**Effects of Stock holding policy on Maize Prices: Evidence from Zambia**

**Yujun Zhou, Kathy Baylis**

**Abstract:** Public stockholding is widely used in developing countries in the past decade. Governments intervene in grain markets by building strategic reserves directly through marketing boards. Despite the massive spending on those stockholding programs, little is known about their effectiveness in mitigating the retail price swings associated with domestic production shocks. This paper estimates the effects of the purchase and sales activities of the Food Reserve Agency (FRA) on maize market prices across more than thirty markets in Zambia using monthly price data from 2003-2008. To deal with the endogeneity in the actual purchase and sales targets, we use predicted FRA purchase and sales targets as instrumental variables. Controlling for other policies in place, we find evidence of stabilizing effects of FRA activities on retail prices in the major district markets. Results also show that FRA purchases raise local prices for surplus maize producers during the time of harvest and FRA sales help to lower the price during the lean season.

**JEL classifications: Q11, Q18**

**Keywords:** Maize marketing board; Strategic grain reserve; Maize prices; Zambia

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1. **Introduction**

Public stockholding is widely used in developing countries including India and Thailand and has come under fire at the WTO as trade distorting. These policies are often used by net food exporters and are often coupled with export bans during times of production shortfalls. These coupled programs have the potential to exacerbate the volatility of international prices and reduce the prices facing domestic farmers exactly when they need the extra income.

However, theoretical work has demonstrated the stockholding can reduce food price volatility for consumers, where food price volatility has been shown to lead to food insecurity and civil conflict (Bellemare 2015; Fjelde 2014). Gouel and Jean (2012) proposed a theoretically optimal food price stabilization policy for a developing country is to maintain a public stock along with a subsidy on agricultural production. They argue that the restrictions on grain exports are necessary since the price soothing effect generated through buffer stocks would leak to the external market when the domestic production shock is positively correlated with a global production shock, and thus an international price spike. This is precisely the policy combination used in Zambia with its public stock building policy with FRA, farm-input subsidy and restrictions on maize exports.

Established in 1996, the FRA purchases substantial maize from small households in various geographic regions since the 2003/04 marketing year (corresponding to the study period in this paper). The high pan-territorial buying price makes the FRA the dominant buyer in the market (Mason and Myers 2013). In 2006 and 2007, the FRA bought more than half of the surplus maize by smallholder farmers (Ricker-Gilbert et al. 2013), which helps to build higher maize stocks. These measures to make higher stocks have led the national maize stocks to reach historically high levels after 2009. These stocks are intended to reduce variability in grain prices and to provide liquidity in the maize market (Govereh, Jayne, and Chapoto 2008). Mason and Myers (2013) showed a stabilizing effect of the FRA purchases in the maize market in Zambia. However, the stock building comes at a considerable financial cost. The procurement and selling of maize at subsidized prices along with the input subsidies account for over 43% of the total agricultural budget (Nkonde et al. 2011). However, the increase in maize price stability seems to have provided relatively small welfare gains for the poor households compared to the massive spending (Mason and Myers 2013).

This paper seeks to provide empirical evidence on whether the FRA stockholding policies stabilize prices both across years and during a year in the lean season. Specifically, we ask: can FRA purchases mitigate or exacerbate the retail price swings associated with domestic production shocks?

Our study makes the following contributions to previous studies on stockholding policies and FRA in Zambia: we control for endogeneity in the number of grains that the FRA purchases which may overestimate the effect of stabilizing prices. Also, we use weather shocks to control for simultaneous shocks in policy and crop production. We also expanded the number of markets to more than 30 districts in Zambia to explore the differential effects across space.

