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Modeling Spatial Price Volatility and Transmission: A Spatial Panel VAR Model for Cereal Price Across East African Community

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ABSTRACT

This paper adopts and explains the application of Panel Vector Autoregressive (PVAR) and Spatial Panel Vector Autoregressive (SPVAR) models to econometrically analyze food price volatility and transmission across countries members of East African Community (EAC). Results revealed that it takes time for spatial effects to influence the price happening at markets and results suggests that price volatility and transmission are more predictable in prices with spatial effects than in those without spatial effects. Impulse response functions show that a one unit shock in one cereal market create persistent and positive cereal price variations in that market and in the other markets. Variance decomposition results show that in terms of 100% variations caused by a one unit shock in the price of cereals at one market create strong variations that, in short and long-run, are reverberated in the price of cereals in the other markets. Two policy implications may flow from this paper: on one hand, policy makers should take measures to stabilize food prices across the EAC in order to ensure food access in the region; on the other hand, trade policies should be formulated considering the gains of trading with the near-neighboring markets in order to avoid delayed spatial effects on price volatility and transmission. The last, is explained by the fact that when a market j is not a neighbor of market i the delayed spatial effects depends on the number of neighboring markets between markets j and market i and on the price prevailing on those markets.

Keywords: Cereals, price volatility and transmission, PVAR and SPVAR, EAC.

PAPER

1. Introduction

Food price volatility is one of the most pressing problems to ensure food security in EAC. Food price volatility in EAC results from four main factors. First, the population growth in EAC is high which has a medium and long term effects on food demand in EAC. Second, EAC as other parts of the world experiences climate change, hence the accumulated effects of impact born from and/or caused by climate variability, result in crop yield and production instability. Third, the link between global food price volatility and agricultural production. From the combined effects of population and climate variability, EAC partner states became more reliant to one each other and to the world market especially in terms of cereals demand. Fourth, the food price volatility as result of spatial effects. Geographical location can determine food price volatility and transmission across the EAC because variations in the distance between a costal country i and non coastal country j or between country i neighbor/far from country j determines the cost of transport between those two countries i and j.

Therefore, this study tries to explore cereals price volatility and transmission among five countries of six member states of EAC (Burundi, Kenya, Rwanda, Uganda and Tanzania) and South Sudan is not included in the current analysis. These countries were chosen based on three dimensions. First, they are in the same community which has implement different agricultural policies to increase cereals productivity and with a common import tariff. Second, they are linked by two commercial corridors (the northern and central corridors) that can facilitate easy market integration in EAC and intra-imports of cereals. Third, they are different in terms of surface, population density and location which may define differences in the level of cereals production and demand across EAC member states and then trade level with the world market determined by the factor that coastal countries (Kenya, Tanzania) have easy access to world market than non-coast countries (Burundi, Rwanda and Uganda).

Given these three dimensions, this study aims to answer the following three main questions: i) Does the volatility in the market price of cereals occurs at the same degree in those five countries? ii) Is there any interrelationship between domestic markets price volatility and transmission in those countries? And iii) If there is any price transmission, what is the speed of cereal price adjustment from price variations caused by a one unit shock in one market to cereal price short-run and long-run equilibrium in other markets and in that market its self?

2. Methodology and data

The literature, James (1998), Michael and Daniel (2005), Michael and Daniel (2007), Jan (2009), Shuai (2012), Fabio and Matteo (2013), has shown the increasing use of PVAR and SPVAR models in measuring volatility and transmission in financial time series. This paper adopts and explains the application of PVAR and SPVAR models with multiple commodities to econometrically analyze food price volatility and transmission across countries members of EAC. The application of Panel VAR model with multiple commodities allows us to combine food commodities and countries to estimate price volatility and transmission. The PVAR and SPVAR models adopted in this paper are panel in the price of commodities at each market (in

this paper we consider each country member of EAC as a market) "Pc_{it}" where P stands for price and c stand for country/market and $\{Pc_{it}$: Price of i^{th} commodity at time t in country/market $c\}$.

Hence the PVAR model of lag 2 can be specified as:

$$Pc_{it} = V + \beta_1 Pc_{it-1} + \beta_2 Pc_{it-2} + u_{it} (1)$$

where i represents different prices of cereal commodities (wheat, rice, maize, and sorghum); V is the vector of cereal price effect at each market (*Pb = cereal price at Burundi market, Pk = cereal price at Kenya market, Pr = cereal price at Rwanda market, Pu = cereal price at Uganda market, and Pt = cereal price at Tanzania market*); β_1 and β_2 are the coefficients of variables (*Pb, Pk, Pr, Pu and Pt*) in lag(1) and lag(2) and u_{it} is the vector of error terms.

The SPVAR of lags 2 can be specified as:

$$Pc_{it} = V + \beta_1 S_1 Pc_{it-1} + \beta_2 S_1 Pc_{it-2} + u_{it} \text{ and } u_{it} = S_2 e_{it} \qquad (2)$$

where S_1 and S_2 are fixed matrix of spatial weights. In this SPVAR model, only the neighbors have dynamic repercussion on market c within one period while the rest is assumed to have negligible effects. SPVAR structure implies that a shock originating in market c can be transmitted after one period to market k if market k is a neighbor of market c. However, if market k is not a neighbor of market c, delayed effects are longer and will depends on how many markets are between market k and market c.

All the original data used in this paper are available and calculated from online database of the FAO that publishes data on the price of agricultural commodities. We consider to use the annual average of the producer price of four cereal commodities at five markets. We choose the sample period covering 1991 to 2014. For incomplete series like Uganda series, the price were sourced from other different sources and extrapolation and interpolation techniques were used to estimate the price of incomplete series. For the purpose of analysis, the price of each i cereal commodity is expressed in USD per Kg. A part from the actual price of cereals used in this paper, this paper acknowledge the effect of spatial distribution of markets across EAC on price volatility and transmission, here to capture the spatial effects we estimate the new prices at each market with spatial effects Pc_{it}^{*} (See Annex 1: Extended methodology).

3. Empirical findings and discussion

3.1. Unit root test

In order to infer the degree of integration and stationary properties of the respective variables and uncover if there are possibilities for undertaking panel co-integration tests, we rely on Pesaran (CIPS, 2007) test. Results in Table 1 reject the null hypothesis that all series are I(1) at 5% and 10% (without and with trend) in prices without spatial effects and at 1% and 5% (without and with trend) level of significance in prices with spatial effect. Therefore, cereal price at all the five markets are I(0). The precondition to test for cointegration is that all of the series must be integrated of order 1 "I(1)". However, as our data are integrated of order Zero "I(0)" we proceed with VAR and there is no evidence of testing for co-integration and then proceed with VECM. As we are using panel data, in this paper we estimate a panel VAR model and a Spatial Panel VAR both of lags(2) in the next section of this paper.

