ECONOMIC ANALYSIS OF ASYMMETRIC COTTON LINT SUPPLY RESPONSE IN NIGERIA.

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Studies on cotton supply response based on linear models have often reported inelastic long run results. These studies assume that the supply response model is linear, and therefore any deviation from equilibrium is adjusted in a symmetric manner. This finding therefore, implies that price-support policies and programs will have a very little or no impact on cotton supply response in Nigeria. This forms the basis for policy bias against the cotton lint sub-sector and agriculture in general. However, this study argues that the main possible reason for such low elasticity estimates is the inappropriate model specification and estimation techniques employed. This is because cotton lint farmers' response to positive and negative price changes is not always the same. This paper therefore, argues that the main possible reason for such low elasticity estimates is the misspecification of the actual functional form of the models. This study therefore, investigates the extent of asymmetry in the cotton lint supply response in Nigeria over the period 1966-2018. To achieve this objective, both linear and Nonlinear Autoregressive Distributed Lag Model (NARDL) were estimated and the result shows that cotton lint supply response is asymmetric in both the short run and long run. This shows that taxing agriculture on the belief that it is not responsive to changes in price incentive may deter the growth of the cotton lint sub-sector and the economy at large. Thus, policies and programs such as the Anchor-Borrower designed to raise cotton lint supply should be redesigned to take into account the cotton lint farmers' differential response to positive

ABSTRACT

Keywords: Supply Response; Asymmetry, Cotton Lint, Nigeria, Nonlinear ARDL

JEL Classification: Q11; C13; Q13; C22

INTRODUCTION

Jaforullah (1993) explains how improved farming practices lead to asymmetry in agricultural supply response; an increase in price induces farmers to adopt new technologically improved production methods and they maintain these production practices even in the face of a price decrease. This is because, by definition, improved production practices reduce unit costs of production due to economies of scale. So, unit costs are lower with improved production practices than without it. Although in the face of price decreases some resources are shifted to the production of other competing crops, other crop-specific assets such as harvesters are still maintained because they cannot be utilized elsewhere. Thus, the rate of decline in the cotton lint supply in response to negative price change is less than that of positive price change. Hence, this leads to asymmetry in the cotton lint supply response. But policies and programs designed to improve cotton supply response do not take this differential response into account.

In 2010 for example, the federal government introduced a ₦100 billion "Cotton, Textile and Garment Revival Fund". But this effort did not yield the much-needed results as the sub-sector experienced yet more output decline from 475000 in the preceding year to 325000 bales in 2011 (USDA, 2019). To reverse this negative trend, the federal government initiated various policies and programs such as Agricultural Transformation Agenda (ATA) where it injected about ₦54 billion to improve cotton production, but output decreased dramatically to 260,000 in 2013 and 200,000 bales in 2014 respectively (USDA, 2019). Until now, the cotton supply to domestic textile mills has continued to experience a consistent decline in Nigeria. More recently, it was observed that cotton farmers in Zamfara State, for example, are gradually shifting to the production of competing crops such as soybeans (Adeoti *et al.,* 2020). Consequently, the cotton lint supply declined to 100,000 tonnes while the quantity demanded by Textile mills was around 215,000 tonnes per annum. This leaves a gap of about 115,000 tonnes which consequently, forced the textile mills to either import to cover the gap or operate below capacity. These negative developments are of great concern given the high domestic demand for cotton lint which leads to more foreign exchange being devoted to the importation of the commodity (Emefiele, 2021). In light of the above, findings from this study will provide invaluable information on the cotton lint supply response in Nigeria. It could also be a giant step towards designing policies aimed at addressing problems associated with the local sourcing of raw materials for textiles and other cotton-allied industries.

Studies on cotton supply response rely on linear models and produce inelastic long-run results (Haile et al., 2016; Magrini et al., 2016; Dupdal & Patil, 2018). This is because their assumption is that cotton farmers' response to positive and negative price changes is the same. Thus, their findings show that price is not a significant determinant of cotton farmers' supply response. This notion forms the basis for policy bias against the cotton sub-sector and agriculture in general. Thus, knowledge of the exact long-run cotton lint supply adjustment process will go a long way in addressing such misperception in terms of policy and research. Furthermore, by correctly estimating the farmers' attitude towards both positive and negative price changes, the government will have a better idea regarding the level of price support to be required to boost cotton lint output supply, especially after the downturn. Hence, it will aid the cotton lint's price stabilisation efforts in Nigeria. Thus, this paper argues that the main possible reason for such low elasticity estimates is the inappropriate model and estimation techniques being used. Along this line, a number of researchers (Jaforullah, 1993; Surekha, 2005) have shown that producers' reaction to an increase in price is quite different from that of a price decrease. This implies that for policies to be effective, empirical models, government policy designs and programmes such as the Anchor-Borrower program that target changes in cotton lint supply should be redesigned to take into account the differential impacts of positive and negative price changes on the cotton lint supply response in Nigeria. Therefore, as an extension to the common approach of using linear models, this study investigates the nature of the adjustment process in cotton lint supply in Nigeria using both linear and nonlinear models.