The endogeneity issue of identifying the effects of FRA purchases on consumer prices is multiple. First, since the FRA targets explicitly areas that are predicted to be in surplus as locations for their purchases, and it targets more sales during years of production shortfalls, we need to control for endogeneity in the amount of FRA purchases. Otherwise, we tend to overestimate the effect of FRA purchases on stabilizing the prices since FRA purchase are typically made in places of surplus maize and price tend to be more stable. To tackle with this endogeneity, we instrument for FRA purchases using long-run shares of production of each district. Also, simultaneous policies are at play, and all to a certain degree endogenous to grain production, local grain production shocks, and maize prices. These policies include but not limited to temporary export bans, government subsided imported maize from South Africa and targeted fertilizer subsidy program for smallholder farmers. However, most of the policies listed above are made at an annual level. We try to proxy them by adding a time trend and agriculture-related weather shocks in each regression. Without controlling for other policies, we are facing the risk of attributing the stabilizing effect only on the FRA stockholding policies, but it may be a combined effect of multiple policies. The primary district markets are in a certain degree connected through trade. As a result, the prices of these markets tend to drive towards the same because of potential arbitrages. Due to the incomplete infrastructure and a lack of market information system, the level of price integration in developing countries is not so much. Prices in markets far away from the primary production and consumer centers respond little (see appendix on analysis on price integration) to prices shocks outside. In this study, we use those regions that are less affected by FRA purchases and sales as controls (both unaffected by price arbitrage or by the FRA purchases) to reflect the effect of stockholding policy. Last but least, a possible reverse causality exists as FRA tends to sell more maize when the price is higher.

Mitigating the effects of price instability on smallholder farmers and rural consumers has been longstanding concerns of developing countries. The effectiveness of stockholding policy on stabilizing prices is at the debate. This paper provides empirical evidence on how governments’ efforts intervening in building a public stock may have affected price volatility. Research results have relevant policy implications and can guide future domestic policies aiming at improving local food security.

The paper is structured as follows. Section 2 gives background information on the Zambia maize market and relevant policies. Section 3 illustrates the empirical strategy by describing the model. Section 4 includes a description of data and a discussion of the empirical results. Section 5 concludes with the main findings of the paper and the relevant policy implications.

1. **Background**

Zambia ranks 139 out of 188 countries in the 2015 UNDP Human Development Report and is classified as a lower middle-income country by the World Bank (Cammelbeeck 2015). With sixty percent of its population below the poverty line and almost fifty percent malnourished, the country suffers from widespread poverty and food insecurity (Sitko et al. 2011).

The agricultural sector in the country comprises of roughly 1.5 million smallholders and 2,000 large-scale farmers. More than ninety percent of maize productions and eighty percent of total maize sales come from smallholder farms (Tembo et al. 2009). Maize production is not evenly distributed across farms. Around two percent of the small and medium farmers generate roughly half of maize output. A large number of small farm households are still net buyers of maize (Sitko et al. 2011). The dependence on the volatile rainfall and a lack of irrigation systems make the agricultural output extremely unstable. Years of drought, flood, and insufficient input supply, which represent on average one year out of three, lead to deficient maize production to satisfy food demand at the national level (Dorosh, Dradri, and Haggblade 2009). Since weather shocks are localized, specific production regions experience more severe shocks than others. Substantial production shortages result in the domestic maize price rising to the Republic of South Africa’s maize import parity (Myers and Jayne 2012). Trade is thus a potentially valuable tool to stabilize the domestic price.

However, past maize price fluctuations and the consequent social unrest have led the government of Zambia to believe food prices are far too strategically and politically important to leave to the market (Chapoto 2012). The government mistrusts private traders in their ability to bring in enough maize to stabilize the market (Myers and Jayne 2012). Individual traders, on the other hand, blame the government for implementing unpredictable policies on tariffs, import licenses, and maize import subsidies. Short-term export bans are often imposed to restrict maize outflows to ensure food security and access to food when the country experiences a maize production deficit. These export bans are usually carried out in an ad-hoc, stop-go nature (Chapoto & Jayne 2009). The effects of export bans on domestic price volatility are not apparent. While in some countries such as India, export bans appear to have decreased prices and price volatility (Baylis, Jolejole-Foreman, and Mallory 2013), in other countries such as Russia the restriction on exports actually increases the food price at the exporting market because of a higher transaction cost (Porteous 2012; Welton 2011).

Stockholding is expensive for developing economies, which makes trade the natural alternative. However, the uncertainties in imports and the transmission of shocks from other countries make trade a less reliable tool to address domestic food shortage. Besides, storage is needed to supply the market before imports arrive. Consequently, developing countries have been rethinking their policies on grain storage and dependence on international trade to secure domestic food security (Dorosh 2009). There were reports of Zambia traders suggesting to the government the existence of a sufficient amount of local stocks, which would make maize imports unnecessary (Chapoto 2012). However, the series of agricultural and trade policies that the government of Zambia has conducted in recent years suggest a turn to the option of building more grain stocks.

