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Do oil prices and exchange rates account for agricultural commodity market spillovers? Evidence from the Diebold and Yilmaz Index

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ABSTRACT
This paper examines the nature of interconnectedness between the returns of the price of oil and foreign exchange on selected agricultural commodity prices. To do this, the authors leverage the novel methodology of a spillover index developed by Diebold and Yilmaz (2012) that reports predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28, no. 1: 57–66) that reports: (i) Net spillovers; (ii) Directional spillovers; (iii) Pairwise net spillovers; and (iv) Total spillover indices. This study also captures all secular and cyclical movements with the aid of rolling window analysis to ensure the robustness of the estimations. Empirical analyses are constructed based on monthly realised frequency data from 2006M1 to 2016M7. The empirical analysis from the full sample size shows that rice, sorghum, price inflation, a nominal effective exchange rate and oil price display weak pass-through among the investigated variables while banana, cocoa, groundnut, maize, soybean and wheat are net transmitters of spillover. Based on these revelations, several policy prescriptions for the agricultural commodity markets and their diverse responses to either exchange rate fluctuations or a dwindling oil price are suggested for Nigeria.

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1. Introduction

The recent rise in food prices since mid-2019 has been unprecedented, especially when considering that the aftermath of the spillovers from the 2006–2008 global food crises is still felt by both developing and developed economies (Fasanya, Odudu, and Adekoya 2018; Nwoko, Aye, and Asogwa 2016; Olasunkanmi and Oladele 2018). These price volatilities spillover, and translates into high inflation rates, trade deficits and poor macroeconomic environments, particularly regarding to developing economies. Indeed, the aftermath is also still present for policymakers and all stakeholders in the agricultural value chain. A plausible explanation for the current rise in food prices is a fluctuation in the price of crude oil (FAO 2008; Mitchell 2008), given that crude oil plays a pivotal role in food production processes (Aliyu 2009; Balcilar, Ozdemir, and Ozdemir 2018). This implies that increases in crude oil prices might translate into increases in food prices. Furthermore, the recent practice of using biofuel as an alternative energy source (Balcilar et al. 2014; Dehn 2000) might also explain the rise in food prices. Biofuel sources are gleaned from some cereals, namely soybean, corn and oil seeds, among others. Thus,

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the current study seeks to investigate the spillovers among the selected crop prices in the face of a dwindling oil price in an inflation-plagued country, using a high frequency monthly dataset from 2006M1 to 2016M7. The study uses novel and state-of-the-art econometrics techniques proposed by the Diebold and Yilmaz (2012) spillover index, which accounts for both secular and cyclical movements.

A concomitant pattern in terms of the movement seen between oil prices and agricultural commodities has also been observed. This trend has caught the attention of energy economists and like-minded scholars, prompting them to investigate empirically the energy–food nexus. The outcomes remain divergent with no consensus among researchers. The findings from previous empirical works can be put into three categories. First, the works of Nazlioglu and Soytas (2011), Reboredo (2012) and Zhang et al. (2010) represent a school of thought that finds no empirical backing for the proposal that crude oil prices cause an increase in agricultural commodity prices. The second divide of the literature support the linkage between agricultural commodity prices and oil prices, known as unidirectional linkage from agriculture to energy (See Chen *et al*., 2010; Du, *et al*. 2011; Nazlioglu *et al*. 2013). Finally, there is a third series of studies where estimation techniques diverge from the usual ones, such as Nazlioglu (2011) and Nazlioglu and Soytas (2012).

Nazlioglu and Soytas (2012) empirically examined the volatility spillover between oil and the agricultural commodity market, especially the selected agricultural commodities of wheat, corn, soybeans and sugar. The study employed newly developed causality in variance test and impulse response functions for daily data from 1 January 1986 to 21 November 2011. The study divided the data set into two strata: the first before the crises (1 January 1986–31 December 2005) and the other post-crises (1 January 2006–21 March 2011). The empirical study found that from the impulse response analysis submitted, a shock to oil price volatility is transmitted to the agricultural market only in the post-crises period. The study also submitted that the dynamics of volatility transmission changes significantly over the investigated period, which also captured and resonates with the global food prices period. In addition, Nazlioglu and Soytas (2011) analysed oil prices, agricultural commodity prices and the dollar via a panel cointegration and causality framework. The study systematically examined the nexus between world oil prices and 24 selected agricultural commodity prices, capturing the fluctuations in the strength of the US dollar in a panel framework. The estimation techniques adopted by the authors were panel cointegration and Granger Causality analysis on monthly prices spanning from January 1980 to February 2011. The revelation of their study found, as well as validated, that world oil prices have an impact on agricultural commodity prices. The outcome is divergent with several other studies, which report the neutral effect of the price of oil on agricultural commodities. The study affirmed the positive impact of a weak dollar on agricultural prices. Furthermore, in other African markets like Uganda, Katusiime (2019) explored the nexus between oil and food price volatility and key macro-economic indicators of its importance to financial stability using the Generalized Vector Auto Regressive (GVAR) methodology and Multivariate Generalized Auto Regressive Conditional Heteroscedasticity (MGARCH) as estimation techniques. The results of the GVAR and MGARCH show a low level of volatility spillover and market interconnectedness, except during periods of crisis. The results further show low but time varying volatility spillover that intensifies during periods of high uncertainty and market crises. However, in the case of Nigeria, Fasanya and Akinbowale (2019) investigated the interconnectedness between crude oil and selected agricultural commodities using the Diebold-Yilmaz methodology for monthly frequency data. The study analysis provides empirical evidence between the outlined commodity price and variables according to the spillover indices. In addition, the returns spillover exhibits trends but no burst, while the volatility spillover shows both trend and burst over the investigated period.

Nazlioglu's (2011) study on oil and agricultural commodity prices shows evidence from nonlinear causality. The study was born out of the incessant fluctuation of oil prices and increasing food prices, to see if any transmission existed. The agricultural commodities investigated were corn, soybeans and wheat. The study employed the Toda-Yamamoto and the non-parametric causality method of Dicks-Panchenko on a weekly data set from 1994 to 2010. The findings from the causality reveal neutrality, that is, there was no causality running from oil to agricultural prices. The study is in line with the neutrality hypothesis. However, the nonlinear causality analysis reveals the following: first, that a nonlinear feedback relationship exists between oil and agricultural prices; and, second, the presence of unidirectional nonlinear causality running from oil prices to corn and soybean prices. The findings from the study provide information for interest groups like policymakers, farmers and global investors.[1]

On the premise of divergence in the energy–food nexus, the current study seeks to bridge the identified gap in the case of Nigeria, where there is little or no focus in terms of research conducted on the current theme under consideration. This study seeks to extend the literature on two major fronts, namely, in terms of scope in the case of Nigeria, as follows:

1) This study concentrates on selected key cash agricultural crops in Nigeria (see Table 1 for a list). The chosen cash crops form the bulk of the staple foods that serve the nation's nutritional needs, given their affordability and availability across the country. The selected cash agricultural crops have export potential on both the international and domestic commodity markets (Akpan and Udoh 2009). This study also claims to be the first to introduce price inflation and foreign exchange, in contrast to other studies (Nazlioglu and Soytas 2012; Nazlioglu, Erdem, and Soytas 2013) which only address the connection between the selected agricultural commodity prices and world oil prices. The need to investigate the return of foreign exchange and dwindling price inflation is necessary for our case study, and has not been addressed in the previous literature.
2) The current study adds to the oil–food nexus literature in terms of methodological innovation. We rely on the recent novel spillover index developed by Diebold and Yilmaz (2012), built on the forecast error variance decomposition framework (FEVD) in vector autoregressive setup. The Diebold and Yilmaz methodology is preferred over previous known volatility models in the literature given its advances in capturing both the cyclical and secular movements of investigated variables, which bring insight to the study. Our method can be useful for all African countries. It shows that exchange rate policies and systems can have consequences on food markets via their impact on commodity prices. We also show how oil price transits to local food prices via spillover.