Table 1 - Pesaran (2007) Panel Unit Root test (CIPS)

	Without spatial effect		With spatial effect	
Variable	Without trend	With trend	Without trend	With trend
Pb	-2.339 (0.010)	-1.337 (0.091)	-3.490 (0.000)	-2.538 (0.008)
Pk	-3.558 (0.000)	-2.366 (0.009)	-3.248 (0.001)	-2.093 (0.018)
Pr	-3.373 (0.000)	-2.267 (0.012)	-2.533 (0.006)	-1.996 (0.023)
Pu	-3.197 (0.000)	-2.304 (0.011)	-3.289 (0.001)	-2.492 (0.006)
Pt	-2.796 (0.000)	-1.718 (0.043)	-3.807 (0.000)	-2.710 (0.003)

3.2. PVAR and SPVAR models estimation

We estimate PVAR and SPVAR using a least squares dummy variable estimator. The estimator fits a multivariate panel regression of each dependent variable on lags of itself and on lags of all the other dependent variables. The analysis of the PVAR and SPVAR models can be divided into three parts. First, PVAR and SPVAR by least squares dummy variable estimator method estimate model coefficients to explain the relationship among variables. Second, they estimate impulse response functions to draw the figures of dynamic shock responses, from which we can observe the dynamic changes of each variable under different shocks. Finally, they estimate result of variance decompositions for each variable, to evaluate the contributions of different stochastic shocks on the variables in the PVAR and SPVAR systems.

On one hand, when spatial effects are not taken into account, PVAR results in Table 2can be summarized under five headings:

- When Burundi cereal market is taken as dependent variable, a one unit shock at Burundi market one time back and Uganda market two time back increase the current cereal price at Burundi market to some degree (0.898 and 1.214) while a one unit shock at Kenya market two time back decreases the current cereal price in Burundi (-0.55).

- When Kenya cereal market is taken as dependent variable, a one unit shock at Kenya market one time back increases the current cereal price in Kenya at some degree (0.731).

- When Rwanda cereal market is taken as dependent variable, a one unit shock at Burundi market two time back decreases the current cereal price in Rwanda (-0.653).

- When Uganda cereal market is taken as dependent variable, a one unit shock in Burundi market two time back decreases the current cereal price in Uganda(-0.461).

- When Tanzania cereal market is taken as dependent variable, a one unit shock at Rwanda market one time back decreases current cereal price in Tanzania (-0.293).

On the other hand, when spatial effects are taken into account, results in Table 2can be summarized under four headings

- When Burundi cereal market is taken as dependent variable, a one unit shock in at Burundi market two time back increases the current cereal price in Burundi (0.785).

- When Kenya cereal market is taken as dependent variable, a one unit shock at Kenya market two time back increase the current cereal price in Kenya (2.681) while a one unit shock at Rwanda market and Uganda market decreases the current cereal price in Kenya to some degree respectively of -2.424 and 2.340.

- When Rwanda cereal market is taken as dependent variable, a one unit shock in cereal price at Kenya, Tanzania and Burundi markets two time back increase the current cereal price in Rwanda (2.89, 1.67 and 0.55), while a one unit shock at Uganda and Rwanda markets two time back decrease the current cereal price in Rwanda (-2.606 and -2.545).

- When Tanzania cereal market is taken as dependent variable, a one unit shock at Burundi and Tanzania markets two time back increase the current cereal price in Tanzania (0.715 and 1.650) while a one unit shock at Uganda and Rwanda markets two time back decrease the current cereal price in Tanzania (-2.281 and -2.608).

Table 2 - Estimation results of PVAR and SPVAR

	Independent variable	Dependent variable: Pb		Pk		Pr		Pu		Pt	
		Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t
Without Spatial Effect	l1_Pb	0.898	0.003	0.082	0.754	0.049	0.906	0.260	0.244	0.369	0.150
	l1_Pk	0.361	0.278	0.731	0.015	-0.232	0.616	0.218	0.381	0.445	0.122
	l1_Pr	-0.026	0.892	-0.054	0.752	0.077	0.775	-0.069	0.634	0.265	0.113
	l1_Pu	-0.559	0.458	0.038	0.955	1.713	0.106	0.555	0.327	-0.696	0.285
	l1_Pt	0.062	0.698	0.183	0.200	0.114	0.609	0.023	0.847	0.335	0.017
	l2_Pb	-0.437	0.119	-0.276	0.267	-0.653	0.096	-0.461	0.030	-0.393	0.104
	l2_Pk	-0.553	0.074	-0.201	0.463	-0.266	0.535	-0.372	0.109	-0.426	0.109
	l2_Pr	-0.188	0.295	-0.119	0.453	0.386	0.124	-0.040	0.765	-0.293	0.059
	l2_Pu	1.214	0.093	0.812	0.205	-0.083	0.934	0.860	0.112	0.966	0.120
	l2_Pt	0.042	0.808	-0.165	0.285	-0.238	0.324	-0.097	0.457	0.066	0.656
	cons	0.090	0.004	0.010	0.703	0.080	0.061	0.053	0.021	0.088	0.001
With Spatial Effect	l1_Pb	0.130	0.769	-0.467	0.139	-0.569	0.072	-0.437	0.227	-0.576	0.085
	l1_Pk	0.599	0.776	-0.770	0.607	-1.485	0.323	0.369	0.830	0.228	0.885
	l1_Pr	-0.056	0.975	1.170	0.361	2.002	0.120	0.145	0.921	0.483	0.721
	l1_Pu	-0.364	0.849	1.221	0.371	1.499	0.273	0.589	0.707	0.325	0.821
	l1_Pt	0.910	0.482	-0.303	0.742	-0.634	0.491	0.473	0.654	0.645	0.507
	l2_Pb	0.785	0.071	0.465	0.131	0.554	0.074	0.577	0.104	0.715	0.030
	l2_Pk	1.930	0.334	2.681	0.061	2.888	0.044	2.012	0.218	2.315	0.125
	l2_Pr	-2.430	0.159	-2.424	0.049	-2.545	0.039	-2.325	0.100	-2.608	0.046
	l2_Pu	-1.899	0.297	-2.340	0.073	-2.606	0.047	-1.895	0.204	-2.281	0.098
	l2_Pt	1.148	0.366	1.524	0.093	1.672	0.066	1.337	0.199	1.650	0.086
	cons	0.084	0.008	0.071	0.002	0.077	0.001	0.059	0.021	0.058	0.014

When results without spatial effects are compared with results that account spatial effects, it is clear to say that the level of two time back to predict variations in the current cereal price across countries member of EAC increases and the number of markets influencing the variations in the current price of cereal at any given market also increases. The typical examples can be taken at Kenya, Rwanda and Tanzania markets. This can be summarized under two headings:

- Results show that it takes time for spatial effects to influence the current price happening at markets (most significant effects are those from two time back from the current price).