The Food Reserve Agency (FRA) was established in 1996 with the aim of building and managing national grain stocks (Govereh, Jayne, and Chapoto 2008). The buffer stocks are intended to stabilize maize price and provide available maize supply to the market. The FRA purchases substantial maize from small households in various geographic regions since the 2003/04 marketing year (corresponding to the study period in this paper). The high pan-territorial buying price (uniform price in the entire country ) makes the FRA the dominant buyer in the market (Mason and Myers 2013). In 2006 and 2007, the FRA bought more than half of the surplus maize by smallholder farmers (Ricker-Gilbert et al. 2013), which helps to build higher maize stocks. In part to protect the dominant market position of the FRA, the government implemented a series of policies including export bans, import tariffs, and imports through the FRA (Tschirley and Jayne 2010). According to grain traders, millers also get subsidized maize stocks from FRA. These measures to build higher stocks have led the national maize stocks to reach historically high levels after 2009 (shown in Figure 1).

1. **Method**

This study relies on differential amounts of FRA purchases to identify the effect of FRA purchases on local prices. These purchases though, are endogenous since the FRA tends to purchase more maize at locations that are in the surplus maize. To help explain how FRA purchases and sales affect retail maize prices, we set up the following model of demand and supply of maize in Zambia. Consider a system of demand and supply of maize as specified in equation (1) and (2):

Where is the supply of maize at district at time t, is the amount of net imports of maize at time t, and is the price of inputs and weather at district in the previous period respectively and is the farm gate price of maize in the previous year; is the demand for maize, affected by the current price of maize, the income of consumers and possible restrictions on export in place.

Equation (3) and (4) are factors associated with FRA activities:

Where is the distance weighted FRA sales of market at time t for its nearest miller, and is the price at the nearby miller location at time t. is the cost of transportation. The FRA purchase can be modeled as a function of past grain stocks and estimated current excess harvest or total storage target. is the pan-territorial FRA buying price set for the year. s

Consider retail maize price as a function of supply and demand of maize, where FRA purchases affect demand and FRA sales affect supply, as is shown in equation (5). Without the FRA, we would expect prices to go up by the cost of storage throughout the year and would be essentially the price of South African maize plus transport price in rural areas. The FRA purchase price is set once every year and stays the same in the entire crop year (May to April). The price is pan-territorial, meaning the price is the same for all districts in the country.

On the other hand, the FRA sales price varies month to month. With FRA increasing purchases at harvest and releasing those sales throughout the year, this should increase the price at harvest up to the FRA price, and lower the prices in urban areas during times when the stocks are sold, essentially 'flattening out' the price surface - both over time and space. As for variation between years, FRA purchases today are a function of current stocks (which can be proxied by FRA purchases from last year) and total country-wide harvest quantities.

With all these factors considered, we can estimate linear regressions of the following form to evaluate the effect of FRA purchase and FRA sales on price levels and price stability:

where Yit is price and price deviations at district i at time t, is a vector of weather variables from the previous growing season, is a vector of other covariates, and ei is a random error term. The coefficient of interest throughout the paper is a, the effect of FRA purchase on the prices. FRA\_sale is currently set as 0 for districts without any milling company, or the total FRA sales in the country in that month weighed by the number of millers in that district.

The potential problem with the above regression is the amount of current FRA purchase is endogenous to current prices . Using directly an OLS regression, we tend to overestimate the effect of FRA purchases on stabilizing the prices, since FRA purchase are typically made in places of surplus maize and price tend to be more stable. Also, it targets more sales during years of production shortfalls, which naturally would mean higher maize prices.

The Zambian government uses the Crop Forecast Surveys, conducted in the spring before harvest, to get an estimate of the local production for the major districts. This gives us the opportunity to have an instrument for purchases by the predicted output from the CFS while controlling for actual district level production shocks that are weather-related.

