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

By

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This paper assesses the impact of local and regional procurement (LRP) of food aid on local market prices in Africa. In particular we study maize in Uganda and Mozambique and beans in Ethiopia. Two complementary modelling approaches are employed: a vector autoregression (VAR) and a computational model (CM). The VAR is a reduced-form econometric approach while the CM is a structural simulation approach. Using two different approaches provides a useful consistency check. Results from the VAR show average price increases brought about by LRP are statistically significant and range from 2% to 16%. The size of the average estimated price effects are economically meaningful for maize in Uganda but much smaller (though still statistically significant) for maize in Mozambique and beans in Ethiopia. In all three country applications, LRP is estimated to have no effect on price variability. Results from the CM fall within a 90% confidence bound around results obtained from the VAR.

1. Introduction

Starting in the late 1990s, food aid began to move away from its traditional dependence on transoceanic shipments towards more local and regional procurement (LRP) – the purchase of food commodities in the country or region where food aid is distributed to targeted groups of households.[1] LRP has at least three advantages over transoceanic food shipments. First, LRP generates large cost savings, making it possible to feed more people with a given emergency response budget (Clay, Riley and Urey, 2005; Tschirley and del Castillo, 2007; GAO, 2009). Second, LRP increases the timeliness of response to food crises, which can save lives (GAO, 2009; Lentz, Passarelli and Barrett, 2013). 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 and increase the satisfaction of beneficiaries.

Despite these advantages, very little is known about the effects of LRP on local markets and prices. Early studies (e.g. 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 World Food Program (WFP) transactions, and may have contributed to increased exports of some foods in Ethiopia. Yet these studies also suggested that LRP had failed to have any appreciable effect on broader trade practices and may have led to price spikes in some instances. 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 price variability. However, these studies focused on US Department of Agriculture (USDA) pilot LRP programs that "were minuscule compared to the size of the market" (Garg et al., 2013). It is thus not surprising they had no detectable effect.

This paper focuses 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 marketed surplus, at least in some years. Specifically, the study evaluates the effects of WFP LRP on the level and variability of prices for maize in Uganda and Mozambique, and beans in Ethiopia. In addition to broadening our understanding of LRP effects on local market prices by offering new empirical evidence, the study makes two methodological contributions.

First, we use two complementary methodologies to investigate the effects of LRP—a vector autoregression (VAR) econometric approach and a "computational model" (CM). The VAR is a data-based econometric approach that imposes minimal identification restrictions while 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, and trade patterns. The advantages of including the CM analysis are: (1) it provides an alternative estimate of the

[1] According to Upton and Lentz (2012), food assistance instruments include transoceanic shipments, prepositioned food aid, local and regional procurement, cash transfers, and vouchers distributions.

LRP effect that can be used as a consistency check on the VAR results; and (2) unlike the VAR, it provides an economic interpretation of the pathways through which LRP effects occur. To our knowledge, this is the first attempt to jointly apply and compare these two methodologies.

Second, we develop bootstrap procedures to place confidence intervals around the estimated average LRP effects obtained from the VAR. Most previous studies investigating agricultural policy effects using VARs (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 effects.

2. Country and Commodity Selection

We selected study countries and commodities based on three factors. First, the size of LRP purchases had to be large relative to the total marketed surplus in the country because this will strongly influence the impact of LRP on markets. Second, the commodity needed to have price data of sufficiently long duration to support meaningful econometric analysis. With 11 years of data (2001-2011) from WFP on their LRP transactions, we looked for price series of at least monthly (more frequent if available) data that covered as much of this period as possible. Third, we looked for commodities that did not feature 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.[2] 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 maize and beans. We excluded HEPS, sorghum and millet because time series price data for these commodities are generally not available. We excluded wheat because WFP's wheat purchases in Ethiopia, the only African country with a meaningful wheat LRP program, have been less than 1% of the marketed surplus in the country.

Figures 1 and 2 show the mean, minimum, and maximum LRP purchases of maize and beans as a share of marketed surplus of these commodities in the main African countries in which WFP operates. Data span 2001 through 2011. LRP purchases were obtained from the WFP Information Network and Global System (WINGS) and 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 data to compute marketed share of each crop during survey years that fell within our study period. In other countries, estimates of marketed shares are obtained from Tschirley and del Castillo (2007).

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. In this regard, Uganda has by far the highest

[2] From the products in the WFP tender data, 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.

maximum share at more than 30%, followed by Zambia at 14% and then Mozambique, Tanzania, and Malawi at 11% to 12% (Figure 1). Figure 2 shows that Ethiopia has the largest LRP share of marketed surplus for beans, with mean and maximum 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.[3] Available price data for Uganda and Mozambique were sufficient to support VAR 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 econometric modeling for beans in Uganda. Therefore, we investigated beans in Ethiopia only.

3. Regions and Market Structures

In this section we provide brief descriptions of geographical regions, regional markets, and agricultural production and trade patterns, which we use later to break each country into key domestic regional markets for modeling purposes.

Uganda has four main regions: Eastern, Central, Northern and Western (see Figure 3). Central Uganda is maize deficit and contains 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 Northern, and Mbale and Kapchorwa in Eastern are key maize 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).

Mozambique has three main agricultural regions: the North consisting of Niassa, Cabo Delgado, Nampula, and Zambezia provinces; the Center including Tete, Manica, and Sofala provinces; and the South encompassing Inhambane, Gaza, and Maputo provinces (see Figure 4). Northern and Central Mozambique are maize surplus regions, while Southern Mozambique is maize deficit. The capital city of Maputo in Southern Mozambique is the largest city and major consumption center. Maputo is also a major maize market where price discovery takes place. In the Central region, Beira is a larger city than Chimoio but lies 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 City is the dominant market in Northern Mozambique.

[3] Mason and Myers (2013) 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.

Northern Mozambique including Tete province are important sources for maize crossing the border into maize-deficit Southern Malawi. Maize from the Central provinces 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, and the resulting maize meal is viewed as a different product in the market than meal from domestically 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 (see Figure 5). The country grows at least three 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 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 bean in Ethiopia, but more recently red haricot beans dominate their purchases due mainly to a government mandate.[4]

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 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 city is the second largest city in Ethiopia and generates a large demand for beans. Because Dire Dawa has large demand and is located in a bean deficit region, we treat Dire Dawa as the main reference market for price discovery.

4. The Vector Autoregression (VAR) Model

A standard econometric approach to modeling the impacts of LRP on local markets might be to build a structural simultaneous equation model (SEM) of supply, demand, and price determination, and then estimate all parameters and LRP effects using the SEM. We instead use a reduced form VAR approach, for two main reasons. First, VAR models have proven useful when data are not available on all variables required to build a full structural SEM (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 application due to data unavailability. In particular, data on consumption, storage, factor prices, and prices of competing commodities are available only sporadically or not at all.

[4] 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, and further required that these beans be exported. This made it impossible for WFP to continue procuring white beans.