- Results also demonstrates that the effects of price variations in one market to the price variations in the other market are high with spatial effects than those estimated without spatial effects. This suggests that price volatility and transmission are more predictable in prices with spatial effects than in those without spatial effects.

3.3. Impulse Response Functions

In order to assess the two-way cereal price effects among Burundi, Kenya, Rwanda, Uganda and Tanzania cereal markets, we compute impulse-response functions of the PVAR and SPVAR models. The usefulness of Impulse Response Functions is to describe the reaction of one variable to innovations in another variable of the system, while holding all other shocks equal to zero. In Annex 3, we present impulse-response functions plots, response being absorbed during 30 periods ahead and their results can be summarized as follows:

In cereal price without spatial effects,

- A one unit shock at Burundi market causes positive and measurable cereal price variations in all other four markets which effects may die out in long-run.

- A one unit shock at Kenya market causes positive and measurable cereal price variations in all other four market which effects may not die out in the long-run and remain positive.

- A one unit shock at Rwanda causes positive and measurable variations cereal price variations in all other four market which effects may die out in the long-run and remain positive.

- A one unit shock at Uganda market causes positive and measurable cereal variations in all other markets which variations effects may die out in the long-run.

- A one unit shock at Tanzania market causes negative and measurable cereal price variations in all other markets which variations effects may die out in the long-run.

In cereal price with spatial effects:

- A one unit shock at Burundi market causes positive and considerable cereal price variations in all other four markets which effects may not die out in the long-run and remain positive.

- A one unit shock at Kenya market causes positive and considerable cereal price variations in all other four markets which variations effects may totally die out in the long-run.

■ A one unit shock at Rwanda market causes positive but not considerable cereal price variations in all other four markets which effects may quickly and totally die out in short-run.

■ A one unit shock at Uganda market causes positive and considerable cereal price variations in all other four markets which effects may not die out in long-run and remain positive.

■ A one unit shock at Tanzania market causes positive and considerable cereal price variations in all other four markets which effects may not die out in long-run and remain positive.

Impulse response functions show that a one unit shock in one cereal market create persistence and positive variations in cereal price at that market its self and at the other markets. The only exceptions were observed when Tanzania is taken as impulse in only cereal prices without spatial effect and when Rwanda cereal market is taken as impulse in only cereal prices with spatial effects.

3.4. Variance Decompositions

Based on the impulse response function above, we can evaluate the relative importance of different structural shocks to endogenous variables by measuring the contributions of shocks on the variance changes of variables. Table 7 reports variance decompositions derived from the orthogonalized impulse-response coefficient matrices. The variance decompositions display the proportion of movements in the dependent variables that are due to their own shocks versus shocks to the other variables, which is done by determining how much of an s-step ahead forecast error variance of mean squared error (MSE) for each variable is explained by innovations to each explanatory variable (we report S until 30). From Table 3, we can highlight five following points:

■ A shock in cereal price in Burundi has the biggest impact on the variations of cereal price in Burundi in both short-run and long-run with a gradual declining trend. With spatial effect, a shock in Burundi, Kenya and Uganda has the biggest impact on the variations of cereal price in Burundi when compared to a shock in other markets.

■ A shock in cereal price in Kenya and Uganda has the biggest impact on the variations of cereal price in Kenya in both short-run and long-run. With spatial effect, a shock in Kenya and Rwanda has the biggest impact on the variations of cereal price in Kenya compared to a shock in other markets.

■ A shock in cereal price in Rwanda and Tanzania has the biggest impact on the variations of cereal price in Rwanda in both short-run and long-run. With spatial effect, a shock in Rwanda and Tanzania has the biggest impact on the variations of cereal price in Rwanda when compared to a shock in other markets.

■ A shock in cereal price in Rwanda, Uganda, Kenya, Tanzania, and Burundi has the biggest impact on the variations of cereal price in Uganda in both short-run and long-run. With spatial effect, a shock in Uganda, Tanzania, Kenya, Burundi and Rwanda has the biggest impact on the variations of cereal price in Uganda both in short-run and long-run.

■ A shock in cereal price in Tanzania has the biggest impact on the variations of cereal price in Tanzania in both short-run and long-run. With spatial effect, a shock in Uganda, Tanzania, Kenya, Burundi and Rwanda has the biggest impact on the variations of cereal price in Tanzania both in short-run and long-run.

Table 3 - Variance decomposition

		Without Spatial Effect					With Spatial effect				
		Pb	Pk	Pr	Pu	Pt	Pb	Pk	Pr	Pu	Pt
Pb	10	0.466	0.012	0.007	0.504	0.010	0.033	0.025	0.006	0.111	0.825
Pk	10	0.047	0.263	0.002	0.681	0.009	0.028	0.136	0.006	0.144	0.686
Pr	10	0.035	0.075	0.062	0.806	0.023	0.024	0.240	0.083	0.097	0.557
Pu	10	0.071	0.108	0.011	0.800	0.010	0.025	0.053	0.004	0.182	0.736
Pt	10	0.063	0.072	0.030	0.611	0.223	0.019	0.088	0.015	0.175	0.702
Pb	20	0.402	0.021	0.006	0.561	0.010	0.022	0.013	0.003	0.113	0.848
Pk	20	0.039	0.172	0.007	0.768	0.015	0.019	0.076	0.004	0.136	0.764
Pr	20	0.024	0.072	0.051	0.824	0.029	0.018	0.145	0.048	0.111	0.679
Pu	20	0.049	0.094	0.015	0.824	0.017	0.017	0.030	0.002	0.153	0.797
Pt	20	0.054	0.074	0.026	0.675	0.171	0.014	0.050	0.008	0.151	0.776
Pb	30	0.371	0.025	0.007	0.585	0.012	0.019	0.010	0.002	0.114	0.855
Pk	30	0.033	0.147	0.011	0.790	0.019	0.017	0.056	0.003	0.132	0.793
Pr	30	0.021	0.071	0.048	0.829	0.032	0.016	0.111	0.036	0.113	0.724
Pu	30	0.041	0.089	0.018	0.831	0.021	0.015	0.022	0.002	0.144	0.817
Pt	30	0.048	0.074	0.026	0.701	0.151	0.013	0.037	0.006	0.142	0.801

In terms of 100% variations along 30 steps ahead from the current price caused by a one unit of shock in the price of cereals at each market, results can be summarized under five headings:

- From a one unit shock at Burundi market, strong variations are reverberated in the price of cereals in Burundi and Uganda in the price without spatial effects, while with spatial effects strong variations are reverberated in the price of cereals in Tanzania.