In this paper, we use an instrument for FRA purchases by using long-run shares of production for each district times the deviation of CFS expected total crop harvest from a long-run average to capture the annual purchase targets. By using this as an IV, we do not need to worry about yearly deviations from district to district affecting our instrumented FRA purchase amounts. The endogenous FRA purchase quantity is specified using the following equation:

Where is the average of production in district i as a percentage of the national harvest over the time from 1999 to 2011, is the deviation of each district’s predicted crop harvest from a long-run average of crop production. The coefficient of the instrumented FRA purchase is estimated via a two-stage least-squares method.

1. **Data and Variable**

Monthly Zambia maize prices observed from Jan. 2003 to Dec. 2008 from 32 different markets that spread out in different geolocations in Zambia (shown in Figure 1). There are considerable variations in the markets, including food demand, population, food production and cost of transportation. Price data were collected by the World Food Program and the Central Statistical Office in Zambia.

We generate measures of agriculturally-relevant precipitation from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset (Funk et al., 2015). We use the total amount of rainfall that fell during the October–April growing season. For the same season, we define the length of the longest dry spell as the number of continuous days with no rain. To measure the beginning of the rainy season, we calculate the number of days after October 1st in which rainfall more significant than 10 mm fell three days out of 5. These three variables are taken from the prior agricultural season to predict food availability for the June/July maize harvest.

Temperature data are from the African Drought Monitor, also limited to the maize growing season. We created average temperature during the growing season, growing degree days (number of days where the temp was between 8 to 32 C) and heat days (days temperature greater than 30 C) following Deschênes and Greenstone (2007). The weather measures used in this paper are more accurate and complete compared to only using precipitation as in Dorosh (2009) and Chaopoto and Jayne (2009b)

Annual Zambia FRA purchases from 2002 to 2009 by the district from the FRA. Yearly stock and crop acreage estimate from USDA. South African prices, net imports from South Africa from Johannesburg Stock Exchange and South African Reserve Bank. List of commercial millers working with the FRA from CSO.

Instrumental Variables To address the potential endogeneity of crop prices, we use one-year lagged corn stock as an instrumental variable for and one-year lagged s an instrument for the . Lagged stock is a valid instrumental variable for crop prices because, as illustrated in Wright (2011) and Roberts and Schlenker (2013), crop stocks in the previous year will affect the current year crop supply (i.e., lagged stock plus new production), and hence is correlated with expected crop prices. Farmers then respond to expected crop prices to make acreage decisions. There does not appear to be any evidence to suggest that lagged stocks will cause changes in current year acreage through channels other than crop prices. One concern with using lagged crop stock as an instrumental variable is the potential autocorrelation of the stock time series. if the crop stock time series is autocorrelated then the lagged crop stock will be more likely to be correlated with the current error term, and therefore the exclusion restriction for lagged stock as a valid instrument will be violated. The national-level stocks are less prone to autocorrelation than the state-level crop stocks are, because local shocks on stocks may cancel each other across regions. Therefore, we

To address the potential endogeneity of the we use the interaction term between the

We believe that this instrument is valid for the following reasons. . affects crop acreage by affecting and does not directly

Second, the amount of is expected to be correlated with the

. The spatial variation in railroads will be absorbed by county fixed effects and the temporal variation of national mandates will be absorbed by the time trend variables; this would weaken the explanatory power of these variables individually if included with county and year variations.

In the regression analyses, we use the Kleibergen-Paap rk LM test to detect underidentification and use the Cragg-Donald Wald F statistic and the Kleibergen-Paap Wald rk F statistic to examine if the instruments are weak. Over-identification does not apply here because we have exactly the same number of instruments as the endogenous variable

1. **Main Results**
2. Full sample, two endogenous variables

Fra no fra

Fra exist

Interpretation of markets

Within a monthly, effects (spatial weights) , dissipate

In lusaka and choma, a km , marginal effect at nearest market

Marginal effect is the same ( one ton of sale in

Livingstone sales effect \* distance\_weighting

Fewer

Regions ( province) central, southern, eastern

Consumer province

Focus on the purchase (

To address the endogeneity of the ethanol capacity and price variables, we apply a panel data instrumental variable estimator with county fixed effects. Specifically, we use an interaction term between railroad density associated with a county and volume of ethanol mandated under the Renewable Fuel Standard (RFS) as an instrument for the effective ethanol capacity variable. Output prices are instrumented by using lagged stocks of corresponding crops and the input price variable (fertilizer index in this study) is instrumented by using natural gas price. We explain the rationale for the choice of instruments in the next section. Furthermore, we employ fixed effects models to control for unobserved time-invariant factors that might affect ethanol plant locations such as a county’s geographical location. As robustness checks, we also use different

The correlation of IV and FRA purchase is quite small since it is an interaction term, perhaps also interact that with one of the rainfall variables?

