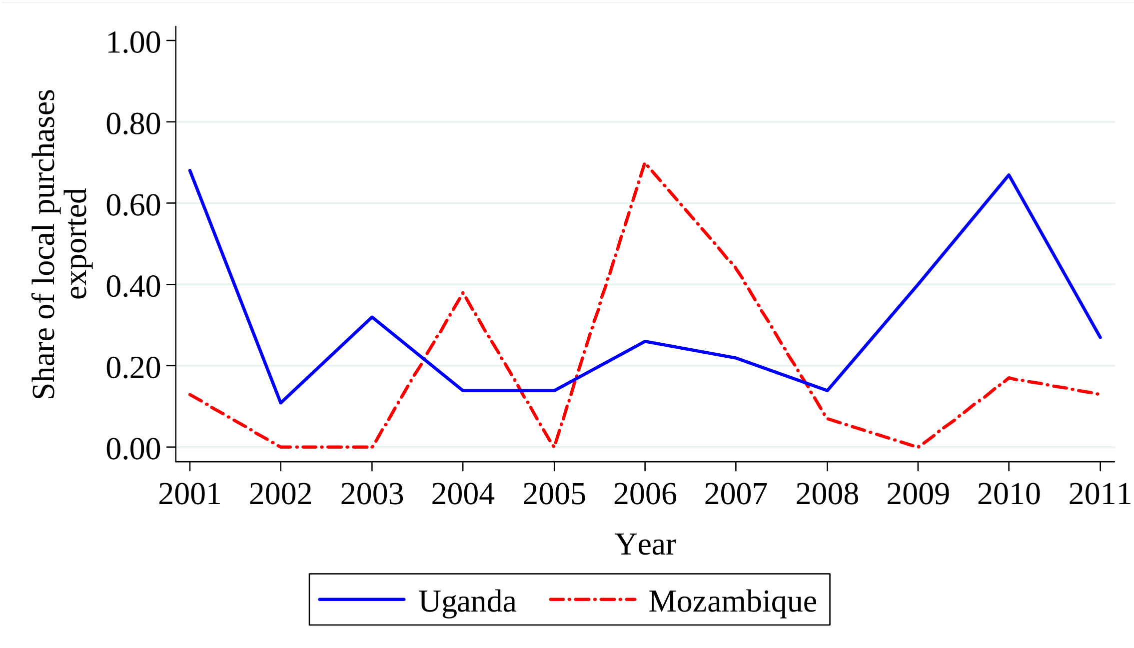
We identify two key patterns from this review. First, food aid procurement in Uganda is now far more dependent than it was in the past on demand outside Uganda. Figure 4.2 showed that WFP procurement of maize in Uganda rose rapidly to a peak in 2007 and has fallen sharply since that time. By 2011, maize procurement was higher only than in 2001 and 2002. This decline is partly related to the signing of the cease-fire agreement in 2006 to end the conflict in Northern Uganda, and the gradual closure of the camps for internally displaced persons (IDPs) since that time. From its peak of 1.8 million at the height of the conflict, the number of IDPs fell to about 30,000 by 2012, driving a sharp decline in the need for WFP purchases of Ugandan maize for use within Uganda.

Figure 4.5 Share of in-country maize food aid distributions out of procured food aid covered by local procurement in Uganda and Mozambique, 2001-2011



The drop in local food aid demand for Ugandan maize is reflected in trends in the share of WFP purchases in Uganda that were exported (Figure 4.6). From 2002 through 2008, the share of WFP maize purchases that were exported fluctuated between 10% and 31%, with no clear trend. This share then jumped to about 40% in 2009 and nearly 70% in 2010. The drop in the export share in 2011 appears to have been driven mostly by the sharp drop in total procurement for any destination. As a result, WFP purchases in Uganda are now more dependent on regional food aid demand than at any time since 2001, prior to the LRP boom in the country. This pattern raises questions about the inter-annual variation in demand by WFP that Uganda is going to face over the coming years. Could WFP purchases become a destabilizing force in the local market, rising to high levels when regional demand is high, and falling when such demand is low?

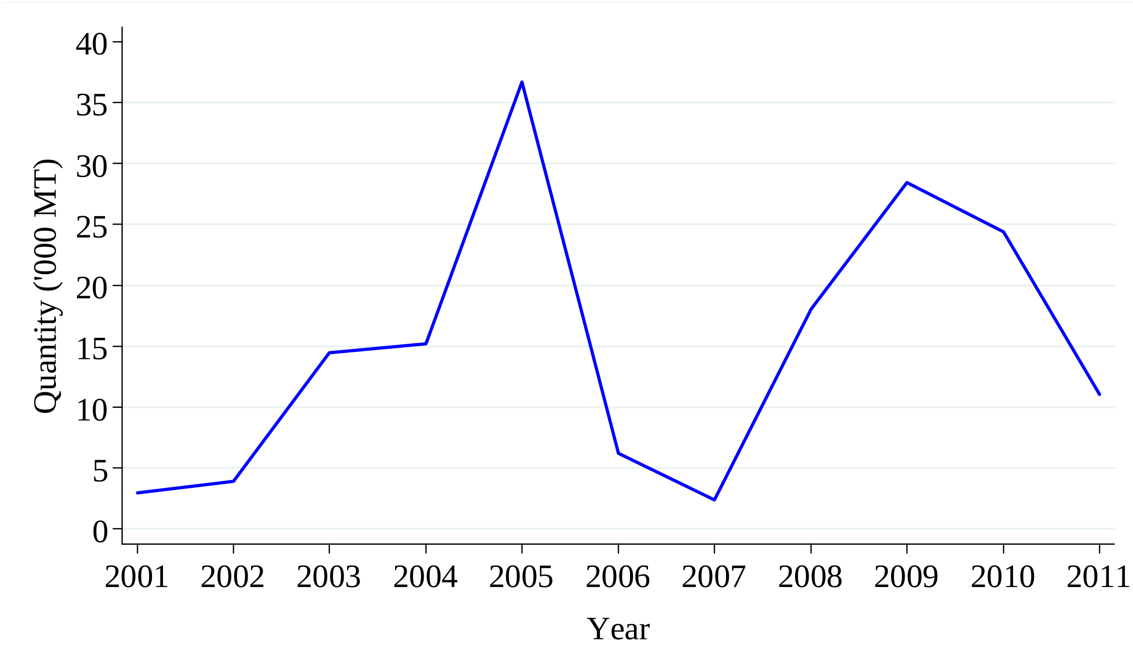
Figure 4.6 Share of in-country LRP exported from Uganda and Mozambique, 2001 - 2011



The second key pattern relates to the extremely high concentration of LRP sales of maize to WFP in Mozambique, which remains much higher than Uganda despite the recent entry of more tender competitors since 2007. Still in 2010 and 2011 the two historically dominant firms together accounted for nearly 80% of all maize sales to WFP. One large new vendor – an international trading firm – held 11% and 12% shares each year, and no one else held more than 3%. While it is possible that the entrance of one additional large seller could drive more competitive tender prices and more responsiveness with respect to WFP quality needs, it does not guarantee such improvements.

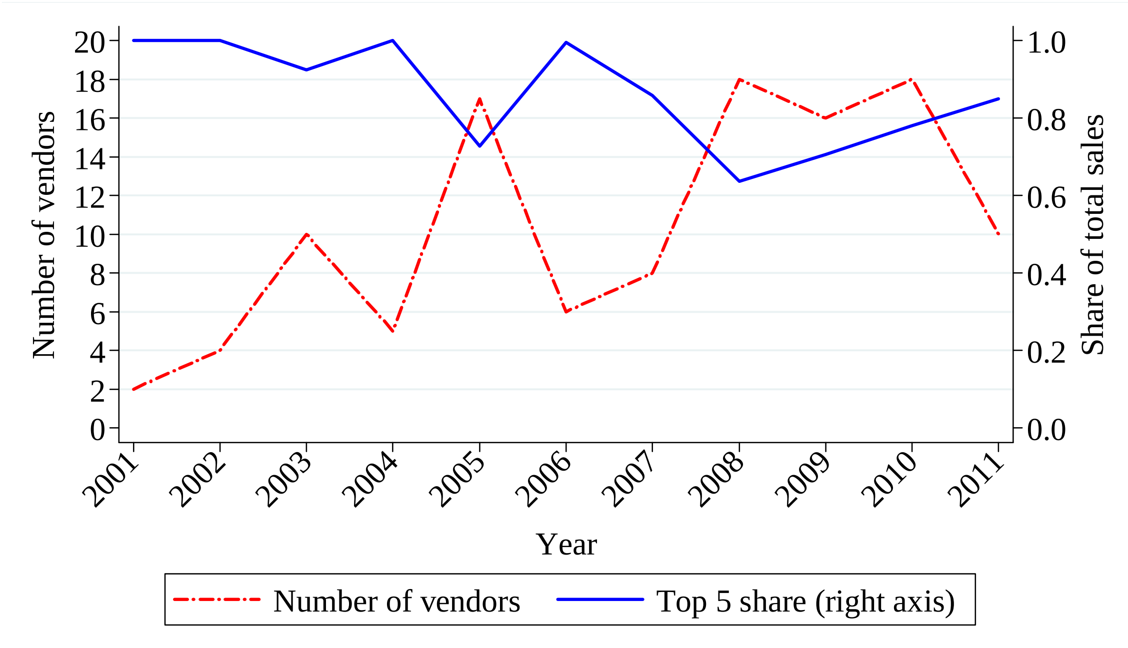
From 2001 to 2011, Ethiopia accounted for 31% of the total quantity of beans procured by WFP in East Africa, with an annual share ranging between 7% and 55%. Figure 4.7 shows annual volumes of beans procured in Ethiopia. WFP purchases reached a record high in 2005, increasing from about 3,000 MT in 2001 to 37,000 MT in 2005. Since then, WFP procurement of beans oscillated greatly, dropping sharply to about 2,000 MT in 2007, rising to nearly 30,000 MT in 2009, and dropping again to 11,000 MT in 2011.

Figure 4.7 Volumes of total bean procurement by WFP in Ethiopia, 2001 – 2011



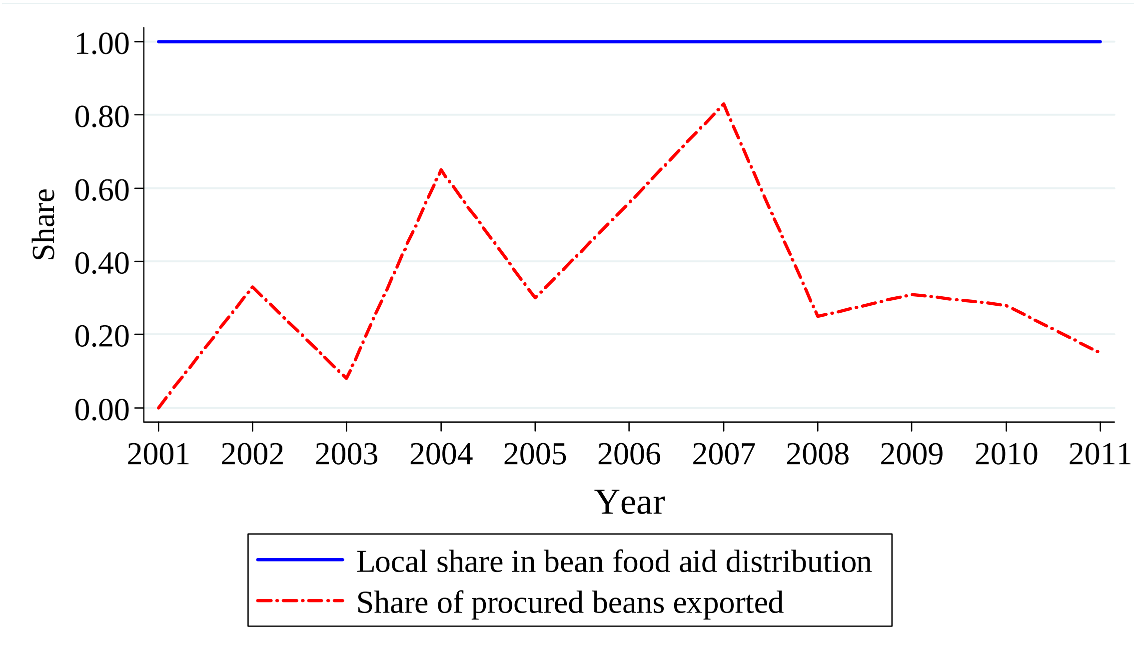
The number of vendors winning WFP tenders for bean purchases has followed the trends in total bean procurement. The number of vendors rose sharply from two in 2001 to 17 in 2005, fell with procurement totals the next two years, and then rose again (Figure 4.8). The share of local purchases accounted for by the top five vendors shows an overall downward trend, though it has risen each year since its low of 64% in 2008, reaching 85% in 2011. WFP in Ethiopia has never imported procured beans from other countries, and does export some of the locally procured beans to other countries (Figure 4.9). The share of locally purchased beans that were exported rose from 0% in 2001 to 83% in 2007. Since then, it has trended downward, dropping to 25% in 2008 and 15% in 2011.

