AGRICULTURAL ECONOMICS

Agricultural Economics 44 (2013) 203–216

The effects of the Food Reserve Agency on maize market prices in Zambia

Nicole M. Mason*, Robert J. Myers

Department of Agricultural, Food, & Resource Economics, Michigan State University, 446 W. Circle Dr., East Lansing, MI 48824, USA

Received 17 December 2011; received in revised form 1 September 2012; accepted 5 November 2012

Abstract

Over the last decade, governments throughout eastern and southern Africa have increasingly used strategic reserves and/or marketing boards to influence grain market outcomes, yet little is known about how these activities are affecting grain markets. This article estimates the effects of the Food Reserve Agency (FRA) on maize market prices in production and consumption regions in Zambia using a vector autoregression model and monthly data from July 1996 through December 2008. In recent years, FRA has become the dominant buyer of smallholder maize in Zambia. Simulations show that FRA activities stabilized market prices throughout the July 1996–December 2008 study period and raised mean prices between July 2003 and December 2008 by 17–19%. The price raising effects of FRA policies have assisted surplus maize producers but adversely affected net buyers of maize in Zambia, namely urban consumers and the majority of the rural poor. The increase in maize price stability is unlikely to have had substantial welfare effects on poor households. In contrast, relatively wealthy producers are likely to have benefited from the higher average and more stable maize prices resulting from FRA policies.

JEL classifications: Q11, Q18

Keywords: Maize marketing board; Strategic grain reserve; Maize prices; Vector autoregression; Zambia; Africa

1. Introduction

After being scaled back during agricultural market reforms in the 1980s and 1990s, direct government involvement in grain marketing through marketing boards and strategic reserves is again on the rise in eastern and southern Africa (ESA) (Jayne et al., 2007). Nowhere is this more prevalent than in Zambia. In recent years, the Government of the Republic of Zambia (GRZ) through the Food Reserve Agency (FRA), a parastatal strategic food reserve/maize marketing board, has become the country's dominant buyer of smallholder maize (Govereh et al., 2008; Tembo et al., 2009). The FRA buys maize from smallholders at a pan-territorial price that typically exceeds wholesale private-sector prices in major maize-producing areas. It then exports the maize or sells it domestically. In low-harvest years, FRA often imports maize and sells it to select large-scale millers at below-market prices.

*Corresponding author. Tel: +260-211-261-294; fax: +260-211-261-199. *E-mail address:* masonn@msu.edu (N. M. Mason).

Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article.

Despite this revival of marketing boards and strategic reserves over the last decade, there has been relatively little empirical analysis of how their renewed activities are affecting grain markets. Two important exceptions are Jayne et al. (2008) and Chapoto and Jayne (2009). Jayne et al. use a vector autoregression (VAR) model to estimate the effects of National Cereals and Produce Board (NCPB) activities on wholesale maize prices in Kenya. They find that NCPB activities had a stabilizing effect on market prices and reduced market price levels during the early 1990s but raised them by approximately 20% between 1995 and 2004. Chapoto and Jayne estimate a single-equation reduced-form model of wholesale maize prices in Zambia as a function of lagged maize prices and variables representing supply and demand shifters, including lagged FRA maize purchases and sales. They find no significant effect of lagged FRA purchases but significant negative effects of lagged FRA sales on maize prices.

In this article, we use a structural VAR approach similar to Jayne et al. (2008) and monthly data from July 1996 through December 2008 to estimate the impacts of the FRA's pricing decisions and net maize purchases on the level and variability of wholesale maize prices in Zambia. The VAR results are used to evaluate the effects of FRA activities on market prices using impulse response analysis. The estimation results are also used

© 2013 International Association of Agricultural Economists

DOI: 10.1111/agec.12004

to simulate the path that market prices would have taken in the absence of the FRA. The level and variability of these simulated prices are compared to those of the realized historical prices to determine the effects of the FRA on maize market prices.

The article makes several contributions to the literature. The first is that it provides new empirical evidence on the impacts of FRA policies on maize markets. Substantial GRZ budgetary resources have been devoted to the FRA. In 2006 and 2007, spending on the FRA accounted for approximately 26% of total government agriculture-related expenditures (Govereh et al., 2009). FRA operations in the 2010/2011 marketing year amounted to nearly 2% of Zambia's GDP and 7% of total government expenditures across all sectors (IMF, 2012). Given the high level of government resources devoted to the FRA, and the importance of maize in domestic production and consumption in Zambia, a better understanding of the effects of FRA activities is needed (Govereh et al., 2009).

The second contribution is that the article provides a useful comparison to Jayne et al.'s analysis of the effects of NCPB policies on maize market prices in Kenya, and broadens our understanding of the effects of state marketing activities on grain prices in ESA. Although there are similarities between the NCPB in Kenya and the FRA in Zambia, there are also important differences and thus additional lessons that can be learned from investigating the Zambia case. The NCPB and FRA are similar in that both buy maize at established depots and at pan-territorial prices that typically exceed market prices in major production areas. One key difference is that the FRA buys mainly from smallholder farmers whereas the NCPB buys almost exclusively from private assembly traders and large-scale farmers (Jayne et al., 2008; Mather and Jayne, 2011). A second difference is that, in recent years, Zambia has generally been a surplus producer of maize whereas Kenya has frequently faced maize deficits. As a result, relative to the NCPB, the FRA has faced lower demand for its maize, has had more difficulty selling it, and has accumulated larger stocks (T. S. Jayne, personal communication, 2012). A third difference is that private networks for grain trade are generally better developed in Kenya than in Zambia (T. S. Jayne, personal communication, 2012). A fourth difference is that NCPB purchases are concentrated mainly in the prime maize-growing areas of Kenya, whereas FRA purchases are fairly well distributed throughout Zambia (NCPB, n.d.; Table 1).

Given these differences, we might expect the effects of FRA policies to be quite different than those of the NCPB. As we will show, however, empirical evidence suggests that despite the aforementioned differences, the estimated effects of the FRA are largely similar to the effects of the NCPB: both raise and stabilize maize market prices.

Our article also goes beyond Jayne et al.: (i) by providing a detailed discussion of the likely welfare effects of the price stabilization brought about by FRA policies; and (ii) by testing for threshold nonlinearities in the effects of the FRA on maize market prices. Although the data ultimately reject several threshold VAR (TVAR) alternatives in favor of a linear VAR, the detailed investigation of potential thresholds gives us more confidence in the estimated effects of the FRA presented here. Finally, to our knowledge this article is the first to apply the Gonzalo and Pitarakis (2002) sequential threshold testing procedure in a VAR setting.[1,2]

The remainder of the paper is organized as follows. In Section 2, we discuss GRZ maize marketing and trade policies from liberalization in the early 1990s to the present, with an emphasis on how the role of the FRA in the maize market has evolved over time. We present the general methodology in Section 3 and then apply these methods to the Zambia maize prices/FRA case in Section 4. In Section 5, we describe the data used in the analysis. Linear VAR estimation results, impulse response analysis, and the estimated effects of FRA activities on the level and variability of market prices are presented in Section 6. The likely welfare effects of FRA activities and associated policy implications are discussed in Section 7, and the paper concludes in Section 8. An overview of the threshold VAR methodology and estimation results is available in Appendix A.

2. GRZ maize marketing and trade policies and FRA activities

Maize is the dominant food crop in Zambia. Approximately, 80% of smallholders grow maize and it accounts for 60% of the calories consumed in the country (Dorosh et al., 2009; Zulu et al., 2007). Prior to liberalization in the 1990s, maize marketing was controlled by the government agricultural marketing parastatal, the National Agricultural Marketing Board (NAMBOARD), which set pan-territorial/pan-seasonal producer prices for maize and also handled GRZ maize imports and distribution. NAMBOARD was abolished in 1989 and, shortly thereafter, private maize trade was legalized and pan-territorial/pan-seasonal maize pricing was eliminated (Govereh et al., 2008; Jayne and Jones, 1997).

The FRA was established by GRZ in 1996 and its original mandate was to establish and administer a national food reserve (GRZ, 1995).[3] Private maize trade remained legal but

[1] Clements and Galvão (2004), Galvão and Marcellino (2010), and Deák and Lenarcic (2010) all mention the Gonzalo and Pitarakis (2002) threshold model selection procedure but use only the Schwarz-Bayesian information criterion (BIC) for model selection. The Gonzalo and Pitarakis (GP) procedure, on the other hand, involves a statistic that is a function of *both* the BIC *and* a likelihood ratio statistic. Therefore, although these studies mention the GP procedure, they do not employ it in their research.

[2] An overview of the threshold VAR methodology and estimation results is provided in Appendix A. The advantage of the GP approach is that it facilitates selection among threshold models with different numbers of thresholds. Most previous threshold VAR applications in the agricultural economics literature have relied on the Hansen approach, which is only valid for testing a linear model against a single threshold alternative (examples include Ben-Kaabia et al., 2005; Goodwin and Piggott, 2001; Goodwin and Smith, 2009; and Serra and Goodwin, 2003; see also Gonzalo and Pitarakis, 2002; Hansen, 1996, 1999; Hansen and Seo, 2002; and Lo and Zivot, 2001).

[3] Crop marketing and price setting were added as official FRA functions in 2005 (GRZ, 2005).