The flip of signs on the FRA purchase and FRA sales

For each regression models, we estimate four specifications as follows. Model (1) is a fixed effects (FE) model, which assumes that all variables are exogenous. Model (2) is a fixed-effects model with instrumental variables (IVs) (FE-IV) and is the preferred model because it controls for endogeneity of various explanatory variables as described above. Models (3) and (4) are the same as Model (2) except that Model (3) excludes effective ethanol capacity as an explanatory variable whereas Model (4) excludes crop price. Estimating Models (3) and (4) allows us to examine the presence of omitted variable bias when either crop price or ethanol capacity are excluded as determinants of crop acreage over the 2003- 2014 period.

Hausman’s endogeneity tests

the Hausman’s endogeneity test does not reject the null hypothesis

that the fertilizer price index is exogenous in the total acreage models.

Results from Hausman’s endogeneity tests for crop price, effective ethanol capacity, and fertilizer price index show that both crop price and effective ethanol plant capacity are endogenous across all the models (p-value < 0.05). For the fertilizer price index, results show that we can reject the null hypothesis that the variable is exogenous (p-value < 0.05) but we fail to reject this null hypothesis in the total acreage models (p-value = 0.1661).

Table 2 presents the regression results By comparing results under Model (1) and those under Model (2) we can see that ignoring the endogeneity of price variables and of effective ethanol capacity will attenuate the estimated coefficients toward zero, underestimating the true underlying effects. When we do not control for effective ethanol plant capacity, we find that a one-dollar increase in corn received price (or about 8.6% of average ) (see Model (3)). If we do not control Both of these effects are significantly larger than those obtained in Model (2), indicating a positive omitted variable bias due to the positive correlation between All the models that involve instrumental variables in Table 2 pass the under-identification test and weak instruments tests. The p-values of the Kleibergen-Paap rk LM statistic are much smaller than the critical value of 0.01 showing that we can reject the null of no correlation between the endogenous variables and the instrumental variables at 1% significance level. Moreover, the Cragg-Donald F Wald statistic and Kleibergen-Paap Wald rk F statistic are much larger than 10 in most cases, indicating that we can safely reject the null hypothesis that the instrumental variables are just

weakly correlated with the endogenous variables (Stock and Yogo 2005).16 Associated first stage results of the regressions are presented in Appendix B

Results under Model (2) in Table 2, the preferred model for , show that effective have positive and statistically significant effect . We find that, all else equal, if effective ethanol plant capacity in a county increases by

then in this county will increase by (or by about 2.2% if evaluated at sample mean of county ). A one-dollar increase in

which represents about a 30% increase in average will . Both

have a negative and statistically significant effect on . April precipitation has a statistically significant and negative impact on all specifications, which is intuitive May precipitation has a positive and statistically significant effect on . The magnitude of May precipitation’s effect is much smaller than that of April

Robustness Tables 4 and 5 investigate the robustness of the effects of crop prices and effective ethanol capacity on , respectively.17 We find that the results are robust to various specifications of explanatory variables, instrumental variables, and datasets.