Figure 4.8 Number of vendors and share of top 5 in bean sales to WFP in Ethiopia, 2001-2011



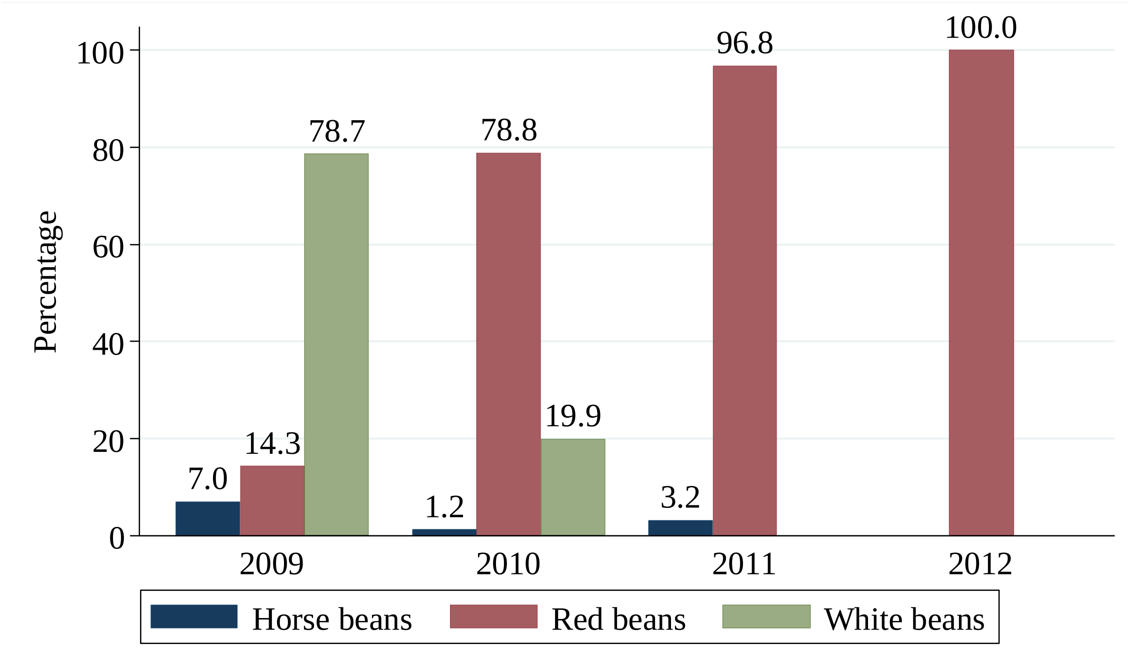
Ethiopia grows at least three different types of bean, each of which is supplied to different domestic and international markets and is affected differently by policy. White haricot beans are almost entirely exported to international markets (Europe, Middle East and South Asia), while red haricot and horse beans are supplied to domestic and regional markets. Fully understanding the impact of WFP on the bean market requires that procurement data be broken down by bean type. Prior to July of 2009, however, all bean purchases by WFP were registered simply as “beans” in the agency’s Information Network and Global System (WINGS) data base. Since that time, data are disaggregated by bean type.

Figure 4.9 Locally procured beans in Ethiopia: share in local distributions, and percent exported, 2001-2011



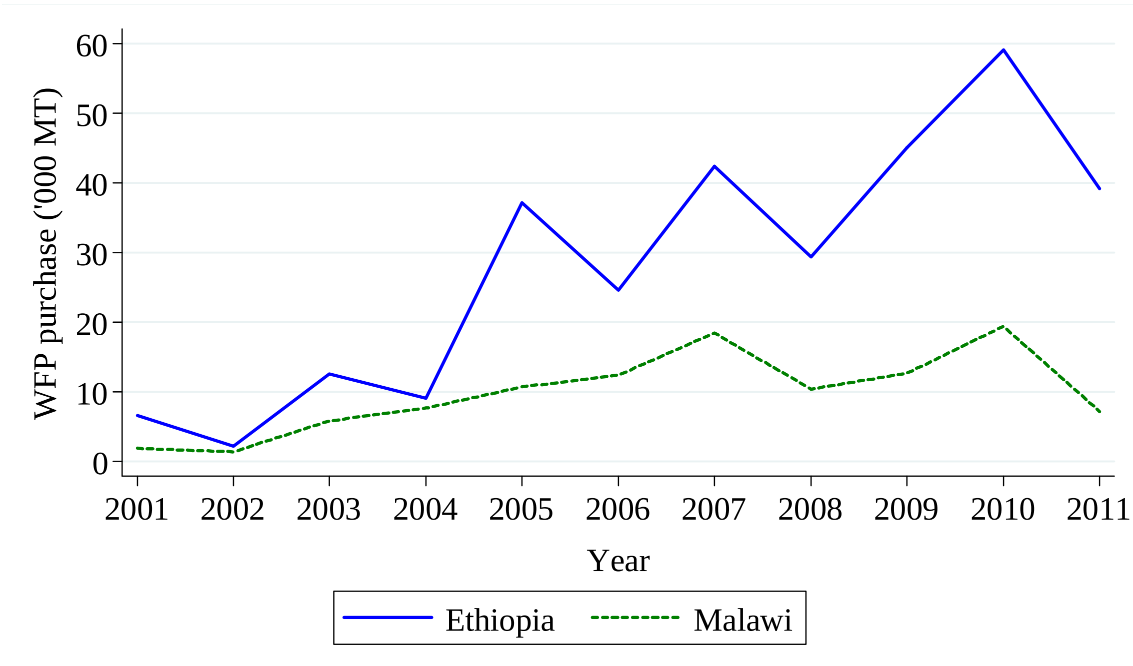
Using the more recent disaggregated data, we graph the share of each type of bean in total WFP bean purchases from July 2009 to July 2012 in Figure 4.10. The figure shows a dramatic shift in the types of beans that WFP has been buying in Ethiopia. While white beans dominated during the last half of 2009, their share plummeted the following year and was zero in 2011 and 2012. Horse bean shares were very small each year through 2011 and zero in 2012. This dramatic shift from white beans to red beans was driven by the Ethiopian government's decision in 2010 that the Ethiopian Commodity Exchange (ECX) be the only channel through which private traders and exporters can trade white haricot beans.

Figure 4.10 Share of WFP purchases of bean in Ethiopia, 2009 - 2012



WFP began to purchase HEPS in an effort to provide more nutritionally valuable products to food aid beneficiaries suffering from malnourishment. Total quantities of all HEPS procured over 2001 through 2011 peaked in Ethiopia in 2010 and in Malawi in 2007 (Figure 4.11). Growth in Ethiopia has been much faster than in Malawi, due mostly to the size of the internal food aid market in the former. HEPS is composed of a large and growing number of products. The basic distinction is between corn-soya blend (CSB), which is typically 70% maize and 30% soybeans, versus a wide range of nutritionally improved products. Historically CSB has been the dominant product. Beginning in the late 2000s, however, spurred by advancing knowledge regarding nutritional quality of foods and the human body's ability to use certain types of lipids and proteins (WFP, 2010; Webb *et al.*, 2011; WFP, 2012), WFP began to take policy decisions to incorporate new products with enhanced nutritional profiles into their programs. These new products include fortified blended foods (FBFs) such as Super Cereal (referred to as CSB+) and Super Cereal Plus (referred to as CSB++).[31] Ready to use foods (RUFs), such as ready to use therapeutic foods (RUTFs) and ready to use supplementary foods (RUSFs), are also product groups that have been in WFP's basket for some time but whose specific products are evolving and whose importance is likely to grow in future.[32]

Figure 4.11 Volumes of total HEPS procurement by WFP in Ethiopia and Malawi, 2001 - 2011

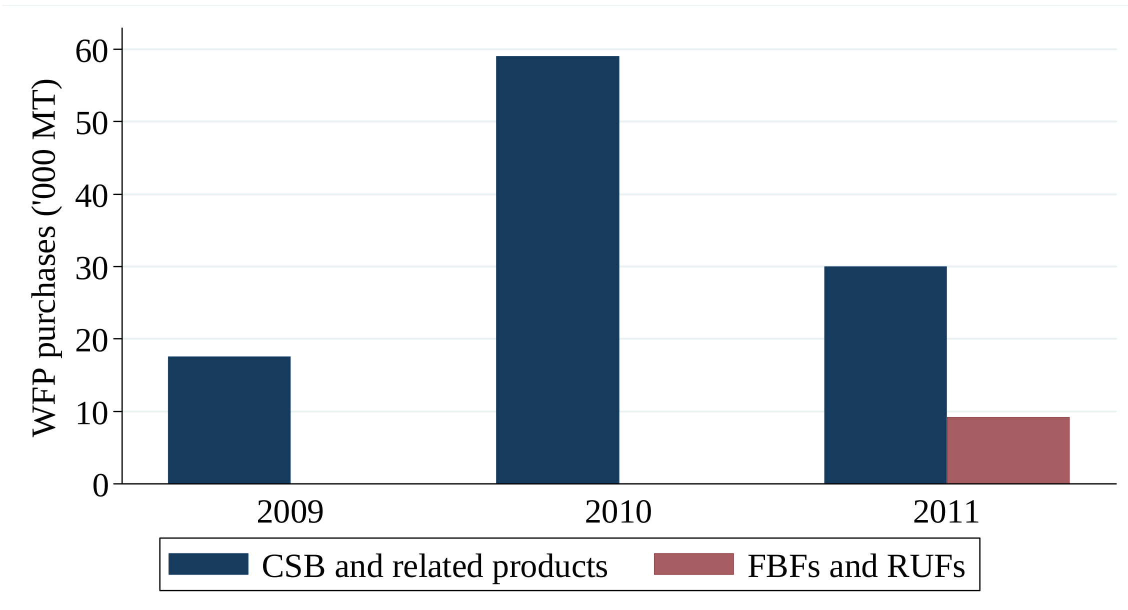


WFP modified its WINGS database to track these new products more carefully starting in July 2009. Data prior to that time do not distinguish between traditional CSB, CSB+, and CSB++, though they do distinguish between CSB (and related products that use wheat, sorghum, or rice rather than maize) and fortified and ready-to-use foods. The 2009 improvement to the database was close to the time that the agency began to move towards CSB+ and CSB++ and away from unfortified products. The overall database thus probably

[31] Other FBFs procured by WFP include wheat-soya blend, rice-soya blend and pea-wheat blend. From 2001 to 2011, CSB accounted for more than 90% of the total quantity of blended products either procured or distributed by WFP in Africa. Hence, our discussion of FBFs focuses on CSB.
[32] RUSFs are also known as lipid-based nutrient supplements and include peanut-based products such as Plumpy Nut, Plumpy Sup, Plumpy Doz, eeZeeRUSF, Nutributter, and other products.