The rest of this study is structured as follows: Section 2 presents the methodology while Section 3 dwells on a preliminary results discussion. Section 4 focuses on further empirical results of the spillover analysis and its interpretation and Section 5 reports on the robustness of tests. The study concludes with relevant policy direction as rendered in Section 6.

2. Methodology

2.1 Diebold and Yilmaz's (2012) framework construction

We previously stated that this study uses the recently advanced novel methodology of Diebold and Yilmaz (2012) (DY), built on the generalised forecast error variance decomposition (FEVD) framework. The DY methodology will aid this study to quantify and capture the spillover effect between selected agricultural commodity prices in the face of foreign exchange and dwindling oil prices in the case of Nigeria

Table 1. Description of data.

Indicator names	Unit of measurement
Cocoa	Cents/kg
Groundnut	$/mt
Soybeans	$/mt
Barley	Cents/kg
Maize	$/mt
Sorghum	$/mt
Rice	$/mt
Wheat	$/mt
CPI	Index
NOIL	US$/barrel
NEER	LCU/US$

using recent high frequency dataset. The DY methodology offers new a perspective to volatility modelling as it renders less computational rigour and help in capturing cyclical and secular movements across our considered interest variables. The Diebold and Yilmaz methodology is built on the vector autoregressive (VAR) model and variance decomposition framework.[2] The earlier, 2009 version of the DY methodology had a pitfall, which was modified in the 2012 version. The 2012 DY version is not sensitive to the ordering of interest variables after that of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) with the aid of Cholesky factorisation, which the earlier version failed to address.

This segment of the paper presents the methodological step employed to achieve our study objectives. The current study leverages the Diebold and Yilmaz (2012) methodology to investigate the magnitude and spillover effects among the variables under consideration over the sampled period. The DY method is structured on the (VAR) model framework, which is time invariant and not sensitive to variable ordering after that of Koop, Pesaran, and Potter (1996), which makes it unique among the previous, already known volatility models in the econometric literature. The DY method is constructed via a covariance stationary VAR (p) process. The current study stationary VAR (p) process is given here:

$$y_t = \alpha + \beta_1 r_{t-1} + \beta_1 r_{t-2} + \beta_{p1} r_{t-p} + \varepsilon_t \tag{1}$$

Here, y_t represents the $k \times 1$ vector endogenous dependent variables while β denotes $(k \times k)$ coefficient matrices. The intercept for the AR process is given by the vector $(k \times 1)$ and ε is the stochastic vector term $(k \times 1)$ which is required to have an expectation of zero and (*iid*) which means independently identically normally distributed with an uncorrelated covariance matrix. Also, the p and subscript (t) are the lag order of the vector autoregressive (VAR) model and the time dimension of the VAR system. The DY is built on the (VAR) model framework, which is time invariant after that of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), and is computed using the moving average (*inter alia* Lütkepohl 2005) as presented here:

$$y_t = (1 - \beta_1 L^1 - \beta_1 L^2 - \beta_1 L^3 \ldots \beta_p L^p) - {}^1\varepsilon_t = \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i} \tag{2}$$

From Equation (2), $\beta_1 L^1 - \beta_1 L^2 - \beta_1 L^3 \ldots \beta_p L^p$ represents lag polynomial with $(k \times k)$ coefficient matrices with the lag operator denoted by β_i and L. In lump sum, the total spillover, directional spillover and net spillover is derived from the MA obtained in Equation (2) from the generalised forecast-error variance decomposition (FEVD). An H-step ahead (FEVD) is constructed as presented:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=1}^{H-1} (e'_i \Psi_h e_j)^2}{\sum_{h=1}^{H-1} (e'_i \Psi_h \Sigma \Psi'_h e_j)^2} \tag{3}$$

here σ_{ij} stands for standard deviation of the stochastic term (ε_t) for j-th equation, while the selection vector is rendered as e_i for the i-th element and zeros if otherwise. The sum of the contribution of variance of the forecast is not equal to unit under the generalised framework $(\sum_{j=1}^{n} \theta_{ij}^{g}(H) \neq 1)$. The normalised generalised entry for each row sum of the variance decomposition H-step ahead is rendered as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{n} \theta_{ij}^{g}(H)} \tag{4}$$

where $\sum_{j=1}^{n} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^{g}(H) = n$ by the construction.

Given what has been highlighted here, we come to the construction of the total spillover (TS) index, which is presented as:

$$S^g(H) = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{5}$$

The total spillover index is measured in Equation (5). In this specific study, we selected agricultural commodities (Table 1) and price inflation, as well as the nominal effective exchange rate. The uniqueness of the DY (2012) methodology gives us the platform to measure the directional flow among the interest variables. The directional spillovers are categorised into "TO" and "FROM" directional spillovers. The "TO" directional spillover accounts for returns/volatility of the spillover transmitted by others. On the other hand, the FROM directional spillover measures the spillover received by one interest variable from the others. This study considers both directions, which can be presented as:

The "TO" directional spillover can be written as

$$(DS)\ S^g_{i\to j}(H) = \frac{\sum_{j=1,j\neq i}^{n} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{n} \tilde{\theta}^g_{ij}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{n} \tilde{\theta}^g_{ij}(H)}{N} \times 100 \tag{6}$$

with the "FROM" directional spillover presented as:

$$(DS)\ S^g_{i\leftarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{n} \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^{n} \tilde{\theta}^g_{ij}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{n} \tilde{\theta}^g_{ji}(H)}{N} \times 100 \tag{7}$$

In addition, to arrive at a net spillover, the difference between Equations (6) and (7), that is, the difference between the "TO" and "FROM" directional spillover, presents the net spillover (*NS*) as:

$$(NS)S^g_i(H) = (DS)S^g_{i\to j}(H) - (DS)\ S^g_{i\leftarrow j}(H) \tag{8}$$

Subsequently, this study proceeds to construct a first order 11 VAR with a 10 step ahead forecast. Furthermore, requisite diagnostic tests are carried out to ensure robustness and precision of analysis.

3. Data and preliminary data analyses

This section of the study focuses on the study data and a preliminary discussion of how the data fare. We start off with the interpretation of the visual graphical plot of all the selected agricultural commodities investigated (Table 1) as well as other macro-economic variables like inflation measured by the consumer price index, nominal effective exchange rate prices and the oil price. It is worthy of mention here that the sample span, from the international financial statistics and the African Development Bank database, is on a monthly frequency from 2006M1 to 2016M7. All the commodities were converted to naira terms; the selected agricultural commodities were also seasonally adjusted in order to circumvent spurious analysis and, by extension, misleading inferences from subsequent analyses. Figure 1 presents the graphical display of all variable returns over the full sample size. From Figure 1 the returns of all investigated commodity prices exhibit a positive trend. For instance barley, cocoa and maize increase from the beginning of the sample, reach a peak in 2008, and from there start to decrease. The obvious reason for the decline is tied to the global financial crises (GFC) that had a ripple effect on global food markets and which coincidentally matched the global food crises period of 2006–2008. A similar positive trend is observed among the rest of the agricultural commodities. However, groundnut, wheat and sorghum display more volatility and variability. Oil price, inflation and nominal effective exchange rates also reveal an upward trend over the full sample period. The monthly return (y_t) for this study is computed by taking the ratio of the natural logarithm of first difference of price (p_t) and multiplying by 100. This can be presented as:

$$y_t = \log(p_t|p_{t-1})*100$$

Tables 2 and 3 report the summary statistics and correlation analysis respectively. The summary statistics of the returns for this study reveal that all variables exhibit positive averages, with the exception of the nominal effective exchange rate. The negative nominal exchange rate implies appreciation over the examined period. Also observed is that soybean records the highest mean followed by cocoa, while the oil price and nominal effective exchange rates have the lowest averages respectively over the full period sampled. In terms of the nature of distribution, all variables are positively skewed, with the exception of groundnut, nominal effective exchange rates and the oil price, while all the

Figure 1. Time variation graphical plot of commodity crop prices investigated.