- From a one unit shock at Kenya market, strong variations are reverberated in the price of cereals in Uganda and somehow in Kenya in prices without spatial effects, while with spatial effects strong variations are reverberated in the price of cereals in Tanzania.

- From a one unit shock at Rwanda, strong variations are reverberated in the price of cereals in Uganda in prices without spatial effects, while with spatial effects strong variations are reverberated in the price of cereals in Tanzania and somehow in Kenya.

- From a one unit shock at Uganda, strong variations are reverberated in the price of cereals in Uganda in the price without spatial effects, while with spatial effects strong variations are reverberated in the price of cereals in Tanzania.

- From a one unit shock at Tanzania, strong variations are reverberated in the price of cereals in Uganda in the price without spatial effects, while with spatial effects strong variations are reverberated in the price of cereals in Tanzania its self.

4. Conclusion

This paper adopts and explains the application of Panel Vector Autoregressive (PVAR) and Spatial Panel Vector Autoregressive (SPVAR) models to econometrically analyze food price volatility and transmission across countries members of East African Community (EAC). The main results of this paper suggest that it takes time for spatial effects to influence the current cereals price happening at markets. This paper uncovered that cereal price volatility and transmission across EAC are more predictable in prices with spatial effects than in those without spatial effects. Furthermore, the results of this paper demonstrate that a one unit shocks in one cereal market across EAC create persistence and positive cereal price variations in that market and in the other markets. Moreover, this paper shows that price variations caused by a one unit shock in the price of cereals at one market create strong variations that, in short and long-run, are reverberated in the price of cereals in the other markets across EAC.

It is very important for policy makers to recognize the relationship among different prices of cereals across different countries, because they provide us with new thoughts into food security analysis. Therefore, two policy implications may flow from this paper. On one hand, since there is a short-run and long-run relationship among cereals prices across EAC, agricultural policies should focus on ensuring crop yield stability and enhancing regional food distribution system in order to stabilize food prices across the EAC in particular and ensure and improve regional food access in general. On the other hand, as the main results of this paper show that spatial distribution of markets highly contributes to cereal price volatility and transmission across the region, trade policies should be formulated considering the gains of trading with the nearneighboring markets. This last may be taken into consideration in order to avoid delayed spatial effects on price volatility and transmission from which when a market *k* is not a neighbor of market *c* the delayed spatial effects depends on the number of neighboring markets between market *k* and market *c* and the price prevailing on those markets.

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Annex 1: Extended Methodology

a. Hausman's (1978) test to choose between fixed and random effects model

Hausman's (1978) specification test compares an estimator $\hat{\theta}_1$ that is known to be consistent with an estimator $\hat{\theta}_2$ that is efficient under the assumption being tested. The null hypothesis is that the

estimator is indeed an efficient (and consistent) estimator of the true parameters. If this is the case, there should be no systematic difference between the two estimators. The Hausman statistic is distributed as chi-square and is calculated as $H = (\beta_c - \beta_e)'(V_c - V_e)^{-1}(\beta_c - \beta_e)$. Where β_c is the coefficient vector from the consistent estimator, β_e is the coefficient vector from the efficient estimator, V_c is the covariance matrix of the consistent estimator and V_e is the covariance matrix of the efficient estimator. When the difference in the variance matrices is not positive definite, a Moore–Penrose generalized inverse is used.

b. Panel cross-section dependence tests

To test for cross-sectional independence in balanced panels,

$$H_0\colon \hat{\rho}_{ij} = \hat{\rho}_{ji} = cor\,(u_{it}, u_{jt}) = 0 \text{ for } i \neq j \text{ and } H_1\colon \hat{\rho}_{ij} = \hat{\rho}_{ji} \neq 0 \text{ for } i \neq j. \quad \text{(A1)}$$

Pesaran's (2004) CD test rely on the following formula

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \text{and } \hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{u}_{it}\hat{u}_{jt}}{(\sum_{t=1}^{T}\hat{u}_{it}^2)^{1/2}(\sum_{t=1}^{T}\hat{u}_{jt}^2)^{1/2}}. \quad \text{(A2)}$$

Where $\hat{\rho}_{ij}$ is the sample estimate of the pairwise correlation of the residuals and $\hat{u}_{it}$ is the estimate of u_{it} (panel residuals). Under the null hypothesis, u_{it} is assumed to be independent and identically distributed *(i.i.d.)* over periods and across cross-sectional units. Under the alternative, u_{it} may be correlated across cross sections, but the assumption of no serial correlation remains. The number of possible pairings (u_{it}, u_{jt}) rises with N. The *CD* formula shows that under the null hypothesis of no cross-sectional dependence $CD \xrightarrow{d} N\,(0, 1)$ for $N \rightarrow \infty$ and T sufficiently large.

Friedman (1937) proposed a nonparametric test based on Spearman's rank correlation coefficient. The coefficient can be thought of as the regular product-moment correlation coefficient, that is, in terms of proportion of variability accounted for, except that Spearman's rank correlation coefficient is computed from ranks. In particular, if we define $\{r_{i,1},\ldots,r_{i,T}\}$ to be the ranks of $\{u_{i,1},\ldots,u_{i,T}\}$such that the average rank is $(T + 1/2)$, Spearman's rank correlation coefficient is given by $r_{ij} = r_{ji}$ and Friedman's statistic which is based on the average Spearman's correlation is given R_{ave}. Hence

$$r_{ij} = r_{ji} = \frac{\sum_{t=1}^{T}\left\{r_{i,t}-(T+\frac{1}{2})\right\}\left\{r_{j,t}-(T+\frac{1}{2})\right\}}{\sum_{1=1}^{T}\left\{r_{i,t}-(T+\frac{1}{2})\right\}} \text{and } R_{ave} = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}. \quad \text{(A3)}$$

where $\hat{r}_{ij}$ is the sample estimate of the rank correlation coefficient of the residuals. Large values of Rave indicate the presence of nonzero cross-sectional correlations. Friedman showed that $FR = (T - 1)\,\{(N - 1)\,Rave + 1\}$ is asymptotically χ^2 distributed with $T - 1$ degrees of freedom, for fixed T as N gets large.

c. Unit root test

Pesaran's (2007) cross-sectionally augmented unit root tests are designed for cases where cross-sectional dependence is due to a single factor. Pesaran (2007) suggests a cross-sectionally augmented Dickey-Fuller (CADF) test where the standard DF regressions are augmented with cross-sectional averages of lagged levels and first differences of the individual series. He also considers a cross-sectional augmented IPS (CIPS) test, which is a simple average of the individual CADF-tests. Null for CIPS tests series is I(1) and CIPS test assumes cross-section dependence is in form of a single unobserved common factor.