Second, the VAR imposes fewer identification restrictions. The VAR estimates historical correlations between variables of interest (in our case, food aid, LRP purchases, and local prices). These correlations are then exploited using minimal identification restrictions to estimate the net effect of LRP purchases. By contrast, an SEM requires a set of assumptions regarding the economic structure of supply and demand relationships when we are often uncertain about what the nature of these relationships really are. Different identification assumptions can then drive very different results, with no easy way of determining which are appropriate. The VAR imposes minimal identification restrictions and therefore can be viewed as more “data-based” than most SEMs.

4.1. *Modeling Procedures*

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, however, we apply 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. First, WFP choice variables consist of food aid deliveries FA_t and LRP purchases LRP_t in month t. These variables are chosen by WFP based on food aid needs, local food availability, and local prices. Second, n local price variables $P_{1t}, P_{2t}, ..., P_{nt}$ represent prices in different local markets in month t. We capture the relationship between the WFP choice variables and local price variables with a flexible dynamic model:

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

$$\mathbf{B}\mathbf{p}_t = \mathbf{Q}^{\mathbf{p}}\mathbf{z}_t^{\mathbf{p}} + \sum_{i=0}^{k}\mathbf{C}_i\mathbf{x}_{t-i} + \sum_{i=1}^{k}\mathbf{B}_i\mathbf{p}_{t-i} + \mathbf{A}^{\mathbf{p}}\mathbf{u}_t^{\mathbf{p}} \tag{2}$$

where $\mathbf{x}_t$ represents the set of WFP choice variables; $\mathbf{p}_t$ denotes the set of local market prices; $\mathbf{z}_t^{\mathbf{x}}$ and $\mathbf{z}_t^{\mathbf{p}}$ are vectors of deterministic components (e.g. a constant term, 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 unknown parameters; 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 to identify structural contemporaneous interactions among variables, leaving the dynamics unrestricted. This is the most extensively used identification scheme in the VAR literature (Sims, 1980; Hamilton, 1994). In particular, we impose identification restrictions $\mathbf{G}_0 = \mathbf{0}$, $\mathbf{D}$ and $\mathbf{B}$ lower triangular with ones along the diagonal, and $\mathbf{A}^{\mathbf{x}}$ and $\mathbf{A}^{\mathbf{p}}$ diagonal. Ordering FA_t first then implies that food aid deliveries do not respond to changes in *current* values of any variables in the system (though, of course, they may be related to changes in past values through the lagged terms). This is a reasonable assumption because food aid deliveries are decided in advance and are unlikely to be responsive to current (i.e., within the delivery month) LRP purchases or local market conditions.

Ordering LRP_t second assumes that LRP purchases may respond to changes in current food aid deliveries and lagged but *not current* prices. This assumption is also reasonable because it makes sense that LRP purchases may respond immediately to changing food aid needs (deliveries). Although LRP choices are undoubtedly sensitive to local prices, the length of the tender process WFP uses to make its purchases 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.

Ordering prices last allows all prices to 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 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 markets.

The recursive ordering is important because it provides identification of $\mathbf{u}_t^{\mathbf{x}}$ and $\mathbf{u}_t^{\mathbf{p}}$ as uncorrelated food aid, LRP, and local market price shocks. This identification allows simulation of 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.

We can estimate the recursive VAR by applying ordinary least squares (OLS) to each equation in the system. If evidence of nonstationarity and cointegration is found, then the VAR is sometimes restricted to a vector error correction (VEC) form. Imposing VEC restrictions can lead to more efficient parameter estimates and improved statistical inference when included variables are nonstationary and cointegrated. However, Sims, Stock and Watson (1990); and Hamilton (1994) show that even with nonstationary and cointegrated variables, OLS estimates of the VAR form will be consistent, although OLS standard errors will be biased and inconsistent so standard statistical inference and hypothesis testing procedures are generally not applicable.

After estimation of the VAR, LRP effects on local market prices are estimated by simulating the VAR over the estimation period assuming food aid is left at historical values throughout the sample period but LRP is set to zero. This allows simulation of the effect of eliminating LRP assuming historical levels of food aid were still provided (i.e., assuming all food aid was sourced by transoceanic shipments).

For the simulation we use the same price shocks estimated from VAR (i.e., we assume that setting LRP to zero does not alter the historical market price *shocks*, though of course prices themselves will be affected). The result is a set of counterfactual local market prices that simulate the path that prices would have taken with no LRP purchases but otherwise no change in food aid deliveries nor in historical supply and demand shocks. Comparing the simulated and historical prices identifies the estimated effect of LRP. Due to sampling error, we also compute 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 illustrate the bootstrap approach to constructing confidence intervals the VAR model can be written more compactly as:

$$\mathbf{y}_t = \sum_{i=0}^{p} \boldsymbol{\psi}_i \mathbf{d}_{t-i} + \boldsymbol{\varepsilon}_t \tag{3}$$

where $\mathbf{y}_t$ is the set of endogenous variables, $\mathbf{d}_{t-i}$ is the set of exogenous and endogenous variables, $\boldsymbol{\psi}_i$ are matrices of unknown parameters, and $\boldsymbol{\varepsilon}_t$ is the vector of error terms. Our bootstrap procedure consists of five steps. First, estimate the VAR and compute a set of residuals using the estimated VAR parameters: $\hat{\boldsymbol{\varepsilon}}_t = \mathbf{y}_t - \sum_{i=0}^{p} \widehat{\boldsymbol{\psi}}_i \mathbf{d}_{t-i}$. Second, from these residuals draw (with replacement) a sample of residuals, $\{\boldsymbol{\varepsilon}_t^*\}_{t=1}^{n}$. Third, use these sampled residuals and the originally estimated VAR parameters to recursively construct a vector of pseudo data $\mathbf{y}_t^* = \sum_{i=0}^{p} \widehat{\boldsymbol{\psi}}_i \mathbf{d}_{t-i} + \boldsymbol{\varepsilon}_t^*$ and re-estimate the VAR parameters $\boldsymbol{\psi}_i^*$ using the generated pseudo data. Fourth, re-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 construct 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 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 prices, which is equivalent to placing a zero probability prior on negative prices. As a robustness check, we also replaced negative simulated prices with minimum historical prices observed during the sample period for each country. These two approaches did not generate meaningfully different confidence bounds.

4.2. *Model Set-Up and Data*

Our applications focus on maize in Uganda and Mozambique and beans in Ethiopia. In Uganda, prices from three wholesale maize markets are included in the VAR: Kisenyi (Central region), Masindi (Western region), and Lira (Northern region). For the recursive ordering of prices, Kisenyi is first, followed by Masindi and Lira. Other relevant markets such as Mbale and Kapchorwa had insufficient price data to be included. We do 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.[5]

We also use three domestic market prices in Mozambique: Maputo (Southern region), Chimoio (Central region), and Nampula (Northern region). For the recursive ordering of prices, we put Maputo followed by Chimoio. The more distant and isolated northern market of Nampula is placed last.

In 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, the disaggregated data are not available prior to July 2009. These data limitations make it impossible to reliably evaluate the impacts of LRP disaggregated by bean type. 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 these prices. Given this observed co-movement, a model using horse bean prices only should 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 VAR: Dire Dawa (Dire Dawa region), Dessie (Amhara region), and Awassa (SNNP region). Addis Ababa price is not included because Awassa is a more important bean surplus market in the combined Oromia and SNNP regions than Addis Ababa. For the recursive ordering of prices we place Dire Dawa first then Dessie and finally Awassa.