We first examine the robustness of the results of the model (i.e., Model (2) in Table 2) to an unbalanced panel dataset in which a county-year observation is

To check the robustness of the aggregate acreage results with respect to county selection in the sample, we further remove county-years with zero aggregate crop acreage from the dataset and then conduct the analysis with everything else being the same as that in Model (2) of Table 3. The results presented in column (2) of Table 5 are robust to this change in the data. Estimates in column (3) show that using state-level aggregated crop stocks as an instrument for the price index only creates a negligible change in the estimated coefficient of effective ethanol capacity (0.604 vs. 0.599), although it increases the estimates of the price index coefficient from 4.484 to 5.656, when compared with Model (2) in Table 3. Lastly, to be in which the fertilizer price index is treated as endogenous, we also estimate the aggregate acreage regression by treating the fertilizer price index as endogenous and by using natural gas price as its instrument. Results are presented in column (4) of Table 5. We find that our results are robust to this change in specification

1. Conclusion

We with a nationwide county-level panel dataset for 2,535 counties over 2003-2014. Our empirical methods allow us to identify the causal effects of ethanol plant proximity and separate these effects from those of crop prices. By covering the 2003-2014 period over which there was substantial fluctuation in crop prices we also examine the extent to which changes in land use due to crop 36 prices. This study differs from the existing literature that has focused on analyzing the direct on land use in its vicinity without explicitly controlling for the effect of crop prices. Given the small but positive correlation between crop prices and countylevel effective ethanol production capacity, our study avoids the omitted variable bias that results in an overestimate of the paper. We leave the analysis of the dynamic effects on crop prices and therefore on land use change to future research

Table 1. Summary Statistics of Variables

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variables | Mean | SD | Min | Max | |
| **Dependent variables** |  |  |  |  | |
| **Production Region** |  |  |  |  | |
| Maize Price (ZMK/ kg) | 550.8408 | 187.2261 | 273 | 1555.6 | |
| Price Deviation Squared | 26342.1 | 66859.62 | 0.5480205 | 674142.8 | |
| FRA Purchase (MT) | 490.7945 | 1255.856 | 0 | 10310.93 | |
| FRA Sales (MT) | 1.467864 | 4.933344 | 0 | 45.03602 | |
| **Consumer Region** |  |  |  |  | |
| Maize Price (ZMK/ kg) | 585.834 | 178.1781 | 235.3799 | 1333.3 | |
| Price Deviation Squared | 25964.17 | 43397.3 | 0.029471 | 390981.3 |
| FRA Purchase (MT) | 135.2461 | 469.6014 | 0 | 7297.968 | |
| FRA Sales (MT) | 7.036251 | 38.99964 | 0 | 655.8752 | |
| **Explanatory variables** |  |  |  |  | |
| Days without rain | 27.453 | 11.520 | 1.000 | 56.000 | |
| Precipitation(mm) | 1068.551 | 197.276 | 550.444 | 1640.263 | |
| Mean Temperature (°C) | 24.918 | 0.837 | 23.220 | 27.064 | |
| Heat days | 3.885 | 5.457 | 0.000 | 28.000 | |
| SAFEX Price (ZMK/ kg) | 789.909 | 217.037 | 468.753 | 1279.758 | |
| **Instrumental variables** |  |  |  |  | |
| **Production Region** |  |  |  |  | |
| Predicted purchase target | 7952.964 | 25715.57 | 0 | 216272 | |
| Predicted sales target | 3548.906 | 10050.16 | 0 | 86699.47 | |
| **Consumer Region** |  |  |  |  | |
| Predicted purchase target | 951.905 | 3854.722 | 0.000 | 53200.760 | |
| Predicted sales target | 1214.412 | 3740.181 | 0.000 | 32649.990 | |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variables | Mean | SD | Min | Max |
| **Dependent variables** |  |  |  |  |
| Maize Price (ZMK/ kg) | 573.8051 | 182.0592 | 235.3799 | 1555.6 |
| Price Deviation Squared | 26094.09 | 52640.71 | 0.029471 | 674142.8 |
| **Key variables** |  |  |  |  |
| FRA Purchase (MT) | 257.4658 | 845.5297 | 0 | 10310.93 |
| FRA Sales (MT) | 5.122118 | 31.83187 | 0 | 655.8752 |
| **Explanatory variables** |  |  |  |  |
| Days without rain | 27.453 | 11.520 | 1.000 | 56.000 |
| Precipitation(mm) | 1068.551 | 197.276 | 550.444 | 1640.263 |
| Mean Temperature (°C) | 24.918 | 0.837 | 23.220 | 27.064 |
| Heat days | 3.885 | 5.457 | 0.000 | 28.000 |
| SAFEX Price (ZMK/ kg) | 789.909 | 217.037 | 468.753 | 1279.758 |
| **Instrumental variables** |  |  |  |  |
| **Production Region** |  |  |  |  |
| Predicted purchase target | 3358.519 | 15746.14 | 0 | 216272 |
| Predicted sales target | 2016.894 | 6715.656 | 0 | 86699.47 |