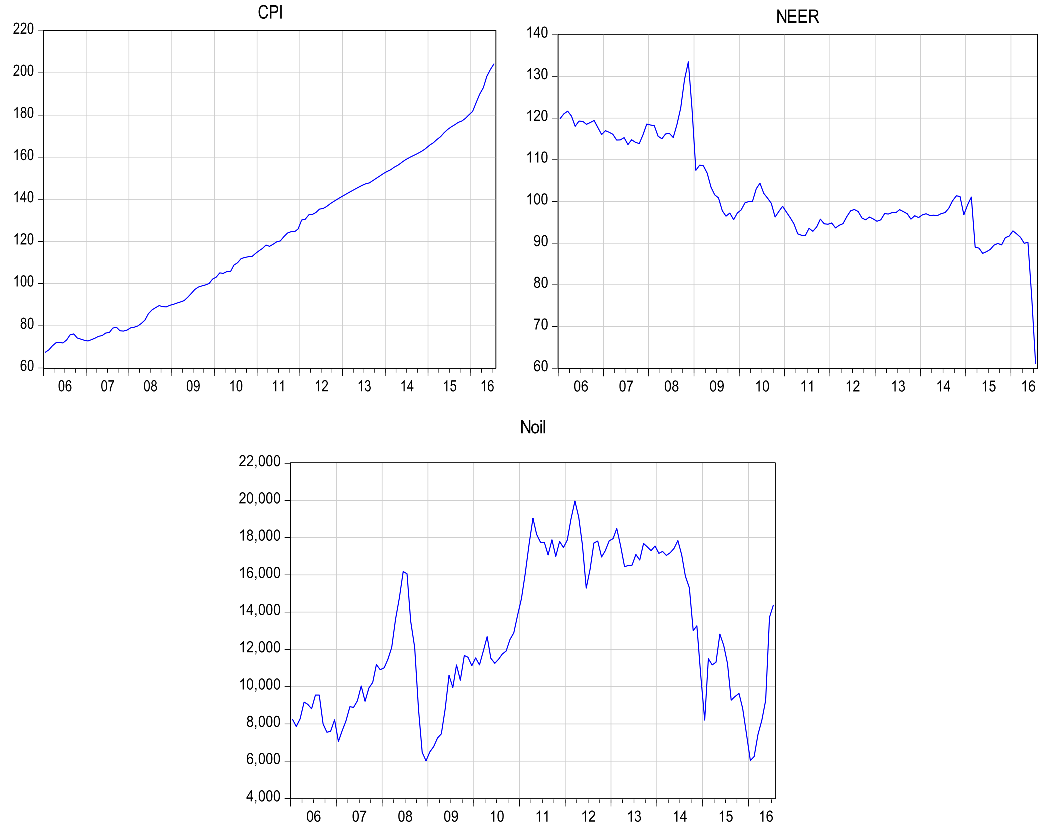

Figure 1. Continued.

series exhibit a fat heavy tail with a kurtosis of more than three. To investigate the relationship between the pairs of variables examined we rely on the Pearson correlation matrix in Table 3. The correlation analysis shows a positive relationship between most of the commodities. For instance, we see a positive and strong correlation between barley and cocoa, maize and cocoa, and soybean and barley. This is an indication that there is some sort of interconnectedness between the investigated commodities. Interestingly, we also observe an inverse relationship between a nominal effective exchange rate and all the selected agricultural commodity prices. This implies that during the observed period there is some sort of appreciation of the naira over other major trading partners' currencies. The plausible reason could be the high demand for agricultural food prices. However, the correlation analysis is not sufficient to substantiate the hypothesised claim. Thus, this study proceeds to conduct a series of further analyses to validate the claim of interrelationship between the variables considered for this study.

Subsequently, this study investigates the stationarity properties of the variables under review. To do this we conduct the traditional unit root test of the Augmented Dickey-Fuller (ADF), proposed by Dickey and Fuller (1979), as well as the Phillips-Perron (PP) unit root test, which accommodates for a possible break, advanced by Phillips and Perron (1988) as an alternative to the Dickey-Fuller. The unit root test is necessary to ascertain the stationarity properties and asymptotic traits of the variables examined. Table 4 renders the ADF and PP unit root tests. The test results confirm that the returns for all the variables are stationary at a 1% significance level with the rejection of the null of unit root (non-stationarity). Furthermore, in order to establish a parsimonious model and estimation, this study uses the Akaike information criterion (AIC) of lag 2 to conduct the Diebold and Yilmaz analysis as optimal lag selection.

Table 2. Summary statistics of returns.

	BA	CO	MA	SO	SB	WH	RI	GA	CPI	NEER	NOIL
Mean	0.9557	1.1941	1.0432	1.1993	1.1026	0.8621	1.0010	0.9484	0.8794	−0.5344	0.4419
Median	0.3373	0.7358	−0.3139	0.3390	0.5451	0.5874	−0.0275	0.1534	0.7501	−0.0641	1.3631
Maximum	33.3655	35.0851	43.7925	554.9475	41.3281	39.1919	42.0191	244.5788	3.6229	5.4231	39.2622
Minimum	−27.5845	−14.7868	−20.7723	−528.0751	−20.0434	−25.0803	−18.1450	−242.0776	−2.5277	−22.9855	−32.0960
Std. Dev.	7.8776	6.1008	7.9369	68.9341	6.6535	8.8705	7.0766	40.5608	0.8866	3.3523	10.1112
Skewness	0.7666	1.5028	1.5724	0.5289	1.7280	0.5783	2.8643	−0.3978	0.0096	−3.9745	−0.1463
Kurtosis	6.6937	10.9003	9.4450	61.6039	13.1211	5.9186	17.0646	30.7276	5.6977	23.1188	5.9002

Note: All series here under review were seasonally adjusted with the exception of CPI, NEER and OIL with census X-13 with additive outlier option type. WH, SB, SO, RI, MA, BA, GA and CO denote wheat, soybean, sorghum, rice, maize, barley, groundnut and cocoa, respectively.

Table 3. Correlation analysis for returns.