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 price series for each market by averaging weekly prices. Uganda prices are reported in Ugandan Shilling per metric ton (UGX/MT). In Mozambique and Ethiopia, lack of complete wholesale market series required that we use retail prices. We obtained retail maize prices for Mozambique from the Ministry of Agriculture's Agricultural Marketing Information System (SIMA). Weekly prices were averaged to construct monthly price series. Mozambique prices are measured in Mozambique Metical per metric ton (MZN/MT). Ethiopian 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.

The price series for all three country applications have missing observations. In Uganda, the proportion 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 prices in each location on prices in all markets for which price data are available, then predicting prices to fill missing observations. In addition to the three markets from the VAR specification the markets of

[5] 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.

Arua, Kabale, Masaka, Mbarara, Nakawa, Owino, Soroti and Tororo were included in the best subset regressions.

Maputo, Chimoio and Nampula markets in Mozambique are missing 2%, 4% and 6% of their price observations. For the best subset regressions, we added prices from Manica, Tete, and Lichinga markets. Dire Dawa, Dessie and Awassa in Ethiopia were missing 8%, 9% and 8% of their price observations, and we added Asossa, Asayita, and Bahir Dar market prices to the best subset regressions.

Daily tender-level data on LRP purchases, measured in metric tons (MT), were obtained from WFP 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. For this reason, we aggregate the daily procurement data into a monthly series by summing LRP purchases within each month.

Food aid data, reported based on the date shipments arrived in a recipient country, were provided by the International Food Aid Information System (INTERFAIS). We aggregate deliveries to create a monthly food aid series, measured in MT, for each country and commodity application.

4.3. *Summary Statistics and Preliminary Tests*

Summary statistics are reported in Table 1. During the sample period, WFP distributed on average 5,837 MT of maize per month and purchased an average of 6,804 MT per month in Uganda. This highlights that not all LRP bought in Uganda was distributed in Uganda. The data show that from 2001 through 2011, 30% of 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 countries, standard deviations indicate that both food aid deliveries and WFP LRP purchases fluctuated considerably over time. Table 1 also shows that 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). All prices have high standard deviations relative to their means, indicating considerable variability.

We tested for nonstationarity. Table 2 shows that in Uganda and Mozambique, the evidence of unit roots is mixed, depending on which statistic is used and whether a time trend is included. In Ethiopia, results support nonstationary behavior in all three prices, but that food aid deliveries and LRP are stationary. Blough (1992) and others argue that unit root tests are known to have low power in finite samples, suggesting that failure to reject the null hypothesis could be a reflection of this low power rather than the presence of unit roots. We chose not to impose VEC restrictions and estimated unrestricted VARs in the levels of all variables, for three reasons. First, OLS estimation of the VAR form remains consistent under nonstationarity and cointegration. Second, our primary goal is policy simulation and not hypothesis testing. Finally, there is some value in applying consistent modeling procedures across all three country applications.

Appropriate lag lengths for VARs are determined using various criteria, each with their advantages and disadvantages. Along with likelihood ratio (LR) tests, information criteria – final prediction error (FPE), Akaike's information criterion (AIC), and Schwarz's Bayesian information criterion (SBIC) – are used. Another key criterion for selection of adequate lag length is to ensure that VAR residuals show no evidence of autocorrelation. For all three country applications, some of these criteria suggest short lag lengths, while others indicate very long lag lengths. Because very long lag lengths can lead to over-parameterized models, we used a procedure of starting with the lowest lag length suggested by the criteria and testing the residuals for autocorrelation. If any residual showed statistically significant evidence of autocorrelation, we increased the lag length by one and repeated the procedure. If no autocorrelation was found we choose that lag length. Based on this procedure, five months for Uganda, and three months for Mozambique and Ethiopia are the appropriate lag lengths.

In all country applications, we expect that data, especially prices, would have a strong seasonal component because agricultural production is predominantly rain-fed and follows seasonal patterns. Hence, in addition to a constant term, we included a seasonal component 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. The deterministic parts of the VAR could also include time trends. There was mixed evidence of time trends in all three study countries. 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.

When estimating VAR models, some authors use untransformed prices while others use a log transformation. We assessed both possibilities by comparing R squareds.[6] Results reported in Table 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. For the food aid and LRP purchases equations the results are mixed. Based on the preponderance of evidence we estimate the VAR models for all three countries using price levels.

4.4. *VAR Results*

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

[6] To compare R-squareds we take logs of prices, but not of LRP or food aid deliveries (both of which have zeros). We then compute correlation coefficients between predicted and observed explanatory variable for each equation in the VAR, first using price levels and then using a log transformation for prices (but converting the predicted log prices back into predicted price levels to compute the correlations). Finally, we calculated squared correlation coefficients under both model specifications and used these as our measure of R squared.

results for all parameters in each country application.[7] However, in Tables 4 through 6, we provide model evaluation statistics for each country. Results generally support the model specifications used.

Table 7 presents simulation results for the WFP LRP effects. Average price level effects – the average percentage reduction in prices over the sample period from eliminating LRP – are reported in the second through fourth columns of Table 7. The table also reports the lower and upper bounds for 90% bootstrap confidence intervals. For Uganda average maize price impacts range from about 13% in Kisenyi (deficit) to 16% in Lira (surplus). Furthermore, the upper and lower bounds suggest that average price impacts of LRP are statistically different from zero (Table 7). Average price effects for beans in Ethiopia are quite small though statistically different from zero. Like Uganda, there is no clear pattern between surplus and deficit areas in Ethiopia. In Mozambique, estimated average maize price effects show larger effects in deficit Maputo and surplus Chimoio markets than in surplus Nampula. Upper and lower bounds show that average prices effects are statistically different from zero for all three markets in Mozambique.

The relatively high effect in Maputo may appear surprising because no LRP purchases are made in Southern Mozambique. 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 Central Mozambique, which serves informal markets in Southern Mozambique can have a meaningful effect on the informal market prices for locally produced maize in Maputo.

The last three columns of Table 7 contain estimates of LRP impacts on the coefficient of variation (CV) of prices, which is a measure of price variability over the sample period. The upper and lower bound estimates again show bounds for 90% confidence intervals. The results suggest that LRP has had no statistically significant effect on price variability in any regional market, except Nampula (Mozambique).

Figures 6 through 8 graph actual and simulated (no LRP) prices, along with associated LRP levels, for different markets. 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 upon initial elimination of LRP but 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

[7] Results are available upon request.

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.

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, although the reported results originate from a careful process to select the appropriate lag length, we acknowledge that the findings appear sensitive to alternative choices for 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 increases in 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 all markets, except Nampula (Mozambique), and even in Nampula, the magnitude of the estimated variability 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.

5. The Computational Model

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 robustness check, 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.