Table 1
FRA maize prices and purchases, and estimated smallholder maize sales, 1996/1997–2010/2011 marketing years

Marketing year	FRA buy price (ZMK/50 kg)[a]	No. of districts in which FRA purchased maize	FRA domestic maize purchases (MT) (A)	Estimated smallholder maize sales (MT) (B)	FRA purchases as % of smallholder maize sales (C) = (A)/(B)
1996/1997	11,800	5	10,500	280,955	3.7
1997/1998	7,880	4	4,989	206,557	2.4
1998/1999	N/A	0	0	175,515	0
1999/2000	N/A	0	0	242,753	0
2000/2001	N/A	0	0	303,738	0
2001/2002	N/A	0	0	209,326	0
2002/2003	40,000[b]	10	23,535	143,453	16.4
2003/2004	30,000	36	54,847	260,885	21.0
2004/2005	36,000	46	105,279	331,006	31.8
2005/2006	36,000	50	78,667	151,514	51.9
2006/2007	38,000	53	389,510	454,676	85.7
2007/2008	38,000	58	396,450	533,632	74.3
2008/2009	45,000[c]	58	73,876	522,033	14.2
2009/2010	65,000	59	198,630	613,356	32.4
2010/2011	65,000	62	878,570	1,062,010	82.7

Source: FRA; CSO/MACO Crop Forecast & Post-Harvest Surveys.
Note: ZMK = Zambian Kwacha.
[a]Prices in 1996/1997 and 1997/1998 are averages across districts where the FRA was active.
[b]Initial price of K30,000 raised to K40,000 in August 2002.
[c]Increased to K55,000 in September 2008.

buffer stocks held by the FRA were intended to reduce maize price variability and to provide liquidity in the maize market as the private sector established itself during market liberalization (Govereh et al., 2008).

FRA's maize purchase volumes and geographic coverage have varied considerably over time. Table 1 summarizes the tonnage of maize purchased on the domestic market by the FRA each maize marketing year from 1996/1997 through 2010/2011, as well as the number of districts from which maize was purchased, the purchase price, and the estimated tonnage of maize sold by smallholders.[4] FRA purchases on the domestic market can be divided into three periods: 1996/1997–1997/1998, when it bought small quantities of maize from smallholders via private traders; 1998/1999–2001/2002, when it made no domestic purchases due to lack of funding; and 2002/2003 to present, when it has purchased substantial quantities of maize directly from smallholders.

During the first period (1996/1997–1997/1998), FRA total maize quantities purchased were small and came from only four or five of Zambia's 72 districts (Table 1). FRA buy prices were uniform within districts but differed across districts to better reflect market conditions (C. Kabaghe, personal communication, 2010). After four years of no purchases on the domestic market, the FRA began to participate more actively in maize marketing in 2002/2003. Then, at the beginning of the 2003/2004 marketing year, the Agency announced plans to purchase over 200,000 MT of maize directly from smallholders in 37 districts at a pan-territorial price of 30,000 Zambian Kwacha (ZMK) per 50-kg bag.[5] This was the first time in more than a decade that GRZ set a pan-territorial price for maize (FEWSNET, 2003a,b). FRA only managed to buy 55,000 MT due to funding shortfalls but its plans clearly signaled that it intended to become a major player in the Zambian maize market.

The FRA has continued to purchase maize directly from smallholders at a pan-territorial price each year from 2003/2004 to the present. During the July 1996–December 2008 study period, the FRA's largest maize purchase campaigns were during the 2006/2007 and 2007/2008 marketing years when it purchased nearly 400,000 MT per year. FRA purchases dropped considerably in 2008/2009 and 2009/2010 before shooting to nearly 900,000 MT in 2010/2011 following a maize bumper harvest (Table 1).[6]

The FRA pan-territorial buy price and target purchase quantities are typically announced in May (the beginning of the harvest season). In most years, FRA maize purchases commence in June or July and conclude at the end of September or October. The Agency aims to pay farmers within 10 days of delivery but long delays are common.[7] Private traders are free to buy from farmers at prices above or below the FRA price

[4] The maize marketing year in Zambia is from May to April.

[5] The exchange rate as of May 2003 was 4,864 ZMK per U.S. dollar.

[6] The drop in FRA purchases in 2008/2009 and 2009/2010 was the result of smaller budget allocations to the Agency, stiffer competition from private buyers, and late starts to the buying exercise due to slow release of funds from the Treasury and high maize moisture content (FEWSNET, 2008a,b, 2009a,b,c,d,e,f).

[7] Preliminary unweighted results from a recent nationally representative survey suggest that farmers were paid within one month of delivery for approximately 22% of the sales transactions to the FRA during the 2011/2012 marketing year. The median time to payment was two months, the 75th percentile was three months, and the 90th percentile was four months (CSO/MAL/IAPRI,

Table 2
FRA buy price and weighted average sell price, and average market wholesale prices, 1996/1997–2009/2010 marketing years (ZMK/50 kg)

Marketing year	FRA buy price	Weighted average FRA sell price[a]	Wholesale price					
			Lusaka	Ndola	Choma	Kabwe	Chipata	Kasama
1996/1997	11,800	No sales	6,815	7,672	4,601	5,944	5,504	6,718
1997/1998	7,880	16,876	10,718	11,262	8,506	11,339	11,634	10,782
1998/1999	N/A	22,357	16,014	18,902	14,617	14,974	16,028	17,161
1999/2000	N/A	N/A	14,768	16,175	12,583	12,166	11,392	11,116
2000/2001	N/A	15,811	15,973	17,304	14,518	13,001	11,922	13,786
2001/2002	N/A	13,392	31,900	26,667	30,344	32,520	24,933	27,975
2002/2003	40,000	49,000	48,290	36,575	40,017	39,193	32,903	34,276
2003/2004	30,000	44,471	31,525	27,757	23,096	26,455	20,543	28,716
2004/2005	36,000	35,332	30,480	26,642	25,859	25,400	25,121	26,863
2005/2006	36,000	36,202	39,113	40,749	39,363	36,801	36,544	37,339
2006/2007	38,000	43,184	29,877	31,062	23,839	26,746	22,737	30,167
2007/2008	38,000	39,821	34,962	37,655	30,673	31,699	26,576	37,474
2008/2009	55,000	63,000	58,877	57,266	51,554	49,175	45,681	48,958
2009/2010	65,000	No data	60,879	58,722	55,518	48,160	48,801	54,599

Source: FRA, AMIC.
Note: ZMK = Zambian Kwacha.
[a]Weighted average sell price based on share of total sales in Zambia in the marketing year sold at a given price.

but in most years since 2005/2006, the Agency has been the dominant buyer of smallholder maize in Zambia (see Table 1, column C).

A major reason for the FRA's dominant maize market position is its high buy price. Table 2 compares the prices at which the FRA bought and sold maize, and average wholesale market prices in six provincial trading centers. Since 2002/2003, the FRA buy price has consistently exceeded average wholesale prices, particularly in major maize-producing areas such as Choma, Kabwe, Chipata, and Kasama (Table 2). The above-market buy prices make it difficult for the FRA to export maize unless treasury funds are available to subsidize exports. For example, FRA exports in 2007/2008 and 2010/2011 generated a trading loss (Govereh et al., 2008; Nkonde et al., 2011).

Much of the maize purchased by the FRA is channeled to large industrial millers and trading firms. Most FRA maize sales occur during the hungry season months of December through March and are done via a tender process. The Agency periodically sells maize at a pan-territorial price that is determined in consultation with stakeholders such as the Zambia National Farmers Union, the Grain Traders Association of Zambia, and the Millers Association of Zambia. Beginning in October 2010, the FRA also sold small quantities of maize (20,000 MT) through an auction-like mechanism on the Zambia Agricultural Commodity Exchange. As a result of these different pricing institutions, the FRA sell price often varies from transaction to transaction. While the Agency typically purchases maize at above-market prices, it sometimes sells maize on the domestic market at below-market prices. In most years, however, the weighted average FRA sell price exceeded average wholesale prices throughout Zambia (Table 2).

2012). Some farmers, however, had still not been paid as of June 2012, more than seven months after the FRA closed its purchase exercise on October 31, 2011 (Zulu, 2012).

In addition to the maize marketing activities of the FRA, the GRZ uses a number of other policy tools to influence maize markets and prices. These are: (i) explicit export bans and implicit export bans through limited issuance of export licenses; (ii) adjusting import tariff rates; (iii) government-arranged maize imports and sales of subsidized maize to large industrial millers; (iv) levies on the interdistrict movement of maize; and (v) targeted fertilizer subsidies (Govereh et al., 2008).[8]

3. Methodology

In this section, we begin by discussing why the VAR approach is preferred over alternative methodologies in the current application. We then present the general linear VAR methodology.

3.1. Rationale for the VAR approach

In this article, we use a structural VAR to estimate the effects of FRA activities on maize market prices in Zambia. There are a number of reasons why we chose the structural VAR approach. First, the complexity of the maize value chain in Zambia and the cobweb-like relationships among subsector actors make structural simultaneous equation modeling (SEM) a daunting task. Myers et al. (1990, p. 244) suggest that "SEMs are most useful when substantial certainty exists regarding the true economic structure generating data." There is substantial *uncertainty* with respect to the true economic structure generating maize prices in Zambia, making the SEM approach less attractive. Second, very little data are available on quantities of maize stored and consumed, and on prices at different levels in the maize value

[8] See Govereh et al. (2008) for a detailed timeline of maize marketing and trade policy changes in Zambia from 1990 to 2007, and Nkonde et al. (2011) for a timeline of key maize market policies and events in 2010.

chain. The lack of such data makes it very difficult to implement an SEM approach. Third, structural VARs are well suited to the goal of evaluating the historical effects of an existing policy *ex post* when the main concern is with the net effects of the policy, as is the case here, as opposed to the pathways through which the effects manifest themselves.