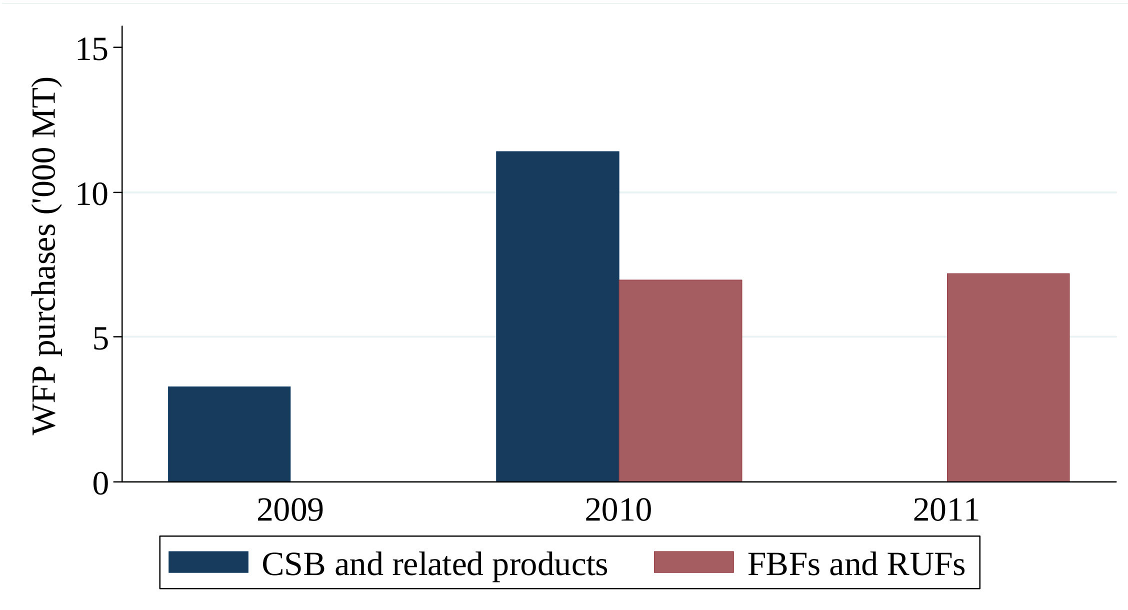
captures most of the trend in the rise of these two enhanced CSB products, though there may be some of these products purchased during 2008 and 2009 that the database does not capture.[33] Procurement of CSB dropped sharply in Ethiopia and Malawi in 2011 (to zero in Malawi), partially made-up for by procurement of FBFs and RUFs (Figures 4.12 and 4.13). Purchases of fortified products began in 2010 in Malawi and 2011 in Ethiopia.

Figure 4.12 Volumes of HEPS procurement by WFP in Ethiopia, classified as CSB and related products, and FBFs and RUFs, July 2009 – December 2011



[33] Interactions with WFP staff regarding the timing of guidance from WFP headquarters on replacement of CSB with CSB+ and CSB++ also suggests that the change in WINGS caught most if not all of these purchases.

Figure 4.13 Volumes of HEPS procurement by WFP in Malawi, classified as CSB and related products, and FBFs and RUFs, July 2009 – December 2011



The number of HEPS vendors to WFP has increased in Ethiopia and Malawi over the period 2001 to 2011 but the share accounted for by the top five vendors has fallen only in Ethiopia (Figures 4.14 and 4.15). The number of vendors in Ethiopia increased from two to three in the early 2000s to seven to nine since 2008, with a related drop in the share of the top five from 100% each year through 2005 to less than 80% in 2011. The number of vendors in Malawi rose from one to two in the early 2000s to five by 2006, with a flat trend since that time – the top five sellers have thus accounted for all sales from 2001 to 2011.

Figure 4.14 Number of vendors and share of top 5 in HEPS sales to WFP in Ethiopia, 2001 - 2011

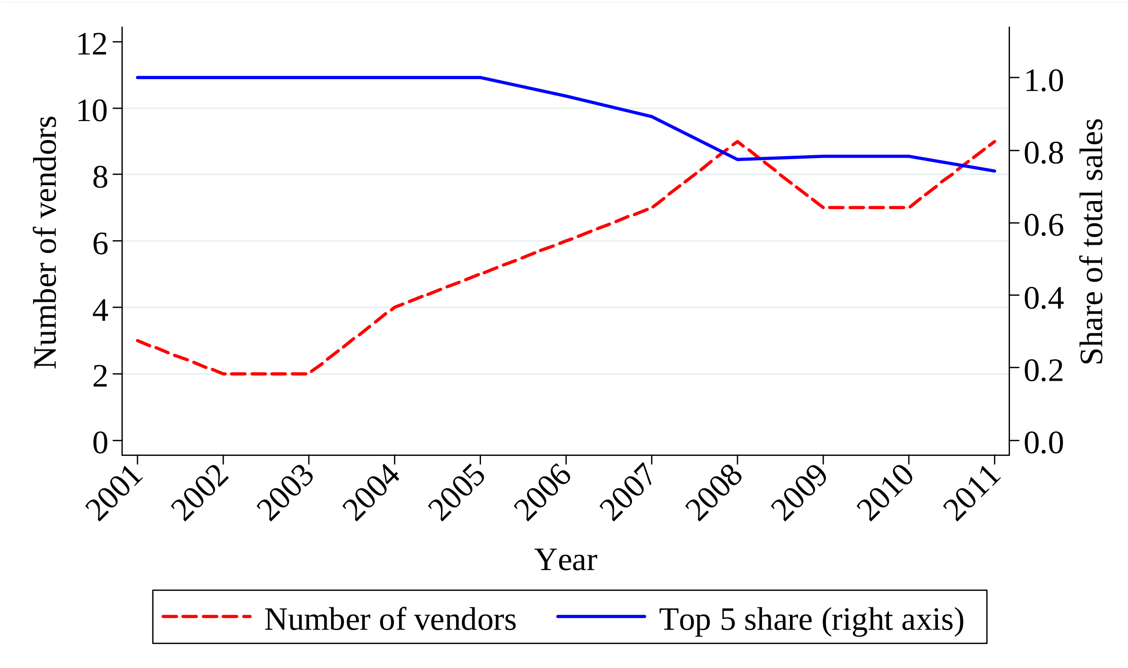
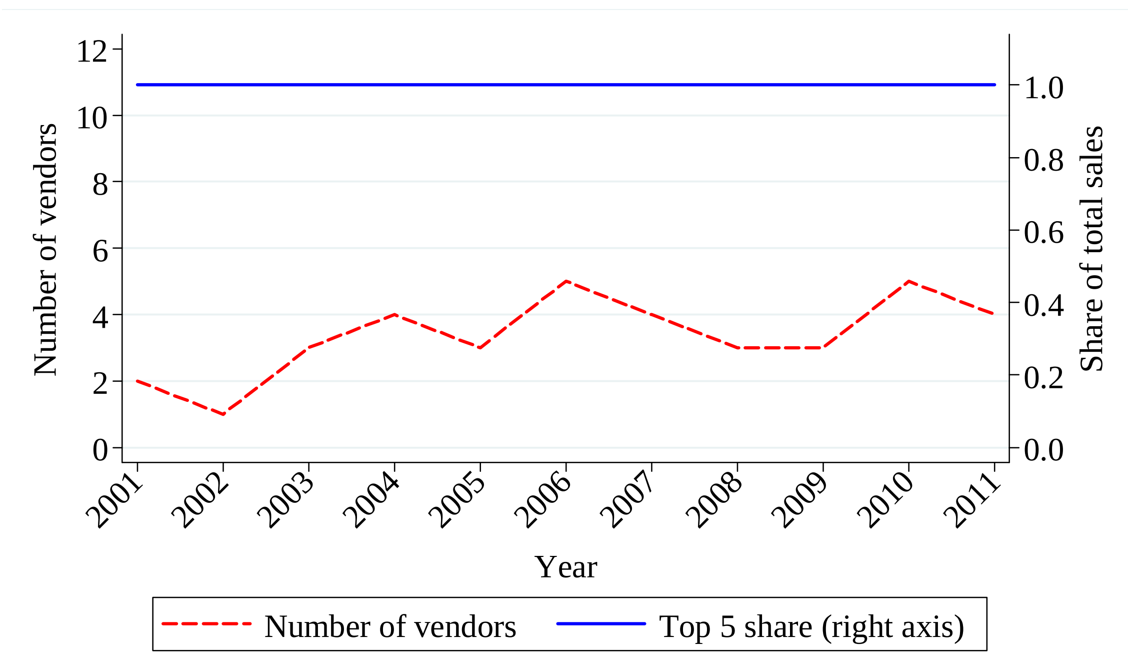


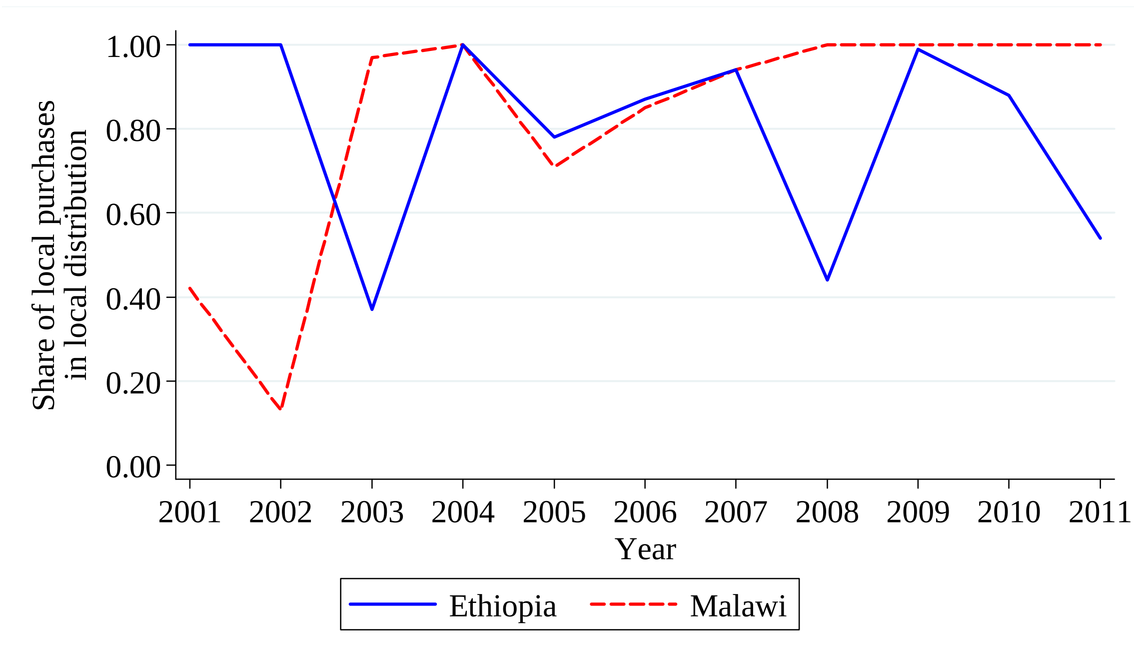
Figure 4.15 Number of vendors and share of top 5 in HEPS sales to WFP in Malawi, 2001 - 2011



The concentration of sales among the top five HEPS vendors in each country is probably not a cause for concern from a pricing perspective. While Ethiopia is the largest single source of

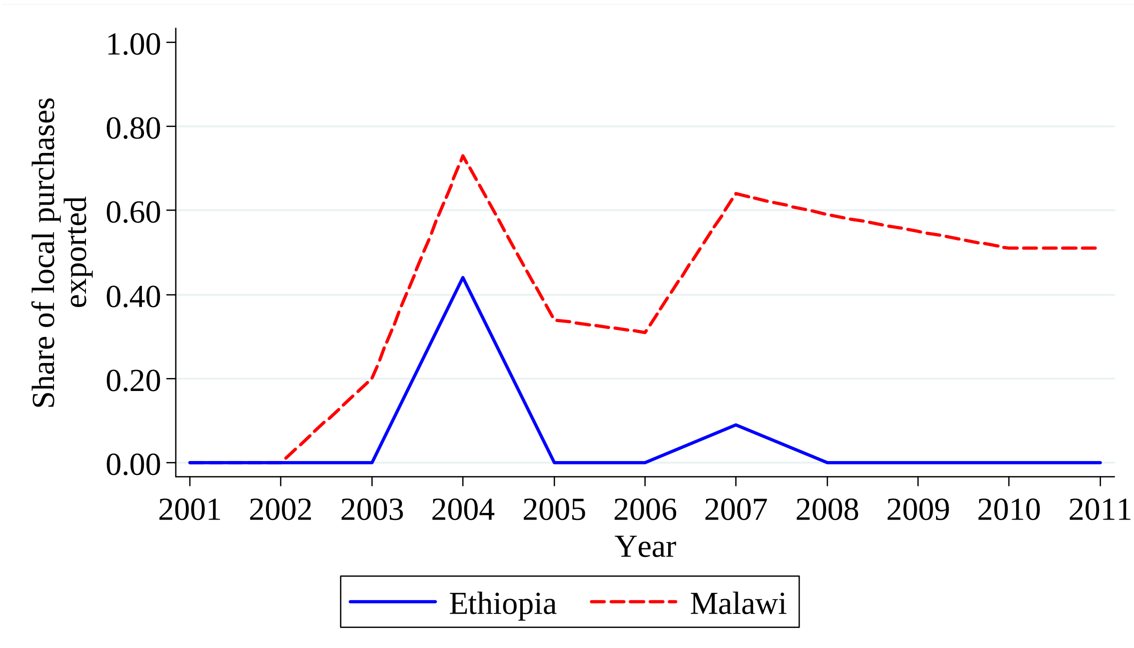
HEPS for the rapidly growing distributions in East Africa, Italy, South Africa, and Belgium are next in line, their share over 2001 to 2011 was about 50% higher than Ethiopia's share, and arrivals from these countries have been growing. Figure 4.16 shows that Ethiopian firms' share of all *locally* distributed HEPS has periodically fallen to 40% to 50%, most recently in 2011; Italy, South Africa, and Belgium are the key foreign suppliers. The question in Ethiopia is less whether there is sufficient competition within the local market and more whether the local HEPS sector can be competitive within and outside Ethiopia.