d. PVAR model of lag 2

We can set the panel VAR model of lag two by writing (1) in matrix form as:

$$\begin{pmatrix} Pb_{it} \\ Pk_{it} \\ Pr_{it} \\ Pu_{it} \\ Pt_{it} \end{pmatrix} = \begin{pmatrix} V_{bj} \\ V_{kj} \\ V_{rj} \\ V_{uj} \\ V_{tj} \end{pmatrix} + \begin{pmatrix} \theta_{11i1} & \theta_{12i1} & \theta_{13i1} & \theta_{14i1} & \theta_{15i1} \\ \theta_{21i1} & \theta_{22i1} & \theta_{23i1} & \theta_{24i1} & \theta_{25i1} \\ \theta_{31i1} & \theta_{32i1} & \theta_{33i1} & \theta_{34i1} & \theta_{35i1} \\ \theta_{41i1} & \theta_{42i1} & \theta_{43i1} & \theta_{44i1} & \theta_{45i1} \\ \theta_{51i1} & \theta_{52i1} & \theta_{53i1} & \theta_{54i1} & \theta_{55i1} \end{pmatrix} \begin{pmatrix} Pb_{it-1} \\ Pk_{it-1} \\ Pr_{it-1} \\ Pu_{it-1} \\ Pt_{it-1} \end{pmatrix} + \begin{pmatrix} \theta_{11i2} & \theta_{12i2} & \theta_{13i2} & \theta_{14i2} & \theta_{15i2} \\ \theta_{21i2} & \theta_{22i2} & \theta_{23i2} & \theta_{24i2} & \theta_{25i2} \\ \theta_{31i2} & \theta_{32i2} & \theta_{33i2} & \theta_{34i2} & \theta_{35i2} \\ \theta_{41i2} & \theta_{42i2} & \theta_{43i2} & \theta_{44i2} & \theta_{45i2} \\ \theta_{51i2} & \theta_{52i2} & \theta_{53i2} & \theta_{54i2} & \theta_{55i2} \end{pmatrix} \begin{pmatrix} Pb_{it-2} \\ Pk_{it-2} \\ Pr_{it-2} \\ Pu_{it-2} \\ Pt_{it-2} \end{pmatrix} + \begin{pmatrix} \mu_{1it} \\ \mu_{2it} \\ \mu_{3it} \\ \mu_{4it} \\ \mu_{5it} \end{pmatrix} \quad \text{(A4)}$$

where i represents different prices of cereal commodities (wheat, rice, maize, and sorghum); v is the vector of cereal commodity effect at each market; θ are the coefficient matrices of variables (*Pb*, *Pk*, *Pr*, *Pu* and *Pt*) in lag(1) and lag(2).

e. The SPVAR model of lags 2

In matrix form, first, we start by estimating the W matrix reflecting first order rook's contiguity relations for the five markets which is a symmetric matrix. As we are dealing with the price of cereal commodities at five markets in EAC (Burundi, Kenya, Rwanda, Uganda, and Tanzania), W is a square matrix of 5X5 dimensions that record neighborhoods among the markets. From the first row: the neighboring markets to Burundi market are Rwanda and Tanzania. From the second row: the neighboring markets to Kenya market are Uganda and Tanzania. From the third row: the neighboring markets to Rwanda market are Burundi, Uganda and Tanzania. From the fourth row: the neighboring markets to Uganda market are Kenya, Rwanda and Tanzania. From the third row: the neighboring markets to Rwanda market are Burundi, Uganda and Tanzania. From the fifth row: the neighboring markets to Tanzania market are Burundi, Kenya, Rwanda and Uganda. Second, we transform W matrix in the way of having row-sums of unity to get a standardized first-order contiguity matrix noted as C. And then we combine C and Pc_{it} a vector column matrix to have new prices Pc^{*}_{it} with spatial effects. And for simplicity, the new price for i commodity at t time at each market is the arithmetic mean of the price of that i commodity at t time of neighboring markets:

$$W = \begin{pmatrix} 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{pmatrix} and C \begin{pmatrix} 0 & 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 0 & 1/2 & 1/2 \\ 1/3 & 0 & 0 & 1/3 & 1/3 \\ 0 & 1/3 & 1/3 & 0 & 1/3 \\ 1/4 & 1/4 & 1/4 & 1/4 & 0 \end{pmatrix} \qquad \text{(A4)}$$

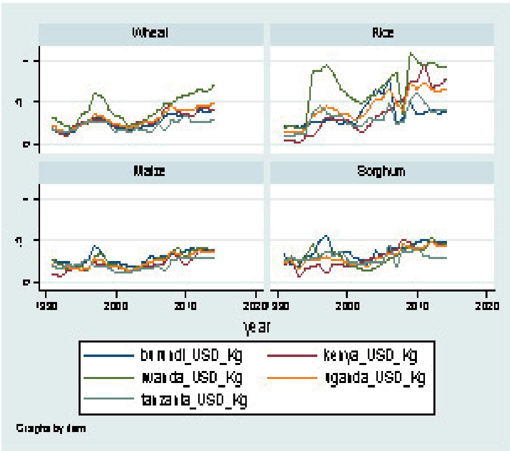
$$\begin{pmatrix} Pb^{*}_{it} \\ Pk^{*}_{it} \\ Pr^{*}_{it} \\ Pu^{*}_{it} \\ Pt^{*}_{it} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 0 & 1/2 & 1/2 \\ 1/3 & 0 & 0 & 1/3 & 1/3 \\ 0 & 1/3 & 1/3 & 0 & 1/3 \\ 1/4 & 1/4 & 1/4 & 1/4 & 0 \end{pmatrix} \begin{pmatrix} Pb_{it} \\ Pk_{it} \\ Pr_{it} \\ Pu_{it} \\ Pt_{it} \end{pmatrix} = \begin{pmatrix} 0.5Pr_{it} + 0.5Pt_{it} \\ 0.5Pu_{it} + 0.5Pt_{it} \\ 1/3Pb_{it} + 1/3Pu_{it} + 1/3Pt_{it} \\ 1/3Pk_{it} + 1/3Pr_{it} + 1/3Pt_{it} \\ 1/4Pb_{it} + 1/4Pk_{it} + 1/4Pr_{it} + 1/4Pu_{it} \end{pmatrix} \qquad \text{(A5)}$$

