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214- A panel cointegration analysis and dynamic causality test of agricultural supply response to prices: The case of rice in West Africa

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Abstract

The paper provides a regional estimate of rice yield and acreage supply response to prices, which reflect respectively, long and short-terms production (or farming) decision variables for rice supply in West Africa. Using pooled time series cum panel data from seven countries covering 1991-2006 from the region, the study employed panel cointegration estimator such as FMOLS and DOLS for the long-run supply elasticities and one-step Blundell-Bond *system* GMM for the estimation of the short-run elasticities. While the empirical findings from both estimators provide similar results, the estimates show that any increase in price of maize decreased significantly rice yield in the long run. In contrast, the estimates also show that any increase in price of maize and cassava increased significantly rice acreage in the long run. The short-run estimates show that rice yield (acreage) increased (decreased) significantly w.r.t price of maize in the study. Short-run Granger causality runs only from maize price, while long run causality of joint effect of the prices to both the yield and acreage supply is also evident in the study. Our results also find that rice yield and acreage supply function are unresponsive to own price in both the short and long run. Given this, one may thus argue that not much can be expected from change in price alone as package of changes including investment in non-price factors such as irrigation, and technology transfer among others may play a significant role in inducing rice supply response in the region.

Key words: Rice, Price, supply elasticity, panel data, West Africa
Jel Classification: Q18, Q21, R58

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Introduction

Rice is not only regarded as a major staple but commodity of strategic significance across sub-Saharan Africa (SSA) and in particular West Africa sub region (Diagne *et al.,* 2011). West Africa remains at the hub of rice production largely by subsistence farmers from both the upland and low land rice production system in SSA. But the region's shortfalls in rice production and share of world rice import have increased significantly as consumption rises at a rate well above that of production growth (AfricaRice, 2007). For example, the annual growth rate of rice production and consumption is about 6 percent and 7 percent, respectively as the region imports about 42 percent of its consumption requirement via international market (AfricaRice, 2007).

However, the slow growth in rice production relative to consumption in the region has been attributed to low yield achieved (AfricaRice, 2007). According to Diagne *et al.,* (2011), seventy percent of rice produce in the region came from land expansion, with just 30 percent attributable to productivity enhancement. Thus, in recognition of the growing gap between the demand and supply of rice in the region and elsewhere in SSA, the AfricaRice Center (formerly known as West Africa Rice Development Association-WARDA) introduced high yielding NERICA rice varieties with promising agronomic practices in Cote d'Ivore in 2001 (Diagne *et al.,* 2011). The technology has since been adopted in more than 30 countries using participatory variety selection (PVS) approach over the years in SSA.

While it is fundamentally important to prioritize adoption of high yielding technology to stimulate/boost rice production to meet rising demand, it is also equally important to understand the responsiveness of rice supply to economic incentives such as price (s) within the context of the short and long terms production (or farming) decision in West Africa sub-region. Since, commodity supply is assumed infinitely elastic in the long run to own price (Deaton and Laroque, 2003), it is likely farmers behavior to produce more can be investigated by understanding how farm output supply is affected by price (s) believed to be inherently unstable in lights of the recent short term volatility in food prices. This observation is in recognition that a rise in rice supply could have a direct effect on the nutrition and food security in the region (AfricaRice, 2007). As noted by Nkang *et al.,* (2007), measurement of supply responsiveness of farmers is a veritable means of assessing the impact of economic reforms with a view that policies, which provide appropriate incentive such as price or non-price factors are likely to bring about high supply responsiveness, while those that act as disincentives are less likely to do so.

Hence, the degree of responsiveness of agricultural supply to prices either in the short or long term production decision is crucial in understanding the role of price incentives and to some extent non-price factors in increasing supply, which may also constitute a further issue for policy formulation. To this end, the paper seeks to investigate rice yield and acreage supply response to own price and prices of other principal staples such as maize and cassava, which connotes respectively, long and short-term production decisions based on panel data from seven countries in West Africa sub-region. Given this, we define farm output supply in this study in terms of acreage and yield responses in recognition of the following argument in the literature. *First*, Mushtaq and Dawson (2002) posit that many supply response studies used acreage because, it measures intended supply and more so that yield is subject to more random variation than acreage due to factors outside the farmers control such as weather. *Second*, as noted by Robert and Schlenker (2009) and Searchinger *et al.,* (2008), productivity through technological progress and intensification is a long-term process, while area expansion and re-allocation is a short- term decision variable for the farmers. Interestingly, yield supply response, which capture technology change in rice production has been increasing marginally according to the recent statistics from the food and agricultural organization (FAO) in the region (FAOSTAT, 2012), perhaps due to large adoption of NERICA rice technologies. Based, on this, it is important to consider both the yield and acreage decision variables in rice supply response to provide policy makers with the long and short-term production decision variables for planning in the region. [2]