The CM is a mathematical representation of supply, demand, and price determination in spatially connected 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. 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. The final step is to use the model, along with relevant parameter estimates, to quantify the effect of LRP purchases on outcomes of interest, which may include price levels, the supply of marketed surplus, and the amount of marketed surplus 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 9, food staple supply and demand responses to price for the first region (surplus) and the second (deficit) are respectively shown in the left and right panels. The middle panel shows equilibrium occurs when excess supply from surplus region equals excess demand from deficit region. The equilibrium price in each region must differ by the cost of transferring the commodity between the two regions (see the transfer cost differential in the middle panel of Figure 9). 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. This shift in demand then shifts the excess supply curve to the left (see the dashed line in the middle panel). For both regions, the new equilibrium features higher prices, increased marketed supply, and decreased consumption. The decrease in consumption occurs because LRP withdraws a certain amount of the commodity from normal market channels, putting upward pressure on prices and downward pressure on consumption. 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.[8] The magnitude of these various effects will depend on the price responsiveness of supply and demand in the two regions, the size of transfer costs, and the magnitude of LRP purchases relative to the marketed surplus. Exports and imports of the commodity can also be incorporated, as shown in the mathematical derivation.

5.1. *Mathematical Derivation*

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

$$S_i = f_i\left(P_i\right) \qquad \text{for } i = 1, 2, \ldots, n \qquad \text{(Supply)} \tag{4}$$

$$D_i = g_i\left(P_i\right) \qquad \text{for } i = 1, 2, \ldots, n \qquad \text{(Demand)} \tag{5}$$

where S_i is quantity of marketed supply in region i, D_i is quantity of consumption purchases, P_i is market price, 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

[8] We realize that food aid targeting in practice is frequently imperfect but argue that 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 despite the empirical evidence of imperfect targeting.

crops on the supply side and income and prices of other consumption goods on the demand side. We do not show these other factors explicitly because they are held constant in the analysis.

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

$$P_i = P_1 - C_i \qquad \text{for } i = 2,3,\ldots,n \qquad \text{(Spatial Price Relationship)} \tag{6}$$

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:

$$X = h\left(P_1\right) \qquad \text{(Net Export Demand)} \tag{7}$$

where X is net exports from the country and h is a net export demand function. Like 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 we hold these other variables constant in the analysis so they are not included.

The model is closed with a market clearing condition given by:

$$\sum_{i=1}^{n} D_i + X + LRP = \sum_{i=1}^{n} S_i \qquad \text{(Market Clearing)} \tag{8}$$

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 (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 supply and demand functions gives:

$$d\ln S_i = \alpha_i d\ln P_i \qquad \text{for } i = 1,2,\ldots,n \tag{9}$$

$$d\ln D_i = \beta_i d\ln P_i \qquad \text{for } i = 1,2,\ldots,n \tag{10}$$

where α_i and β_i are regional supply and demand elasticities, respectively. Similarly, totally differentiating the spatial price relationships (6) we get:

$$d\ln P_i = r_i d\ln P_1 \qquad \text{for } i = 2,3,\ldots,n \tag{11}$$

where r_i is the ratio of price in the reference region to the price in region i. Total differentiation of the net export demand function (7) leads to:

$$d\ln X = \gamma d\ln P_1 \tag{12}$$

where γ is the export demand elasticity with respect to the reference region price. Finally, totally differentiating the market clearing condition (8), holding transfer costs constant,[9] leads to:

$$\sum_{i=1}^{n} s_i^d d\ln D_i + s^x d\ln X + s^{LRP} d\ln LRP = \sum_{i=1}^{n} s_i^s d\ln S_i \tag{13}$$

where s_i^d is the share of each region's consumption purchases, s^x is the share of net exports, s^{LRP} is the share of LRP purchases, and s_i^s is each regions share of marketed surplus. All these shares are relative to total country-wide marketed surplus. Adding up requires:

$$\sum_{i=1}^{n} s_i^d + s^x + s^{LRP} = \sum_{i=1}^{n} s_i^s = 1 \tag{14}$$

Solving the set of simultaneous equations (9) through (13) yields:

$$\frac{d\ln P_i}{d\ln LRP} = \frac{r_i s^{LRP}}{\sum_{i=1}^{n} s_i^s \alpha_i r_i - \sum_{i=1}^{n} s_i^d \beta_i r_i - s^x \gamma} \tag{15}$$

$$\frac{d\ln S_i}{d\ln LRP} = \alpha_i \frac{d\ln P_i}{d\ln LRP} \tag{16}$$

$$\frac{d\ln D_i}{d\ln LRP} = \beta_i \frac{d\ln P_i}{d\ln LRP} \tag{17}$$

Given parameter values for supply and demand elasticities, shares of marketed surplus, and regional price ratios, equations (15) through (17) can be used to estimate the proportional comparative static effects of a change in LRP.

5.2. *Computational Model Set-Up and Parameterization*

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. 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 consistent with historical LRP purchases in each country.

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9 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.

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. We also account for maize exports to Kenya, South Sudan and DRC.

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 Central and Southern Mozambique. Hence 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. This characterization is based on market observations and market information system data showing regular flows of maize from the Central region to markets in Southern Mozambique, particularly into Maputo. Millers in Maputo import large volumes of South African maize at the same time that maize from Northern Mozambique crosses the border into Southern Malawi. Hence, we account for maize imports in the Southern region and maize exports in the Northern region.

In 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 to Kenya, South Sudan and Djibouti.

Table 8 presents the base case parameters used for each country application. We set supply and demand elasticities based on estimates from the literature (Chhibber, 1989; Karanja, Renkow and Crawford, 2003; Ulimwengu and Ramadan, 2009; Tefera, Demeke and Rashid, 2012; Zant, 2012). Regional supply and demand elasticites are respectively set at 0.7 and -0.8 for maize in Uganda, and 0.6 and -0.6 for maize in Mozambique and bean in Ethiopia. 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 changing prices.

Beans are not a major food staple in Ethiopia and accounted for only 6% of the total cultivated area in the 2011/2012 agricultural season (CSA, 2012). It is 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. Given 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.

We also investigate the sensitivity of results to alternative elasticity assumptions. On the supply side, we investigated sensitivity over the range from 0.5 to 0.9 for Ugandan maize, and 0.4 to 0.8 for Mozambican maize and Ethiopian bean. On the demand side, we considered the range from -0.6 to -1.0 for Ugandan maize, and -0.4 to -0.8 for Mozambican maize and Ethiopian bean.

We could not find any existing empirical estimates of the maize export demand elasticity facing Uganda and Mozambique, and bean export demand elasticity facing Ethiopia. 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. Based on similar arguments, we set a base value of -0.24 for the Malawi demand elasticity for Northern Mozambique maize exports. In Mozambique, there is also 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 appears as 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. Like in Uganda (for maize), 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.

Sensitivity analysis shows that reasonable changes in the magnitude of export demand elasticity have little impact on the estimated LRP effects in all country applications. Therefore we do not report any sensitivity results to changes in the export demand elasticity.

We use household-level data to estimate base estimates for the shares of marketed surplus. We estimated consumption purchases using the Uganda National Panel Survey (UNPS) 2009/10 for maize in Uganda, the Household Budget Survey (IOF) 2008/09 for maize in Mozambique, and Household Income, Consumption and Expenditure Survey (HICES) 2004/05 for bean in Ethiopia. Maize sales from UNPS 2009 and the National Agricultural Survey (TIA) 2008 are used as our estimates of marketed supply in Uganda and Mozambique, respectively. Bean production in Ethiopia is estimated from the Agricultural Sample Survey (ASS) 2011/12. Assuming that 30% of bean production is sold (Ferris and Kaganzi, 2008), production multiplied by this marketed shares gives marketed surplus.