3.2. Linear VAR methodology

Consider a vector of maize market variables ($\boldsymbol{y}_t$) and a vector of government policy variables influencing maize market outcomes ($\boldsymbol{p}_t$). The goal of this article is to measure the effects of $\boldsymbol{p}_t$ on $\boldsymbol{y}_t$ and to simulate the historical path of $\boldsymbol{y}_t$ under alternative counterfactual policy scenarios. A linear structural VAR of the dynamic relationships between $\boldsymbol{p}_t$ and $\boldsymbol{y}_t$ can be written as

$$\begin{aligned} \boldsymbol{B}\boldsymbol{y}_t &= \sum_{i=1}^{k} \boldsymbol{B}_i \boldsymbol{y}_{t-i} + \sum_{i=0}^{k} \boldsymbol{C}_i \boldsymbol{p}_{t-i} + \boldsymbol{A}^y \boldsymbol{v}_t^y, \\ \boldsymbol{G}\boldsymbol{p}_t &= \sum_{i=0}^{k} \boldsymbol{D}_i \boldsymbol{y}_{t-i} + \sum_{i=1}^{k} \boldsymbol{G}_i \boldsymbol{p}_{t-i} + \boldsymbol{A}^p \boldsymbol{v}_t^p, \end{aligned} \tag{1}$$

where $\boldsymbol{B}$, $\boldsymbol{B}_i$, $\boldsymbol{C}_i$, $\boldsymbol{A}^y$, $\boldsymbol{G}$, $\boldsymbol{D}_i$, $\boldsymbol{G}_i$, and $\boldsymbol{A}^p$ are matrices of unknown parameters, k is the maximum lag length for variables in the system, and vectors $\boldsymbol{v}_t^y$ and $\boldsymbol{v}_t^p$ are mutually uncorrelated "structural" error terms or innovations (Bernanke and Mihov, 1998; Jayne et al., 2008). $\boldsymbol{v}_t^y$ and $\boldsymbol{v}_t^p$ represent "random shocks to the fundamental supply, demand, and policy processes that are generating data for $\boldsymbol{y}_t$ and $\boldsymbol{p}_t$" (Jayne et al., 2008, p. 315). $\boldsymbol{A}^y$ and $\boldsymbol{A}^p$ allow error terms from one equation to enter other equations in the block, so the assumption that the error terms within each of these vectors are mutually uncorrelated is not restrictive. Neither is the assumption that $\boldsymbol{v}_t^y$ and $\boldsymbol{v}_t^p$ are uncorrelated because "independence from contemporaneous economic conditions [is] part of the definition of an exogenous policy shock" (Bernanke and Mihov, 1998, p. 874).

Model (1) is clearly underidentified so in order to estimate the dynamic response of market variables to a policy shock we need to impose identification restrictions. In the structural VAR approach, identification is achieved by restricting the contemporaneous relationships among variables and leaving the dynamics of the model unrestricted. In other words, identification requires restrictions on $\boldsymbol{C}_0$, $\boldsymbol{D}_0$, $\boldsymbol{B}$, $\boldsymbol{G}$, $\boldsymbol{A}^y$, and/or $\boldsymbol{A}^p$. The specific identification restrictions used in the Zambia/FRA application will be discussed in Section 4.

The reduced form of (1) is unrestricted and can be estimated by ordinary least squares (OLS, Jayne et al., 2008; Myers et al., 1990). Given an identification scheme and a normality assumption, the reduced-form residuals can then be used to solve for the structural parameters in (1) using maximum likelihood, as described in Fackler (1988) and Myers et al. (1990).

Given the estimated VAR, one can simulate what the historical paths of the market variables would have been under alternative policy scenarios. This is achieved by setting the market structural error terms ($\boldsymbol{v}_t^y$) to their estimated historical values, recursively constructing the policy innovations ($\boldsymbol{v}_t^p$) to obtain the desired alternative policy scenario, and then constructing dynamic forecasts for the market variables (Jayne et al., 2008). The simulated paths of the market variables can then be compared to their historical (actual) paths in order to evaluate the effects of alternative policies on the market variables. The estimated VAR can also be used to conduct impulse response analysis, which shows the dynamic response of a given market variable to a one-time random shock to one of the policy variables, holding other shocks fixed.

The VARs in this article are estimated under the assumption of stationarity. Full sample unit root test results generally support this assumption for four of the six endogenous variables in the Zambia/FRA VAR (see Table B1 in Appendix B). However, these tests are known to have low power, particularly in the presence of nonlinearities (Perron, 1989; Pippenger and Goering, 1993). The tests may therefore be giving incorrect results for the two endogenous variables for which we fail to reject the null hypothesis of a unit root (South African Futures Exchange [SAFEX] and Mchinji prices). Moreover, if there are unit roots (and potentially cointegration), OLS estimates of the VAR parameters are still consistent, though not efficient (Hamilton, 1994). A second cost of not imposing valid unit root and cointegration restrictions is inconsistent impulse response estimates at very long horizons (Phillips, 1998). However, this is not a major concern in the current article because the main policy conclusions are based on the simulated counterfactual prices, not on long-horizon impulse response analysis.

A final point to note here is that model (1) assumes that the relationships among the variables in the system are constant over time. It may be, however, that these relationships change depending on the level of one or more threshold variables. We explored the possibility of threshold nonlinearities in the current application. Four candidate threshold variables were tested: (i) FRA's share of smallholder maize sales; (ii) smallholder maize marketable surplus remaining after FRA purchases; (iii) the quantity of maize harvested by smallholders at the most recent harvest; and (iv) time. However, results indicate that a linear VAR is favored over the TVAR alternatives. The TVAR methodology and results are outlined in Appendix A.

4. A VAR model for Zambian maize market prices and FRA activities

To apply the framework described in Section 3 to analyze the effects of FRA activities on maize market prices in Zambia, we need to specify the market variables ($\boldsymbol{y}_t$) and FRA policy variables ($\boldsymbol{p}_t$), and choose an identification scheme. We discuss each of these elements in turn.

4.1. Market variables

Since 2003, the FRA has purchased maize directly from smallholders at a pan-territorial price. Private traders also buy maize from smallholders and the FRA buy price might affect the prices paid by private traders to farmers. Thus, a logical variable to include in $\boldsymbol{y}_t$ is farmgate maize market prices in Zambia. Unfortunately, reliable, high-frequency time series data on farmgate maize prices are not available. However, monthly data on into-mill wholesale maize prices are available for several urban centers in Zambia. In this study, we include in $\boldsymbol{y}_t$ wholesale maize market prices in Lusaka and Choma. Lusaka is the national capital and largest city in the country, and represents a major maize consumption area. Choma in Southern Province represents a major maize production area. Over the 1993/1994 to 2009/2010 agricultural seasons, Southern Province accounted for 21% of national smallholder maize production and 18% of smallholder maize sales. Among Zambia's nine provinces, only Eastern Province had a larger share of smallholder maize production (26%) and only Central Province had a larger share of smallholder maize sales (25%).

In addition to wholesale maize prices in Lusaka and Choma, also included in $\boldsymbol{y}_t$ are wholesale maize prices on the SAFEX and retail maize prices in Mchinji, Malawi, near the border with Zambia's Eastern Province. (Wholesale price data are not available for Malawi.) South Africa is the major source of formal maize imports for Zambia, accounting for 72% of such imports between 1999 and 2006 (FAOSTAT, 2010). Malawi is a major source of informal maize trade with Zambia, with much of this maize crossing the Eastern Province border near Mchinji (FEWSNET, 2010).[9] The SAFEX and Malawi prices are converted to ZMK and adjusted by the historical tariff rate.

4.2. FRA policy variables

The variables in the $\boldsymbol{p}_t$ vector are intended to capture FRA policies that affect maize prices in Zambia. We follow Jayne et al. (2008) and define three candidate policy variables: (i) the FRA buy price premium (BPP, the FRA buy price minus the wholesale price in the major maize production area, Choma); (ii) the FRA sell price premium (SPP, the weighted average FRA sell price minus the wholesale price in the major maize consumption area, Lusaka); and (iii) net FRA maize purchases (FRA domestic purchases minus domestic sales).[10]

A positive shock to the BPP is expected to put upward pressure on maize market prices because it means that the FRA buy price has increased relative to the market price in the major production area. This is expected to attract more maize sales to the FRA marketing channel and shift the private-sector supply curve to the left. A positive shock to the SPP is also expected to put upward pressure on maize market prices because it means that the FRA sell price has increased relative to the market price in the major consumption area. This would likely attract more maize purchases to the private-sector channel and shift its demand curve to the right.

The other GRZ policies discussed at the end of Section 2 may also affect the level and variability of maize market prices in Zambia but our focus in this article is on the effects of FRA policies. Furthermore, it is not feasible to include most of these other policies in the VAR due to data constraints (e.g., data are not available on implicit export bans and government-arranged imports and subsidized sales of maize to select millers) or because the policy is not conducive to modeling in a VAR framework.[11] We therefore do not explicitly include variables capturing these other policies in the VAR reported here.[12] Nonetheless, the historical effects of these policies are implicitly captured in the dynamics of the model and so the FRA policy simulations implicitly assume these other factors continue to play the same role in influencing maize market prices as they did historically (Jayne et al., 2008). Variable maize import tariffs are implicitly included in the models through the SAFEX and Malawi prices, which are adjusted by the tariff.

4.3. Identification scheme

For identification, we use Cholesky decomposition, the most commonly used identification scheme in structural VAR modeling (see, for example, Hamilton, 1994; Sims, 1980). This entails the following assumptions: (i) $\boldsymbol{C}_0 = 0$, that is, there is no contemporaneous response of market prices to changes in FRA policies; (ii) $\boldsymbol{A}^{\boldsymbol{p}}$ is a diagonal matrix; and (iii) the recursive ordering of the FRA policy variables is BPP then SPP.[13] Note that

[9] We also estimated a VAR that included net (formal) maize imports from all trading partners in addition to the South Africa and Malawi prices. The base model results suggest that FRA activities raised market prices by 17–19% and stabilized (i.e., reduced the coefficient of variation [CV] of) prices by 34–36% between July 2003 and December 2008. The results from the model including net maize imports suggest similar though slightly larger FRA effects: 21–24% increases in price levels and 38–40% reductions in the CV of prices (see the online data appendix). The monthly trade data used for this exercise were obtained from the Zambia Central Statistical Office.