Figure 4.16 Share of in-country HEPS food aid distributions out of procured food aid covered by local procurement in Ethiopia and Malawi, 2001-2011



In Malawi's case, WFP runs its HEPS tenders through the regional office in South Africa, meaning that firms from Zambia, South Africa, and other countries are competing against the Malawian firms for supplies to Malawi. The fact that Malawian firms have steadily increased their share of locally distributed HEPS, capturing all of that market every year since 2008 (Figure 4.16), suggests that they have competed well in this arena. Figure 4.17 shows that Malawian HEPS firms have also competed well regionally: from zero in 2001 and 2002, the share of locally procured HEPS exported out of Malawi rose to about 70% in 2004 and has averaged about 50% since that time. Meanwhile, except for 2004 and 2007, WFP has not exported any Ethiopian HEPS outside the country.

Figure 4.17 Share of in-country HEPS LRP exported from Ethiopia and Malawi, 2001 - 2011



Overall, this review suggests that the Malawian HEPS sector may be on a more sustainable footing than the Ethiopian sector. Firms in Malawi are less dependent on HEPS, less dependent on the food aid market in their overall (HEPS plus other products) portfolio, have entirely replaced CSB with FBFs and RUFs, and have captured the entire Malawian WFP market while winning regional tenders and exporting (through WFP) roughly 50% of their production since 2004.[34] The differing patterns in the two countries are a sharp counterpoint to what has to be considered the much more promising market setting in Ethiopia compared to Malawi: the former's population is dramatically larger and its economy has been growing far faster, providing rapidly growing commercial opportunities for local firms.

[34] This finding emerged in interviews in Malawi.

These patterns raise some questions: how much help will African companies need to meet quality, safety, and packaging standards for HEPS products, will they be able to do so at a price point that allows them to win WFP tenders on the basis of price, and if not, should WFP be flexible in their contracting approach with these companies until they can do so? Additionally, what can WFP do to get these companies, especially Ethiopian companies, into regional tenders? These questions go to the core of WFP's ability to drive positive systemic change in the food systems in which it operates. With Ethiopia's economy growing so rapidly, several firms we interviewed were investing for the commercial market and confident that the market "would be there for (them)." That same thinking, however, is drawing large multi-nationals to Ethiopia, each with the possibility of much larger scales of production than local firms and probably with greater financial capacity to endure losses for some period of time while they establish themselves. WFP needs to consider carefully the range of contributions it can make to Ethiopian firms' development of cost-competitive production capacity in this setting.

WFP's presence has led to major investment in the HEPS sector in Ethiopia, potentially positioning it for a robust response to emerging commercial opportunities in Ethiopia's rapidly growing economy. For about 30 years up to the early 1990s, only one company supplied HEPS to the food aid market. However, over the past six to seven years, many more firms have entered the sector. One of the HEPS companies we interviewed has plans to invest 42 million Ethiopia BIRR (about US$2.3 million) in a CSB factory that would depend primarily on the WFP market, at least to start. Our interviews highlighted that the HEPS sector currently has capacity to produce approximately 300,000 MT per year, which is well beyond the current or any likely future size of the food aid market, even if WFP succeeds in helping Ethiopian firms become competitive in regional tenders.[35]

In contrast to Malawi, none of the HEPS manufacturers we interviewed in Ethiopia had broader food trade businesses; all were focused entirely on food manufacturing. In light of the current over-capacity when compared to the size of the food aid market, entering the

[35] WFP procurement data show that annual WFP purchases of HEPS in Ethiopia from 2001 to 2011 averaged about 28,000 MT with a maximum of about 60,000 MT.

commercial processed food market is central to the success of nearly every firm in the sector. Our interviews highlighted strong interest on the part of all firms to either enter or expand their presence in that commercial market, with several mentioning a range of commercial products they produce, including iodized salt, peanuts, peanut butter, Super Cereal Plus as a baby food, soybean meal and soybean oil. However, the highest commercial share of total business that we found among interviewed processors was 30%, while several manufacturers reported that they had no commercial presence at all but were working to develop it.

4.4 Knowledge, Practices and Investments Concerning Quality

We divide this section into three subsections dealing with what we learned from our interviews concerning quality. The first subsection describes structural factors that could reduce grain quality at farm level, while the second briefly characterizes traders' and farmers' quality perceptions and practices to improve quality. The last subsection discusses some of the WFP's initiatives to improve quality.

4.4.1 Structural Factors Reducing Grain Quality

Maize quality at farm level is a major problem in both Uganda and Mozambique, with the burden of delivering acceptable quality grain falling almost entirely on traders. Uganda's bimodal rainfall pattern – and apparently greater unpredictability in recent years regarding when the rains will start, according to numerous persons interviewed – combines with very small scale of production to hinder the pursuit of high quality grain at farm level. While many production areas of southern Africa receive less than one inch of rainfall during at least three consecutive months at the end of the cropping year, production areas of Uganda outside the southwest typically do not experience a single month with less than 2.5 inches of average rainfall.[36] Thus, harvests in Uganda typically take place when rain is falling. In the absence of mechanical drying capacity, achieving storable levels of humidity in maize (no more than 14%) becomes extremely difficult. The so-called first season is perceived as especially problematic in

[36] This discussion of rainfall patterns is based on country- and sub-location data from http://www.weather-and-climate.com.

this regard, as the harvest occurs in June-July when an average of about four inches of rain falls each month, with even more in August.

The small scale of maize marketing in Uganda exacerbates the weather problem by making it difficult for local traders to reliably generate the volumes needed to justify investment in mechanical drying capacity. Data from the 2005 Uganda National Household Survey (UNHS) and the 2009 Uganda National Panel Survey (UNPS) show that about 70% of all maize sales are of less than US$90, and over 40% fall below US$20. The extremely small scale of most sales means that farmers are not investing in any drying capacity beyond tarps or mats, and that even this practice is likely limited to a small minority.

Mozambique has a unimodal rainfall pattern and by about June is able to harvest adequately dried maize from the farm without the need for mechanical drying. However, the country suffers from the same extremely small scale of production as Uganda and its production and marketing system is perceived by traders to be weaker than many other countries in several respects. First, several traders in Mozambique with experience in at least two other Sub-Saharan Africa countries indicated that farmer knowledge is lower in Mozambique, leading to, among other things, large amounts of foreign matter in sold grain. They also report lower use of improved varieties than in neighboring countries (consistent with available empirical data), which leads to grains of varying size and a mixture of white and yellow, all of which reduce quality.[37]

The structure of Mozambique's trading system makes it very difficult to ensure the type of coordination needed to begin changing farmer practice. Maize in Uganda and beans in Ethiopia have well-recognized market places frequented by farmers in nearly every town visited during the case studies; these may be specific market places or recognized areas of a town where various traders have their small stores and scales, typically nearly side-by-side. Under such circumstances, comparable information flows rapidly among traders and between traders and farmers. In Mozambique, in contrast, rural market towns are substantially less important

[37] Between 2002 and 2008, data from National Agricultural Surveys administered by the Mozambique Ministry of Agriculture with nationally representative samples show the share of smallholder farmers using improved maize seeds ranged from 6% in 2005 to 10% in 2008.

than in Uganda and Ethiopia. Instead, literally thousands of small traders in Mozambique, many of them working as agents of large traders, fan out to rural areas to make purchases in villages, and funnel the majority of their supplies directly to large traders without passing through any more centralized market places. Information flow under such circumstances, even with the use of cell phones, is likely to be more fragmented. The result of these factors is that the burden of delivering acceptable quality grain falls entirely on traders, since farmers are not now and are unlikely for some time to pay meaningful attention to quality improvement.

Like maze in Uganda and Mozambique, assuring bean quality at the farm level in Ethiopia is challenging. This is in part because farmers lack mechanical drying capacity and bean harvest usually occurs in November/December when rains are still usually falling. Farmers and small traders we interviewed indicated that immediately after harvest, many farmers give their beans surplus to local small traders without receiving immediate payment. After selling the commodity, local traders pay the farmers. This is happening because local small traders have greater and better storage capacity than smallholder farmers do, allowing local small traders to sell beans a few months after harvest when prices are higher. Investments in mechanical drying capacity by Ethiopian farmers are likely to be unprofitable due in part to their small scale of production.

4.4.2 Quality Perceptions and Practices at Local Level

Our interviews in Ethiopia suggest that small and large traders there are more quality conscious than farmers, but some small traders stated that they purchase beans with no attention to quality. They also indicated that they do not pay any price premium for quality beans. With regard to quality awareness at farm level, a mixed picture emerged from our interviews. Some farmers do pay attention to quality by cleaning, sorting out foreign matter and drying their bean production before selling it in the market, while others sell their harvest with no such quality improvements. Awareness of the need for improved quality proved to be surprisingly broad and strong among farmers and town traders in Uganda. There is also evidence in Uganda that traders sometimes pay price premiums for better quality (or discounts for poor quality), with most focus on moisture level. In both respects Mozambique showed less awareness of quality issues or use of quality premiums or discounts.

Interviews in Uganda consistently indicate that individuals at every level of the system are acutely aware of the need for greater quality. Various market observers, while aware of the quality problems in the country and the need for much more progress, reinforced this finding, making statements such as "*people have started to understand what quality means*", "*there is a trend in Uganda and the region for quality*", and "*some key players are seeing this and trying to adapt*." Farmers consistently indicated that traders do pay price premiums for quality, with a typical differential involving payment of 500-600 Ugandan Shillings (UGX) per kg for poor quality grain, and UGX800/kg for good quality grain. Farmers made statement such as "*traders do not buy half-dry grain*" and "*traders have always sorted grain and paid according to quality*".

Yet farmers in Uganda also admitted that, when supplies are short and prices high, traders purchase without regard to quality; this tendency was also mentioned in many other interviews at all levels of the system, with a typical statement being "*all maize has a market*" and "*maize at 15.5% may get the same price as maize at 13.5%*". The informality of much of the regional trade from Uganda reinforces this tendency. Traders in South Sudan have typically bought with little if any attention to quality, much of what Kenyan traders purchase goes to animal feed, not maize meal (suggesting lower quality standards), and purchases by traders from the Democratic Republic of the Congo (DRC) go largely into the small-scale milling sector where quality is not emphasized.

It is also unlikely that farmers with little or no training in proper grain handling and quality specifications will define "good quality" maize as rigorously as a formal trader would. Drying at farm and among local traders takes place entirely in open air, often on the ground, sometimes on cane mats, and very seldom on plastic tarpaulins or cement slabs. Farmers are thus dependent on dry weather to be able to dry their maize, and they frequently do not get such weather.

A mixed picture thus emerges at farm level in Uganda: farmers are aware of the need for quality and desire to produce it because (at least when supplies are not tight) they receive a premium, but they have imperfect understanding of what good quality is, sharply limited *ability* to produce it, especially during the first season harvest when intermittent rains often continue to fall, and frequently little *incentive* to produce it due to trader practices.