After then, we write (2) in matrix form as follows:

$$\begin{pmatrix} Pb^*_{it} \\ Pk^*_{it} \\ Pr^*_{it} \\ Pu^*_{it} \\ Pt^*_{it} \end{pmatrix} = \begin{pmatrix} V_{1j} \\ V_{2j} \\ V_{3j} \\ V_{4j} \\ V_{5j} \end{pmatrix} + \begin{pmatrix} \rho_{11i1} & \rho_{12i1} & \rho_{13i1} & \rho_{14i1} & \rho_{15i1} \\ \rho_{21i1} & \rho_{22i1} & \rho_{23i1} & \rho_{24i1} & \rho_{25i1} \\ \rho_{31i1} & \rho_{32i1} & \rho_{33i1} & \rho_{34i1} & \rho_{35i1} \\ \rho_{41i1} & \rho_{42i1} & \rho_{43i1} & \rho_{44i1} & \rho_{45i1} \\ \rho_{51i1} & \rho_{52i1} & \rho_{53i1} & \rho_{54i1} & \rho_{55i1} \end{pmatrix} \begin{pmatrix} Pb^*_{it-1} \\ Pk^*_{it-1} \\ Pr^*_{it-1} \\ Pu^*_{it-1} \\ Pt^*_{it-1} \end{pmatrix} + \begin{pmatrix} \rho_{11i2} & \rho_{12i2} & \rho_{13i2} & \rho_{14i2} & \rho_{15i2} \\ \rho_{21i2} & \rho_{22i2} & \rho_{23i2} & \rho_{24i2} & \rho_{25i2} \\ \rho_{31i2} & \rho_{32i2} & \rho_{33i2} & \rho_{34i2} & \rho_{35i2} \\ \rho_{41i2} & \rho_{42i2} & \rho_{43i2} & \rho_{44i2} & \rho_{45i2} \\ \rho_{51i2} & \rho_{52i2} & \rho_{53i2} & \rho_{54i2} & \rho_{55i2} \end{pmatrix} \begin{pmatrix} Pb^*_{it-2} \\ Pk^*_{it-2} \\ Pr^*_{it-2} \\ Pu^*_{it-2} \\ Pt^*_{it-2} \end{pmatrix} + \begin{pmatrix} \varepsilon^*_{it} \\ \varepsilon^*_{it} \\ \varepsilon^*_{it} \\ \varepsilon^*_{it} \\ \varepsilon^*_{it} \end{pmatrix} \quad \text{(A6)}$$

where i represents different prices of cereal commodities (wheat, rice, maize, and sorghum); v i the vector of cereal commodity effect at each market; ρ are the coefficient matrices of variables (*Pb*, *Pk*, *Pr*, *Pu* and *Pt*) with spatial effect in lag(1) and lag(2).