METHODOLOGY

Analytical Framework

The study is based on the Nerlovian model which allows analysing both the speed and the process of adjustment from the actual towards the desired output level as in Magrini et al. (2016). Hence the following specification

$Q_t^* = \alpha_1 + \alpha_2 \rho_t^* + \alpha_3 Z_t + U_t$ ….. (3.1)

Where Q_t* is the desired cotton lint to be supplied in period t; P_t* is the current expected own and competing crops' real prices; Z_t represents a set of other factors such as input price, weather, etc. and u_t represents random factors affecting supply response. Since due to certain constraints the desired output level cannot be attained instantaneously, Nerlove postulates the following partial adjustment hypothesis to account for such time lags in agricultural supply:

$Q_t = \lambda Q_t^* + (1-\lambda) Q_{t-1} + \varepsilon_t$……. (3.1b)

The farmers' price expectation formation is based on adaptive expectation hypothesis expressed as:

$P_t^* = \delta P_{t-1} + (1-\delta) P_{t-1}^* + \varepsilon_t$…. (3.1c)

The unobservable variables P* and Q* are eliminated in the reduced form below from equation (3.1.a), (3.1.b) and (3.1.c) (Magrini et al., 2016):

$InQ_t = b_0 + b_1 InP_{t-1} + b_2 InZ_t + b_3 InQ_{t-1} + V_t$….. (3.2a)

Equation (3.2.a) is the theoretically modified Nerlovian model.

Testing for Co-integration: Linear Model

We use the linear ARDL model to check for the possibility of linear co-integration among the variables under study. Furthermore, because our sample size is relatively small (53 observations), we use Narayan's critical values for F-statistics. Hence, we specify the Autoregressive Distributed Lag model as:

$$\Delta InQ_t = \rho Q_{t-1} + \alpha_1 Inclp_{t-1} + \alpha_2 Infp_{t-1} + \alpha_3 Insbp_{t-1} + \alpha_4 InR_t + \sum_{j=0}^{q-1} \delta_j \, \Delta Inclp_{t-j} + \sum_{=0}^{q-1} \delta_2 \Delta In\,fp_{t-j} + \sum_{=0}^{q-1} \delta_3 \, \Delta Insbp_{t-j} + \varepsilon_t \ldots\ldots (3.3a)$$

If the F-statistics F_{PSS} is greater than the upper bound critical value, we reject the null hypothesis of no (symmetric) co-integration and accept the alternative of co-integration among the variables. Otherwise, we accept the null.

Testing for Cointegration under Nonlinear Specification

Following Shin et al. (2014), we specify the non-linear Autoregressive Distributed Lag model (NARDL) (p; q) by decomposing the price variable into positive and negative price changes as:

$$\Delta \mathrm{InQ}_t = \rho InQ_{t-1} + \alpha_2^+ Inclp_{t-1}^+ + Inclp_{t-1}^- + \alpha_3 Infp_{t-1} + \alpha_4 Insbp_{t-1} + \alpha_5 InR_t + \sum_{j=1}^{p-1} \gamma \Delta In\, Q_{t-i} + \sum_{j=0}^{q-1} (\delta_j^+ \Delta Inclp_{t-j}^+ + \delta_j^- \Delta Inclp_{t-j}^-) + \sum_{j=0}^{q-1} \delta_2 \Delta Infp_{t-j} + \sum_{j=0}^{q-1} \Delta\, \delta_3 Insbp_{t-j} + \mathcal{E}_t \ldots\ldots (3.3b)$$

The null hypothesis of no long-run relationship among the variables will be tested as in the case of the linear ARDL model above.

Testing for Asymmetry in Cotton Lint Supply Response.

To check the existence of asymmetry or otherwise, we test the null hypothesis of symmetry against the alternative of asymmetry in the long run coefficients $(\beta_2^- = \beta_2^+)$ and in the short run

$$\sum_{j=0}^{q-1} \delta_j^+ \Delta\, Inclp_{t-j}^+ = \sum_{j=0}^{q-1} \delta_j^- \Delta\, Inclp_{t-j}^-$$

using the standard Wald Test as in Shin *et al*. (2014). If the F-statistic of the Wald test ($W_{LR}\ \alpha^+_2 = W_{LR},\ \alpha_{-2}$) is statistically significant, we reject the null hypothesis of symmetry and conclude that the cotton lint supply response is asymmetric, otherwise we accept the null.