Table 2: IV Regression of Maize Price

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | | (1) | | (2) | | (3) | (4) |
| Price | | FE | | FE+IV | | FE+IV  Production Region | FE+IV  Consumer Region |
| FRA Purchase | 0.022\*\*\* | | 0.030\*\*\* | | 0.029\*\*\* | 0.046\*\*\* | |
|  | (0.003) | | (0.010) | | (0.008) | (0.017) | |
|  |  | |  | |  |  | |
| FRA Sales | -0.447\*\*\* | | -7.848\*\*\* | | -19.479\*\*\* | -3.523\*\*\* | |
|  | (0.130) | | (1.631) | | (4.364) | (0.436) | |
|  |  | |  | |  |  | |
| Days without rain | 2.232\*\* | | 2.502\*\* | | 1.178 | 2.768\*\*\* | |
|  | (0.920) | | (1.071) | | (1.063) | (0.979) | |
|  |  | |  | |  |  | |
| Precipitation | 0.117 | | 0.124\*\*\* | | -0.109\* | 0.170\*\*\* | |
|  | (0.065) | | (0.047) | | (0.058) | (0.038) | |
|  |  | |  | |  |  | |
| Mean Temperature | -157.829\*\*\* | | -196.870\*\*\* | | -228.225\*\*\* | -159.419\*\*\* | |
|  | (22.366) | | (23.743) | | (27.605) | (17.672) | |
|  |  | |  | |  |  | |
| SAFEX Price | -0.337\*\*\* | | -0.373\*\*\* | | -0.500\*\*\* | -0.301\*\*\* | |
|  | (0.051) | | (0.035) | | (0.037) | (0.029) | |
|  |  | |  | |  |  | |
| Heat Days | -0.694 | | 0.034 | | 7.050\*\*\* | -4.623\*\* | |
|  | (2.772) | | (2.255) | | (2.536) | (1.830) | |
|  |  | |  | |  |  | |
| Trend | -30.908\*\*\* | | -20.791\*\*\* | | -22.873\*\*\* | -24.458\*\*\* | |
|  | (3.292) | | (5.030) | | (5.213) | (3.705) | |
| N | | 2304 | | 2304 | | 792 | 1512 |
| Cluster | | 32 | | 32 | | 11 | 21 |
| *Anderson canon. corr. LM statistic* | | - | | 27.913 | | 70.473 | 110.817 |
| *Cragg-Donald Wald F statistic* | | - | | 13.815 | | 37.213 | 58.209 |

Notes: Standard errors in parentheses. \* *p* < 0.10, \*\* *p* < 0.05, \*\*\* *p* < 0.01

Specifications of the models: (1): FE, (2): FE-IV (Instrumental variables), (3) Cragg-Donald Wald statistic and Kleibergen-Paaprk Wald statistic are distributed as chi-squared with degrees of freedom of 1.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
| Price | FE | FE+IV | FE+IV | FE+IV |
| FRA Purchase | 0.011\*\* | 0.016\*\* | 0.017\*\*\* | 0.021\*\*\* |
|  | (0.003) | (0.007) | (0.007) | (0.007) |
|  |  |  |  |  |
| FRA Sales | -0.382\*\* | -5.673\*\*\* | -5.513\*\*\* | -5.522\*\*\* |
|  | (0.125) | (1.296) | (1.293) | (1.203) |
|  |  |  |  |  |
| Lag price | 0.552\*\*\* | 0.502\*\*\* | 0.487\*\*\* | 0.441\*\*\* |
|  | (0.074) | (0.032) | (0.031) | (0.033) |
|  |  |  |  |  |
| Year Dummy  Weather Vars  Net Imports | No  Yes  No | No  Yes  No | No  Yes  Yes | Yes  No  Yes |
| N | 2232 | 2232 | 2232 | 2232 |
| Cluster | 32 | 32 | 32 | 32 |
| *Anderson canon. corr. LM statistic* | - | 25.007 | 24.128 | 27.983 |
| *Cragg-Donald Wald F statistic* | - | 12.362 | 11.917 | 13.845 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
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Table 3: IV Regression of Maize Price Deviation