[10] The FRA net purchases variable was ultimately dropped from the model because sensitivity analysis shows that its inclusion has no substantive impact on the estimated effects of FRA policies on maize market prices in Zambia; the FRA buy and sell price premiums capture most of the FRA effects. Jayne et al. (2008) find the same in their Kenya/NCPB VAR analysis.

[11] For example, targeted fertilizer subsidies are distributed once per year and are therefore not amenable to inclusion in a monthly VAR model. During the study period, levies on interdistrict movements of maize were in place from 2002 to 2008. The levies were set by district councils and varied widely across districts (Mwiinga et al., 2005), making them incompatible with a "national" VAR model. Furthermore, we do test for a threshold nonlinearity related to time (i.e., structural change, e.g., before and after the introduction of maize levies) but reject the structural break VAR in favor of the linear VAR. See Appendix A for details.

[12] As a robustness check, we estimated a VAR that included in the policy vector a dummy variable for periods during which there was an explicit maize export ban. Compared to the base model results, the results from the model including the export ban suggest slightly smaller FRA effects on the level of market prices between July 2003 and December 2008: increases of 15–17% as compared to 17–19% according to the base model. The effects on the CV of prices are more or less unchanged (34% reduction according to the export ban model compared to 32–34% reductions according to the base model). See the online data appendix.

[13] Bernanke and Blinder (1992) show that if $\boldsymbol{C}_0 = 0$, then the effects of policy shocks on market variables are independent of the identification scheme used in the market variables block (the $\boldsymbol{B}$ and $\boldsymbol{A}^{y}$ matrices).

these identifying assumptions are required only for the orthogonalized impulse response analysis. The identification scheme chosen has no bearing on the "no FRA" price path simulations, which provide the main policy results in this article.

The rationale for assumptions (i) and (iii) is as follows. For assumption (i), adjustment costs and rigidities may prevent an immediate change in market prices when FRA policies change (Jayne et al., 2008). In Zambia, it is costly for farmers and traders to obtain maize market information, and thus information on changes in the BPP and SPP. There is no well-developed public market information system (MIS). In the absence of a public MIS, some farmers and traders may establish private market information networks and share information over mobile phones. However, while mobile phone network coverage and ownership have expanded rapidly in Zambia, particularly since 2005, as of June 2008 (near the end of our study period) only 24% of smallholder households owned a mobile phone (CSO/MACO/FSRP, 2008). Data on mobile phone ownership among private traders are not available but ownership rates are likely to exceed those among smallholders.

Once armed with information on changes in the BPP or SPP, maize buyers and sellers may not immediately change marketing channels because factors other than the price premiums may also affect their marketing channel choices. For example, farmers may build social capital with individual private traders by selling to them year after year. These relationships may be undermined and future opportunities to sell to the private trader may be jeopardized if the farmer abruptly switches to selling to the FRA. Furthermore, even if the FRA is offering a large BPP, farmers may be loath to sell to the FRA given the risk of long delays between delivery and payment. They may forgo a large BPP with potential payment delays in favor of selling to a private trader for immediate payment.

The rationale for assumption (iii) is that the FRA rarely buys and sells maize in the same month, and most of the FRA's emphasis with respect to pricing has been on setting its buy price level/premium. The buy price level/premium may then be taken into consideration when the sell price level/premium is determined. This suggests an ordering of BPP then SPP. Although the impulse response results reported below use this ordering, results using the reverse order are very similar.[14]

5. Data

This article uses monthly data from July 1996 through December 2008. The FRA first became active in the Zambian maize market in July 1996 and the most recently available data on FRA maize sales are for December 2008. (The FRA has not released sales data for January 2009 to present.) Data on FRA purchase and sales quantities and prices are from the FRA. The original sales quantity and price data, which are at the transaction level, are aggregated to the monthly level. As sale prices differ across transactions, a weighted average sell price is computed for each month, where the weights are the share of total monthly maize sales at that price.

[14] See the online data appendix for details.

Table 3
Autocorrelation test results for linear VAR(3) residuals

Test	Equation					
	Choma price	Lusaka price	SAFEX price	Mchinji price	BPP	SPP
AR(1)	0.036	0.455	0.005	0.1224	0.208	0.122
	(0.849)	(0.500)	(0.942)	(0.726)	(0.648)	(0.727)
AR(6)	0.912	3.314	3.501	4.371	1.503	7.784
	(0.989)	(0.769)	(0.744)	(0.627)	(0.959)	(0.254)
AR(12)	12.439	14.925	7.295	11.770	9.917	14.138
	(0.411)	(0.246)	(0.838)	(0.464)	(0.623)	(0.292)

Source: Own calculations.
Note: Values in the AR(j) rows are Ljung–Box Q statistics for jth order autocorrelation in the residuals of the series. Numbers in parentheses are P-values.

Lusaka and Choma wholesale maize prices are from the Agriculture Market Information Center (AMIC) of the Zambia Ministry of Agriculture and Cooperatives (MACO). The Lusaka (Choma) series is missing price observations for 20.0% (20.7%) of the months during the 150-month study period. Missing values for a given wholesale maize price series were imputed using best-subset regressions on retail maize grain prices in that location as well as wholesale and retail maize prices in the other eight locations for which wholesale price data are collected by AMIC.[15] The retail maize prices used in this procedure are from the Zambia Central Statistical Office (CSO).

The SAFEX maize price data are monthly average wholesale spot prices. Monthly South African Rand–U.S. dollar exchange rates are also from SAFEX. The Mchinji, Malawi maize price data are monthly retail prices from the Malawi Ministry of Agriculture and Food Security. Malawian Kwacha–U.S. dollar exchange rates are from the Reserve Bank of Malawi. ZMK–U.S. dollar exchange rates are from the Bank of Zambia. Import tariff rates applied to the SAFEX and Mchinji prices are from the Zambia Revenue Authority.

6. Results

6.1. Linear VAR estimation and impulse response results

Before estimating the VAR, the lag order of the model must be determined. Ljung–Box Q test results suggest that a minimum of three lags is required to eliminate autocorrelation in the reduced-form linear VAR residuals. We therefore use a lag order of three. Ljung–Box Q test results from the three-lag model are reported in Table 3.

Reduced-form linear VAR estimation results are reported in Table 4. These estimation results are used to compute orthogonalized impulse response functions (IRFs) for the Choma

[15] The nine locations are Kabwe, Ndola, Chipata, Mansa, Lusaka, Kasama, Solwezi, Choma, and Mongu.