Annex 2: Price trends by commodity and market



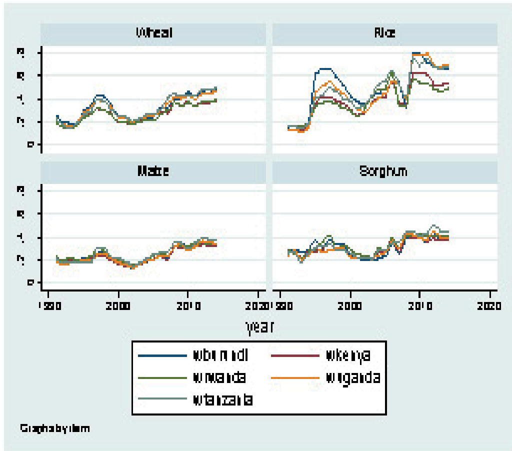


Figure 1: *Actual cereal prices* **Figure 2:** *Price with spatial effects*

Annex 3: Impulse responcse functions

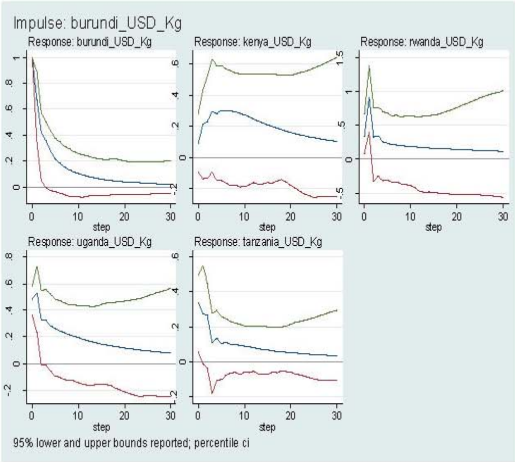


Figure 3: *Without spatial effects*

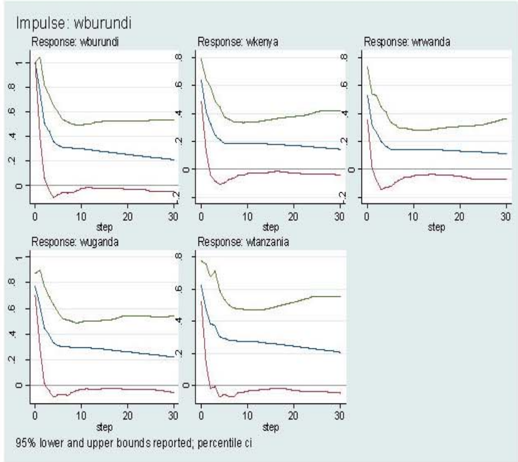


Figure 4: *With spatial effects*

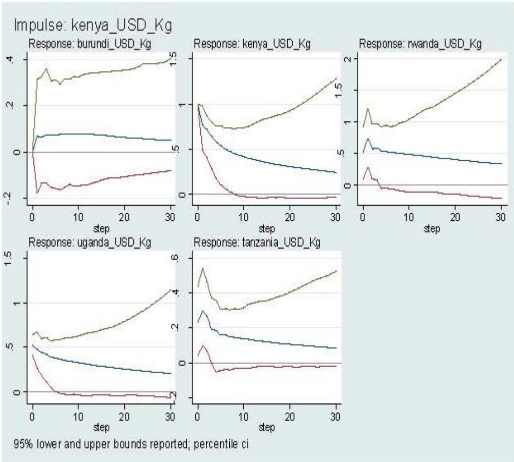


Figure 5: *Without spatial effects*

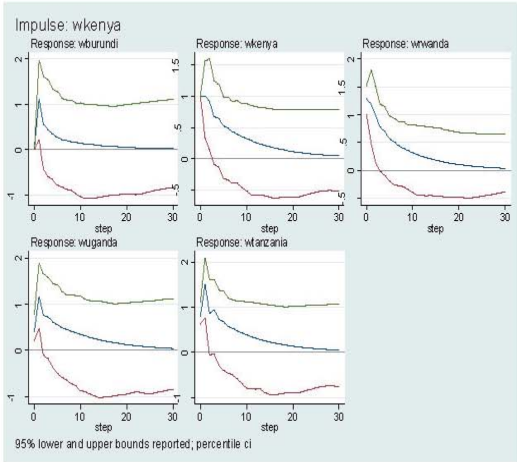


Figure 6: *With spatial effects*

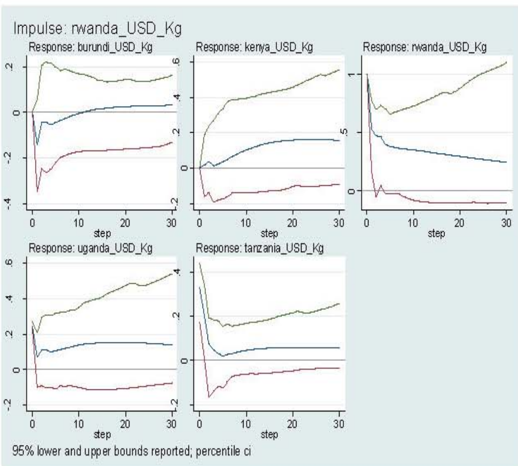


Figure 7: *Without spatial effects*

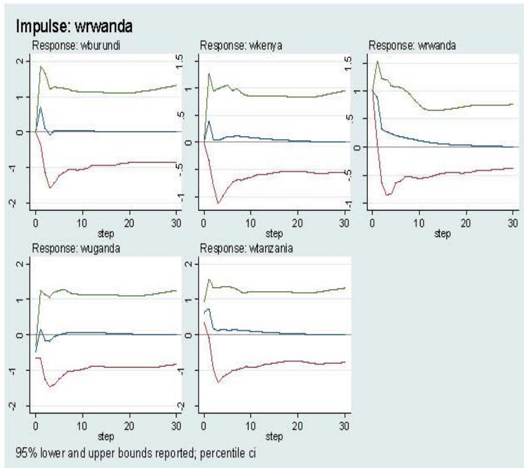
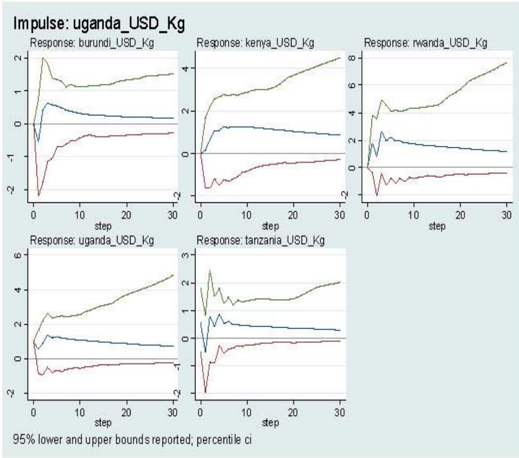
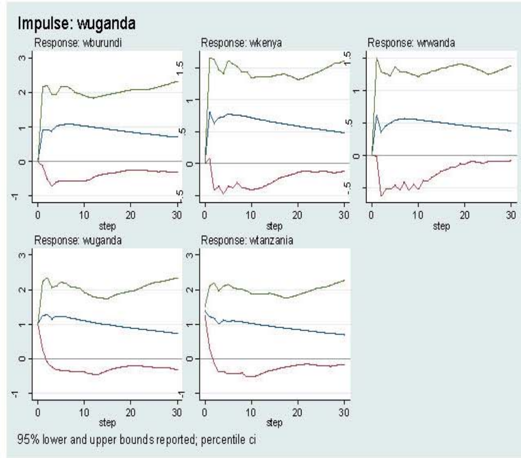
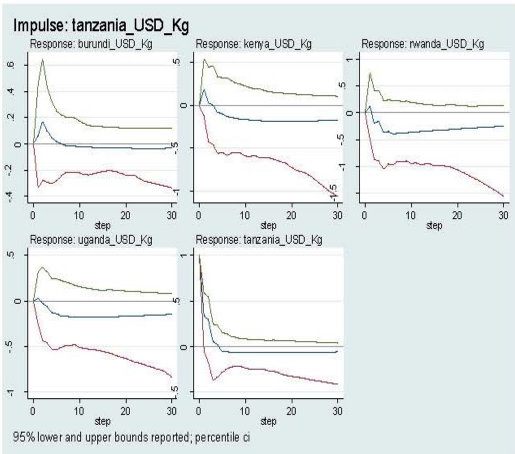


Figure 8: *With spatial effects*







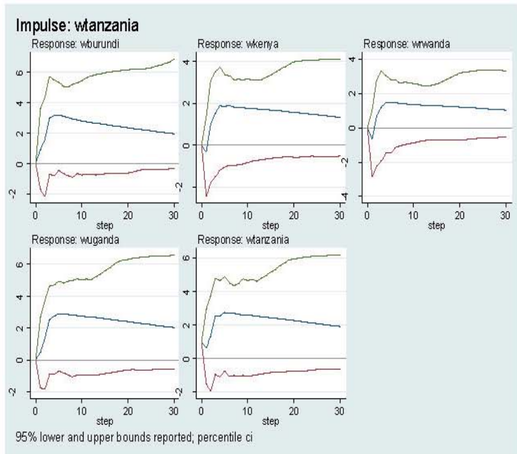
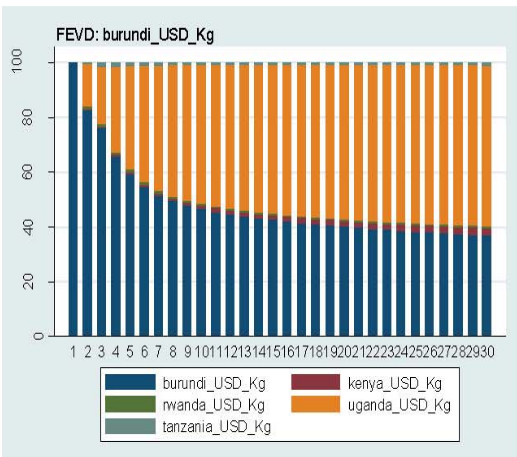