Data Sources and Description

The study uses annual data on the variables of interest from 1966-2018. Data on Consumer Price Index is drawn from the International Monetary Fund (IMF), cotton acreage is from the United State Department of Agriculture (USDA); cotton lint, cotton seeds and soybeans nominal prices are obtained from Food and Agricultural Organization statistical database (FAOSTAT); while annual precipitation (Rainfall) data are sourced from the World Bank database. All the price data have been transformed into real and logarithmic forms so as to normalize and calculate the coefficients as elasticity estimates.

RESULTS AND DISCUSSION

The Stochastic Properties of the Variables

Table 1 presents the results from both Augmented Dickey-Fuller (ADF) and Phillip-Perron tests. The results show that all the variables, except cotton lint supply, and soybeans, are stationary at levels I(0), the soybeans price and cotton lint supply are, however, stationary at the first difference, meaning that they are integrated of order one, I(1). Hence, we proceed with the estimation of the ARDL model since none of the variables is integrated of order higher than one, I (1). Furthermore, we estimated the nonlinear ARDL model to account for the differential response of cotton lint farmers to both positive and negative price changes.

Table 1: ***Results of ADF and Phillip-Perron tests. (H0: there is unit root).***

Variable	Level	1st difference	Inference	Level	1st difference	Inference
INQ_t	-2.25093	-6.7678*	I(1)	-2.55949	-6.7806*	I(1)
$INRCLP_t$	-3.7109*	-	I(0)	-3.7334*	-	I(0)
$INFP_t$	-3.8475*	-	I(0)	-3.9238*	-	I(0)
$INRSBP_t$	-0.4278	-2.5089*	I(1)	-0.59388	-9.2428*	I(1)
INRNF	-6.0657*	-	I(0)	-6.12334*	-	I(0)

Source: Eviews, version 10

Critical values: -4.14458, -3.4986, and -3.17857 at 1%, 5%, and 10% respectively.

COINTEGRATION TESTS UNDER BOTH LINEAR AND NONLINEAR MODELS.

The results from table 2 show that the calculated F-statistics result (4.4983) from the linear model is less than the upper bound F- statistics calculated at a 5% level of significance (4.70). Therefore, we conclude that the symmetric model does not support the existence of long-run relationship between cotton lint supply and the explanatory variables. However, the F-statistics calculated from the nonlinear ARDL model is greater than both the lower and upper bound critical values at 5% level of significance. Thus, this indicates asymmetric long run relationship between cotton lint supply and the explanatory variables. Hence, the long-run relationship is therefore nonlinear.

Table 2: ***Cointegration Tests for Linear and Nonlinear Models***

Model specification	F-statistics	F-Bound CV (5%) I(0)	I(1)	
Linear ARDL model	$F_{PSS\ ARDL}$ 4.4983	3.5	4.7	Not Cointegrated
Nonlinear ARDL model	$FPSS_{NARDL}$ 9.3600	3.1	4.4	Cointegrated

Source: Eviews, Version 10

Test of Asymmetric Response in Cotton Lint Supply

Specifically, the results show that in the short run, a 1% increase in cotton lint price brings about an 0.39% increase in cotton lint supply. On the other hand, a similar decrease in cotton lint price leads to a decrease in cotton lint supply by about 0.38% *ceteris paribus*. This result shows some possibility of differential response in the short run. However, it remains an empirical question the Wald test result will address.

The Wald test for the short run reported in table 4 has a $p-value$ of 0.0286, which is statistically significant at the 5% level. It, therefore, means that there is evidence of a differential response of cotton lint supply to positive and negative price changes in the short run. Thus, the short-run cotton lint supply response is asymmetric. From the results, cotton lint farmers respond more to an increase in price than a price decrease. This may be attributed to the fact that those cotton-specific assets' salvage value is often less than their acquisition costs, and consequently, it becomes more profitable for the farmers to retain the assets and continue with their production in the next farming season.

Consequently, cotton lint producers adjust cotton lint supply with greater intensity in response to positive price change than they cut supply in the case of negative price change in the short run. This finding support Shin *et al*. (2014) who conclude that imposition of linear co-integration models where a nonlinear relationship exists would produce a spurious dynamic response. The result is also in line with Kohli **(**1996**)** Jaforullah **(**1993**)**; Surekha **(**2005**)**, who show that most agricultural output supplies have the tendency to behave in a nonlinear fashion. However, the result is at variance with studies such as Ozkan & Karaman (2011); Magrini *et al*. (2016); Meenakshi (2017); Dupdal & Patil (2018) etc which are based on linear models.