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
| Price Deviation | FE | FE+IV | FE+IV  Production Region | FE+IV  Consumer Region |
| FRA Purchase | 3.919\*\*\* | 4.257 | 4.851 | 5.657 |
|  | (1.103) | (2.609) | (3.471) | (4.676) |
|  |  |  |  |  |
| FRA Sales | -33.934 | -1449.359\*\*\* | -4267.616\*\* | -588.358\*\*\* |
|  | (21.409) | (416.052) | (1788.112) | (117.839) |
|  |  |  |  |  |
| Days without rain | 1148.854\*\*\* | 1186.421\*\*\* | 1965.170\*\*\* | 582.973\*\* |
|  | (251.948) | (273.061) | (435.533) | (264.881) |
|  |  |  |  |  |
| Precipitation | 50.409\*\*\* | 51.556\*\*\* | 20.285 | 64.725\*\*\* |
|  | (12.734) | (12.001) | (23.656) | (10.219) |
|  |  |  |  |  |
| Mean Temperature | -10651.414 | -18320.487\*\*\* | -36332.117\*\*\* | -9517.163\*\* |
|  | (8572.316) | (6055.183) | (11312.209) | (4779.315) |
|  |  |  |  |  |
| SAFEX Price | -29.177\*\*\* | -35.643\*\*\* | -24.537 | -42.999\*\*\* |
|  | (7.041) | (8.990) | (15.045) | (7.824) |
|  |  |  |  |  |
| Heat Days | 15.823 | 126.983 | 2103.008\*\* | -1004.714\*\* |
|  | (619.203) | (575.206) | (1039.109) | (494.835) |
|  |  |  |  |  |
| Trend | -6565.623\*\* | -4550.044\*\*\* | -8831.587\*\*\* | -2906.360\*\*\* |
|  | (2343.967) | (1282.693) | (2136.339) | (1002.133) |
| N | 2304 | 2304 | 792 | 1512 |
| Cluster | 32 | 32 | 11 | 21 |
| *Anderson canon. corr. LM statistic* | - | 27.913 | 70.473 | 110.817 |
| *Cragg-Donald Wald F statistic* | - | 13.815 | 37.213 | 58.209 |

Table 4. Robustness Checks for Determinants

Table 5. Changes in price due to changes in FRA purchases in Different Periods

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | 2003-2014 | 2003-2012 | 2008-2014 | 2008-2012 |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |

Table A2. Autocorrelation tests

Figure 1. Map of Major District Markets in Zambia

A close up of a map

Description generated with high confidence

Figure 2. Monthly shares of FRA purchase and sales

In this appendix we describe the autocorrelation tests for crop stocks and that are used as instrumental variables in the regressions. We consider three types of autocorrelation tests here: the Durbin-Watson test, white noise test, and a Wooldridge type test. The DurbinWatson test is performed by following Roberts and Schlenker (2013, footnote 17 on page 2275). Specifically, we first regress a variable on a linear time trend and then perform the DurbinWatson test by using Stata command “estat durbinalt”. The white noise test is performed by Stata command “wntestq”. The Wooldridge type test is based on Wooldridge (2002, p.282) who use the following property of a time series to test if it is not autocorrelated. That is, if a time series , {1,..., } t u t ∈ T is not autocorrelated, then its first-order difference, t tt 1 e u u − ≡ − , satisfies 1 cov( , ) 0.5. t t e e − = − See Drukker (2003) for more details about this test. The Durbin-Watson test and the white noise test used here are not applicable to panel data; so we do not have the pvalues of these two tests for the state-level data which are in panel format. The test results are presented in Table A1 below

Table A1. p-values of autocorrelation tests for crop stocks and yield shocks (null hypothesis: no autocorrelation)

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Durbin-Watson | White noise test | Wooldridge type test |

Table A2. First stage results for

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  |  |  |  |  |