Annual data on exports are gathered from various annual Statistical Abstracts published by Uganda Bureau Office of Statistics (UBOS) for maize in Uganda, the Famine Early Warming Systems (FEWSNET) for maize in Mozambique, the Ethiopia's Central Statistical Agency (CSA) for bean in Ethiopia. Annual data on South African maize imports to Mozambique were obtained from the South African Grain Information Service (SAGIS), while LRP purchases were provided by WINGS.

To compute regional shares of marketed surplus we took the regional sales data and divided by the aggregate sales across the country. We obtained a consistent estimate of total purchases by summing consumption purchases across regions 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 (14) hold. The effects of LRP on local markets are most sensitive to the share of LRP in total marketed surplus. Therefore, we conduct sensitivity analysis with respect to this parameter. We use historical high and low LRP shares relative to marketed surplus to undertake sensitivity analysis with respect to this parameter. The base estimates are historical average LRP shares in each country.

We use previously discussed prices data to obtain estimates of the base price ratios. 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.

5.3. *Computational Model Results*

CM estimated percentage price reductions from eliminating LRP under base case elasticity assumptions are shown in Table 9.[10] The first column shows results under historical mean LRP shares of marketed surplus while the second and third columns show sensitivity of the estimated price effects to decreasing the LRP shares to their historical lows and increasing them to their historical highs. We find that, at historical mean LRP shares, eliminating LRP would decrease maize prices by about 11% in Uganda, decrease maize prices by 4-8% in Mozambique, depending on the region, and decrease bean prices by 2-3% in Ethiopia, depending on the region. Impacts fall to about 1% in Uganda, 2-3% in Mozambique, and below 1% in Ethiopia when LRP share of marketed surplus is at its historical low, and rise to about 20% in Uganda, 6-13% in Mozambique, and 6-8% in Ethiopia when LRP share is at its historical high. Findings show minor differences in price effects across regions in each country. LRP price effects are highly dependent on LRP share of marketed surplus, as expected.

We also conducted sensitivity analysis on how changing assumptions about supply and demand elasticities influence LRP price effects (Table 10), assuming the share of LRP relative to total marketed surplus remains at its historical average level. The inelastic supply and demand scenario gives the largest impact: about 15-16% in Uganda compared to 11-12% in the base case; about 5-11% in Mozambique compared to 4-8% for the base case; and 4-5% in Ethiopia compared to 2-3% for 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 case.

Overall, the CM analysis indicates that for the base case scenario LRP price effects on maize in Uganda are meaningful, but for maize in Mozambique and beans in Ethiopia the effects are far more modest. Under the most extreme case of--inelastic supply and demand and historically high LRP, maize

[10] Due to modeling requirements, the method for computing marketed surplus in this section differs from the approach we initially used in Section **Error! Reference source not found.** to select study countries. These two approaches thus provide a robustness check for our estimates. In the case of maize, 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.

price effects in Mozambique and bean price effects in Ethiopia are more meaningful (about 14% and 10%, respectively).[11]. However, these more meaningful effects occur only if supply and demand are much more inelastic than we believe, and only then in the few periods when the LRP share is at a historically high level. Under the extreme case in Uganda (inelastic supply and demand and historically high LRP share) maize price effects are even greater than in the base case (around 20%).

In all three countries, the results from the CM are quite consistent with those from the VAR. In Uganda, the average estimated price effects from the VAR range from 13-16% depending on the region while the base case CM estimates range from 11-12% VAR and CM. Results for maize in Mozambique and beans in Ethiopia are similarly consistent. Furthermore, in all three countries, CM results under the base case scenario (see Table 9) lie within the 90% confidence interval from the average VAR results (see Table 7). This shows that major conclusions regarding the extent to which WFP LRP has raised local market prices are robust to our two alternative modeling approaches.

[11] This combination is not shown in the tables

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Figure 1 LRP purchases of maize as a share of marketed surplus, 2001-2011