In this regard, the study contributes to supply response in the region and elsewhere in SSA in two folds: *First*, the study simultaneously provide comparative analysis, through which production (or farming) decision of rice farmers to boost rice supply can be studied and subsequently model viz., increase in rice supply associated with yield increase-long term variable for planning or through land expansion/acreage-short term variable for planning. *Second*, instead of drawing inferences from aggregate time series from each of the rice producing countries in the region, we constructed a panel of time

[2] Agbola and Evans (2012) in their study of rice response function in Australia focused on acreage rather yield supply response because the country has one of highest rice yield in the world (8-10 tons/ha) but with declining land area under rice cultivation. Meaning that production (or farming) decision based on acreage, which represent short-term supply response is likely to provide meaningful step to increase rice supply in Australia.

series cum panel data, which has a distinct advantage of providing a global estimate of agricultural supply for policymaking in the region. Within this context, we believe such global cum regional estimate can be useful in explaining the growing gap between the demand and supply of rice in West Africa. Besides, it could also serve as yardstick or reference point for assessing rice supply response across rice producing countries in the region. To this end, the study uses panel cointegration analysis and dynamic causality test because the methodology ensures the use of both the long and short run elasticities of supply, thus avoiding spurious results.

A search of literature shows that there are large empirical studies of agricultural supply response with a focus on different crops from many countries in the region. Some of these studies that address rice supply response in SSA include Kuwornu *et al.,* (2011), Ayanwale *et al.,* (2011), Ogazi (2009) and Rahji *et al.,* (2008) among others. While Ayanwale *et al.,* (2011), Ogazi (2009) and Rahji *et al.*, (2008) focused on Nigerian's rice supply response, Kuwornu *et al.,* (2011) addressed rice supply response in Ghana. Although, the results from the studies are mixed, nevertheless, it is rational to ask whether such individual country level results ensue at the regional level for policymaking. The regional cum global estimate appears to be more important as such result is useful in assessing the global food supply and thus food security situation. This observation however, motivated this study.

The rest of the paper is organized as follows. Section two focuses on the theoretical framework and empirical model, while section three provides detailed descriptive statistics of the data used. Section four presents the results and discussion. Conclusions and policy implications are provided in section five.

2.0. Theoretical framework and empirical models

2.1. Theoretical framework

Agricultural supply response is based on two identified frameworks viz. Nerlovian expectation model and profit-maximizing approach. While the former captures the dynamics of agriculture by incorporating price expectations and /or adjustment costs; the later involves joint estimation of output supply and input demand functions (Mythili, 2008). In contrast to the Nerlovian model, the profit maximizing approach requires detailed information on the quantities and input prices, which is not available for the present study. Based on this, the present study employed Nerlovian expectation model as a framework to model rice supply response in West Africa.

As earlier mentioned, the Nerlovian expectation model is a dynamic model, which captures the delay in agricultural production due to resource availability within one or two agricultural production cycles (Nerlove, 1958). Thus, following Nerlovian framework for supply response where vector of desired output (X_{it}^{*}) from *i-th* country is expressed as a function of price expectations P_{it}^{e} in period "t" and defined as

$$X_{it}^{*} = a_{i} + bP_{it}^{e} + e_{it} \qquad 1$$

where, X_{it}^{*} is vector of desired output or a given output ($X_{it} = \left[Y_{it}^{rice}, A_{it}^{rice} \right]'$,which in this case represents vector of rice yield in kg/acre Y_{it}^{rice} and rice acreage A_{it}^{rice}), P_{it}^{e} is the expected relative price at period "t" ; b is the long-run price elasticity of supply, and e_{t} is unobserved random term for the regression. But in equation 1, we assumed that only information on expected prices are taken into account by the economic agents involved in supply of X_{it} .[3]

Furthermore, following the work of Nerlove (1958), the dynamics agricultural supply, which shed light on the partial adjustment of the output supply is expressed as a weight sum of past output, in which the weights decline as one goes back in time and defined as

$$X_{it} = X_{it-1} + d\left(X_{it}^{*} - X_{it-1}\right) + n_{it} \qquad 2$$

where, X_{it} is the vector of actual output supply; X_{it}^{*} is as defined earlier; d is the partial; adjustment coefficient $\left(1 \pounds d \pounds\right)$, and n_{it} is the error/random term for the regression.

The implication of equation 2 is that actual output produced (X_{it}^{*}) may differ from the desired output (X_{it}), since farmers may not have ability to make instantaneous adjustment to their production decisions due to changes in price and, or external factors

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[3] The structural Nerlovian model of equation 1 can also be extended to include non-price factors Z such as weather, credit, fertilizer usage etc., as $Y_{t}^{*} = a + bP_{t}^{e} + gZ_{t} + e_{t}$. Lack of data on Z prevented us from estimating this equation.

(Thieriault *et al.,* 2013). In this case, the decision makers (i.e., farmers) are believed to make partial adjustment in their output toward their long-term desired output.