Small wholesale traders in local towns of Uganda have no mechanical drying capacity.[38] They adapt to this situation by (a) paying low prices for very wet maize to discourage its delivery (unless supplies are tight), (b) selling their maize quickly to larger traders that do have drying capacity, and (c) channeling the lower quality maize into the local milling sector. This latter strategy was mentioned frequently by local traders, suggesting that much of the lowest quality maize may remain in the small-scale, largely informal local trading and milling sector.

We found less evidence of any price differentiation in Mozambique even when supplies were not tight. Farmers consistently stated that "*all maize has a market*", and traders repeatedly indicated that they buy all maize that comes to them at a single price, checking only for egregious violations such as the placement of rocks or additional moisture into sacks of maize. Two specific examples from interviews illustrate this pattern. First, when asked why they did not differentiate on price, trader agents we spoke with cited the cell phone, and the fact that farmers, if offered a price they considered too low, would call contacts elsewhere to bargain. With villages typically having 20 and more small traders and agents competing against each other during the harvest season (Jayne *et al.*, 2010), and in light of the poor quality of the great majority of maize on offer, there appears to be no room to insist on quality.[39] Second, DECA – a milling firm and major maize buyer in Central Mozambique – began its buying in April 2013, when maize was still quite humid, paying 8 Mozambique Metical (MZN) per kg. By late May – when maize was much drier but also when more maize was in the market – they had *reduced* their price to 7 MZN/kg. Farmers thus reasonably perceived a *negative* return that year to dryer maize.

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[38] Some traders operating nationally indicate that they have invested in drying capacity in production areas. Farmer-held installations such as the Kapchorwa Commercial Farmers' Association (KACOFA) and Masindi Seed Grain Growers' Association (MSGGA) also have some capacity. Yet together this capacity is miniscule relative to the amount of grain being marketed, and at least the farmer installations in Kapchorwa and Masindi are not used at capacity.

[39] Traders consistently noted that quality tended to be better in Central Mozambique, in Manica and western Sofala provinces. Yet this relative improvement should be interpreted against the backdrop of quite poor quality very broadly in the country.

Despite these differences between Ethiopia, Uganda and Mozambique, the end-result in all three countries is that larger traders receive poor quality grain and bear the burden of drying it (in Uganda and Ethiopia) and cleaning it (in all three countries) to standards specified by WFP. In addition, our interviews indicate that Mozambique suffers from greater problems of variable color and grain size than Uganda.

4.4.3 WFP Quality Initiatives

WFP is by any measure the most stringent buyer of quality processed maize in Uganda and Mozambique. Yet one stark difference emerged from interviews in the two countries: while complaining strenuously about WFP's quality *practices* in Uganda, traders uniformly and strongly praised the quality *training* that WFP has provided. We found this same pattern for HEPS in Ethiopia and Malawi and beans in Ethiopia. Yet in Mozambique not a single trader volunteered any comments about quality training from WFP, and when asked, they indicated that WFP had provided no such formal training.

Around mid-2010, WFP in Uganda began to tighten substantially its quality practices in an effort to purchase according to East African Community (EAC) standards. Prior to this time, the agency followed a "fair average quality" (FAQ) approach to grading.[40] FAQ is a flexible approach, being based on an assessment of the average quality of grain in the market in which the buyer is operating. Thus, the FAQ standard for Uganda could be meaningfully lower than in countries with more pronounced dry seasons after harvest or larger scales of production and marketing that facilitate better quality practices at farm and post-farm levels. In contrast, EAC grades are based on specified quantitative limits on measureable parameters.[41] EAC in 2007 defined standards for three grades – EAC 1, EAC 2, and EAC 3 – and WFP moved to these grades in 2010. After initially moving to an EAC 1 standard in 2010, WFP began to accept EAC 2 but says – and traders concur – that it insists on rigorous grading against that standard.

[40] We received somewhat inconsistent feedback from WFP Uganda Country Office as to whether they practiced a FAQ approach prior to 2010. We continue to characterize their practice as FAQ in large measure due to the clear sense from traders that they were previously not accustomed to meeting specified quantitative standards on a range of defined parameters.

[41] See UNBS (2011) for the detailed definition of EAC maize grades.

Quality standards such as those of the EAC cannot be instituted in a trading system without an inspection system that is properly trained and reliable. Inspection companies operating in Uganda have received training from WFP but concerns remain about the quality of inspections, based on several incidents of grain being cleared for shipment to a WFP warehouse by the inspection company then judged by WFP, upon arrival, to not have met the declared standards.

The move from an FAQ approach to the use of EAC standards represented a fundamental shift for WFP, with major implications for traders. It created a need for traders to invest in more cleaning and drying capacity. Above all, it required them to put procedures in place to monitor relevant parameters and ensure that it could provide the agency with the quality it was requiring. Cognizant of the significance of the change, WFP also offered training to traders in how to ensure adequate quality grain.

Several of the large traders in Kampala that have competed for WFP tenders mentioned that this training was helpful, and some indicated that it had allowed them to dramatically improve their procedures. Yet it was clear from interviews with all these traders that the transition from FAQ to EAC standards was exceptionally difficult for many and still gave rise to strong opinions. Three themes were repeated in most of these interviews. First, traders still demonstrated a strong negative reaction to the more rigorous inspection standards and the perceived suddenness with which they were instituted – though WFP indicates that it introduced the new process gradually over one full year.

Yet the second common theme was that many traders retained a great desire to continue operating in the WFP market, due in large part to the possibility it created for much greater operational efficiencies through large sales at known prices they can bid: winners of tenders can sell from 1,000 MT to 4,000 MT in each tender, far more than will be purchased at any one time by traders from South Sudan or Kenya or even large local buyers, and they can make these sales at a known price they can bid. Moving such large volumes under such circumstances allows operational efficiencies that reduce costs and improve the bottom line. Third, every large trader with whom we spoke indicated that they were expanding their cleaning and drying capacity. While many said they were doing this for the regional commercial trade, not just for WFP, two factors make it likely that WFP's changed practices played a major role in moving traders in this direction. For one, regional trade continues to be largely informal and operates on a *de facto* FAQ basis, not the more stringent and precise EAC standards. Additionally, large-scale formal regional transactions such as with governments or large regional processors, which would require EAC standards, are too infrequent at this time to provide an adequate basis for investing in expensive cleaning and drying equipment only for that market.

As the largest single buyer of quality processed maize in the country, WFP has been in a position to drive investments and changed procedures that would have been much slower to emerge without their presence and that may, over time, allow the country to produce the kind of quality, in the short timeframes needed, to enter into larger and more remunerative formal trading networks in the region. The training that the agency has done, its related efforts to improve quality knowledge and practices within its own staff, and its insistence on quality standards with traders are central to this effort. This finding represents clear progress compared to the early 2000s, when Wandschneider and Hodges (2005) and Coulter (2007) criticized the agency for not doing enough to drive the type of behavioral change needed to enter regional markets. The continuing bottleneck to achieving this objective – and one on which there appears to have been little progress since the earlier studies – is the lack of mechanical drying capacity outside of Kampala.

A major feature of maize procurement in Mozambique is the use of WFP Purchase for Progress (P4P) initiative to procure from small- and medium traders.[42] The explicit purpose for using P4P in this way was to try to reduce the heavy concentration that was apparent in the country's wholesale maize trade. Concern over the concentrated sales led WFP to use P4P to purchase from smaller traders to determine whether such a relationship could help these traders grow their business to provide greater competition to the two dominant vendors. As a result, P4P amounted to 32% of total maize procurement in 2009, the first year of P4P. Though

[42] P4P also purchased from farmer associations in Mozambique, as it primarily did in other countries. Because the focus of this study is not on P4P but on LRP, we did not investigate that process. We examined trader participation in P4P due to its explicit linkage to LRP.

these shares fell to 13.8% in 2010 and 10.1% in 2011, they remained high compared to most other countries. A surprising fact that emerged from the interviews with these P4P traders in Mozambique is that none of them received any formal training in quality procedures.

The absence of any formal training in Mozambique is a concern for two reasons. First, nearly all traders in other countries spoke in highly favorable terms about the formal training that they received from WFP, suggesting that such training would have been welcomed also in Mozambique. Second, the small- and medium-scale traders that were the focus of P4P in Mozambique were, without question, in even greater need of such training if they were to become capable of routinely meeting WFP tenders and using them as a springboard to growing their business and becoming more competitive on a larger scale. In the meantime, as WFP was conceiving and then implementing its P4P program, the structure of the maize trade, and of agricultural trade in general, dramatically transformed in response to changes in Mozambique's broader economy. This led to a substantial increase in the number of large maize buyers and competition especially in Central and Northern Mozambique starting in the late 2000s.

The main implication of this new market structure is that WFP Mozambique Country Office should now be able to generate substantially more competitiveness in its maize tenders by engaging more of these large traders. We cannot show analytically that prices paid by WFP in Mozambique have been affected by the dominance of two vendors. Yet such an effect is at least consistent with the fact the prices paid in Mozambique have been persistently higher than in other countries of the region while quality has likely been among the poorest. The agency may be able to reduce its costs in the country – and potentially leverage more response from traders on quality improvement – by successfully engaging more of the large traders. Most of the small- and medium size traders who have been selling through P4P are unlikely to provide serious competition to these large players. Our interviews suggest that, if WFP wants to make meaningful contributions to the professionalization of this sector through P4P, it must organize quality trainings along the lines of those seen in Uganda for maize, Ethiopia for beans, and Ethiopia and Malawi for HEPS.

In Ethiopia, WFP has raised quality awareness in the Ethiopia bean market. This might have contributed to strengthening the domestic beans sector's ability to enter export market in recent years, especially for white haricot beans. Over the years, WFP provided extensive training to traders on how to ensure quality. One of the large traders we interviewed stated that "*the contribution of WFP is very high. We learned about the details of quality dimensions from them. So, we were able to enter the export market, which requires even higher quality*". Our interviews consistently reported that WFP has contributed to quality awareness, especially among traders, in the bean market when no other local market stakeholder was paying much attention to quality.

However, some wholesalers supplying beans to the export market felt that WFP had no impact on their practices to improve quality standards. These wholesalers stated that they have taken actions to improve quality in response to tightened quality demand from the export market and not in response to WFP. This stringent quality demand is, to a large extent, driven by importers in Europe, the Middle East and South Asia because regional markets place relatively less emphasis on quality. Farmers and traders we talked to indicated that Kenyan traders purchase Ethiopian beans, especially red haricot beans, with almost no attention to quality. Our interviews also suggested that volumes of beans exported, especially of white haricot beans, increased considerably in the last five years. Estimates from the Ethiopian Central Statistical Agency (CSA) indicate that exports of haricot beans – both white and red – have risen from 52,000 MT in 2006 to 108,000 MT in 2011 to 99,000 MT in 2012.

WFP quality training has also had a major positive impact on some of the newer HEPS processors in Ethiopia. Over the past three to four years, WFP in Ethiopia has carried out a few formal quality trainings. While the two most established HEPS firms felt that these trainings had not had a major impact on their business, some of the newer manufacturers were highly complementary regarding the trainings and the follow-up engagement and feedback through the inspection process, and asserted that they had a major impact on their firms' business.

The major story concerning HEPS in Malawi relates to simultaneously sharp criticism of WFP's quality requirements and strong praise for their quality training. Criticisms related to the charge that on more than one occasion, winning tenders for HEPS in Malawi were based on prices that were "impossibly low" given the WFP recipe for the tendered product. Some firms explicitly suggested that unapproved (and cheaper) ingredients had been used to reach the required protein content or possibly that expired vitamin and mineral mixes had been used. Traders indicated that "*the best price wins regardless of quality, and quality is not tested at any rate*." We are not in a position to evaluate this claim but note that it was independently and voluntarily raised by at least three firms we interviewed. The praise for quality training was equally strong and quite broad across manufacturers.

In somewhat accentuated fashion, the findings on quality in Malawi – some frustration with WFP's move to strengthened standards, sometimes very strong criticism of particular aspects of implementation, but real praise for the quality training that WFP has done – echo feedback from maize traders in Uganda and bean traders in Ethiopia regarding WFP's quality practices and training. The consistency of this feedback across these countries leads us to believe that the positive quality findings of the interviews are robust. It appears that WFP's procurement of HEPS in Ethiopia and Malawi has had important effects on expansion of the sector and on improved quality practices of firms in both countries. Both effects bode well for the sectors' ability to expand into the commercial markets that are emerging as Africa's economies urbanize and as consumer purchasing power rises.