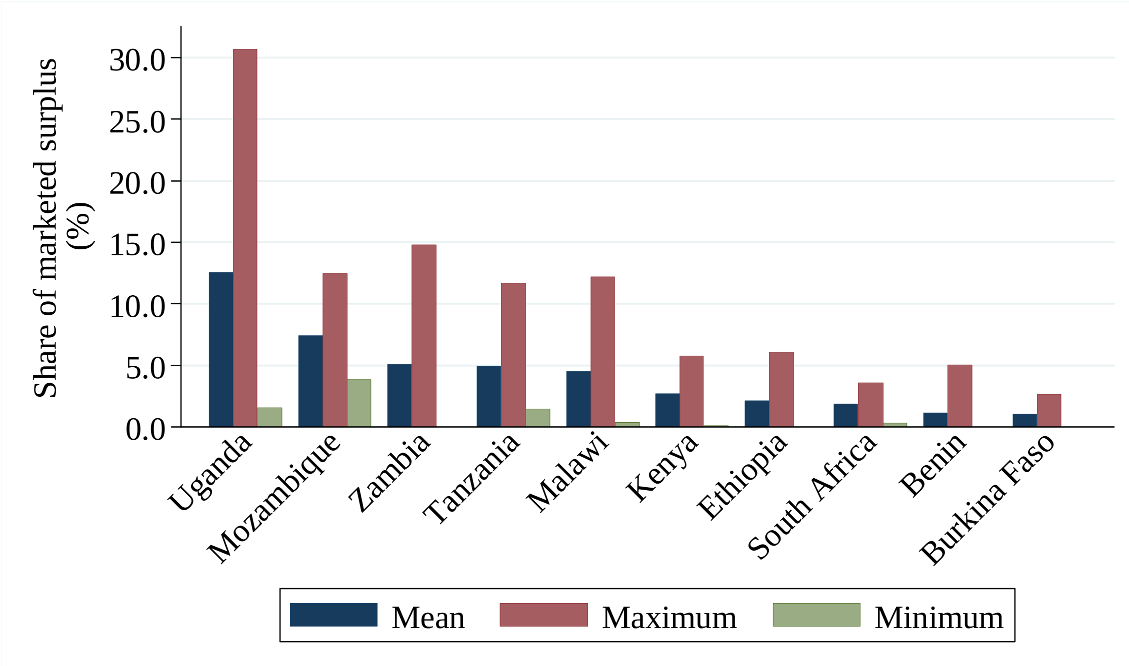

Figure 2 LRP purchases of beans as a share of marketed surplus, 2001-2011

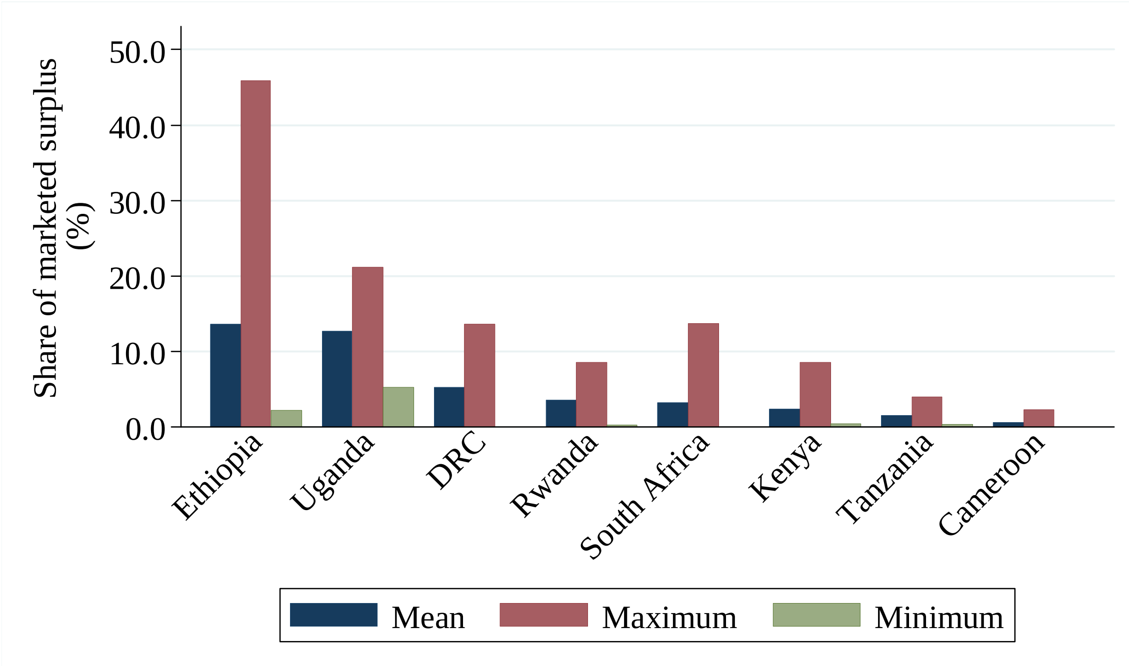

Figure 3 Map of Uganda showing regions and key markets

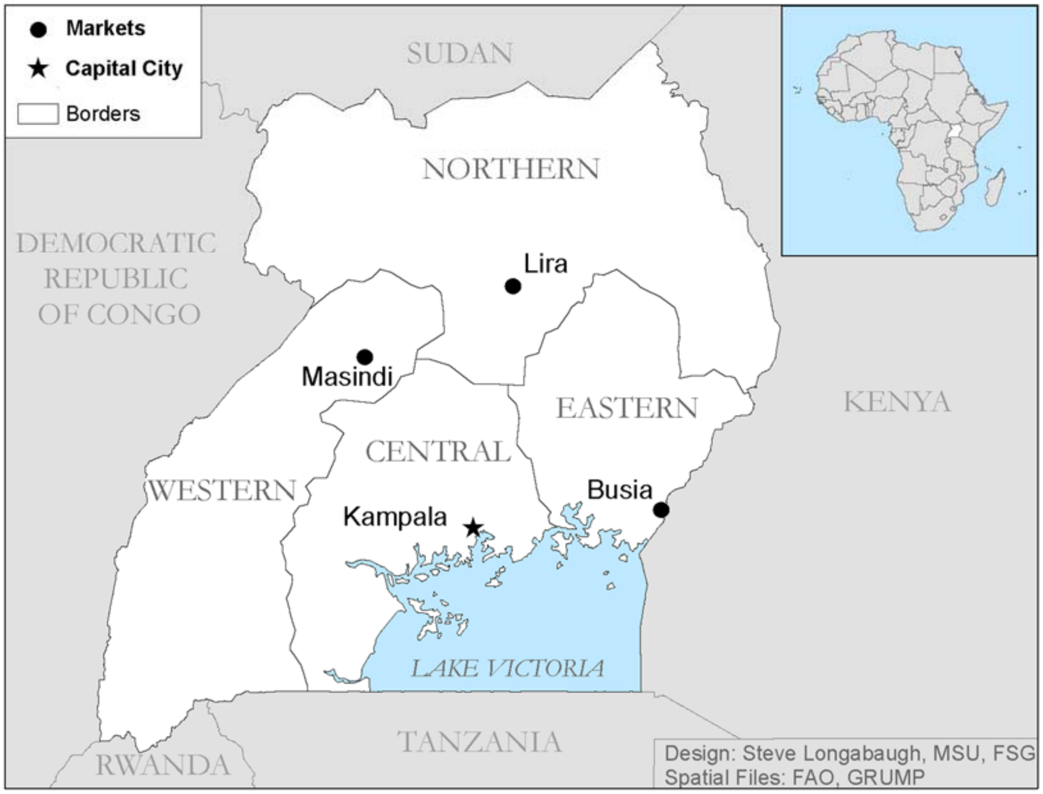

Figure 4 Map of Mozambique showing provinces and key markets

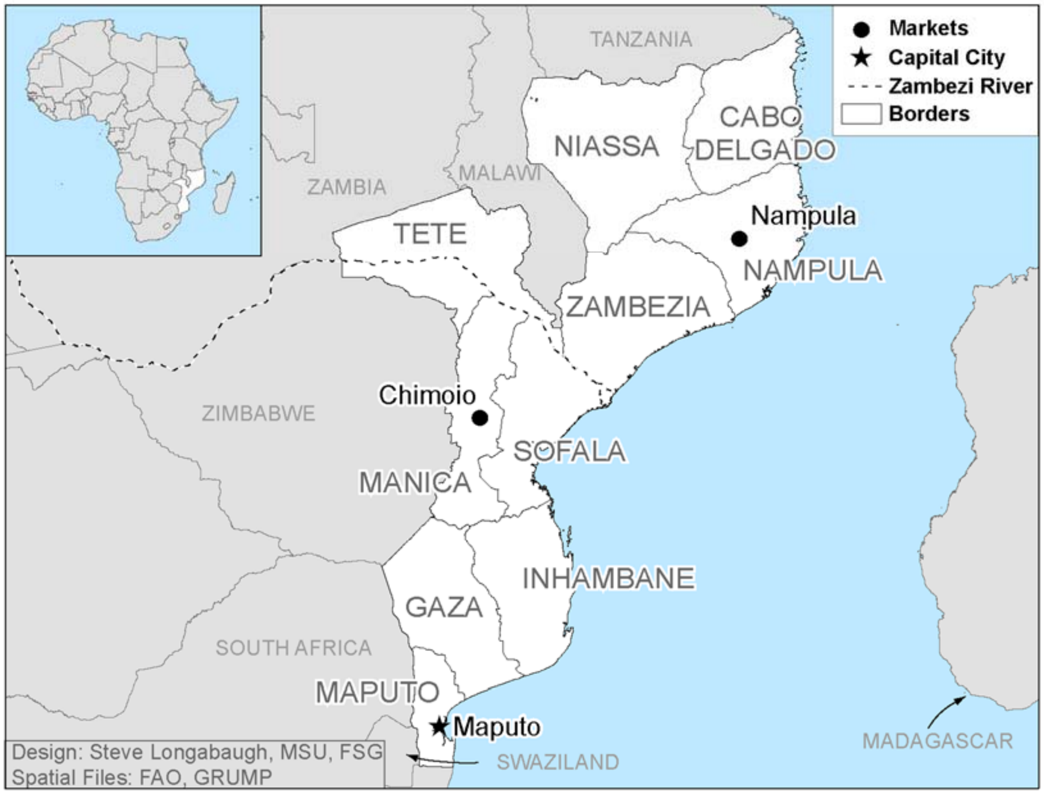

Figure 5 Map of Ethiopia showing regions and key markets

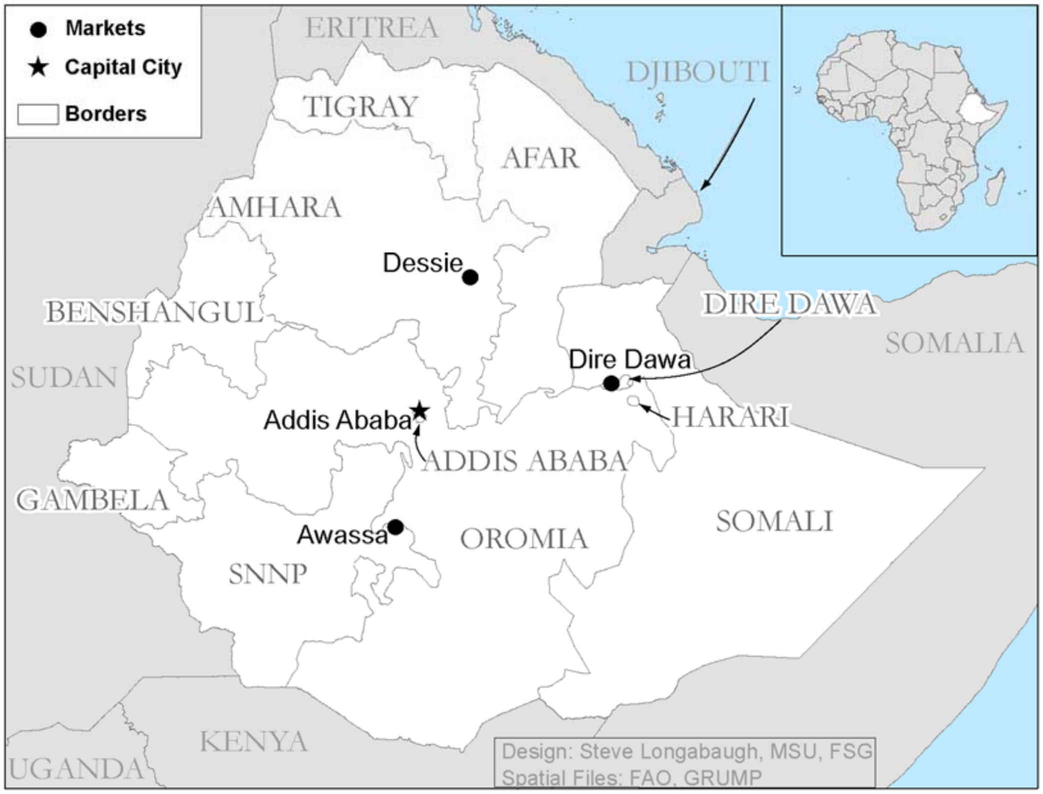