Table 4
Linear VAR estimation results

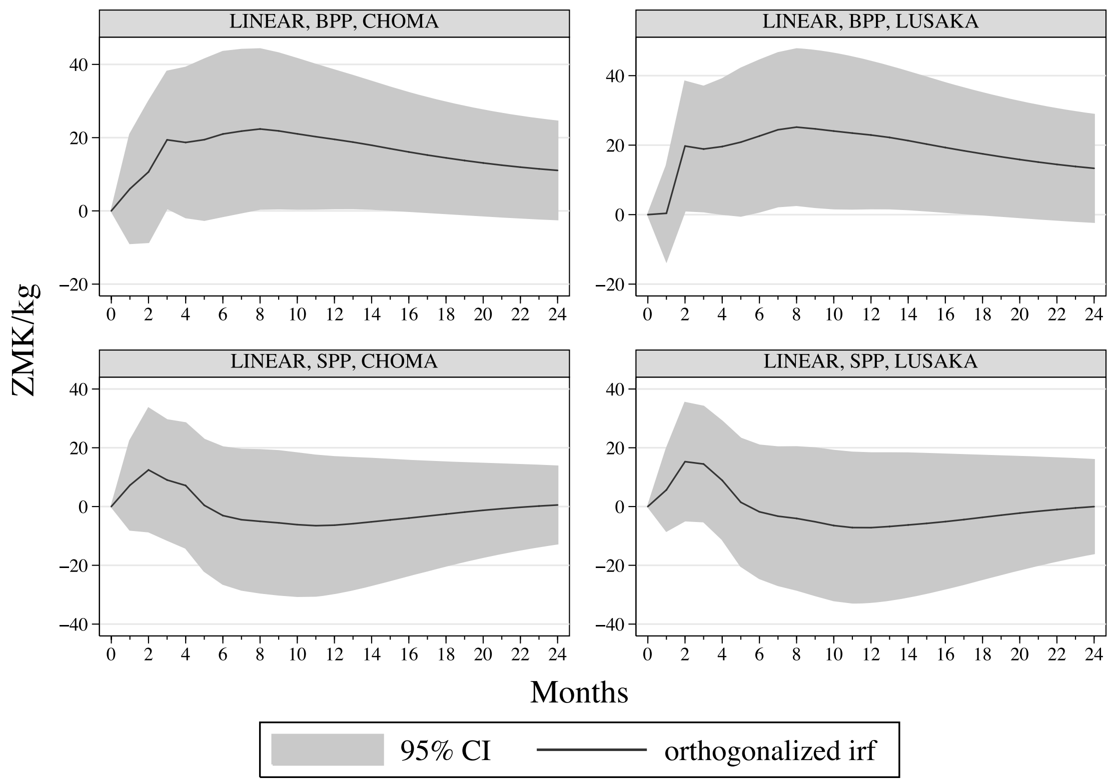
Coefficient	Equation					
	Choma price	Lusaka price	SAFEX price	Mchinji price	BPP	SPP
Choma ($t-1$)	0.757***	0.431***	−0.034	0.670***	−0.164	−0.379**
	(4.976)	(3.069)	(−0.384)	(3.013)	(−1.340)	(−2.026)
Choma ($t-2$)	0.111	0.184	0.023	−0.218	0.070	−0.330
	(0.674)	(1.213)	(0.237)	(−0.910)	(0.529)	(−1.633)
Choma ($t-3$)	0.296**	0.132	0.063	−0.171	−0.074	−0.013
	(2.024)	(0.979)	(0.728)	(−0.799)	(−0.631)	(−0.071)
Lusaka ($t-1$)	0.179	0.548***	0.047	0.207	−0.027	0.241
	(1.468)	(4.859)	(0.654)	(1.160)	(−0.277)	(1.600)
Lusaka ($t-2$)	−0.253*	−0.250*	0.018	−0.381*	0.089	0.566***
	(−1.654)	(−1.773)	(0.196)	(−1.705)	(0.724)	(3.012)
Lusaka ($t-3$)	−0.303**	−0.273**	−0.059	−0.161	0.155	0.042
	(−2.298)	(−2.242)	(−0.767)	(−0.834)	(1.459)	(0.260)
SAFEX ($t-1$)	−0.127	0.002	1.072***	−0.041	0.116	−0.124
	(−0.893)	(0.016)	(12.843)	(−0.195)	(1.015)	(−0.707)
SAFEX ($t-2$)	0.408*	0.182	−0.165	−0.047	−0.269	−0.147
	(1.942)	(0.938)	(−1.339)	(−0.154)	(−1.592)	(−0.568)
SAFEX ($t-3$)	−0.183	−0.038	−0.004	0.150	0.202*	0.184
	(−1.278)	(−0.287)	(−0.043)	(0.717)	(1.749)	(1.045)
Mchinji ($t-1$)	0.239***	0.204***	0.043	0.729***	−0.030	−0.171**
	(3.885)	(3.596)	(1.197)	(8.119)	(−0.603)	(−2.262)
Mchinji ($t-2$)	−0.273***	−0.302***	−0.008	0.045	0.070	0.266***
	(−3.772)	(−4.524)	(−0.188)	(0.426)	(1.194)	(2.992)
Mchinji ($t-3$)	0.125**	0.241***	−0.018	0.164*	−0.119**	−0.204***
	(2.104)	(4.403)	(−0.508)	(1.890)	(−2.483)	(−2.790)
BPP ($t-1$)	0.144	0.029	0.094	0.330	0.616***	−0.077
	(0.970)	(0.210)	(1.081)	(1.522)	(5.148)	(−0.422)
BPP ($t-2$)	−0.010	0.282	0.055	0.126	0.150	−0.117
	(−0.053)	(1.642)	(0.506)	(0.462)	(1.002)	(−0.509)
BPP ($t-3$)	0.011	−0.167	0.024	−0.308	−0.104	0.046
	(0.077)	(−1.211)	(0.278)	(−1.407)	(−0.866)	(0.249)
SPP ($t-1$)	0.077	0.061	0.036	−0.120	−0.071	0.779***
	(0.936)	(0.796)	(0.732)	(−0.999)	(−1.061)	(7.672)
SPP ($t-2$)	0.047	0.076	0.034	−0.001	−0.028	−0.048
	(0.447)	(0.781)	(0.551)	(−0.006)	(−0.332)	(−0.372)
SPP ($t-3$)	−0.091	−0.075	−0.056	0.058	0.071	0.039
	(−1.114)	(−0.997)	(−1.169)	(0.485)	(1.084)	(0.384)
Constant	6.794	−4.777	8.456	55.360*	8.877	20.575
	(0.315)	(−0.240)	(0.667)	(1.756)	(0.511)	(0.776)
R^2	0.876	0.9113	0.964	0.8943	0.6951	0.7626

Source: Own calculations.
Note: Numbers in parentheses are z-statistics.
$^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.10$.
$T = 147$.

and Lusaka maize market prices with respect to one-time, one-ZMK/kg shocks to the BPP and SPP. The IRFs and associated 95% confidence intervals (CIs) are shown in Fig. 1. As expected, positive shocks to the BPP generally raise maize market prices in Choma and Lusaka and the effect is quite persistent. In the case of the SPP, a shock also raises prices in the two markets but effects are shorter lived and turn slightly negative before dissipating. Perhaps this is because the SPP directly affects larger trading and milling firms (as opposed to the BPP, which directly affects small-scale producers) and these larger firms respond more rapidly to price differences between the marketing channels.

6.2. Linear VAR estimates of the effects of FRA activities on maize market prices

Figs. 2 and 3 show historical and simulated no FRA maize prices in Choma and Lusaka, respectively. The two sets of results are summarized in Table 5. With the exception of 1996/1997 (the FRA's first marketing year in operation), there is little difference between the levels of historical and simulated prices prior to mid 2003. From October 1996 through June 2003, mean historical prices exceed mean no FRA prices by less than 1% in both Choma and Lusaka (Table 5). The FRA began buying maize directly from smallholders through-



Source: Own calculations.

Fig. 1. Impulse response functions based on linear VAR estimation results.

out Zambia at a pan-territorial price in July 2003. Since then, simulated no FRA maize market prices are substantially lower than historical prices in all marketing years except 2005/2006 (Figs. 2 and 3).[16] Between July 2003 and December 2008, the FRA's activities are estimated to have raised mean maize market prices by 19% in Choma and 17% in Lusaka (Table 5).

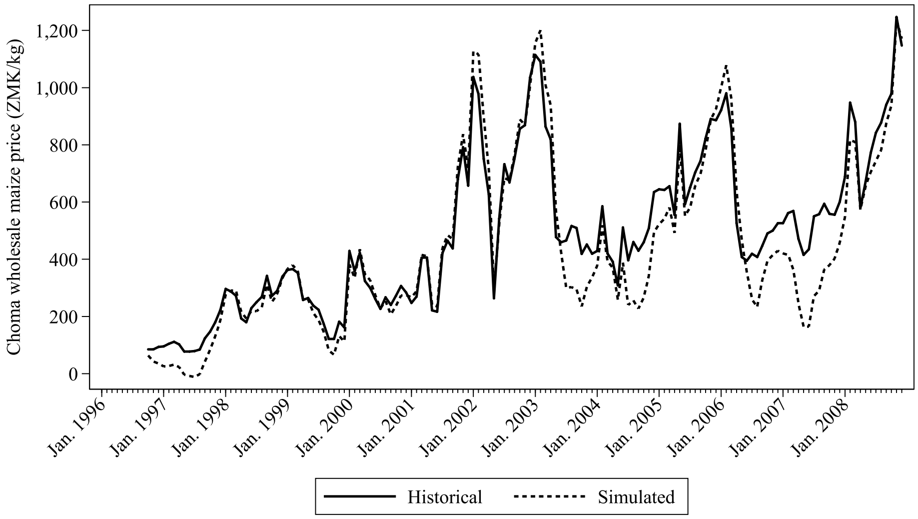
Although FRA activities had little effect on mean maize market prices prior to July 2003, these activities reduced the standard deviations (SDs) of Choma and Lusaka wholesale prices over this period by 13%, resulting in 14% reductions in the coefficients of variation (CV). The market price stabilizing effects of the FRA's involvement in domestic maize marketing are even greater in the July 2003–December 2008 period; the Agency's activities are estimated to have reduced the CV of maize market prices in Choma and Lusaka by 34% and 36%, respectively. The CV reductions are due to both large increases in mean market prices and large decreases in the SD of market prices (Table 5).

7. Welfare effects and policy implications

The results in this article suggest that two of the major outcomes of the FRA's activities since mid 2003 have been an increase in the average level of and a reduction in the variability of maize market prices in Zambia. Who are the likely winners and losers? In general, higher average maize market prices are beneficial for net sellers and detrimental to net buyers of maize. In Kenya, for example, Mghenyi et al. (2011) find that a discrete 25% maize price increase is associated with significant welfare losses in areas where most households are net buyers. In Zambia, nationally representative household survey data collected by the government CSO and MACO indicate that only approximately 28% of smallholder farm households sell more maize than they buy; the remaining 72% either buy more maize than they sell (49%) or neither buy nor sell maize (23%) (CSO/MACO/FSRP, 2008). Thus, higher maize prices hurt urban consumers and the nearly 50% of smallholders that are net buyers of maize. Large-scale farmers and the 28% of smallholders that are net-maize sellers benefit from higher average maize prices.