Accordingly, the adjustment coefficient "δ" represents the actual change in output between two periods, which also represents a fraction of the change required to achieve the optimal output level X_{it}^{*}. If "δ" is close to zero, then it implies that farmers adjustment of actual output to desired output is slow. Likewise, if "δ" is close to 1, it is an indication that farmers' adjustment of actual output to desired output is fast.

Hence, the structural Nerlovian model represented by equations 1 and 2 when combined gives the reduced form defined as[4]

$$X_{it} = \delta\alpha + (1-\delta)X_{it-1} + \delta\beta P_{it}^{e} + \tau_{it} \qquad 3$$

where, $\tau_{it} = \varepsilon_{it} + \nu_{it}$; $\delta\beta$ and β are the short-run and long-run price elasticities of supply, respectively; X_{it} is the vector of output supply defined earlier, X_{it-1} is the lagged value of X_{it}, P_{it}^{e} is the price expectation; δ, α, and β are the parameters to be estimated, and τ_{it} is the error term for the regression.

Since, price expectation are updated from one period to another in proportion, the difference between observed price and expected price levels of the previous period can be defined as (see; Nerlove, 1958 for details)

$$P_{t}^{e} - P_{t-1}^{e} = \beta\left(P_{t-1} - P_{t-1}^{e}\right) \Rightarrow P_{t}^{e} = \beta P_{t-1} - (1-\beta)P_{t-1}^{e} \qquad 4a$$

According to Kanwar, (2006), if quasi-rational expectation hypothesis is considered, then equation 4a can be expressed as infinite-order of autoregressive process such as

$$P_{t}^{e} = \sum_{i=1}^{\infty} \beta(1-\beta)^{i-1} P_{t-i} \qquad 4b$$

where β is the adapted price coefficient also known as price elasticity of supply, which ranges $0 < \beta < 1$.

Therefore by substituting equation 4b into 3 gives the reduced form of standard Nerlovian model with one-year adjustment defined as

[4] For the manipulation, see Lim, 1975 for the details.

$$X_{it} = \delta\alpha + (1-\delta)X_{it-1} + \delta\beta P_{it-1} + \tau_{it} \qquad 5$$

Equation 5 shows that vector of output supply X_{it} can be expressed as a function of its lagged value included to maintain the dynamics nature of agricultural production as earlier discussed and lagged observed/spot prices, which include own and cross prices. In this case, we assumed that only information on the past prices P_{it-1} represented by are taken into account in modeling X_{it} as expected prices P_t^e are difficult to obtain. Theoretically speaking, in case of agricultural supply function, we expect vector of output supply X_{it} to respond to own price with higher output and complementary (or competing/substituting) crops with positive (or negative) cross-price elasticities. But equation 5 can also be extended to include control variables other than price such as time trend, variables representing weather such as rainfall, fertilizer usage, policy indicator etc. to capture imperfect information in the variables.[5]

But Thiele (2000) argued that a fundamental methodological weakness of the Nerlovian model comes down to the assumption that production adjusts to a fixed target supply, after which actual supply adjusts. But this assumption has been found to be unrealistic under dynamic conditions such as equation 5, unless with stationary model. In this regard, Thiele (2000) argued further that estimating Nerlovian method is unlikely to capture the full dynamics of supply response, thus biasing elasticity downwards. Besides, since most economic time series used for estimating Nerlovian model often exhibit non-stationary tendencies, it means estimated output supply elasticities based on equation 5 are likely to be subjected to danger of spurious regression outcome.

Thus, an alternative approach to Nerlovian method to overcome the limitations mentioned above is to employ cointegration analysis as noted by Abdulai and Rieder, (1995) and Thiele (2000). This approach was used in this paper.

2.2. Empirical model

2.2.1. *Long-run Supply Response to Prices: A Panel Co-integration Regression*

The long-run equilibrium supply response function for the study can be defined as follows

[5] The structural Nerlovian model of equation 5 can be extended to include non-price factors Z such as weather, credit, fertilizer usage etc., as $X_{it} = \delta\alpha + (1-\delta)X_{it-1} + \delta\beta P_{it-1} + \gamma Z_{it-1} + \tau_{it}$

$$lnX_{it} = i_0 + b_1 lnP_{it}^{rice} + b_2 lnP_{it}^{maize} + b_3 lnP_{it}^{cassava} + u_{it} \qquad 6$$

where $X_{it} = \left[Y_{it}^{rice}, A_{it}^{rice} \right]'$ represents vector of output supply defined as rice yield in kg/acre Y_{it}^{rice} and rice acreage A_{it}^{rice} ; P_{it}^{rice}, P_{it}^{maize} and $P_{it}^{cassava}$ represent price per kg of rice, maize, and cassava, respectively; b represents the estimated long-run price elasticity of supply; u_{it} represents random error.