Figure 6 Historial (with LRP) and simulated (without LRP) prices of maize in Kisenyi market, Uganda, 2001-2011

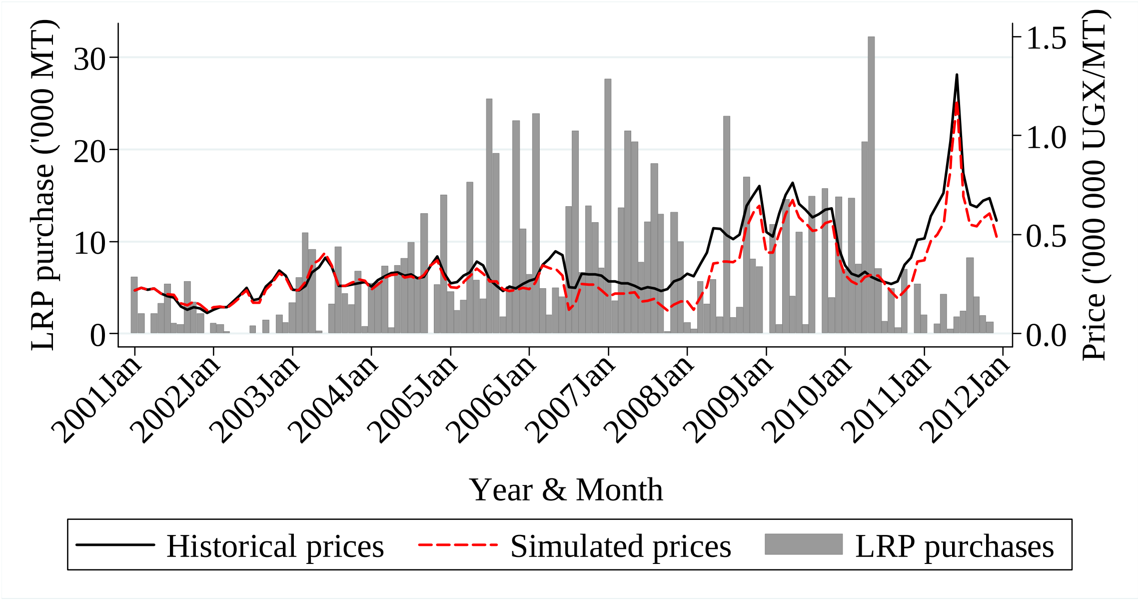

Figure 7 Historical (with LRP) and simulated (without LRP) prices of maize in Chimoio market, Mozambique, 2001-2011

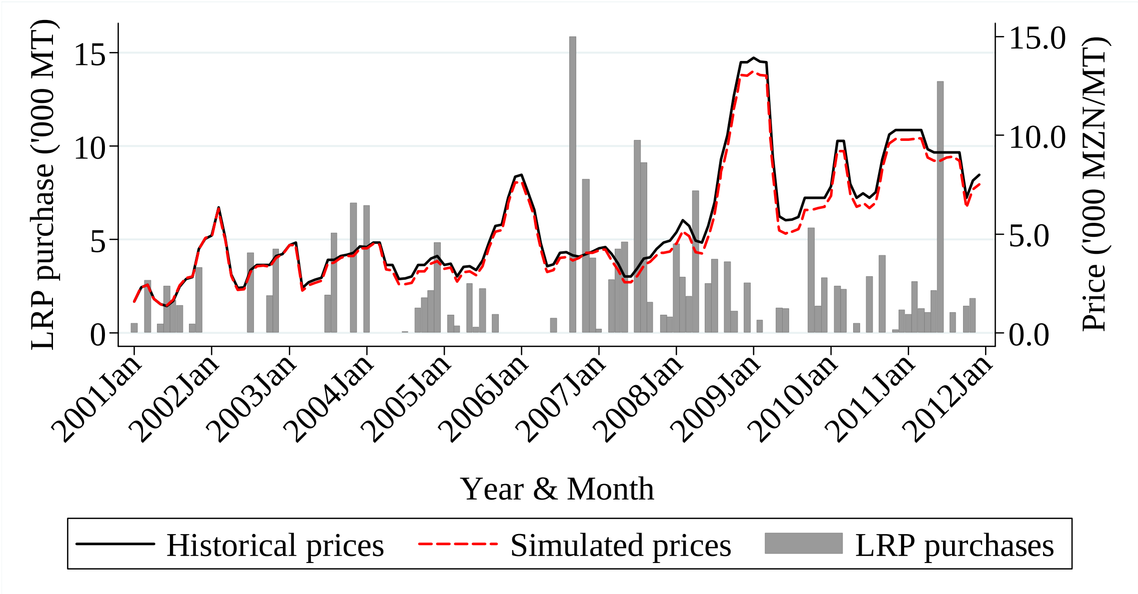

Figure 8 Historical (with LRP) and simulated (without LRP) prices of horse beans in Awassa market, Ethiopia, 2001-2011