	BA	CO	GA	MA	RI	SO	SB	WH	NOIL	NEER	CPI
BA	1.0000										
CO	0.3430	1.0000									
GA	0.0668	0.1719	1.0000								
MA	0.6598	0.4752	0.0871	1.0000							
RI	0.3962	0.3761	0.1412	0.4165	1.0000						
SO	0.1751	0.1199	0.0256	0.1035	0.0420	1.0000					
SB	0.6370	0.5709	0.1144	0.7296	0.4134	0.1279	1.0000				
WH	0.6242	0.3812	0.0737	0.6142	0.1903	−0.0005	0.6343	1.0000			
NOIL	0.4024	0.4537	0.0458	0.4515	0.3763	0.1893	0.5977	0.2750	1.0000		
NEER	−0.2944	−0.5052	−0.0684	−0.3865	−0.3594	−0.0816	−0.5472	−0.3232	−0.3446	1.0000	
CPI	−0.0008	0.0673	−0.1169	0.0030	0.0289	−0.0367	0.0424	−0.0431	0.2201	−0.0755	1.0000

Note All above series under review were seasonally adjusted with the exception of CPI, NEER and OIL with census X-13 with additive outlier option type. WH, SB, SO, RI, MA, BA, GA and CO denote wheat, soybean, sorghum, rice, maize, barley, groundnut and cocoa respectively.

Table 4. Unit root results for returns.

Variables	ADF	PP
Unit root analysis for returns		
Cocoa	−9.5242***	−9.4686***
Maize	−9.8318***	−9.8429***
Sorghum	−7.3102***	−10.9407***
Soybeans	−8.6327***	−8.6327***
Groundnut	−5.2503***	−5.2411***
Wheat	−9.7599***	−9.6847***
Rice	−7.0017***	−6.8396***
Barley	−8.7717***	−8.6874***
CPI	−7.9822***	−7.7955***
NEER	−4.7784***	−4.6628***
NOIL	−5.7069***	−8.5288***

Source: Authors' computation.

Note: The models reported are those with intercept and trend for all test statistics. The superscripts ***, ** and * denote 1%, 5% and 10% statistical significance rejection levels respectively.

4. Empirical results and interpretation

4.1 Analysis of the spillover results

The spillover analysis is explained in this section of our study. The parsimonious model is built on the VAR framework with optimum lag as suggested by the Akaike information criterion (AIC). The spillover analysis is structured for 11 variable 10-step-ahead ($H = 10$) FEVD setup following recent studies (Balcilar and Bekun 2018; Diebold and Yilmaz 2012; Salisu, Oyewole, and Fasanya 2018). The current study is aligned with the FEVD built on the VAR framework to estimate the pairwise spillovers, directional spillovers, net spillovers and, finally, the total spillovers indices. Table 5 presents the spillover analysis for the full sample of returns for the interest variables of this study. This study also computes the net directional spillovers from the receivers and transmitters of spillovers table. Worthy of mention here for clarity of analysis is that variables on the row of the spillover table represent transmitters (contributors) of spillovers and contributions to own. On the other hand, variables in the column denote receivers of the spillover from others as well as including own. Thus, the "*to others*" on the bottom of Table 5 displays the effect of one commodity on another while the "*from others*" in the row indicates spillover from other variables. The total spillover is computed by the aggregation of the row and column, with the exclusion of the own variables spillover shock. Furthermore, the net spillover is computed by the difference between the "*to others*" and the "*from others*". Also, very important in our analysis is the identification of net transmitters or net receivers in the agricultural market over the full sampled period considered. Finally, the total spillover is computed by the addition of row and column totals, that is, the "*to others*" and "*from other*" columns, and dividing by the numbers of variables on the bottom of Table 5 that demonstrate the total net spillover index.

Empirical simulation from the spillover analysis (Table 5) reports a slightly above average total spillover index of approximately 56.51% on average. This implies slightly high interconnectedness among the examined agricultural commodity prices and the macro-economic variables under review, with over half of the total forecast variance among the selected agricultural commodities. Price inflation and spillover effects explain the nominal exchange rate over the full sample, while over 43.49% of the forecast variances are credited to the idiosyncratic shocks. This finding is close to the recent study by Balcilar and Bekun (2018) on the spillover dynamics of some selected agricultural commodities, in which they found over 75% of the forecast variance among the investigated commodity explained by spillover effects. The present study also resonates with the finding of Fasanya and Akinbowale (2019) for the case of Nigeria, where interconnectedness was traced among crude oil and food prices based on the spillover indices.

This study also proceeds to analyse the bi-directional returns spillover shock across other commodities. Soybeans show the highest contribution to the FEVD with a magnitude of 101.19%, followed by maize and banana, with values of 93.73% and 75.38% respectively; the lowest

Table 5. DY return of variables.

	BA	CO	GA	MA	RI	SO	SB	WH	CPI	NEER	NOIL	FROM
BA	31.73	4.29	0.66	15.8	5.6	0.56	14.31	16.82	0.31	3.72	6.22	68.27
CO	5.81	34.79	1.52	11.14	6.6	1.57	13.19	5.45	0.61	10.87	8.44	65.21
GA	0.91	2.74	83.53	1.34	2.14	1.25	1.48	0.87	1.67	3.16	0.92	16.47
MA	12.08	8.43	1.12	27.72	8.52	1.17	14.62	12.48	0.18	7.13	6.54	72.28
RI	9.32	8.39	1.13	11.61	42.8	0.6	8.2	6.51	1.11	3.27	7.06	57.2
SO	0.79	2.14	12.31	2.54	3.57	69.44	1.39	3.3	1.18	1.78	1.55	30.56
SB	12.09	9.71	0.71	14.16	4.8	0.77	26.56	11.6	0.19	9.17	10.25	73.44
WH	17.23	5.22	0.72	13.65	4.05	1	14.11	33.79	0.31	6.5	3.44	66.21
CPI	1.29	1.76	4.7	1.21	3.91	1.59	2.63	1.59	71.96	1.74	7.63	28.04
NEER	8.71	13.2	0.48	12.6	6.13	0.69	15.8	7.67	1.03	24.52	9.18	75.48
NOIL	7.14	9.56	0.47	9.68	7.34	0.6	15.45	5.98	2.01	10.17	31.61	68.39
Directional TO others	75.36	65.44	23.82	93.73	52.65	9.79	101.19	72.27	8.59	57.5	61.22	621.57
Directional including own	107.09	100.23	107.35	121.45	95.44	79.23	127.75	106.06	80.54	82.02	92.83	TCI
NET directional connectedness	7.09	0.23	7.35	21.45	−4.56	−20.77	27.75	6.06	−19.46	−17.98	−7.17	56.51

Note: WH, SB, SO, RI, MA, BA, GA, CO, CPI, NEER and NOIL denote wheat, soybean, sorghum, rice, maize, barley, groundnut, cocoa, consumer price inflation, nominal; effective exchange rate and oil price in naira terms respectively; TCI represents the total connectedness index, that is, the total spillover index computed by the addition of row and column total divided by the number of variables.