To estimate the long-run supply response to prices presented above, we employed new generation cointegration regressions techniques such as dynamic panel ordinary least square (DOLS) and Philip-Hansen's panel fully modified ordinary least square (FMOLS) estimators. According to Smyth and Narayan (2009), cointegration regressions are believe to be robust in the presence of endogenous regressors, which are often inherent in production decision-making models, such that the model gives asymptotically median-unbiased estimators. Besides, it believes cointegration regression overcomes problem of omitted variables and measurement errors, it eliminates sample bias and correct for serial correlation, and also allows for heterogeneity of the long-run parameters. But, Kao and Chiang (2000) argued further that the DOLS method tends to outperform the FMOLS estimators in term of mean biases. These observations motivated the application of both estimators in the present study.

2.2.2. **Short-run Dynamics Supply Response: One-step System GMM**

A typical short-run dynamic function for estimating short-run elasticity can be defined using the relationship below

$$DlnX_{it} = s_0 + J_j DlnX_{it-1} + j_{1j} DlnP_{it-1}^{rice} + j_{2j} DlnP_{it-1}^{maize} + j_3 DlnP_{it-1}^{cassava} + VECT_{it-1} + v_{it} \qquad 7$$

where X_{it}, P_{it}^{rice}, P_{it}^{maize} and $P_{it}^{cassava}$ are as previously defined; D is the differencing operator; $ECT_{t-1} = \hat{u}_{t-1}$ is the error correction term, which is equivalent to the lagged value of the error term from equation 6; j represents the short run price elasticity of supply; V is the coefficient of the error correction term, which denotes the speed of adjustment towards long run equilibrium. The later measures the period of feedback or convergence of rice supply into a long-run equilibrium following changes in the prices, and v_t is the error term of the regression.

The short-run dynamic supply response above is estimated using one-step *system*-generalized method of moment (GMM) style based on Roondman (2009). Estimation of equation 7 without accounting for possible correllation between the lagged dependent variables and the error terms likely to give biased result in panel setting, especially when conventional OLS is used (Baltagi, 2005). In contrast to the conventional OLS method, GMM does not assume normality and controls for heteroskedasticity (Jaunky, 2012). Thus, in order to take the correlation and endogenity problem in equation 7 into consideration, Arellano and Bond (1991) first suggested a *difference* GMM approach, where lags of explanatory variables in levels are used as instruments. But the approach is believed to suffer from a lack of power of internal instrument which led to the introduction of the *system* GMM by Blundell and Bond (1998), where the linear combination of the lagged levels and differences explanatory variables are used as instruments. According to Jaunky (2012), the sysytem GMM makes an exogeneity assumption where any correlation between endogenous variables and unobserved or fixed effects are constant over time. This allows the inclusion of level equations in the system and use of lagged differences as instruments for the levels. Thus, we employed one-step system GMM approach in the present study because standard error of two steps system GMM tend to be biased downward in small sample. This observation is very important considering the fact that we have just 112 observations for the study.

2.2.3. **Dynamic panel Causality test**

Since existence of a long run equilibrium relationship is an indication of causality in at least one direction, it is fundamentally important to test the direction of causality between economic data, especially where there is a strong indication of endogeneity in the series. To this end, we employed Canning and Pedroni's (2008) error correction based panel causality test contrary to the conventional Granger causality test, which has been shown to have some weakness, in particular the difficulty of its applicability in situations where variables are integrated or co integrated (Ngepah, 2013).

Short-run causality

The underlying null hypothesis for testing whether short-run causality exist is based on joint significance of the lagged coefficient of the prices in equation 7 as

$$H_0^1 : b_{1i} = b_{2i} = b_{3i} = 0\left(\text{i.e., short runs from } P^* \text{to } X_{it}\right) \qquad 8$$

Long-run causality test

Also, the underlying hypothesis for testing long-run causality is based on the significance of the coefficient of the speed of adjustment in equation 7 as

$$H_0^2 : V = 0 \qquad 9$$

Strong causality test

However, the strong causality test is carried further to examine the joint significance of the short and long-run causality of rice supply as

$$H_0^3 : b_{1i} = b_{2i} = b_{3i} = V = 0 \qquad 10$$

3.0. The data and sources of the data

The study is based on balanced panel data of annual time series from 1991-2006 from seven West African countries which include Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Mali, Nigeria and Togo. The data were sourced from FAOSTAT (2012) and this include acreage and yield in kg/acre and price per kg in US$ of rice. Other information sourced includes spot price per kg in US$ of principal staples in the region such as cassava and maize for the analysis. Detailed descriptive statistics of the data used for the analysis are presented in Table A of the appendix.