4.5 Seasonal Pricing for Maize

Due to seasonality in agricultural production, maize prices at various levels of the supply chain fluctuate in predictable ways during the year. These fluctuations can be quite pronounced in the types of production and marketing systems seen in our country applications, with small-scale production, inadequate storage capacity to minimize physical losses, poor information flows, and very high costs of credit. Analysis of price data in Mozambique shows annual average maize price rises of between 85% and 90% in major markets of production areas over the period 2001 to 2011. These compare to annual average rises of less than 20% in South Africa, which has similar seasonal variation in production but where the production, trading, storage, and financial sectors are far more developed.[43] With two annual harvests helping to reduce seasonal variation, Uganda shows seasonal rises of 37% in Kisenyi and 50% in Masindi – lower

[43] For the South Africa figure, see Tschirley *et al.* (2006).

than in Mozambique but still higher than in South Africa despite the single annual harvest in that country, which *ceteris paribus* should drive greater seasonal price variation.

WFP may have two reasons to want to engage in “counter-seasonal” purchasing whereby it preferentially purchases its supplies during the low price season. First, because its borrowing costs and physical storage costs are low when compared to typical seasonal price changes, it could reduce total procurement costs by such a strategy. Second, because pronounced seasonality can impact the welfare of farmers and consumers, WFP may be able to increase overall welfare of the rural population by buying counter-seasonally and increasing prices during the harvest period rather than later in the season when supplies may be tighter. The likely benefits to rural households stem from the fact that their sales are heavily concentrated in the two to three months during and immediately after harvest, and their purchases are likely to occur later in the season.

Two factors could limit WFP’s ability to take advantage of seasonal price movements. First, emergency needs are not always fully known months in advance, suggesting that some purchases are inevitably made when needs are revealed during high price months. Second, in the absence of access to the agency’s forward purchase facility (FPF), LRP purchases can be made only when WFP has cash on hand from donors. We do not analyze FPF in this paper but do analyze the agency’s seasonal buying pattern to provide insights into the potential gains from FPF. Specifically, we quantify the percent by which WFP has paid above or below a simple annual average price each year from 2001 to 2011 by comparing yearly average market prices weighted by WFP purchase volumes to simple averages of the same market prices. We use market prices in our weighting – rather than prices paid by WFP – because they are the prices WFP needs to be referencing as they attempt to purchase in counter-seasonal fashion. The ratio of the weighted average prices to the simple average prices – which we call WFP’s seasonal pricing indicator (SPI) – quantifies how counter- or pro-seasonal WFP’s purchases were during that year: ratios above (below) one indicate the percent by which WFP average purchase prices exceeded (fell below) prices in a hypothetical “seasonally neutral” approach of buying equal amounts each month of the year.

We computed SPI using maize market prices for Uganda and Mozambique gathered from Farmgain Africa and Ministry of Agriculture Marketing Information System (SIMA), respectively. Results are shown in Figures 4.18 and 4.19 for Uganda and Mozambique, respectively. The solid bold line in the Uganda figure is based on Kisenyi wholesale market prices, the largest and most referenced market in the country. The average SPI over all three markets and years in Uganda is one, indicating that the agency paid prices exactly equal, on average, to what they would have achieved through equal quantity purchases each month. Year-by-year variation, however, was high: the average SPI for 2008 (the most pro-seasonal buying year) was 1.12, compared to 0.91 in 2006 (the most counter-seasonal buying year). If WFP Uganda Country Office's seasonal purchase pattern in 2008 had been the same as in 2006, it would have reduced its average purchase price by 19%. Overall the SPI shows no clear trend, suggesting no clear trend in the seasonality of purchases over the years by WFP in Uganda.

Mozambique shows a different outcome. On average over all years and markets, its maize SPI was 0.95, indicating prices 5% lower than the hypothetical seasonally neutral buying pattern. Yet because WFP Mozambique Country Office buys in producing areas of the Central and Northern regions of the country, the SPIs for Chimoio in Central Mozambique and Nampula in Northern Mozambique are better indicators of actual seasonal pricing patterns; these were 0.95 and 0.93, respectively. Chimoio and Nampula SPIs are also far more variable, reflecting the greater seasonality of prices in those areas compared to Maputo. During the two most counter-seasonal purchasing years (2005 and 2006) and focusing on the SPIs for Chimoio and Nampula, WFP Mozambique Country Office paid on average about 36% less than it would have paid had it followed the purchase pattern of the most pro-seasonal purchasing year, 2004.

Figure 4.18 WFP seasonal pricing indicator for maize in Uganda, 2001-2011

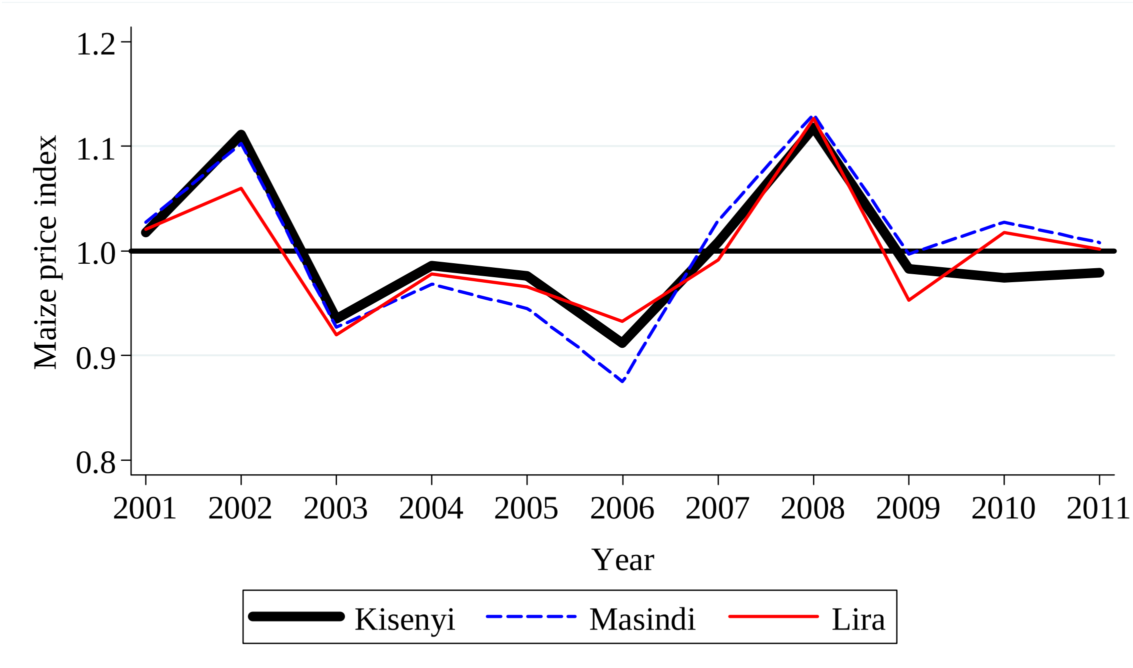
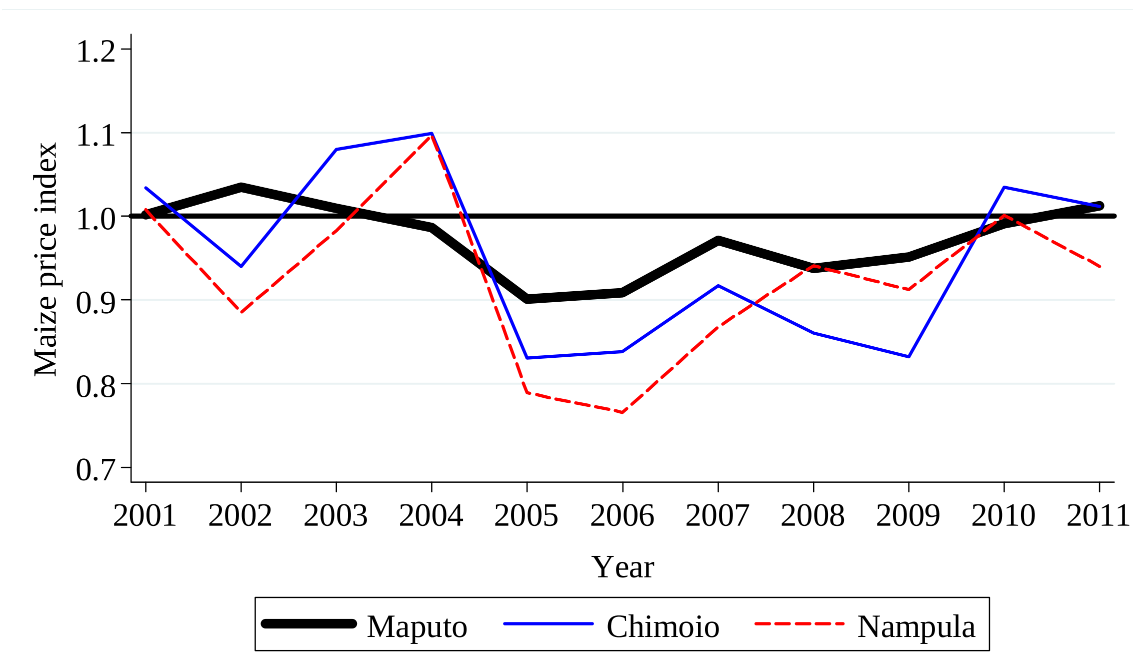


Figure 4.19 WFP seasonal pricing indicator for maize in Mozambique, 2001-2011



These findings suggest that there is scope for WFP to reduce its own costs while likely improving the welfare of poor farmers and consumers through use of FPF to purchase more pro-seasonally, but that this scope varies across countries. Seasonal production patterns suggest that these opportunities would be greater in Mozambique than in Uganda. Compared to observed historical purchasing patterns, however, opportunities for improvement are greater in Uganda. More detailed analysis beyond the scope of this paper is needed to develop more refined estimates of potential gains.

4.6 Regional and Local Market Pricing Performance

Average maize prices paid by WFP in the two countries over the period 2001 to 2011 were close, at US$242/MT in Uganda and US$254/MT in Mozambique. Comparing each to their regional neighbors, weighting prices by purchase quantities, and limiting our data to months in which maize was purchased in the country of interest and also somewhere in the region outside the country, we find that prices paid by WFP in Uganda (US$244/MT) were on average nearly identical to those paid in the rest of East Africa (US$245/MT) (Figure 4.20).[44] Beyond this average, we see that prices in Uganda were very similar to those in the rest of the region throughout the period.[45]

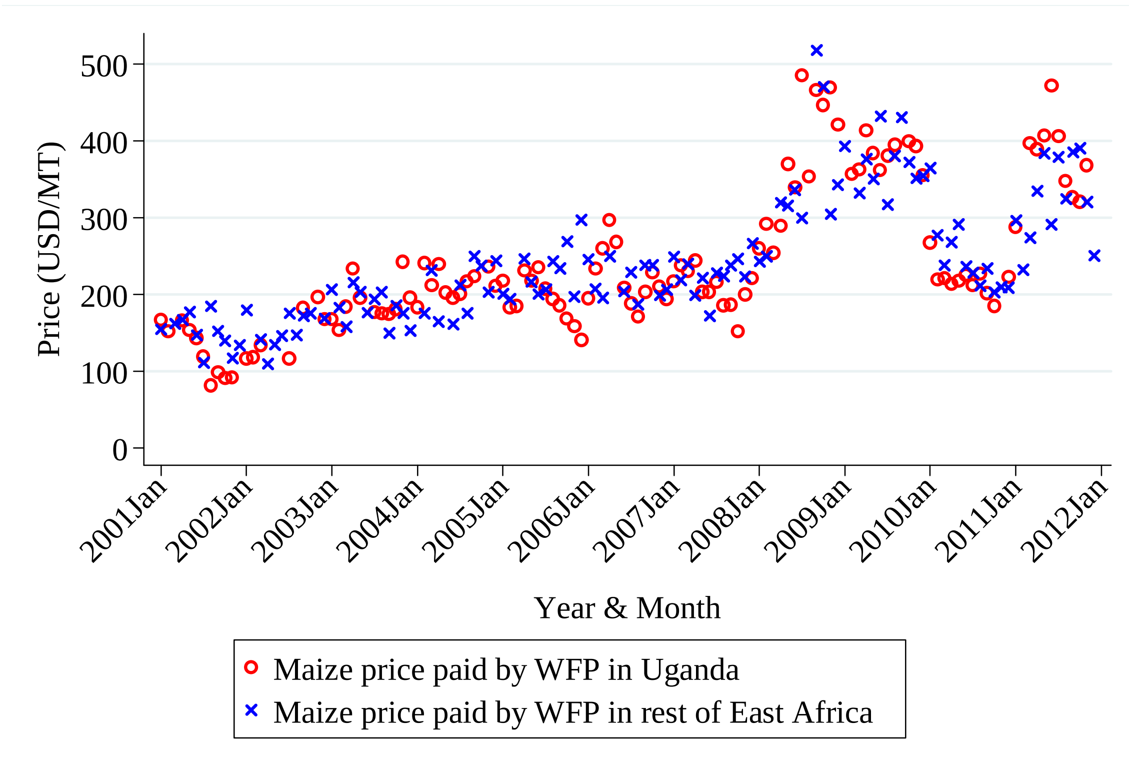
A similar comparison shows that WFP paid meaningfully higher prices in Mozambique than were paid in the Southern Africa region, by an average of 10.6% over the entire period (US$254/MT versus US$228/MT); (see Figure 4.21). Prices paid in Mozambique exceeded average prices paid in the region in 71% of all purchase months. This pattern changed over time, however. Prior to June 2008, average maize prices paid by WFP were 11% higher in Mozambique than in the rest of Southern Africa (US$207/MT versus US$188/MT) and higher than every individual country in the region. Between June 2008 and May 2010, the difference between these two maize prices increased dramatically to 31%, with an average of US$363/MT