Table 3: ***Estimation Results of the NARDL Model***

Variable	Coefficient	Standard error	t-statistic	Prob
C	8.5946	2.5375	3.3871	0.0027
INQ(-1)*	-0.497	0.0796	-6.249	0.0000
$INCLP^{+}_{t-1}(-1)$	1.1795	0.4131	2.8553	0.0092
$INCLP^{-}_{t-1}(-1)$	1.2537	0.4380	2.8621	0.0091
INFP(-1)	-1.284	0.4467	-2.875	0.0088
$INSBP_{t-1}$	0.0730	0.0434	1.7024	0.1028
$D(INCLP^{+})$	0.3920	0.1926	2.0348	0.0541
$D(INCLP^{-})$	0.3878	0.1812	2.1399	0.0437
INRNF	-0.018	0.2303	-0.078	0.9388
D(INSBP)	-0.092	0.2303	-1.406	0.1742
Panel B: Long run NARDL estimates				
$INCLP^{+}$	2.3722	0.8719	2.7308	0.0125
$INCLP^{-}$	2.5214	0.9254	2.7247	0.0124
INFP	-2.583	0.9444	-2.735	0.0121
INSBP	0.1487	0.0852	1.7453	0.0949
Panel C: Diagnostic tests				
F_{SC}	0.0530			0.9476
F_{NORM}	4.1238			0.1272

Ramsey Reset	0.7612	0.3928
F_{het}	0.5721	0.9076
DW	2.0532	
$F_{statistic}$	12.001	0.0000

Source: Eviews, Version 10

Table 4.4: Wald tests for long-run and short-run asymmetries

W_{LR}	Value	Probability	W_{SR}	Value	Probability
F- statistic	6.818	0.0159	F-statistic	5.489	0.0286
t-statistic	-2.611	0.0159	t-statistic	-2.32	0.0286
Chi-square	6.818	0.0090	Chi-square	5.489	0.0191

Source: Eviews, version10

In the long-run, however, the Wald test result reported in Table 4 has $p-value$ of 0.0159 which is also statistically significant at 5%. This means cotton lint supply response to price is also asymmetric in the long run. This suggests that cotton lint real price movements (P_c^- or P_c^+) have statistically and significantly different effects on cotton lint supply response decisions in the long run**.** Thus, in the long run, the cotton lint supply response is asymmetric in favour of negative price change. This result is also confirmed by the long-run elasticity estimates reported in panel B of table 3 which reveals that a negative price change has a stronger effect on cotton lint supply than the positive one. This result may be explained by the fact that when cotton lint farmers observe a decrease in the cotton lint price in the long run, they cut supply with greater intensity than they increase in the case of price increase. This is because, having exhausted capacity utilization of assets in the long run, to expand cotton lint supply even if there is a price increase, cotton lint farmers need to incur additional costs in acquiring new assets. This is feasible only if the expected cotton lint price is attractive enough to warrant such new investments. Moreover, cotton lint farmers significantly increase supply only when they view a positive price change as permanent. But in the case of a negative price change, the cotton lint farmers dispose of those assets and shift to more attractive competing crops. This makes the effect of the negative cotton lint price change stronger than that of the positive one. This finding confirms the notion that cotton lint farmers are averse to a negative price change in Nigeria. This result is in line with Adeoti et al. (2020) who report that, in the face of the cotton price decrease, cotton farmers in northern Nigeria gradually shift to the growing of more attractive competing crops such as soybeans. This effect of negative cotton lint price is further confirmed by the recent data released by the National Bureau of Statistics (NBS) which reveals that despite cotton being among the main target crops in the current Anchor-Borrowers Program, it is not even among the top ten Nigeria's export crops in 2020 (NBS, 2021: Q2). These results suggest that for any government policies and programs designed to raise the cotton lint supply to succeed, cotton lint farmers' differential response to price has to be taken into account.

Post Estimation Diagnostic Tests

To check the model reliability in terms of predictions and policy recommendations, diagnostic tests were conducted and panel C in table 3 presents the results. From the table, the LM and Breusch-Godfrey F_{het} tests show that the model is free from serial correlation and heteroscedasticity problems respectively; while the Ramsey RESET test in the same table shows that the model is correctly specified**.** Also, both CUSUM and CUSUMSQ tests in figure 4.1 and figure 4.2 show that the model is stable as both lie within the critical bound at a 5% significance level. Furthermore, the Jaque-Bera normality test in Figure 4.3 indicates that the errors are normally distributed.