4.0. Results and discussion

4.1. Panel unit root and panel co integration tests

4.1.1. *Panel unit root test*

Because many economic data (either in time series or panel data of annual time series) may not be stationary at level, thus suggesting unit root may exist. In this case, it is important to investigate the properties of the data. Thus, Table 1 presents the result of the panel unit root carried out in the study. We employed two of the first generation panel unit root tests, viz., LLC and Hadri-LM tests. While LLC is under the null hypothesis of unit root in the panel (I (1)), the Hadri-LM test is under the null hypothesis of stationarity in the panel (I (0)). The tests were carried out with maximum lag of one and with intercept only since we observed that the variables did not exhibit any trend over time as revealed by the plots. Within this context, the results from both tests show that the variables in panel are stationary (i.e., I (0)) at both the level and first differences. Meaning that the variables in the panel are of the same order of integration at level.

4.1.2. *Panel cointegration tests*

Unlike Pedroni and Kao residual test that are useful for bivariate panel cointegration, we employed Johansen Fisher Panel cointegration test proposed by Maddala and Wu (1999) because the methodology is preferred in multivariate case as noted by Eregha (2012). Based on this, we presented in Table 2a and 2b the results of the Fisher panel cointegration test for the yield and acreage response function, respectively in the study. Thus, from the tables, the results of both the trace and max-eigen statistics show that at most, two long-run cointegration relationships exist between the four panels employed in the yield and acreage response functions.

Table 1A: Panel unit root test based on LLC and IPS tests

Variables	Levin-Lin-Chu (LLC) Test				Hadri-LM Test			
	Level		Difference		Level		Difference	
	P-value	Decision	P-value	Decision	P-value	Decision	P-value	Decision
Rice Yield	0.0006	I (0)	0.0000	I (0)	0.8306	I (0)	0.9854	I (0)
Rice Acreage	0.0041	I (0)	0.0000	I (0)	0.9564	I (0)	0.5380	I (0)
Rice Price	0.0000	I (0)	0.0000	I (0)	0.9688	I (0)	0.9873	I (0)
Maize Price	0.0000	I (0)	0.0000	I (0)	0.8763	I (0)	0.9891	I (0)
Cassava Price	0.0000	I (0)	0.0575	I (0)	0.6000	I (0)	0.6330	I (0)

Note: Variables are defined in logarithm; LLC and Hadri-LM stand for Levin, Lin and Chu (2002) and Hadri (2000) tests, respectively.

Table 2A: Johansen fisher panel cointegration test for yield response function

# of co-integration	Trace test		Eigen test	
	Statistics	Probability	Statistics	Probability
None	310.50	0.0000	1006.00	0.0000
At most 1	84.35	0.0000	60.66	0.0000
At most 2	35.74	0.0011	33.97	0.0024
At most 3	14.41	0.4197	14.41	0.4197

Note: Variables in yield response function are Rice Yield, Rice Price, Maize Price, & Cassava Price

Table 2B: Johansen fisher panel cointegration test for rice acreage response function

# of co-integration	Trace test		Eigen test	
	Statistics	Probability	Statistics	Probability
None	233.30	0.0000	455.70	0.0000
At most 1	76.50	0.0000	65.08	0.0000
At most 2	27.07	0.0189	21.53	0.0888
At most 3	15.95	0.3167	15.95	0.3167

Note: Variables in co-integration are Rice Acreage, Rice Price, Maize Price, & Cassava Price

4.2. Panel cointegration analysis of the long-run supply elasticities

Table 3a and 3b present the results of the panel cointegration analysis for the long-run supply elasticities as *ceteris paribus* for yield and acreage response function, respectively with other variables remaining constant. As discussed earlier, the study employed both the FMOLS and DOLS estimators for the respective supply response functions. Thus, the empirical results show that rice yield responds significantly and negatively to the price of maize, while it responds positively but insignificantly to own price and price of cassava in both estimators. In contrast, our results show that rice acreage responds positively and significantly to price of maize and cassava, while it responds negatively and insignificantly to own price in the study. Unresponsive of rice yield and acreage to own price perhaps suggest that price was also observed in the study, which incentives alone are not enough to increase rice supply in the region.

A closer look at the results further show that when the price of maize rises by 1 percent, rice yield supply decreased significantly by about 0.25 percent and 0.30 percent, while 1 percent increase in the price of rice (cassava) increased (decreased) insignificantly rice yield supply by about 0.13 percent and 0.16 percent (0.01 percent and 0.01 percent) from the FMOLS and DOLS estimators, respectively. Thus, making maize a major competing crop to long-term rice yield supply in the study. Given that yield response reflects long-term policy variable decision, it means for any increase in price of maize could attract rice farmers in the region to shift from rice to maize production and vice-versa in the long-run. Also, when the price of maize (cassava) rises by one percent, rice acreage increased significantly by about 1.4 percent and 1.7 percent (1.4 percent and 1.3 percent) as revealed by the FMOLS and DOLS estimators, respectively. Since, acreage response represents short-term measure in supply decision process, it means that maize and cassava are complementary crops to rice, from short-term supply response, thus highlighting the value of maize and cassava in the production mix in the region. Interestingly, these findings provide a strong support to the farming system operating in the region; where farmers in most cases cultivate these crops side by side as in a mixed crop system.