contributors to the FEVD are price inflation (CPI), sorghum and groundnut respectively, with magnitudes of 8.59%, 9.79% and 23.82% respectively. A similar ranking trend is observed with regard to receivers of spillover shocks, with similar figures for soybean, maize and nominal effective exchange rates, with magnitudes of 73.44%, 72.28% and 75.48% respectively. From Table 5, we observe that banana contributes approximately 5.81% to the cocoa market and a negligible 0.9% to the groundnut market. The banana markets spill more into the wheat market, to the tune of 17.23%. Also, the banana market is responsible for approximately 1.29% of the price inflation and 8.71% of the variability in the nominal effective exchange rate. Similarly, the cocoa market spills approximately 4.29% into the banana market and 2.74% into the groundnut market, while it shares the highest effect on exchange rate variability, with 13.20% for the full sample size. The groundnut market contributes its highest spillover into the soybean market with a magnitude of about 12.31%, as well as a record low to oil prices and the nominal exchange rate, with close spillover numbers of 0.47% and 0.48% respectively. This implies that both oil and exchange rates have a negligible impact on the groundnut market. Looking at other macroeconomic indicators, we see that price inflation contributes significantly to the selected agricultural crop commodity prices, for instance 0.31% to the banana market and 0.61% to the cocoa market, and 1.11% and 1.18% respectively to the rice and sorghum markets. Oil price fluctuation in Nigeria plays a crucial role in affecting commodity prices. This is observable on the spillover Table 5 as a 6.22% spillover contribution into the banana market and high spillover to the soybean market with magnitude of 10.25% and a low of 0.92% into the groundnut market. This indicates that oil prices are sensitive to certain markets, as oil exerts more impact on some commodity markets relative to others. Exchange rate variability over the year has been identified as a key contributor to the volatility of agricultural commodity prices (Nazlioglu 2012). Our study reports high interconnectedness between currencies' parity effect on the response of agricultural commodity prices. For instance, a nominal effective exchange rate contributes a record high 10.87% contribution into cocoa and a 9.17% contribution into the soybean market, while its lowest impact is on the sorghum market, with a magnitude of 1.78%. Furthermore, on average, the effect of spillovers between the selected agricultural commodity prices, nominal effective exchange rates and price inflation over the full sample size shows that rice, sorghum, oil price, price inflation and the nominal effective exchange rate display weak pass-through among the investigated variables, while the other variables are net transmitters (banana, cocoa, groundnut, wheat, maize, soybean). This implies that the earlier net receiver markets are vulnerable to spillover shocks; as such, policymakers and all stakeholders in the agriculture value chain should pay more attention to the net transmitters of spillover shock. This is necessary as adequate information will help farmers and investors in the respective markets take decisive action to maximise their investment.

4.2 Rolling sample analysis

This section focuses on the rolling window sub-sample analysis. Earlier analysis of the spillover indices and corresponding interpretations and coefficients was based on "averages" of the spillover dynamics among the investigated agricultural commodity prices, price inflation and nominal effective exchange rate. Furthermore, all previous VAR analysis on the returns coefficients were built on the assumption that the spillover coefficients are time invariant, that is, that the coefficients are constant over time. However, the time invariant assumption of coefficients is inadequate given it cannot capture secular and cyclical episodes and this may lead to false results and misleading policy direction in the period of jumps (rise and fall), cycles and regime shifts in key macroeconomic indicators in the economy at large. As such, in these highlighted cases the considered coefficients are invalid. For instance, during the financial distress period of 2008–2009, which rocked the whole world, and the global food crises of 2006–2008, among others, the general expectation is to experience observable spillovers varying over time. Other plausible explanations could be the impact of globalisation and the diffusion of information/technological innovation. In order to circumvent the pitfall of the erroneous time invariant spillover assumption, this study re-estimates the VAR model

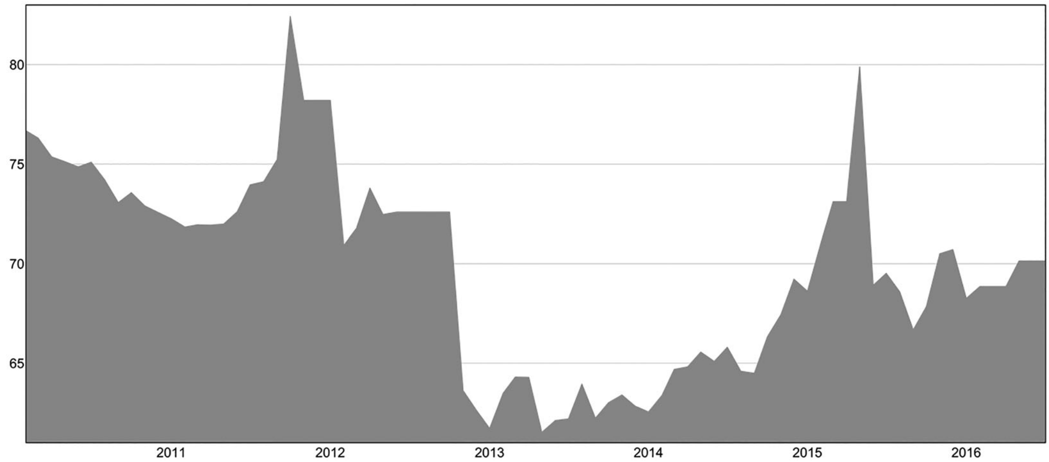

Figure 2. Rolling total spillover.
Note: Rolling window size is 48 months (four years).

using a sub-48-month rolling window[3] and estimates the total time dynamics of return for the selected crop prices, price inflation and nominal effective exchange rate.

Figure 2 reports the total returns spillover of the selected agricultural commodity prices, price inflation and nominal effective exchange rate market. The graphical plot shows a record high spillover impact in late 2011 and early 2015. However, the 48-month subsample (four-year) estimate started with over 75% and declined in the first window in 2006–2011; the corresponding years of sharp decline to less than 75% coincidentally matches the global financial crisis period. That may be a plausible explanation for the decline. Also observable in the explanation for the late 2011 decline could be the presidential general elections, with a record high of almost 100% and a sharp decline of 77%. Around early 2012 and 2013 there was a sharp plunge to a record low of 30%. This period coincides with the removal of the petroleum subsidy in Nigeria, a period characterised by massive national unrest, which probably triggered a rise in prices and the high volatility of commodity prices. Relative stability is observable around 2013 until late 2015, before another peak to 80%. In 2015, Nigeria experienced another election cycle, which could also be responsible for the hike. However, after mid-2015, prices stabilised until the end of the time horizon. In summary, it is noticeable that the returns for total spillover display both trends and bursts with peaks in 2011, 2012 and 2015, and sharp decline in 2013 and 2014, before gradually picking up again in 2015.

4.3 Directional spillover analysis

This study proceeds to investigate the directional spillover after the total net spillover. The need to examine the directional spillover is pertinent for more robust discussion on the direction of the spillover as expressed in Equations (6) and (7) in the methodology section. The directional spillover of "TO" and "FROM" is reported in Figures 3 and 4 of the returns of the spillovers to others. The returns for both directional spillover of "FROM" and "TO" show that shock transmission "FROM" reveals more volatility relative to "TO". Figure 3 shows the trend of high fluctuation with an average of 7% from all commodities to the end of the rolling window; it also shows that all "FROM" directional shocks peak peculiarly in late 2011 and 2015 and subsequently experience sharp decline. These identified years coincide with Nigerian election cycles for political offices. These periods were characterised by slight political upheavals and regime changes that affected the agricultural markets and subsequently other macroeconomic indicators. Similarly, the "TO" directional spillover presented in Figure 4 shows a similar pattern, but more stable variability – except in