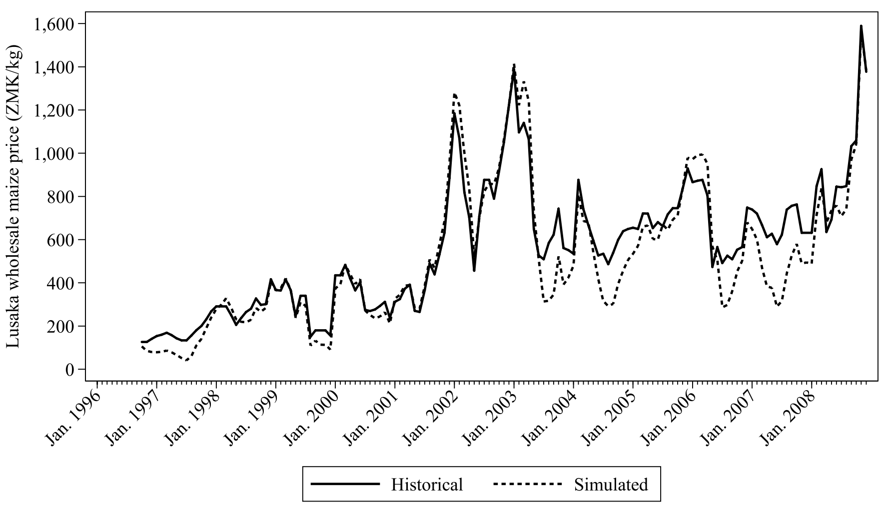
Among smallholder net-maize sellers, gains from higher maize market prices would be highly concentrated in the hands of the 3–5% of maize-growing smallholders that account for 50% of all smallholder marketed maize (Kuteya et al., 2011). This group tends to have more land and nonland assets than other smallholders. Therefore, to the extent that they raise average maize market prices in Zambia, the FRA's policies are regressive: higher maize prices harm urban consumers and a large proportion of rural households, and help larger scale farmers and a small number of relatively better off smallholders.

[16] The 2005 smallholder maize harvest was by far the smallest of the 2003–2008 period, and FRA maize purchases in 2005/2006 were relatively small (Table 1).



Source: AMIC and own calculations.

Fig. 2. Historical and simulated (no FRA) Choma wholesale maize prices.



Source: AMIC and own calculations.

Fig. 3. Historical and simulated (no FRA) Lusaka wholesale maize prices.

There may be additional welfare impacts associated with the market price stabilizing effects of FRA policies. However, the welfare effects of FRA-induced increases in the average *level* of maize market prices are likely to dwarf any welfare effects that result from price *stabilization* (Newbery and Stiglitz, 1981). Furthermore, just as in the case of higher mean maize prices, relatively better off producers are likely to be the principal beneficiaries of more stable maize prices (Naylor and Falcon, 2010). For example, simulations in Myers (2006) suggest that a large reduction in food price variability (i.e., from a CV of 0.3 to 0) results in a welfare increase equivalent to nearly 9% of income among affluent producers. The same degree of price stabilization results in the equivalent of income increases of only 2.7% and 1.4% among poor producers and poor consumers, respectively. Similarly, empirical evidence from rural Ethiopia indicates that the benefits from food price stabilization are concentrated in the hands of the wealthiest 40% of households (Bellemare et al., 2011). Moreover, Bellemare et al. find that many poor rural households are actually hurt by more stable food prices. If similar results hold in Zambia, it would indicate that both the mean maize price raising and the price stabilizing effects of FRA policies are regressive: they disproportionately benefit relatively better off households and have negative net effects on relatively poor households.

8. Conclusions

Over the last decade, governments in ESA have shown a renewed propensity to use strategic reserves and/or marketing boards to influence grain market outcomes. Kenya, Malawi, Zimbabwe, Ethiopia, Tanzania, and Zambia all have one or both of these entities, and their level of involvement in grain

Table 5
Summary of FRA effects on Choma and Lusaka wholesale maize prices

	Choma price (ZMK/kg)			Lusaka price (ZMK/kg)		
Period, statistic	Historical	Simulated	Percent difference	Historical	Simulated	Percent difference
(i) Full sample period (October 1996–December 2008)						
Mean	486	439	10.5%	559	512	9.2%
SD	271	298	−9.1%	296	326	−9.0%
CV	0.559	0.679	−17.7%	0.530	0.636	−16.7%
(ii) October 1996–June 2003:						
Mean	377	374	0.8%	435	433	0.4%
SD	272	312	−12.9%	309	356	−13.1%
CV	0.721	0.835	−13.6%	0.710	0.821	−13.5%
(iii) July 2003–December 2008:						
Mean	618	519	19.1%	711	609	16.8%
SD	204	261	−21.7%	192	256	−24.8%
CV	0.331	0.503	−34.2%	0.270	0.420	−35.6%

Source: Own calculations.
SD = standard deviation; CV = coefficient of variation.

marketing has generally increased in recent years (Jayne et al., 2007). Yet, to date, relatively little is known about how the resurgent activities of strategic reserves and marketing boards are affecting grain market prices.

In this article, we estimate a structural VAR using monthly data from July 1996 through December 2008 to determine the impacts of FRA pricing policies and net maize purchases on the level and variability of maize market prices in Zambia. The Zambia maize market prices in the VAR are wholesale prices in Lusaka (the major maize consumption area) and in Choma (a major maize production area). The FRA's pricing policies are modeled as a BPP (the FRA buy price minus the market price in Choma) and a SPP (the FRA sell price minus the market price in Lusaka). The estimated VAR is used to simulate the path of market prices that would have occurred in the absence of the FRA. Four key findings emerge from the analysis.

First, consistent with the general perception in Zambia (Govereh et al., 2008), simulation results suggest that the FRA's activities have indeed raised average market prices, particularly since the Agency began buying maize directly from smallholders throughout Zambia at a pan-territorial price in mid 2003. FRA activities are estimated to have increased mean maize market prices between July 2003 and December 2008 by 17% in Lusaka and 19% in Choma.

Second, in line with the FRA's strategic goal to stabilize market prices (FRA, n.d.), wholesale maize prices were less variable between October 1996 and December 2008 than they would have been in the absence of the FRA. Simulation results suggest that the FRA's activities reduced the CV of maize market prices by 14% between October 1996 and June 2003, and by 34–36% between July 2003 and December 2008.

Third, the estimated effects of the FRA on maize market prices in Zambia are similar in direction and magnitude to the findings of Jayne et al. (2008) for the effects of the NCPB on maize market prices in Kenya. Their results suggest that NCPB policies raised average maize market prices in Kenya by approximately 20% and reduced the CV of these prices by 36–45% between July 1995 and October 2004. The FRA and NCPB are similar in that both seek to stabilize maize market prices and buy maize at established buying points at pan-territorial prices that typically exceed market prices in surplus maize production areas. However, as discussed in the introduction, there are important differences between FRA and NCPB procurement practices, and between the grain marketing environments in which the two agencies operate. Yet, despite these differences, the FRA and NCPB have similar effects on maize market prices.

Finally, our analysis of the potential welfare effects of FRA activities suggests that the likely losers are the rural poor and urban consumers while the likely winners are relatively wealthy maize producers. The price raising effects of FRA policies are likely to have adversely affected urban consumers and the majority of the rural poor because they are net buyers of maize. In contrast, relatively wealthy, net-selling maize producers are likely to have benefited from both the higher average and more stable maize prices resulting from FRA policies.

Acknowledgements

The authors thank Thom Jayne and an anonymous reviewer for providing helpful comments on this article. They are also grateful to the FRA for releasing detailed data on the Agency's maize purchases, sales, and prices, and to Antony Chapoto, Masiliso Sooka, Stephen Kabwe, Solomon Tembo, Nick Sitko, and Kasweka Chinyama for liaising with the FRA to obtain these data. The authors acknowledge financial support from the United States Agency for International Development (USAID) Zambia Mission and the Bill and Melinda Gates Foundation. Any views expressed or remaining errors are solely the responsibility of the authors.

Appendix A. Threshold VAR extension—methodology and results

A.1. Threshold VAR (TVAR) extension of Eq. (1)

Equation (1) assumes that the relationships among the variables in the system are constant over time. It may be, however, that these relationships change depending on the level of one or more threshold variables. Let $\boldsymbol{q}_t$ be a vector of exogenous threshold variables and $\boldsymbol{\theta}$ be a vector of threshold parameters. Define a structural TVAR as

$$\left.\begin{aligned} \boldsymbol{B}^j \boldsymbol{y}_t &= \sum_{i=1}^{k} \boldsymbol{B}_i^j \boldsymbol{y}_{t-i} + \sum_{i=0}^{k} \boldsymbol{C}_i^j \boldsymbol{p}_{t-i} + \boldsymbol{A}^{y,j} \boldsymbol{v}_t^y \\ \boldsymbol{G}^j \boldsymbol{p}_t &= \sum_{i=0}^{k} \boldsymbol{D}_i^j \boldsymbol{y}_{t-i} + \sum_{i=1}^{k} \boldsymbol{G}_i^j \boldsymbol{p}_{t-i} + \boldsymbol{A}^{p,j} \boldsymbol{v}_t^p \end{aligned}\right\} \text{for } \boldsymbol{q}_t \in R_j(\boldsymbol{\theta}), \tag{A.1}$$

where $R_j(\boldsymbol{\theta})$ is a set of nonintersecting and exhaustive sets. In the case of a single threshold (two regimes), the TVAR could be written as

$$\left.\begin{aligned} \boldsymbol{B}^1 \boldsymbol{y}_t &= \sum_{i=1}^{k} \boldsymbol{B}_i^1 \boldsymbol{y}_{t-i} + \sum_{i=0}^{k} \boldsymbol{C}_i^1 \boldsymbol{p}_{t-i} + \boldsymbol{A}^{y,1} \boldsymbol{v}_t^y \\ \boldsymbol{G}^1 \boldsymbol{p}_t &= \sum_{i=0}^{k} \boldsymbol{D}_i^1 \boldsymbol{y}_{t-i} + \sum_{i=1}^{k} \boldsymbol{G}_i^1 \boldsymbol{p}_{t-i} + \boldsymbol{A}^{p,1} \boldsymbol{v}_t^p \end{aligned}\right\} \text{for } q_{1t} \leq \theta_1, \tag{A.2a}$$

$$\left.\begin{aligned} \boldsymbol{B}^2 \boldsymbol{y}_t &= \sum_{i=1}^{k} \boldsymbol{B}_i^2 \boldsymbol{y}_{t-i} + \sum_{i=0}^{k} \boldsymbol{C}_i^2 \boldsymbol{p}_{t-i} + \boldsymbol{A}^{y,2} \boldsymbol{v}_t^y \\ \boldsymbol{G}^2 \boldsymbol{p}_t &= \sum_{i=0}^{k} \boldsymbol{D}_i^2 \boldsymbol{y}_{t-i} + \sum_{i=1}^{k} \boldsymbol{G}_i^2 \boldsymbol{p}_{t-i} + \boldsymbol{A}^{p,2} \boldsymbol{v}_t^p \end{aligned}\right\} \text{for } q_{1t} > \theta_1. \tag{A.2b}$$

Equations (A2a) and (A2b) are similar to the model in Saxegaard (2006), which extends the structural VAR framework of Bernanke and Mihov (1998) to incorporate a threshold nonlinearity.