Nevertheless, the implication of these findings is that in the long-run, rice yield and acreage price elasticities of supply gave contrasting results from both estimators. This observation perhaps provide a useful insight into possible effect of price incentives on rice supply, especially when domestic rice farmers in the region purse a long-term production (or farming) decision that is associated with yield increase or a short-term acreage expansion and vice-versa in an attempt to stimulate rice production/supply. Furthermore, our results probably imply that production decision to increase rice supply based on the long-term yield increase rather than the short-term acreage expansion is likely to be induced positively and significantly by maize–rice substitutability or negatively and significantly by maize-rice complementarity when short-term acreage expansion rather is pursue as rice production decision in the region. This assertion is made in recognition of recent finding that seventy percent of the rice production increase came from land expansion, with just 30 percent attributable to productivity enhancement since the introduction of NERICA rice technology in 2001 in the region (Diagne *et al.,* 2011).

Table 3a: Long-run yield response elasticities using panel cointegration regressions

Estimated Coefficients	FMOLS estimates				DOLS estimates			
	i_0	lnP_t^{rice}	lnP_t^{maize}	$lnP_t^{cassava}$	i_0	lnP_t^{rice}	lnP_t^{maize}	$lnP_t^{cassava}$
/	6.3269***	0.1390	-0.2471**	-0.0137	6.2697***	0.1568	-0.2986*	-0.0096
Std. Error	0.1261	0.1003	0.1165	0.0484	0.1524	0.1349	0.1613	0.0543
Diagnostics	R^2=0.0152				R^2=0.1622			

*Note: Dependent variable is Rice Yield in kg/acre; Figure in parentheses are the standard error; *, **, *** implies that the estimates are significant at 10%, 5%, and 1%, respectively.*

Table 3b: Long-run acreage response elasticities using panel cointegration regressions

Estimated Coefficients	FMOLS Estimates				DOLS Estimates			
	i_0	lnP_t^{rice}	lnP_t^{maize}	$lnP_t^{cassava}$	i_0	lnP_t^{rice}	lnP_t^{maize}	$lnP_t^{cassava}$
/	17.6836***	-0.3950	1.3903**	1.3603***	17.9335	-0.6015	1.7474**	1.3063***
Std. Error	0.7032	0.5594	0.6497	0.2696	0.7763	0.6875	0.8221	0.2765
Diagnostics	R^2=0.4014				R^2=0.5889			

*Note: Dependent variable is area of rice planted in acreage; Figure in parentheses are the standard error; *, **, *** implies that the estimates are significant at 10%, 5%, and 1%, respectively.*

4.3. **Short Run Rice Supply Dynamics:** ***Yield and Acreage Response functions***

Table 4a and 4b present the result of one–step Blundell-Bond *system* GMM within the framework of short-run supply dynamics for the long-term yield and short-term acreage response functions decisions, respectively by assuming a one-year lag. Model 1 and 2 respectively; represent the inclusion of the lagged error correction term from equation 7 based on the FMOLS and DOLS estimators in the *system* GMM.

Before we discuss the results, it is important to address robustness of the estimated system GMM presented in the tables. While we recognize the small sample of observations used in the study, the results of Sargan test of over-identification of the instruments reported in the lower panels of the tables justify the validity of the instruments used as Sargan test rejects the null hypothesis that the over-identifying restriction is valid. Likewise, the null hypothesis of no first-order autocorrelation (AR (1)) in residuals is rejected as shown by the significance of AR (1) in the tables, while the second-order AR (2) show no evidence of autocorrelation in the residuals. The first-order autocorrelation does not imply that estimates are inconsistent, just second order autocorrelation. According to Yu *et al.,* (2011), the GMM estimator is consistent only if there is no second-order-serial correlation in the idiosyncratic error term of the system of equations as observed in the present study.

Hence, the empirical results presented in Table 4 show that rice yield supply responds significantly and positively to price of maize, while it responds insignificantly but positively and negatively to own price and price of cassava, respectively in the short run. In contrast, Table 4b shows that rice acreage supply responds negatively and significantly to price of maize, while it responds insignificantly and negatively to own price and positively to cassava price in the study. Meaning that in the short run, the relationship between rice yield and price of maize indicate maize-rice complementarity in production mix in the region, while rice acreage response to price of maize indicates maize-rice substitutability.