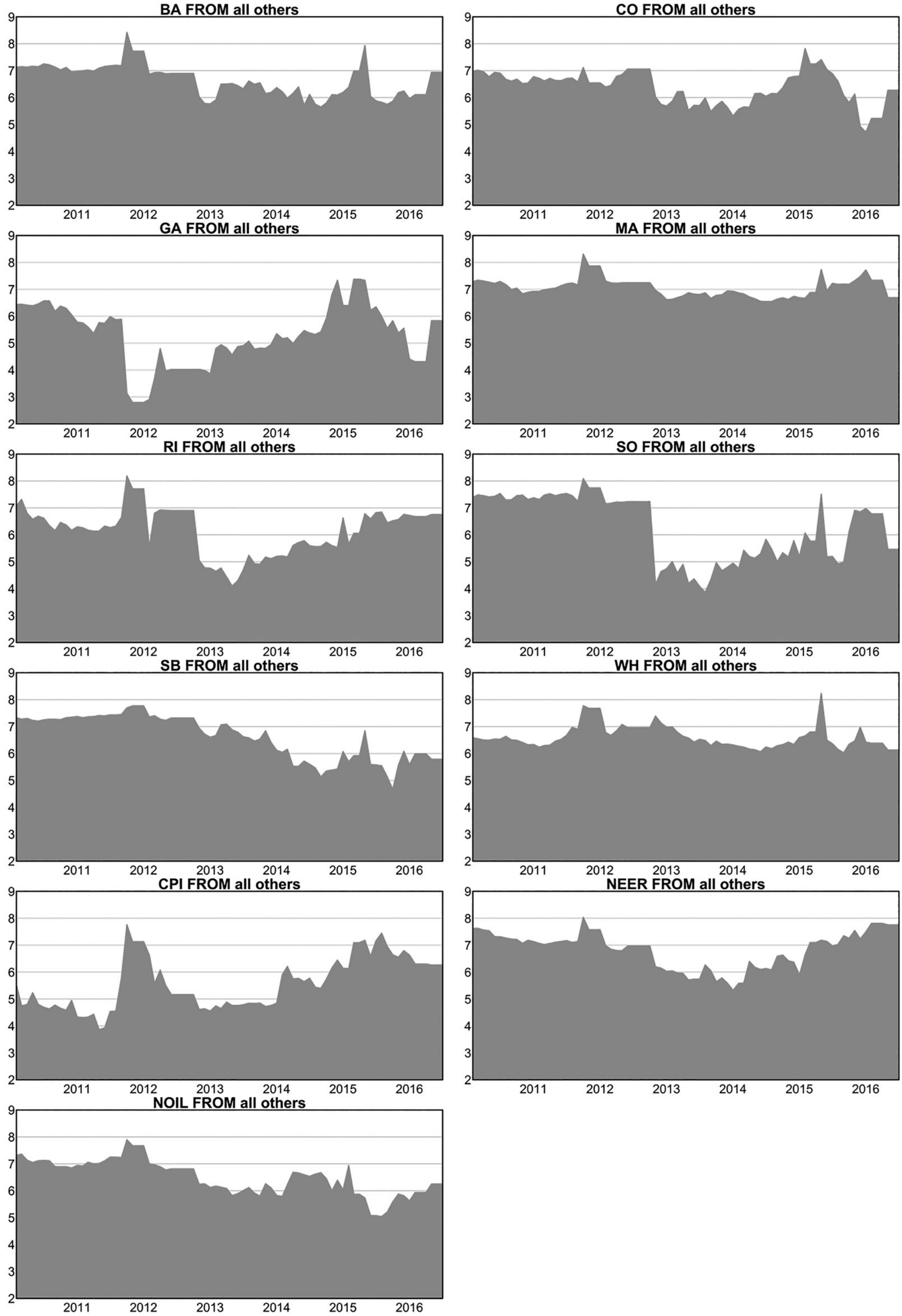

Figure 3. Rolling FROM spillovers.

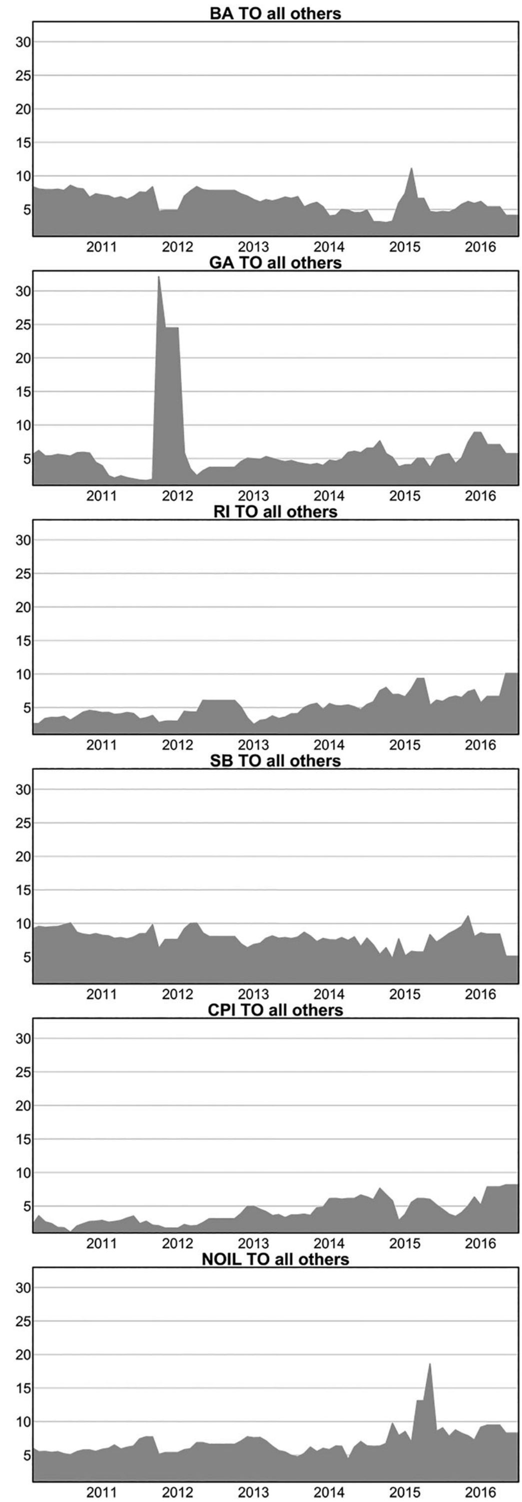

Figure 4. Rolling TO spillovers.

that of groundnut to other markets which peaks at a height of 2012 and plunge sharply and before maintaining fair stability with an average of 5%–7%. One possible reason could be the low budgetary allocations to the agricultural sector in Nigeria over the last five consecutive years. Noticeable from the directional spillover is that the investigated commodity prices, price inflation and nominal effective exchange rate react more to external shocks from other markets than to its own market. This is instructive for decision makers to insulate the commodity from external impacts.

4.4 Net and pairwise spillover analysis

The need to investigate the net directional spillover of the "TO" and "FROM" spillovers is crucial in order to ascertain the VAR net transmitters and net receivers to the total spillover. Figure 5 renders the time varying evolution of the returns for the selected agricultural commodity prices under review. From Figure 5 it is observable that bananas start off from early 2000 to 2012 as net transmitters of spillover to other agricultural commodity markets; only towards the end of the rolling window do bananas become net receivers. Cocoa, maize, sorghum, soybean and wheat all started off within the rolling window sub-periods as net transmitters to the other commodity markets, while on the other hand, rice, price inflation, nominal effective exchange rate and oil price were net receivers of the return spillovers. This is insightful as most of the commodities transmit spillovers to the other markets. Distinctive among the commodities is the groundnut market, where there is an observable hike in the 2011–2012 sub-period. This is not surprising, as that period coincides with an election cycle in Nigeria characterised by political unrest, which spilled over into the agricultural market. On average, on the net directional spillover graphical plot the impact of the global financial crises had mixed effects across the selected variables for this study. For instance, the banana, cocoa, maize, sorghum and wheat markets were net transmitters of spillover effect while others like the rice and groundnut markets were net receivers. Beyond the obvious impact of the global financial unrest period, the Nigerian economy had, at the same time, regulations in place to reduce imports of paddy rice from Western countries to help nearby countries with fledgling rice manufacturing industries. These are the plausible explanations for the orientation of the rice and wheat markets.