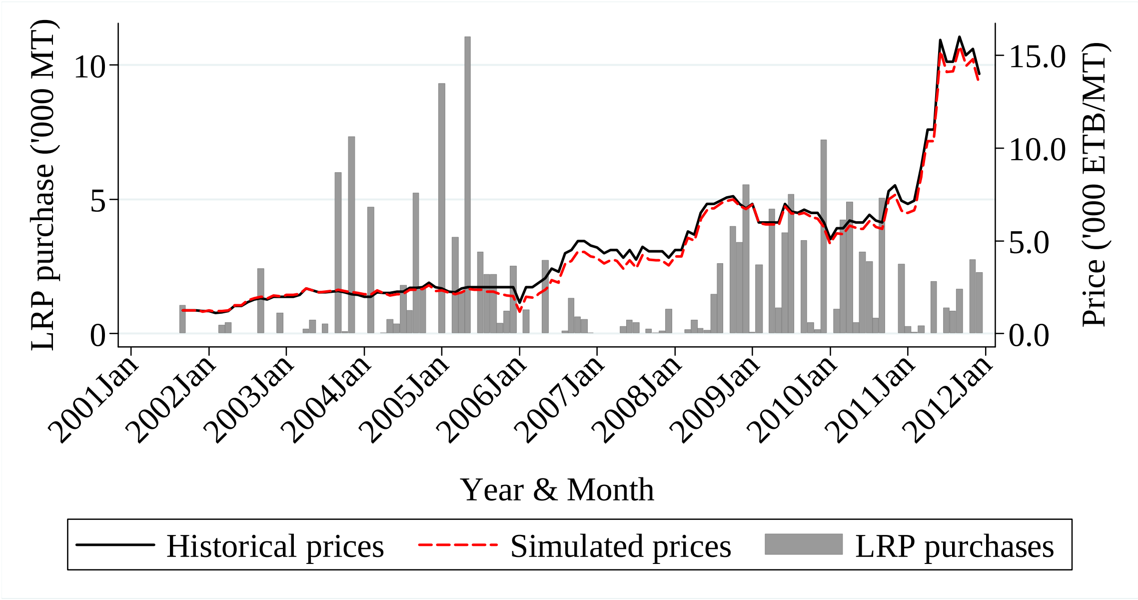

Figure 9 Graph of effects of LRP on local markets

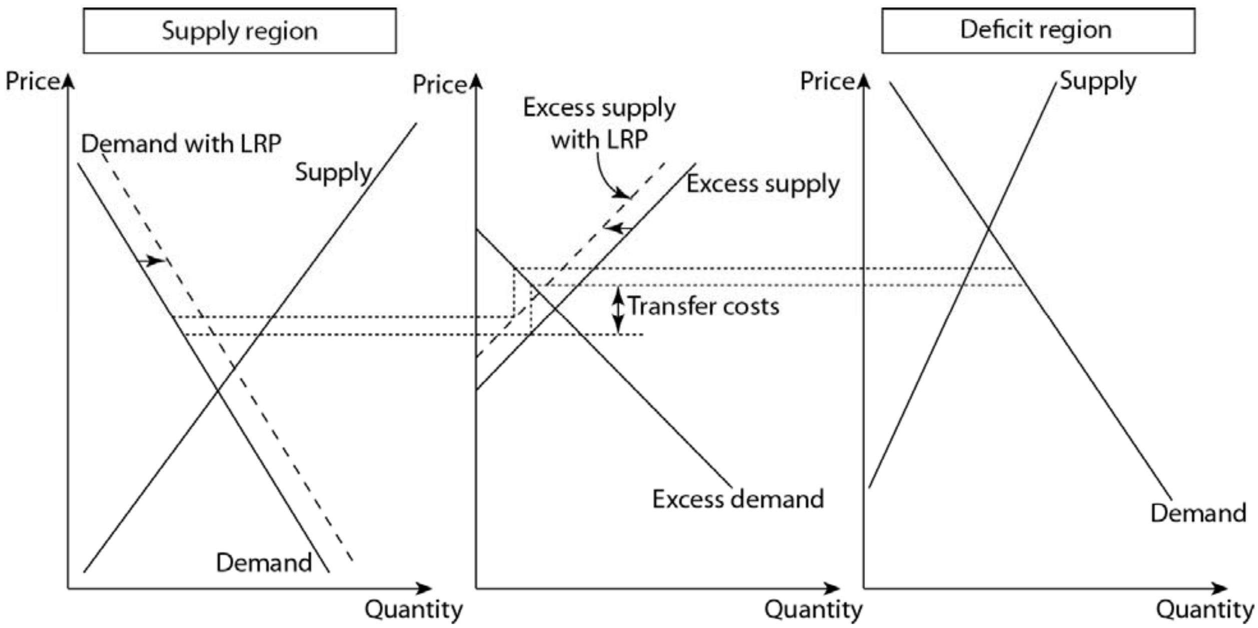

Table 1 Descriptive statistics for the Uganda, Mozambique and Ethiopia VAR variables

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 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.

Table 3 Comparison of R squared for two specifications: price levels and log 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
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).

Table 4 Fifth-order VAR model evaluation statistics for Uganda maize

Statistic	Equation				
	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)

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 5 Third-order VAR model evaluation statistics for Mozambique maize

	Equation				
Statistic	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 6 Third-order VAR model evaluation statistics for Ethiopia beans

	Equation				
Statistic	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 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
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%

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.

Table 8 Base case parameters for the computational models: maize in Uganda and Mozambique, and beans in Ethiopia

	Country/Region/Parameter value			
		Mozambique		
Parameter	**Uganda**	**Northern**	**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 (14) in Section 5.1).

Table 9 Base case and sensitivity analysis for estimated effects of LRP on price levels for maize in Uganda and Mozambique, and beans in Ethiopia

Variable and Region	Base Case (Historical mean LRP)[1]	Historical low LRP[2]	Historical high LRP[3]
	------------------ % impact	------------------	
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% share of marketed surplus for Uganda, 7% for Mozambique, and 3% for Ethiopia; [2] 2% share of marketed surplus for Uganda, 3% for Mozambique, and 1% for Ethiopia; [3] 25% share of marketed surplus for Uganda, 13% for Mozambique, and 8% for Ethiopia.

Table 10 Sensitivity of LRP effects to changes in supply and demand elasticities

	Scenario				
Variable	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.