Furthermore, the significance of the variables representing previous seasons yield (Y_{it-1}) and land area (A_{it-1}) in both table 4a and 4b is an indication that these variables are important determinants of the current seasons' rice yield and land areas allocation in the study. Meaning that production (or farming) decision based on the long-term yield increase or short-term acreage expansion depends on the performance of the previous season.[6] Also, the coefficient of the error correction term ECT_{t-1}in the table represents how fast deviations from the long-run equilibrium are eliminated. While the coefficients have appropriate signs, the results show that about 33 percent and 38 percent of the deviation of rice yield supply from long-run equilibrium due to shocks in the price(s) is corrected in the current period as reveal by the FMOLS and DOLS estimators, respectively. Also, we found that about 0.05 percent and 0.07 percent of the deviation of the rice acreage supply from the long run equilibrium due to shocks in the price(s) is corrected in the current period as reveal by the FMOLS and DOLS estimators, respectively. Meaning that the speed of adjustment to long-run equilibrium is far weak

[6] But with significant negative coefficient of these lagged dependent variables as observed in the study, imply that higher rice yield and acreage growth in a certain year is associated by a lower growth in the coming year.

when short-term acreage expansion rather than the long-term yield increase drives the decision of the domestic rice farmers to increase rice production/supply in the region. The slow/weak adjustment for rice acreage perhaps means that there are greater technological and institutional constraints that are hindering farmers from realizing the long run equilibrium level in rice production in West Africa sub region with a short-term period. Interestingly, Mythili (2008) observed similar results in India.

Also, attempt was made to compare the results of the short and long-run price elasticities of supply obtained in the present study with other regional and global estimates in the literature. Thus, our search shows that Molua (2010) found maize to be a competing crop to rice yield supply as it responds positively to own price in the long-run in Cameroon-an important rice producing country in the Central Africa region. Anyway, this finding is consistent with the results obtained in this study. In contrast to our finding, Haile *et al.,* (2013) in recent study of annual global estimate of short-term crop acreage response to international food prices found evidence that annual rice acreage respond positively and significantly to own price in the long run but insignificantly and positively to the price of maize in the short-run. Likewise, Mythili (2008) estimates of rice acreage supply shows that it responds positively and significantly to own price in the short and long run in India.

4.4. **Causality Test**

The long run cointegration relationship of equation 6 says nothing about the direction of causality. Based on this, we presented in the lower panel of Table 4a and 4b, the results of the causality tests for the long-term yield and short-term acreage supply response decisions, respectively. From both tables, the results show that short-run causality runs only from the price of maize to rice yield and rice acreage, while empirical evidence also support joint effect of the long-run causality and strong causality of the price(s) to both the rice yield and acreage supply in the study. The later provide additional channel of causality, which measure the joint effect of the short and long run Granger causality on the rice yield and acreage supply in the study. Likewise, it provides the test of validity of restrictions implied by the Nerlovian partial adjustment in the study. In this case, since the Wald test of the joint significance of the coefficients of the differences terms is significantly different from zero, implied that the Nerlovian framework is inappropriate for the study and thus favor the more general dynamic adjustment defined by the error correction specification for modeling rice supply response in West Africa sub-region. Hence, the implication of these findings is that price of maize is regarded as a major driver of rice supply as joint effect of the prices is likely to induce rice production in the region. Also, the direction of causality of maize price on rice supplies either with increasing or decreasing state is strongly associated with production decision pursue by the rice farmers viz., long-term rice yield increase or short-term land expansion in the region.

Table 4a: Estimated GMM's Short-Run Dynamics elasticities for Yield Response

Variables	Parameters	Model 1 (ECT_{t-1} from FMOLS)		Model 2(ECT_{t-1} from DOLS)	
		Coefficients	Std. Error	Coefficients	Std. Error
$D lnY_{t-1}^{rice}$	J	-0.1579*	0.0924	-0.5131***	0.0363
$D lnP_{t-1}^{rice}$	b_1	0.0224	0.0537	0.0394	0.0526
$D lnP_{t-1}^{maize}$	b_2	0.1518***	0.0492	0.1362**	0.0481
$D lnP_{t-1}^{cassava}$	b_3	-0.0534	0.0442	-0.0683	0.0476
ECT_{t-1}	V	-0.3316***	0.0679	-0.3779***	0.0781
Constant	s_0	0.0145	0.0103	0.0153	0.0103
Degree of freedom		98		98	
Sagan test		0.216		0.254	
AR (1)		0.041**		0.032**	
AR (2)		0.995		0.982	
Short run causality test:		$p-value$		$p-value$	
$P_t^{rice} \rightarrow Y_t^{rice}$		0.6764		0.4544	
$P_t^{maize} \rightarrow Y_t^{rice}$		0.0020***		0.0046***	
$P_t^{cassava} \rightarrow Y_t^{rice}$		0.2270		0.1514	
Long run causality test		0.0000***		0.0000***	
Strong causality test		0.0000***		0.0000***	

*Figure in parentheses are the standard error; *, **, *** implies that the estimates are significant at 10%, 5%, and 1%, respectively.*