An account of pairwise returns for this study is presented in Figure 6. The banana market loosely receives spillover from the cocoa, groundnut, maize and wheat markets precisely between the periods of the global food crises in 2006–2008 to early 2012. For instance, the banana market demonstrates a noticeable impact on the rice market as a net transmitter over almost the entire sub-sample period. For the pairwise spillover between cocoa and the rest of the other variables, cocoa has a positive impact on the rice market from 2006–2010 and 2011–2012, while on the rest of the commodities it exerts a negative effect over the rolling window sub-sample. For instance, it can be observed from Figure 6 that cocoa exerts a negative value on the maize market precisely between late 2011 and 2014 to the end of the rolling window. A similar trend of mixed impacts is seen across the pairs on the net pairwise graphical plot.

In summary, the agricultural commodity crops investigated were very vulnerable to shocks in the periods of global food crises in early 2006–2008 and also during the 2009 global financial unrest, as is evident on the pairwise graphs on the estimated rolling window analysis.

5. Robustness check

This study proceeds to examine the robustness check for the estimated results. The step is necessary in order to ascertain the validity of our study results. In order to achieve this objective, this study relies on the sensitivity of the spillover returns to VAR lag structure and the forecast horizon between the time varying rolling window periods. Figure 7 depicts the VAR lag structure sensitivity test of 1–3 lags. It is observed that there is no noticeable distinction across the rolling window over the VAR lags structure. The forecast horizon analysis for 5–10 was also conducted to ascertain the sensitivity of the spillovers as reported in Figure 6. Both the VAR lag structure and forecast horizon sensitivity test reveal

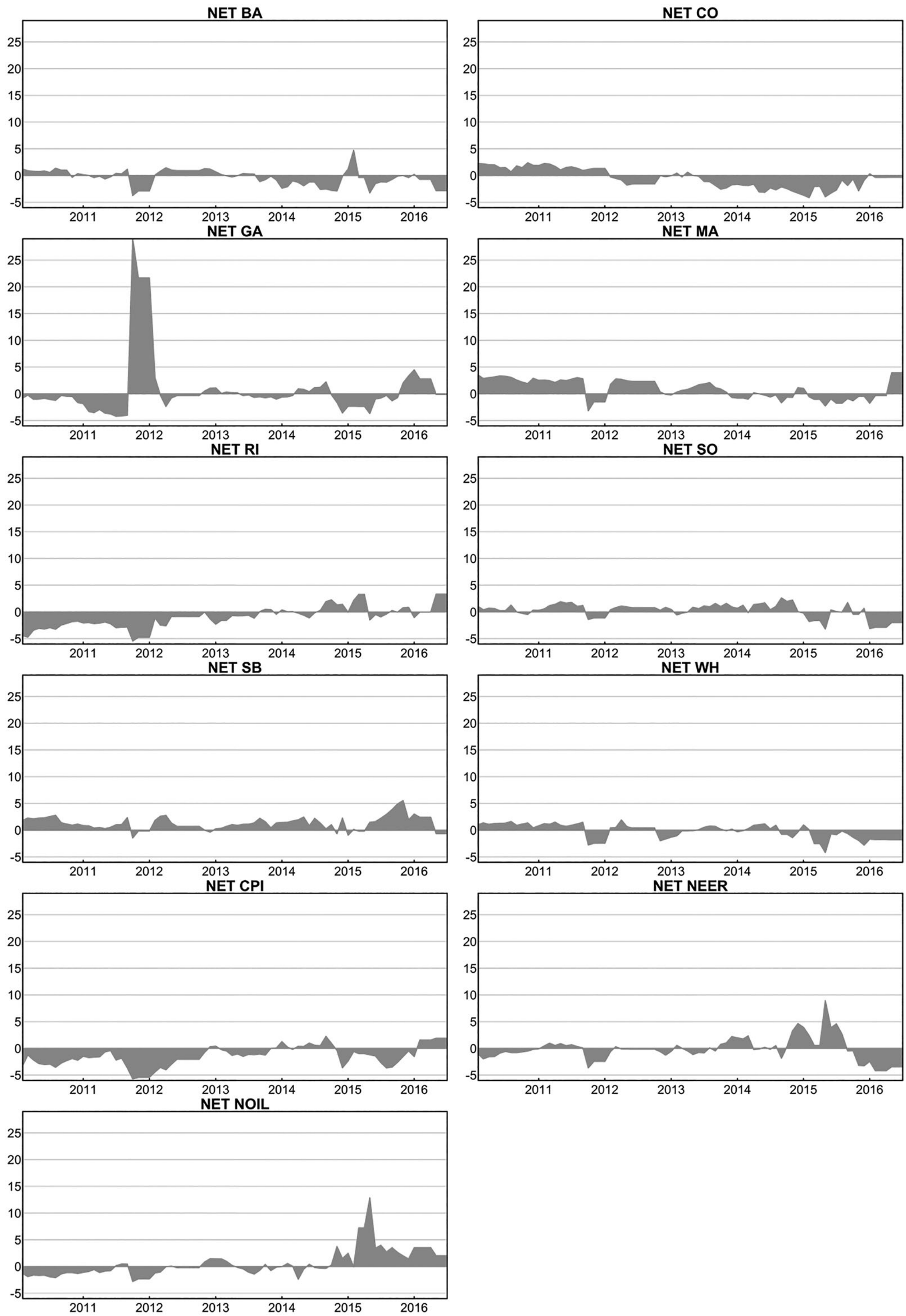

Figure 5. Rolling NET spillovers.

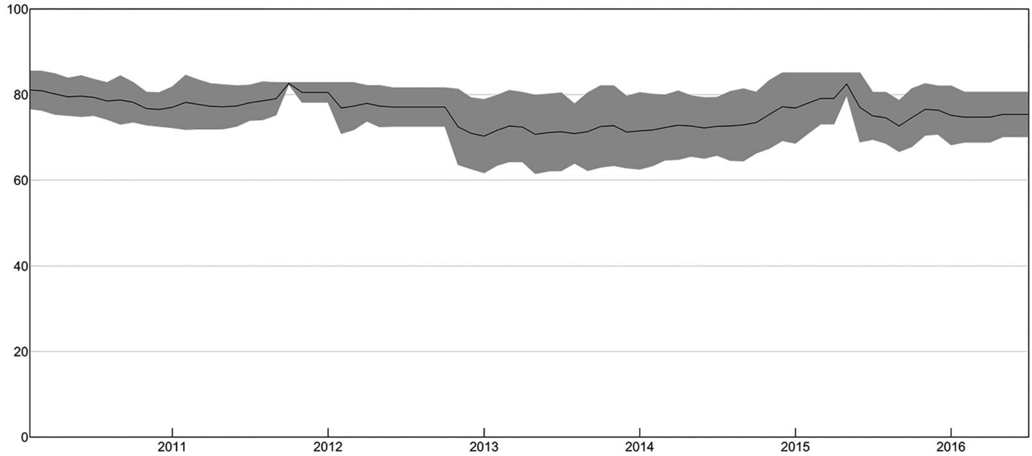

Figure 6. Sensitivity analysis of rolling spillover index for lag order.
Note: Lags from 1 to 3 are analysed.