[44] We compared Uganda to Ethiopia, Sudan, Kenya, Somalia, Rwanda, Burundi, and Tanzania. Mozambique was compared to Malawi, Zambia, Zimbabwe, Swaziland, Tanzania, and South Africa.

[45] Note that prices in Uganda were most markedly below those in the region in 2007, the peak year of WFP maize purchases. Consistent with these relative prices, 2007 is also the year that Ugandan maize captured the largest percentage of the regional WFP market, with 35,056 MT (the all-time high to that point) accounting for 37% of that market, compared to previous highs that never exceeded 25%. Finally, 2007 was the high point for local distributions of locally procured maize, at more than 127,000 MT.

compared to US$278/MT, and again WFP paid higher average prices in Mozambique than in every other country of the region. From May 2010 through December 2011, average prices paid by WFP in Mozambique were *below* those in the rest of the region, at US$292/MT compared to US$303/MT. The pattern during this latter period, however, was driven by Malawi, where WFP paid extraordinarily high prices for maize; average prices paid in Mozambique were still higher than in every other country of the region with the exception of Malawi.

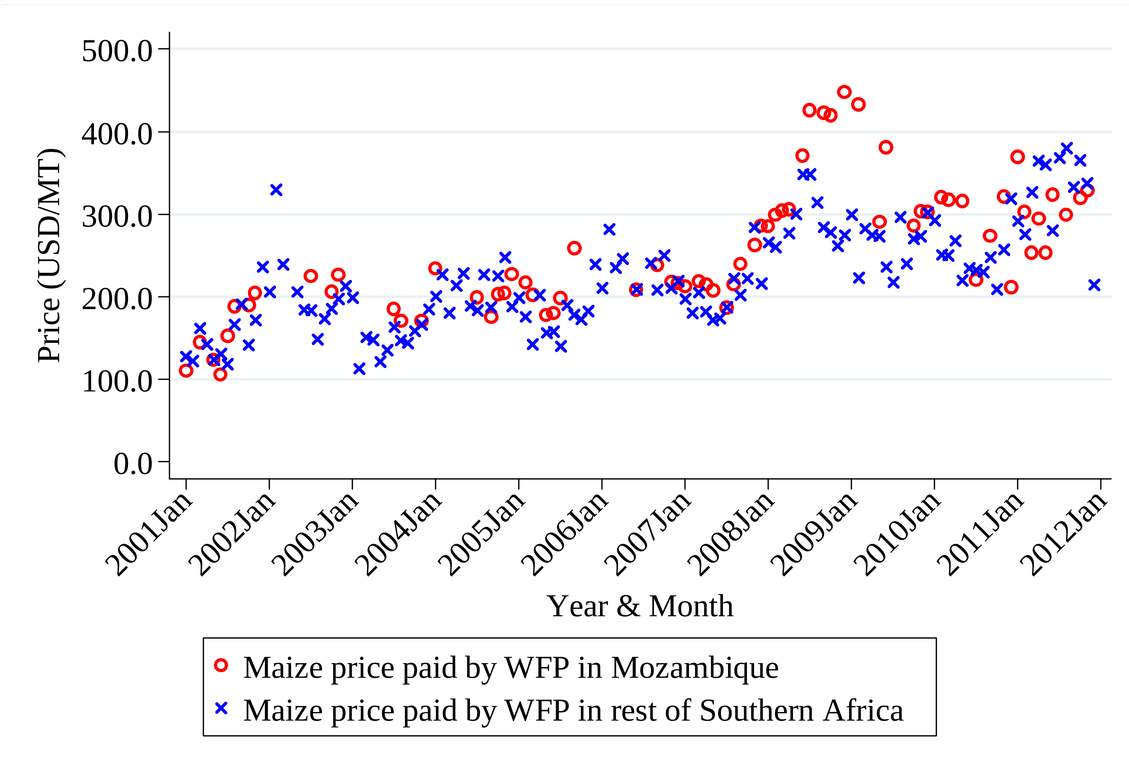
Figure 4.20 Maize prices paid by WFP in Uganda and rest of East Africa, 2001-2011



Figures 4.22 and 4.23 compare monthly prices paid by WFP to local market prices in Uganda and Mozambique, also showing monthly quantities purchased. Because Kisenyi is the reference market in Uganda, we present only Kisenyi prices in the Uganda graph. For months during which WFP purchased, their average purchase price exceeded market prices in Kisenyi by 32%, at US$242.5/MT compared to US$183.7/MT. Maize in Mozambique does not have a single dominant market, so we present the graph with Nampula and Beira. Results are very

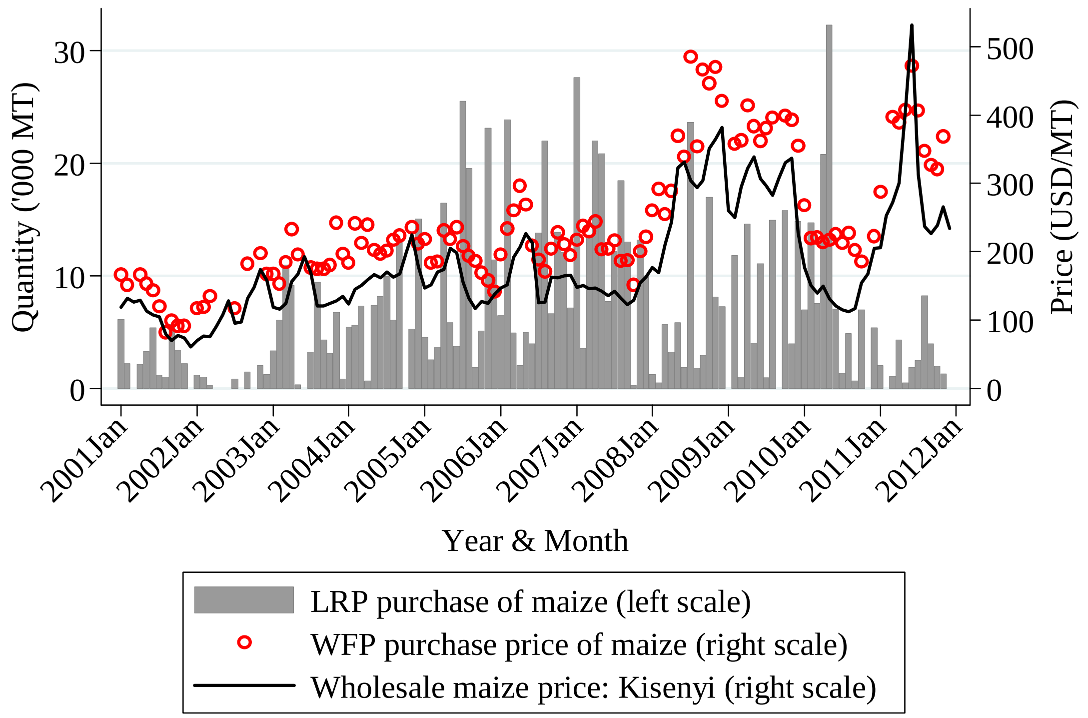
similar to Uganda, with WFP paying average price premiums over wholesale of about 30% in both markets (US$254.4/MT compared to US$194.5/MT in Beira and US$195.8/MT in Nampula).

Figure 4.21 Maize prices paid by WFP in Mozambique and rest of Southern Africa, 2001-2011



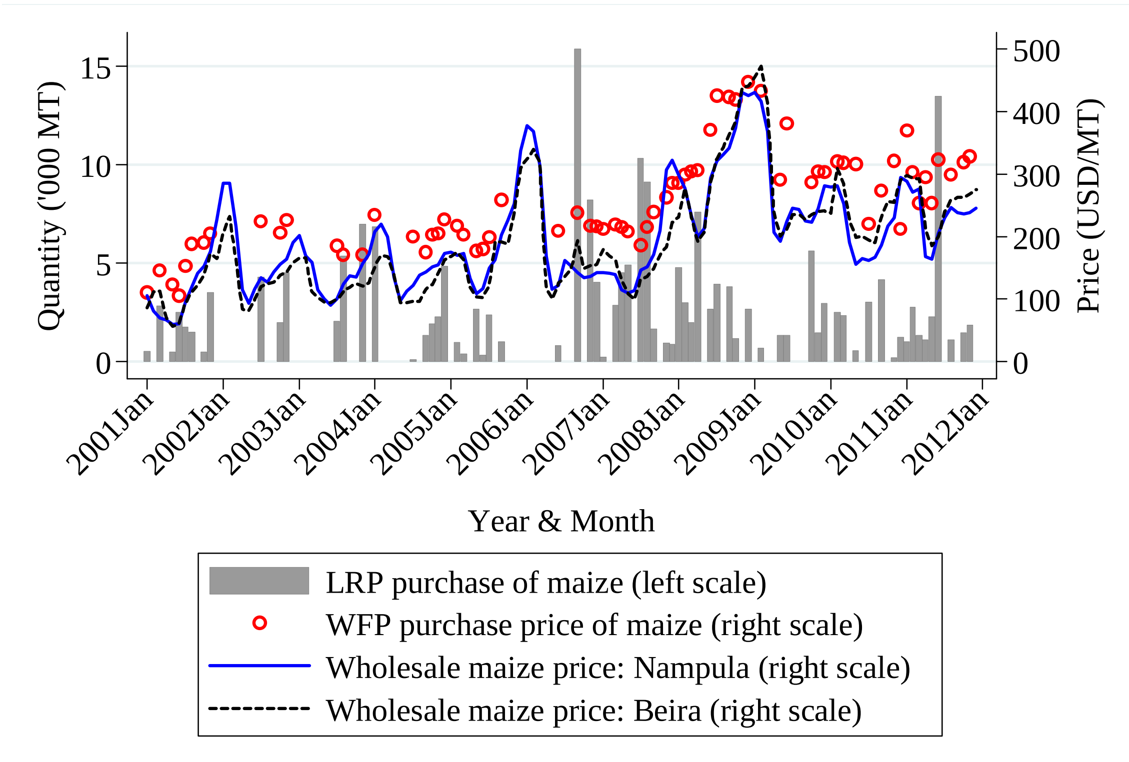
It is not clear how much of these price premiums are due to the higher costs of selling to WFP (more cleaning, lower moisture levels than typical in the trade, special bagging, and other costs). In discussions with traders in Uganda, their estimates for these costs were very close to the 32% premium that we computed. Traders in both countries repeatedly cited these higher costs and also persistently complained that WFP tenders were “too competitive”. At the same time, several WFP officials doubt that the higher costs fully explain the price premiums, most traders do admit that the WFP market is profitable for them, and interviews make it clear that they work hard to remain in that market.