Table 4b: Estimated GMM's Short-Run Dynamics elasticities for Acreage Response

Variables	Parameters	Model 1 (ECT_{t-1} from FMOLS)		Model 2 (ECT_{t-1} from DOLS)	
		Coefficients	Std. Error	Coefficients	Std. Error
$DlnA_{t-1}^{rice}$	J	-0.2586***	0.0527	-0.3065***	0.0724
$DlnP_{t-1}^{rice}$	b_1	-0.0613	0.0546	-0.0696	0.0535
$DlnP_{t-1}^{maize}$	b_2	-0.1210*	0.0634	-0.0811*	0.0500
$DlnP_{t-1}^{cassava}$	b_3	0.0402	0.0413	0.0874*	0.0495
ECT_{t-1}	V	-0.0549***	0.0185	-0.0655***	0.0208
Constant	s_0	0.0374***	0.0088	0.0352***	0.0098
Degree of freedom		98		98	
Sagan test		0.109		0.138	
AR (1)		0.101*		0.098*	
AR (2)		0.650		0.656	
Short run causality test:		$p-value$		$p-value$	
$P_t^{rice} \rightarrow A_t^{rice}$		0.2610		0.1935	
$P_t^{maize} \rightarrow A_t^{rice}$		0.0620*		0.1013*	
$P_t^{cassava} \rightarrow A_t^{rice}$		0.3297		0.0778*	
Long run causality test		0.0030***		0.0016***	
Strong causality test		0.0020***		0.0007***	

*Figure in parentheses are the standard error; *, **, *** implies that the estimates are significant at 10%, 5%, and 1%, respectively.*

5.0. Conclusions and Policy Implications

The paper provides regional estimate of rice supply response to price(s) with a focus on West Africa sub-region based on time series cum panel data covering 1991-2006. The study hypothesized that rice farmers' production and or farming decision can be modeled in terms of yield and acreage response to price(s), which represent long and short-term supply policy variables, respectively in the region. Within this context, we estimated the long-run supply elasticities using the panel FMOLS and DOLS estimators, while the short- run supply elasticities and subsequently panel causality test were estimated using Blundell-Bond one step system GMM. However, an important finding of this study is that both the long run estimators gave similar results, which is in contrast to the finding of Kao and Chiang (2000) that DOLS outperform FMOLS estimators in term of means biases. Nevertheless, the empirical results show that price of maize is only significant determinants of rice yield supply, while price(s) of maize and cassava are regarded as important determinants of rice acreage supply in the long run. Also, an interestingly outcome of this findings is the fact that maize is regarded as competing crop to rice long-term yield supply decision in the long run, while maize and cassava are regarded as complementary crops to short-term rice acreage supply decision. Besides, the results also show that yield supply responds significantly and positively to the maize price, while it responds insignificantly to own price and price of cassava. In contrast, the result also reveals that acreage supply responds significantly and negatively to maize price. The short-run Granger causality runs significantly only from maize price, while there is evidence of long-run and strong Granger causality from joint effect of the prices to rice yield and acreage supply in the study.

Other results also show that both the rice yield and acreage supply responds insignificantly to own price in the short and long-run. This perhaps suggesting that price incentives alone are not enough to induce rice supply in both the long and short-term process as non-price factors could also dominate price factors in farmers' decision-making process in the region. One may also argue that unresponsive of both the rice yield and acreage supply to own price does not necessarily suggest that rice farmers are unresponsive to prices in both the short and long-run. But rather it can be inferred that other non-price incentives may be hindering translation of price incentives to stimulate rice supply in the region as also noted by Ocran and Biekpe, (2008) in their study. Within this context, we suggest, investment in irrigation facility and farm equipment services; better access to input markets viz. fertilizer, improved seeds, well organized output market, improved road network linking commodity producing areas with major agricultural market centers, well coordinated market information system to help farmers have access to prevailing market prices of rice, as well as research and agricultural extension services are capable of inducing rice supply with price policy playing an important secondary role in the region and elsewhere in SSA.

To this end, the analysis provides a regional long and short-term supply response within the context of rice yield and acreage respectively, in relation to current prices of rice and other principal crops like maize and cassava in the region. But there remains one major limitation of this study, which is non-inclusion of non-price factors in the empirical analysis, in particular annual rainfall, fertilizer and credit usage among others due to lack of reliable data on these variables from the countries in the region. Hence, the future challenge is to be able to consider these variables to address this issue in the region.

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Table A: Descriptive statistics of the variable used in the analysis

Variables	Unit	Mean	SD	Min.	Max.
Rice Yield	Kg/acre	734.43	143.41	384.38	1091.73
Rice Acreage	Acreage (1000)	1278.97	1660.61	33.74	6733.61
Rice Price	Per kg (US$)	0.3173	0.2119	0.1194	0.1459
Maze Price	Per kg (US$)	0.2220	0.1593	0.0913	1.2012
Cassava Price	Per kg (US$)	0.1715	0.1169	0.0244	0.5419