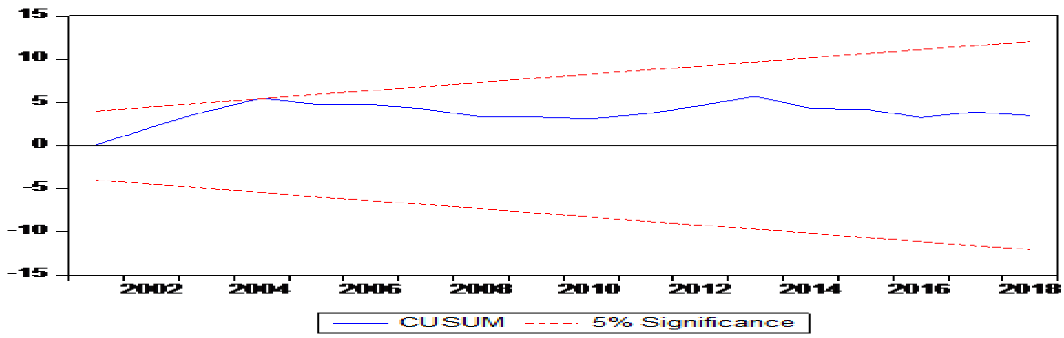

FIG 4.1 NARDL CUSUM.

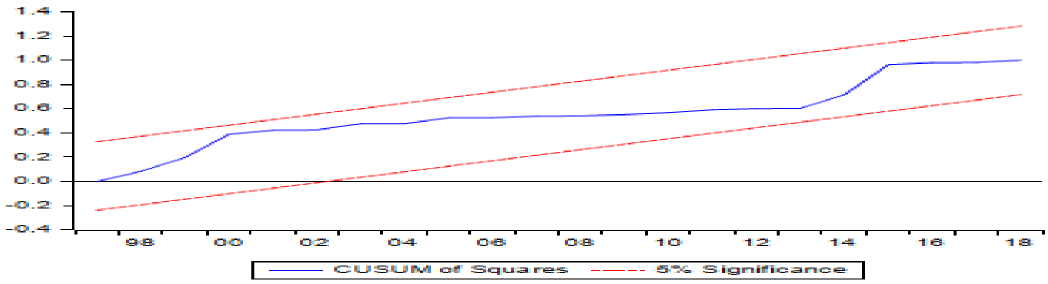

FIG 4.2 NARDL CUSUM OF SQUARES.

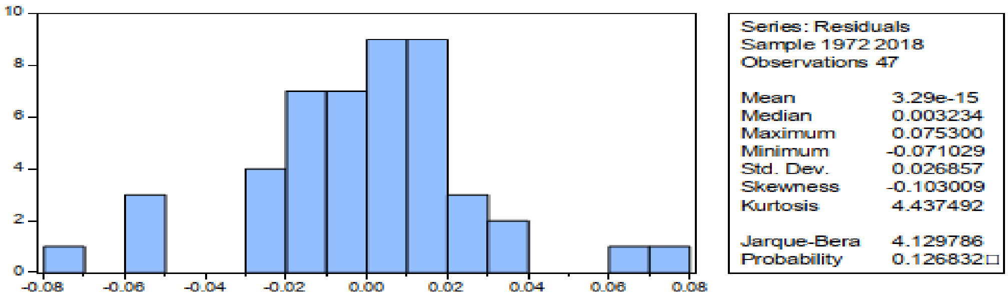

FIG 4.3 NARDL NORMALITY TEST.

CONCLUSIONS

This study examines the adjustment pattern of cotton lint supply to price signal in Nigeria using annual data from 1966 to 2018. To achieve this objective, we estimated both linear and nonlinear ARDL models to determine which of the models performs better in explaining cotton lint supply response to price. The results from the linear ARDL model revealed no evidence of a long-run relationship between cotton lint supply and other explanatory variables. Using the nonlinear ARDL model, however, the long-run relationship among the variables was established. Hence, the long-run relationship between cotton lint and other variables can best be captured in a nonlinear form.

Furthermore, in both the short and long run, positive and negative price changes have different effects on the cotton lint supply, implying that the response is asymmetric. Therefore, government policies and programs designed to improve the cotton lint supply such as the current Anchor-Borrowers Program should take into account the cotton lint farmers' differential response to positive and negative price changes in Nigeria.

Since policy recommendations based on the inappropriately specified cotton lint supply response model could be very costly if implemented, there is a need for policymakers and researchers to embrace modern econometric techniques such as nonlinear ARDL in tracing the cotton lint supply adjustment paths.

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