Figure 4.22 Monthly purchase order quantities, prices paid by WFP, and wholesale market prices, maize in Uganda (2001-2011)



We identify two main issues from this section on pricing performance relative to local and regional price levels. First, WFP's purchasing behavior in Mozambique during the market peak of late 2008/early 2009 raises some questions. During the earlier market peaks of 2001/02 and 2005/06, WFP avoided purchasing locally in the country. Yet the agency did purchase in the midst of the very high market peak of 2008/09, and they paid much more locally than they were paying regionally at that time (Figure 4.21). They also purchased in the midst of the market peak of 2010/11, but at that time prices paid in Mozambique were comparable to those paid in the rest of the region. Without further information we cannot fully evaluate the 2008/09 event, but raise the question of why WFP would purchase in the country at such high prices when prices paid in the region outside Mozambique were far lower.

Figure 4.23 Monthly purchase order quantities, prices paid by WFP, and wholesale market prices, maize in Mozambique (2001-2011)



Second, Mozambique remains a relatively high-cost supplier of maize in the region, generating lower prices than only one country (Malawi) and even then only in 2010 and 2011. Given the quality problems in the country (Mozambique's grain quality is clearly lower than South Africa and also Zambia, where better and more consistent seed is used), these pricing patterns suggest that the country is unlikely to be a regular supplier of maize to the region unless prices drop substantially.

4.7 Conclusions

Local and regional procurement of food aid by WFP can have meaningful effects on prices of commodities the agency procures and consequently on welfare of households who sell and/or purchase those commodities. In addition, the way that WFP goes about its local and regional procurement of food aid can generate potential systemic effects on the food systems of countries where commodities are sourced from. The case studies discussed in this paper focused on such potential systemic effects by investigating five related issues: (1) whether WFP LRP contributed to knowledge, practices, and investments of traders and farmers concerning quality; (2) whether WFP LRP led, where relevant, to greater competitiveness in the sectors where WFP operates; (3) whether WFP LRP helped traders be more competitive in the commercial (and especially the regional) market; (4) whether the seasonal pattern of WFP LRP purchases has increased or moderated what are typically very large seasonal price movements; and (5) whether WFP pays "market prices" when procuring commodities. These are the types of effects that, accumulating over time, drive transformational change in food systems over the course of development.

Several findings stand out from our case studies. ***Our first broad findings is that WFP has positively influenced the "quality culture" on maize in Uganda, beans in Ethiopia, and HEPS in Ethiopia and Malawi***. In all these cases, traders and processing companies have invested in new machinery and new practices to satisfy WFP's market. In Ethiopian beans and HEPS, and Malawian HEPS, companies repeatedly indicated that WFP's quality training – both formal training and ongoing interactions on quality matters – helped them in multiple ways: to focus more analytically on quality parameters, rather than assessing quality more qualitatively (and subjectively); to understand and implement practices to achieve and document these parameters; in this way to consolidate and spread within their company the good but inconsistent practices that they already had; and, for Malawian HEPS and Ethiopian beans, to use these improved practices to enter the export market more strongly.

The "quality story" is positive but inconclusive on maize in Uganda. WFP faced three major challenges in trying to improve quality in this country. First, Uganda's bimodal rainfall pattern means that maize comes off the farm with moisture levels too high for storage, necessitating mechanical drying capacity. Yet the small scale of production and local marketing make it difficult for small traders operating in production zones to invest in such capacity and, in fact, little private investment has taken place outside of the capital city (Kampala). Second, even many of the larger maize traders in Uganda had little experience with international trade, being oriented towards local markets and the largely informal export markets of Kenya and, more recently, South Sudan and DRC. International trade is more formal and demanding in contracting procedures and quality guarantees, and companies must learn these skills if they are to compete; the lack of such experience in Uganda made WFP's challenge greater. Finally, and closely related to the previous point, local and regional markets provide robust demand with little if any insistence on quality, providing traders with strong sales options if WFP standards are too demanding.

The fact that the traditional regional maize market does not reward quality implies that the drive to improve quality in Uganda must be pursued in a regional context. The East African Community (EAC) and the East African Grains Council (EAGC) provide an institutional framework for doing this. WFP has supported this framework by moving its purchases in Uganda to EAC standards and by participating in various fora sponsored by EAC and EAGC. Continued active engagement by WFP at this level will be needed as it works to further enhance the quality and reduce the cost of grain that it purchases.

WFP has had relatively little impact on quality practices in Mozambique, for multiple reasons: the highly dispersed marketing system that raises the cost of coordination for quality improvement, the dominant position of the two early trading firms who had no meaningful competition in supplying WFP, and the lack of any organized quality training program, even for the small- and medium-scale traders selling under P4P.

Our second broad findings is that traders are able to generate greater operational efficiencies selling to WFP, due to the relatively large size of tenders and the price that is known once a tender is won. Both factors were repeatedly cited by traders when asked why, despite WFP's strict and burdensome requirements, they wished to continue selling to the agency. If firms are able to use their WFP experience to increase their scale of operation more generally, then these efficiency gains will be long-lasting and generate high returns to the farmers and consumers operating in the local food system.

Finally, on the question of market entry, we found that WFP operations have spurred market entry in the Malawian and Ethiopian HEPS sectors, have facilitated greater commercial competitiveness of the Malawian HEPS and Ethiopian bean sectors, but have had limited effect on market entry in Mozambique's maize sector. By spurring entry into the

Ethiopian HEPS sector, WFP has potentially facilitated a robust response by that sector to growing commercial markets, but that response has to date been limited, and WFP has not facilitated any entry by these firms into regional operations. As WFP moves now to include Ethiopian HEPS firms in regional tenders – as have done successfully for several years in Malawi – these companies may begin to be able to take broader advantage of the quality training they have received.

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CHAPTER 5:

CONCLUSIONS

Food aid agencies had traditionally responded to food crises by shipping food commodities from donor countries to recipient countries. This modality of food aid assistance is referred to as transoceanic shipment of food aid. However, starting in the late 1990s, concerns about the disincentive effects of transoceanic food aid shipments on recipient countries combined with changing agricultural policies in donor countries to make food aid agencies – including the United Nations World Food Programme (WFP) the World's largest agency administering multilateral food assistance – move away from transoceanic food aid shipments. This led to emergence of innovative alternative modalities of food assistance. Among these alternative forms of food assistance, local and regional procurement (LRP) – the purchase of food commodities in the country or region where food aid is being distributed to targeted groups of households – became one of the chief modalities, with its share of global food aid deliveries rising from less than 5% prior to 1995 to 8% in 2001 to about 30% in 2011.

Policy makers, development practitioners and researchers have also raised importance concerns about the potential impacts of LRP on procurement countries. However, there are limited empirical studies that assess quantitatively the LRP impacts, despite the growing importance of LRP. In fact, we are not aware of any existing studies of LRP effects on local markets and households in countries where LRP purchases have been a significant share of total marketed surplus. This study addresses this knowledge gap by focusing on four countries and commodities where WFP LRP has had a meaningful share of the market: maize in Uganda and Mozambique, beans in Ethiopia, and high energy protein supplements (HEPS) in Ethiopia and Malawi. This study investigates three potential impacts of WFP LRP: (1) the effect of LRP on the level and variability of local market prices, (2) the impacts of resulting price changes on the welfare of households selling and/or consuming commodities procured by WFP, and (3) the effect of LRP purchases and related training and inspection activities on investment decisions and trading practices of traders and processors in the food system, and hence on the development of the food supply chain.

This study is structured into three self-contained, but related, essays. Several broad findings emerge from the three essays. First, findings from essay one indicate that even though WFP LRP effects on local market maize prices in Mozambique and bean prices in Ethiopia were estimated to be modest on average, effects were substantial in particular years when the recent history of LRP purchases were especially high. Because we chose countries with the highest LRP as a share of marketed surplus for the study, it is likely that LRP price effects in other African countries will be lower. Second, results from essay two show that there is a large group of households in Mozambique and Uganda whose welfare is little affected by any reasonable estimate of LRP-induced maize price increases. Average welfare effects are less than a 1% loss for maize in both countries, and about three-quarters of all households experience impacts between 1% and -1%.

Third, findings from essay two also suggest that welfare effects are significant for some households, though the impacts are fairly small on average and for most households. In Uganda, 8.9% of households are estimated to experience welfare gains or losses greater than 3%, while in Mozambique 6.9% experience such effects. Welfare gains and losses are distributed relatively evenly across the income distribution in Mozambique (as many low income as high income households benefit and are harmed). However, the distribution of welfare gains and losses in Uganda suggests that higher welfare losses tend to be more concentrated among low income households due to these households' greater reliance on maize for their consumption. Focusing on the bottom third of the income distribution in that country, over 13% had estimated losses of greater than 3%, and nearly 6% had losses greater than 5%. Because this study focuses on countries where WFP LRP had a meaningful share of marketed surplus, welfare gains and losses will be smaller in countries with lower WFP LRP shares.

Although WFP LRP effects on local market maize prices in Mozambique and bean prices in Ethiopia were estimated to be modest on average, effects were substantial in particular years. In Uganda, average LRP effects on maize prices are meaningful. Welfare gains and losses resulting from this induced price increases were estimated to be substantial among some households in Uganda and Mozambique, although they are fairly small on average. This suggests that WFP does need to pay attention to possible local market price increases and corresponding welfare effects when LRP purchases become significant relative to the size of the marketed surplus. When price effects are generally modest and welfare effects are small for the vast majority of households, then the overall effect of WFP LRP depends on the systemic effects on the food systems that WFP is able to induced by the way in which it goes about its procurement. The last essay of this research focused on three such potential systemic effects: improved knowledge, practices, and investments regarding quality; operational efficiencies stemming from larger-scale transactions under less uncertain prices and quantities, which allow unit costs to be driven down; and effects on entry into sectors and on companies' and sectors' ability to compete in the commercial sector. These are the types of effects that, accumulating over time, drive transformational change in food systems over the course of development.

Our fourth broad finding is that WFP has positively influenced the "quality culture" on maize in Uganda, beans in Ethiopia, on HEPS in Ethiopia and Malawi, but not on maize in Mozambique. In all these cases, traders and processing companies have invested in new machinery and new practices to satisfy WFP's market. Many companies indicated that WFP's quality training and ongoing interactions on quality have caused them to focus more analytically on quality parameters; to understand and implement practices to achieve and document these parameters; to consolidate and spread within their company the inconsistent quality practices that they already had; and in some cases to use these improved practices to enter the export market more strongly.

Our fifth finding is that traders are able to generate greater operational efficiencies selling to WFP, due to the relatively large size of tenders and a price that is known once a tender is won. If firms are able to use their WFP experience to increase their scale of operation more generally, then these efficiency gains will be long-lasting and generate high returns to the farmers and consumers operating in the local food system.

Finally, we found that WFP operations have spurred market entry in the Malawian and Ethiopian HEPS sectors, have facilitated greater commercial competitiveness of the Malawian HEPS and Ethiopian bean sectors, but have had limited effect on market entry in Mozambique's maize sector. By spurring entry into the Ethiopian HEPS sector, WFP has potentially facilitated a robust response by that sector to growing commercial markets, but that response has to date been limited, and WFP has not facilitated any entry by these firms into regional operations. As WFP moves now to include Ethiopian HEPS firms in regional tenders – as have done successfully for several years in Malawi – these companies may begin to be able to take broader advantage of the quality training they have received.

In recent years, the importance of vouchers and cash transfers as food assistance instruments has been rapidly growing. For instance, according to WFP (2011), the value of vouchers and cash transfer projects administered by WFP increased about eight-fold from US$5.4 million in 2008 to US$41.0 million in 2010. Furthermore, it is projected that vouchers and cash transfers account for 30% of WFP assistance programs by 2015. Like LRP, vouchers and cash transfers increase local demand for food commodities, leading to price increases in local markets and corresponding household welfare effects.[46] Hence, with the shift to increased use of vouchers and cash transfers, WFP and other food assistance agencies have to be mindful of the impacts of vouchers and cash transfers on local market prices and household welfare. This is because vouchers and cash transfers could potentially have significant effects on local market prices and welfare for some households as shown by our findings for the case of LRP.

[46] This assertion is consistent with findings by Hidrobo *et al.* (2014) showing that vouchers and cash transfers significantly increased per capita food consumption in Northern Ecuador.

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