A.2. Threshold estimation and testing methodology

The optimal threshold level ($\hat{\theta}$) for a given candidate threshold variable (q) can be estimated using a grid search procedure. (See, among others, Balke (2000); Galvão (2003); and Goodwin and Smith (2009) for details.) Two approaches for testing the null hypothesis of a linear VAR versus the alternative hypothesis of a TVAR with threshold level $\hat{\theta}$ are the Hansen bootstrap *P*-value approach (Hansen, 1996, 1999; see also Lo and Zivot, 2001; and Hansen and Seo, 2002) and the Gonzalo and Pitarakis (GP) sequential procedure (2002).

Hansen's approach is valid for testing no thresholds against one or multiple thresholds but its validity has not been demonstrated for testing one threshold model against another (Gonzalo and Pitarakis, 2002; Hansen, 1999). Unlike the Hansen *P*-value approach, the GP method can discriminate between threshold models with different numbers of thresholds, as well as between linear and threshold models. The GP approach was developed for the single equation case but Pitarakis indicates that it readily extends to the VAR case and suggests that the log-likelihood form of the statistic be used (J. Pitarakis, personal communications, 2010, 2011). In the VAR setting, the GP Schwarz-Bayesian information criterion (GP BIC) value is calculated as

$$GP\ BIC\,(m) = \frac{-2}{T}[\ln L_T - \ln L_T(\hat{\theta})] - \frac{\ln T}{T} mn(nk+1), \tag{A.3}$$

where m is the number of threshold parameters to be estimated, n is the number of endogenous variables in the VAR, k is the lag order of the VAR, T is the total number of observations, and L_T and $L_T(\hat{\theta})$ are, respectively, the maximized likelihoods for the single regime model and the multiple regime model with optimal threshold. The decision rule is to select the threshold model if the GP BIC is greater than zero, and to prefer the single regime model otherwise. If the GP BIC suggests the existence of a threshold and if there are sufficient observations in one or both of the regimes of the two-regime model, the GP BIC procedure can be repeated to test for additional thresholds.

Table A1
Threshold estimation and testing results

Threshold variable	Threshold estimate	T (Low)	I (High)	GP BIC	Bootstrap *P*-value
(i) FRA market share (%)	9.059	99	48	–[a]	0.088
(ii) Marketable surplus after FRA (kg/cap)	18.260	54	93	−1.312	0.002
(iii) Maize quantity harvested (kg/cap)	105.263	84	63	−0.914	0.001
(iv) Time	Oct. 2003	85	62	−0.360	0.014

Source: Own calculations.
[a]GP BIC cannot be computed because the variance–covariance matrix for the high regime is not positive definite.

A.3. TVAR application to the Zambia/FRA case

Four candidate threshold variables were considered in this article: (i) FRA's share of smallholder maize sales (%), which we also refer to as the FRA market share; (ii) smallholder maize marketable surplus remaining after FRA purchases (in kg per capita); (iii) the quantity of maize harvested by smallholders at the most recent harvest (in kg per capita); and (iv) time. Table A1 summarizes the threshold estimation and testing results.[17] GP BIC values are not greater than zero for any of the candidate threshold variables, indicating that a linear VAR is favored over the TVARs. In contrast, Hansen bootstrap *P*-values are less than 0.10 for all of the candidate threshold variables, indicating that the TVARs are favored over a linear VAR.

Given the Hansen test support for the various candidate threshold variables, we estimated the corresponding two-regime TVARs. However, many simulated no FRA Choma and Lusaka prices based on these TVARs are unreasonably low and/or high (e.g., negative or many times higher than the highest historical value). The linear VAR is supported by the GP BIC procedure and produces plausible no FRA price paths. Therefore, the main policy conclusions in this article are based on the simulated counterfactual prices from the linear VAR.

Why might the Hansen and GP approaches lead to conflicting inferences regarding the existence of threshold nonlinearities?

[17] GAUSS code for estimating the optimal threshold level was adapted from Galvão (2006, http://qed.econ. queensu.ca.proxy2.cl.msu.edu/jae/datasets/galvao001) and GAUSS code for the Hansen bootstrap *P*-value procedure was adapted from Lo and Zivot (2001, http://129.3.20.41/md/2001-v5.4/lo-zivot/) and Hansen and Seo (2002, http://www.ssc.wisc.edu/∼bhansen/progs/joe_02.html). Many thanks to these authors for making their code publicly available. See the online data appendix for the GAUSS code used in the current article.

And why does the GP approach perform better (i.e., lead to a model specification with more plausible simulation results) than the Hansen approach in the current application? One potential reason is the relatively small number of degrees of freedom and the inclusion of a penalty function in the GP approach but not in the Hansen test. The linear VAR estimated in this article is based on 147 observations. Given the lag order (three) and number of endogenous variables (six), each equation in the reduced form has 19 parameters to be estimated (114 total parameters in the system). With 147 observations, each regime in a one-threshold, two-regime VAR could have at most 74 observations, leaving relatively few degrees of freedom. The GP approach includes a penalty function (e.g., the BIC—the second term on the right-hand side of Eq. A.3) so that the benefit of a more flexible TVAR specification is weighed against the cost of more parameters to be estimated. Moreover, the cost of adding more parameters is larger when the number of observations is small, as in the current application. The Hansen test does not include a penalty function. In applications with few degrees of freedom, the GP approach may therefore perform better than the Hansen approach.

Appendix B. Unit root tests results

Table B1
Full sample unit root test results

Test and hypotheses	Choma price	Lusaka price	SAFEX price	Mchinji price	BPP	SPP
KPSS (H_1: Unit root)						
(1a) H_0: Trend stationary	0.186 (<0.05)	0.233 (<0.01)	0.110 (>0.10)	0.242 (<0.01)	0.147 (<0.05)	0.085 (>0.10)
(1b) H_0: Level stationary	2.21 (<0.01)	2.34 (<0.01)	2.99 (<0.01)	0.856 (<0.01)	0.582 (<0.025)	0.116 (>0.10)
ADF (H_0: Unit root)						
(1c) H_1: Trend stationary	−3.382 (0.054)	−3.477 (0.042)	−2.972 (0.140)	−2.060 (0.569)	−4.033 (0.008)	−4.123 (0.006)
(1d) H_1: Level stationary	−2.040 (0.269)	−1.974 (0.298)	−1.626 (0.470)	−1.615 (0.476)	−3.833 (0.003)	−4.112 (0.001)
PP (H_0: Unit root)						
(1e) H_1: Trend stationary	−3.569 (0.033)	−3.377 (0.055)	−2.728 (0.225)	−2.218 (0.480)	−4.167 (0.005)	−3.913 (0.012)
(1f) H_1: Level stationary	−2.069 (0.257)	−1.798 (0.381)	−1.500 (0.534)	−1.737 (0.412)	−3.987 (0.002)	−3.901 (0.002)

Source: Own calculations.
Note: Approximate *P*-values in parentheses. Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) statistics computed using automatic bandwidth selection and autocovariance function weighted by quadratic spectral kernel. Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) values are $Z(t)$ statistics. The number of lags used for the KPSS, ADF, and PP tests were three, one, and four, respectively.

References

Balke, N.S., 2000. Credit and economic activity: Credit regimes and nonlinear propagation of shocks. Rev. Econ. Stat. 82, 344–349.

Bellemare, M.F., Barrett, C.B., Just, D.R., 2011. The welfare impacts of commodity price volatility: Evidence from rural Ethiopia. Available at: http://dyson.cornell.edu/faculty_sites/cbb2/Papers/BellemareBarrettJustPriceVolatilityJDESubmission.pdf, Accessed December 2011.

Ben-Kaabia, M., Gil, J.M., Ameur, M., 2005. Vertical integration and non-linear price adjustments: The Spanish poultry sector. Agribusiness 21, 253–271.

Bernanke, B.S., Blinder, A.S., 1992. The federal funds rate and the channels of monetary transmission. Am. Econ. Rev. 82, 901–921.

Bernanke, B.S., Mihov, I., 1998. Measuring monetary policy. Q. J. Econ. 113, 869–902.

Central Statistical Office/Ministry of Agriculture and Cooperatives/Food Security Research Project (CSO/MACO/FSRP), 2008. 2008 Supplemental Survey data. Lusaka, Zambia.

Central Statistical Office/Ministry of Agriculture and Livestock/Indaba Agricultural Policy Research Institute (CSO/MAL/IAPRI), 2012. 2012 Rural Agricultural Livelihoods Survey data, preliminary results. Lusaka, Zambia.

Chapoto, A., Jayne, T.S., 2009. Effects of maize marketing and trade policy on price unpredictability in Zambia. Food Security Research Project Working Paper No. 38. Available at: http://www.aec.msu.edu/fs2/zambia/wp38.pdf, Accessed December 2011.

Clements, M.P., Galvão, A.B., 2004. A comparison of tests of nonlinear cointegration with application to the predictability of US interest rates using the term structure. Int. J. Forecasting 20, 219–236.