Figure 9: *Without spatial effects*

Figure 10: *With spatial effects*

Annex 4: Forecast-error variance decomposition



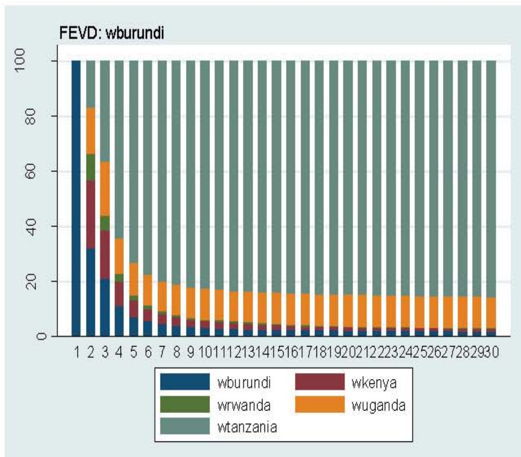


Figure 11: *Without spatial effects*

Figure 12: *With spatial effects*

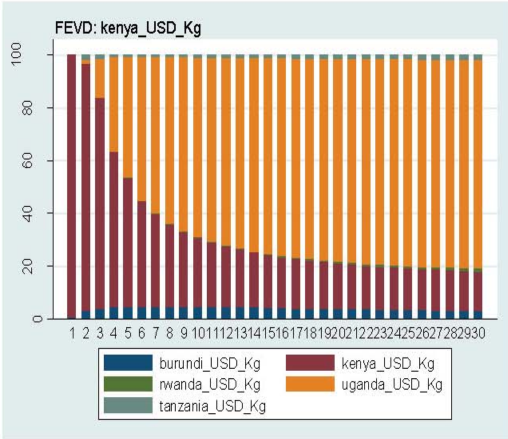


Figure 13: *Without spatial effects*

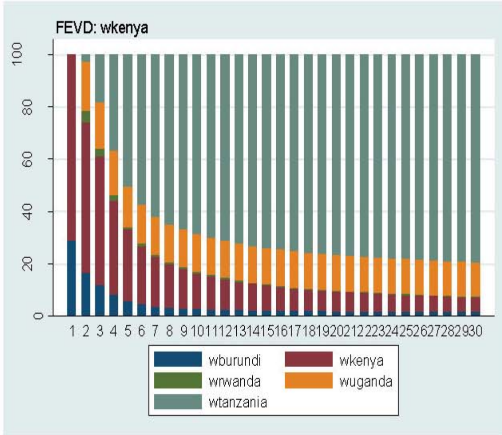


Figure 14: *With spatial effects*

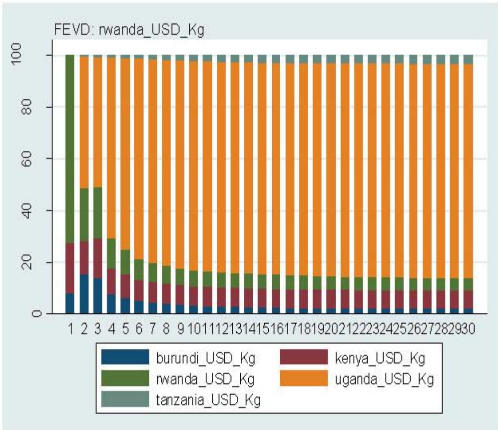


Figure 15: *Without spatial effects*

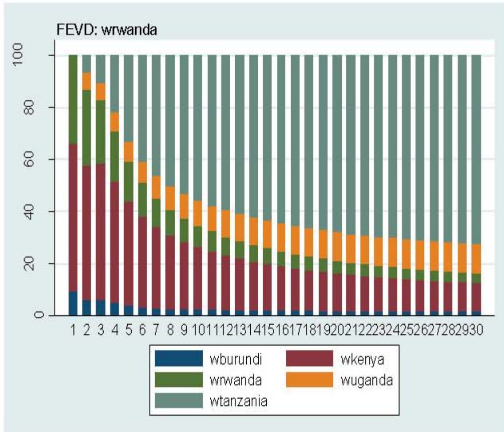


Figure 16: *With spatial effects*

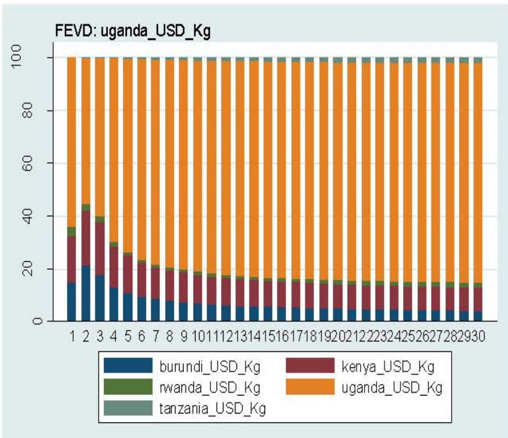


Figure 17: *Without spatial effects*

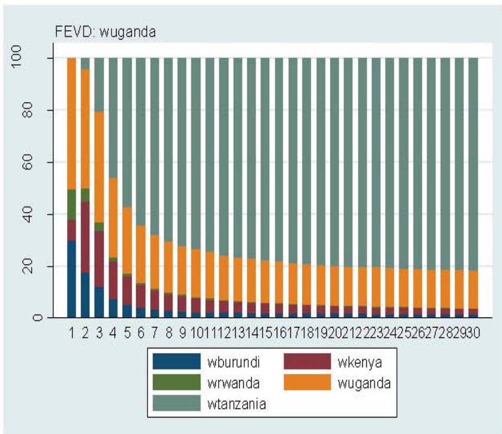


Figure 18: *With spatial effects*

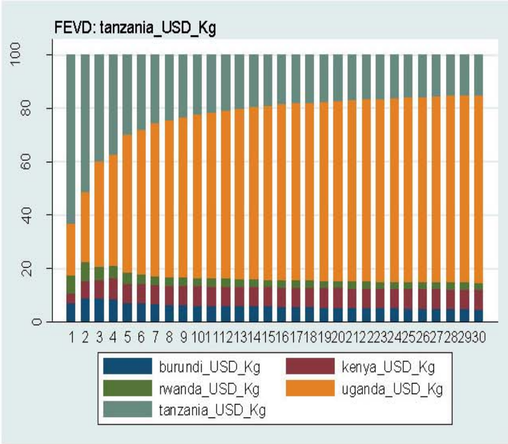


Figure 19: *Without spatial effects*

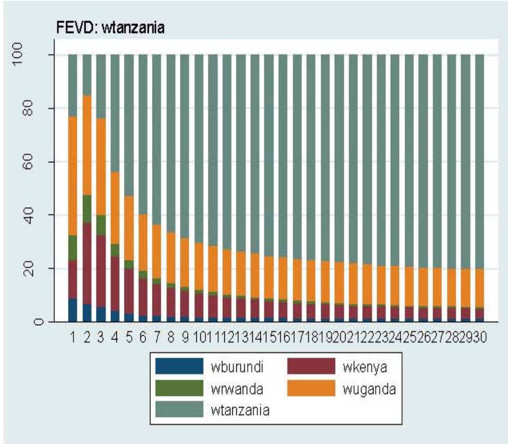


Figure 20: *With spatial effects*