Deák, S., Lenarcic, A., 2010. The macroeconomic effects of fiscal policy shocks in good times and bad. Available at: https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=res2011&paper_id=1095, Accessed December 2011.

Dorosh, P.A., Dradri, S., Haggblade, S., 2009. Regional trade, government policy and food security: Recent evidence from Zambia. Food Policy 34, 350–366.

Fackler, P.L., 1988. Vector autoregressive techniques for structural analysis. Rev. Anál. Econ. 3, 119–134.

Food and Agriculture Organization Statistical Databases (FAOSTAT), 2010. TradeStat database. Available at: http://faostat.fao.org/site/406/default.aspx, Accessed December 2011.

Famine Early Warning Systems Network (FEWSNET), 2003a. Zambia: Monthly report, May 2003. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed December 2011.

FEWSNET, 2003b. Zambia: Monthly report, June 2003—Food security position improves. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed December 2011.

FEWSNET, 2008a. Zambia Food Security Update, May/June 2008. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed July 2012.

FEWSNET, 2008b. Zambia Food Security Update, August 2008. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed July 2012.

FEWSNET, 2009a. Zambia Food Security Update, May 2009. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed July 2012.

FEWSNET, 2009b. Zambia Food Security Outlook, July to December 2009. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed July 2012.

FEWSNET, 2009c. Zambia Food Security Update, August 2009. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed July 2012.

FEWSNET, 2009d. Zambia Food Security Update, September 2009. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed July 2012.

FEWSNET, 2009e. Zambia Food Security Outlook, October 2009 to March 2010. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed July 2012.

FEWSNET, 2009f. Zambia Food Security Update, November 2009. Available at: http://www.fews.net/Pages/countryarchive.aspx?pid=500&gb=zm&l=en, Accessed July 2012.

FEWSNET, 2010. Southern Africa Informal Cross Border Food Trade dataset. Provided by Phumzile Mdladla, Regional Representative, FEWSNET.

Food Reserve Agency (FRA), n.d. FRA website. Available at: http://www.fra.org.zm/, Accessed December 2011.

Galvão, A.B., 2003. Multivariate threshold models: TVARs and TVECMs. Braz. Rev. Econom. 23, 143–171.

Galvão, A.B., 2006. Structural break threshold VARs for predicting US recessions using the spread. J. Appl. Econom. 21, 463–487.

Galvão, A.B., Marcellino, M., 2010. Endogenous monetary policy regimes and the great moderation. EUI Working Paper ECO 2010/22. Available at: http://cadmus.eui.eu/bitstream/handle/1814/13797/ECO2010_22.pdf?sequence=1, Accessed December 2011.

Gonzalo, J., Pitarakis, J., 2002. Estimation and model selection based inference in single and multiple threshold models. J. Econom. 110, 319–352.

Goodwin, B.K., Piggott, N.E., 2001. Spatial market integration in the presence of threshold effects. Am. J. Agric. Econ. 83, 302–317.

Goodwin, B.K., Smith, V.H., 2009. Harvest-time protein shocks and price adjustment in US wheat markets. J. Agric. Resour. Econ. 34, 237–255.

Govereh, J., Jayne, T.S., Chapoto, A., 2008. Assessment of alternative maize trade and market policy interventions in Zambia. Food Security Research Project Working Paper No. 33. Available at: http://www.aec.msu.edu/fs2/zambia/wp_33.pdf, Accessed December 2011.

Govereh, J., Malawo, E., Lungu, T., Jayne, T.S., Chinyama, K., Chilonda, P., 2009. Trends and spatial distribution of public agricultural spending in Zambia: Implications for agricultural productivity and growth. Food Security Research Project Working Paper No. 36. Available at: http://www.aec.msu.edu/fs2/zambia/wp_36.pdf, Accessed December 2011.

Government of the Republic of Zambia (GRZ), 1995. Food Reserve Act, 1995. Available at: http://www.fao.org/docrep/w4979e/w4979e0l.htm, Accessed December 2011.

GRZ, 2005. Act No. 20 of 2005: An Act to Amend the Food Reserve Act. Available at: http://www.parliament.gov.zm/index.php?option=com_docman& task=doc_download&gid=543, Accessed December 2011.

Hamilton, J.D., 1994. Time Series Analysis. Princeton University Press, Princeton, NJ.

Hansen, B.E., 1996. Inference when a nuisance parameter is not identified under the null hypothesis. Econometrica 64, 413–430.

Hansen, B.E., 1999. Testing for linearity. J. Econ. Surv. 13, 552–576.

Hansen, B.E., Seo, B., 2002. Testing for two-regime threshold cointegration in vector error-correction models. J. Econom. 110, 293–318.

International Monetary Fund (IMF), 2012. Zambia: 2012 Article IV consultation. IMF Country Report No. 12/200. Available at: http://www.imf.org/external/pubs/ft/scr/2012/cr12200.pdf, Accessed August 2012.

Jayne, T.S., Chapoto, A., Govereh, J., 2007. Grain marketing policy at the crossroads: challenges for eastern and southern Africa. Available at: http://www.fao.org/es/esc/common/ecg/17/en/JAYNE_et_al_paper_FAO_conference_V2.pdf, Accessed December 2011.

Jayne, T.S., Jones, S., 1997. Food marketing and price policy in eastern and southern Africa: A survey. World Dev. 25, 1505–1527.

Jayne, T.S., Myers, R.J., Nyoro, J.K., 2008. The effects of NCPB marketing policies on maize market prices in Kenya. Agric. Econ. 38, 313–325.

Kuteya, A., Kabwe, S., Beaver, M., Chapoto, A., Burke, W.J., Mason, N.M., Weber, M.T., 2011. Statistical report on categorization of rural cropping households in Zambia. Food Security Research Project Working Paper No. 51. Available at: http://www.aec.msu.edu/fs2/zambia/wp51/index.htm, Accessed December 2011.

Lo, M.C., Zivot, E., 2001. Threshold cointegration and nonlinear adjustment to the law of one price. Macroecon. Dyn. 5, 533–576.

Mather, D., Jayne, T.S., 2011. The impact of state marketing board operations on smallholder behavior and incomes: The case of Kenya. Michigan State University International Development Working Paper No. 119. Available at: http://ageconsearch.umn.edu/bitstream/120742/2/idwp119.pdf, Accessed July 2012.

Mghenyi, E., Myers R.J., Jayne, T.S., 2011. The effects of a large discrete maize price increase on the distribution of household welfare and poverty in rural Kenya. Agric. Econ. 42, 343–356.

Mwiinga, B., Shawa, J., Jayne, T.S., Shaffer, J., 2005. Levies on agricultural commodities: Who benefits? Food Security Research Project Working Paper No. 12. Available at: http://www.aec.msu.edu/fs2/zambia/wp12.pdf, Accessed July 2012.

Myers, R.J., 2006. On the costs of food price fluctuations in low-income countries. Food Policy 31, 288–301.

Myers, R.J., Piggott, R.R., Tomek, W.G., 1990. Estimating sources of fluctuations in the Australian wool market: An application of VAR methods. Aust. J. Agric. Econ. 34, 242–262.

Naylor, R.L., Falcon, W.P., 2010. Food security in an era of economic volatility. Popul. Dev. Rev. 36, 693–723.

National Cereals and Produce Board (NCPB), n.d. Historical data on NCPB maize purchases and sales, 1995–2009. NCPB, Nairobi, Kenya.

Newbery, D.M.G., Stiglitz, J.E., 1981. The Theory of Commodity Price Stabilization. Oxford University Press, New York, NY.

Nkonde, C., Mason, N.M., Sitko, N.J., Jayne, T.S., 2011. Who gained and who last from Zambia's 2010 maize marketing policies? Food Security Research Project Working Paper No. 49. Available at: http://www.aec.msu.edu/fs2/zambia/wp49.pdf, Accessed December 2011.

Perron, P., 1989. The great crash, the oil price shock, and the unit root hypothesis. Econometrica 57, 1361–1401.

Phillips, P.C.B., 1998. Impulse response and forecast error variance asymptotic in nonstationary VARs. J. Econom. 83, 21–56.

Pippenger, M.K., Goering, G.E., 1993. A note on the empirical power of unit root tests under threshold processes. Oxford Bull. Econ. Stat. 55, 473–481.

Saxegaard, M., 2006. Excess liquidity and effectiveness of monetary policy: Evidence from sub-Saharan Africa. Working Paper No. 06/115. Available at: http://www.imf.org/external/pubs/ft/wp/2006/wp06115.pdf, Accessed December 2011.

Serra, T., Goodwin, B.K., 2003. Price transmission and asymmetric adjustment in the Spanish dairy sector. Appl. Econ. 35, 1889–1899.

Sims, C.A., 1980. Macroeconomics and reality. Econometrica 48, 1–48.

Tembo, G., Chapoto, A., Jayne, T.S., Weber, M.T., 2009. Fostering agricultural market development in Zambia. Food Security Research Project Working Paper No. 40. Available at: http://www.aec.msu.edu/fs2/zambia/wp40.pdf, Accessed December 2011.

Zulu, B., Jayne, T.S., Beaver, M., 2007. Smallholder household maize production and marketing behavior in Zambia and its implications for policy. Food Security Research Project Working Paper No. 22. Available at: http://www.aec.msu.edu/fs2/zambia/wp_22.pdf, Accessed December 2011.

Zulu, I., 2012. Mkushi maize farmers still not paid—Chibuye. The Post Newspapers Zambia, June 2. Available at: http://www.postzambia.com/post-print_article.php?articleId=27809, Accessed July 2012.