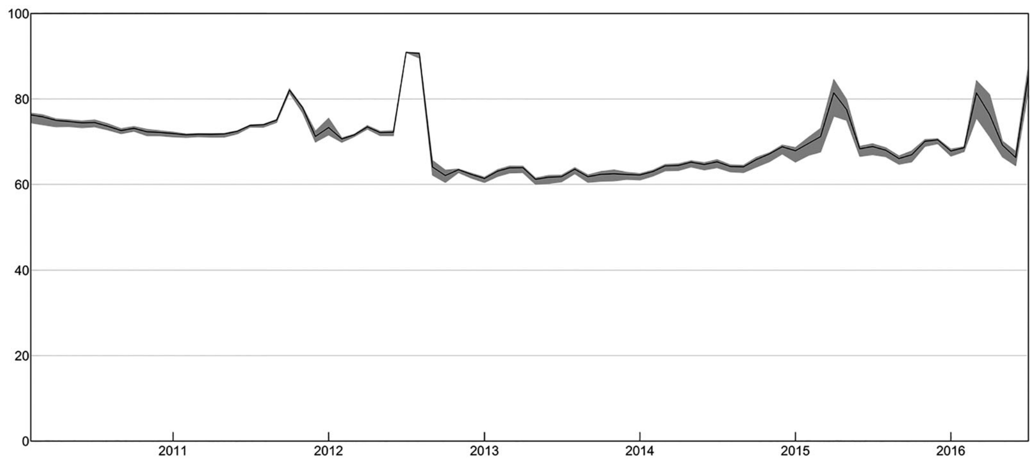

Figure 7. Sensitivity analysis of rolling spillover index for forecast horizon.
Note: Horizons from 5 to 10 are analysed.

no significant variation. That is, the estimated spillover returns for this study are not sensitive to forecast horizon (H) and varying VAR lag structure over the rolling window period. Thus, this study claims that the results are robust and reliable for a policy framework.

6. Conclusion

Adequate information regarding the fluctuation of agricultural commodity prices is pertinent for farmers, policymakers and all stakeholders in the agricultural value chain for decisive farming strategies and decision-making processes, especially in large-scale farming. To this end, the current study attempts to investigate the returns on selected agricultural cash crop prices, price inflation, foreign exchange and oil prices in the face of inflation and dwindling oil prices in Nigeria after the global food crises. This study uses the novel DY techniques to examine the interconnectedness among the interest variables with data sourced from international financial statistics and the African development database on a monthly frequency from 2006M1 to 2016M7. Empirical findings show that rice, sorghum, price inflation, nominal effective exchange rate and oil price display weak pass-through among the investigated variables while banana, cocoa, groundnut, maize, soybean and wheat are net transmitters of spillover.

To further validate the robustness of the coefficients, we conducted a rolling window analysis, which reports insightful episodes for this study area. The total spillover reports a couple of fluctuations in terms of economic patterns especially after the global financial crises period and a record high in 2015, before a sharp decline on the total spillover graph (Figure 2). A similar trend is observed in the directional spillover analysis that shows trends and bursts across the pairs of commodity prices investigated. The study shows the strong presence of the effect of dwindling oil price fluctuations on the selected agricultural commodity prices over the period considered. This position is also reflected in the study by Fasanya, Odudu, and Adekoya (2018), where they argue that oil price fluctuations spill onto the agricultural market. This implies that the earlier net receivers' market is more vulnerable or less resistant to spillover effects, and, as such, policymakers and all stakeholders are enjoined to pay more attention to the net transmitters of spillover shock. This is a call to government administrators to be more pragmatic in understanding the movement of oil price volatility and fluctuation on foreign exchange. This is necessary given that agricultural commodity prices are vulnerable to shocks from them. Furthermore, a clear insight into the mechanism underpinning the dynamics between the outlined variables offers a more robust policy direction in terms of stability and the optimisation of agricultural commodity prices. This is indicative as the agricultural market in Nigeria and other related agricultural commodity markets, like the Eastern and Southern African markets, needs to be insulated from external shocks from key macroeconomic indicators like foreign exchange volatility and further oil price movements. Furthermore, we also explain how the methodology can be used in other contexts, as it is a novel approach to show spillover onto agricultural prices from exchange rates and, thus, illustrates further consequences for food prices. In summary, this study offers the following policy prescription for decision makers:

1) The need for an extension service to inform farmers and all key players in agriculture and agribusiness to avoid asymmetric information is clear, given the interconnectedness established among cash agricultural crops and macroeconomic variables;
2) There is a need for alternative energy sources, as some agricultural commodities are substitutes for oil sources;
3) Government officials also need to intensify efforts for more comprehensive policy frameworks on external shocks that have adverse effects on agricultural markets. This is in order to enhance food availability and security and in the long run improve the standard of living of the main agents in the value chain.

Notes

1. For brevity, see Table 1A in Appendix section for literature table.
2. More insights into Diebold and Yilmaz (2009, 2012) methodology can consult generic papers.
3. The author in quest to establish robustness in estimation re-estimated the VAR at several sub-sample and do not observe any obvious disparity among the time-varying results. However, the forecast horizon was held constant at 10 month.

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References

Adämmer, P., and T.M. Bohl. 2015. Speculative bubbles in agricultural prices. *The Quarterly Review of Economics and Finance* 55: 67–76.

Akpan, S.B., and E.J. Udoh. 2009. Relative price variability of grains and inflation rate movement in Nigeria. *Global Journal of Agricultural Sciences* 8, no. 2: 147–51.

Aliyu, S.U.R. 2009. Impact of Oil price shock and exchange rate volatility on economic growth in Nigeria: An empirical investigation. *Research Journal of International Studies* 5: 4–15.

Balcilar, M., and F.V. Bekun. 2018. Spillover dynamics across price inflation and selected agricultural commodity prices (No. 15–42).

Balcilar, M., S. Chang, R. Gupta, V. Kasongo, and C. Kyei. 2014. The relationship between oil and agricultural commodity prices: A quantile causality approach. University of Pretoria, Department of Economics, working paper series, 68.

Balcilar, M., Z.A. Ozdemir, and H. Ozdemir. 2018. Dynamic return and volatility spillovers among S&P 500, crude oil and gold (No. 15–46).

Busse, S., B. Brummer, and R. Ihle. 2010. Interdependenc ies between fossil fuel and renewable energy markets: The German biodiesel market. DARE discussion paper 10–10.

Chen, S., H. Kuo, and C. Chen. 2010. Modeling the relationship between the oil price and global food prices. *Applied Energy* 87: 2517–25.

Dehn, J. 2000. *Commodity price uncertainty in developing countries*, vol. 2426. World Bank, Development Research Group, Rural Development. Washington, DC., Washington, US.

Dickey, D.A., and W.A. Fuller. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Sstatistical Aassociation* 74, no. 366a: 427–31.

Diebold, F.X., and K. Yilmaz. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal* 119, no. 534: 158–71.

Diebold, F.X., and K. Yilmaz. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28, no. 1: 57–66.

Du, X., C.L. Yu, and D.J. Hayes. 2011. Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. *Energy Economics* 33: 497–503.

Fang, C.R., W.C. Lee, and C.F. Chang. 2014. The co-movement between oil and agricultural commodity prices: Evidence from the emerging market of China. *Issues & Studies* 50: 111–41.

FAO (Food and Agricultural Organization). 2008. Soaring food prices: Facts, perspectives, impacts and actions required. Proceedings of the High-Level Conference on World Food Security, Rome, 3–5 June 2008.

Fasanya, I., and S. Akinbowale. 2019. Modelling the return and volatility spillovers of crude oil and food prices in Nigeria. *Energy* 169: 186–205.

Fasanya, I.O., T.F. Odudu, and O. Adekoya. 2018. Oil and agricultural commodity prices in Nigeria: New evidence from asymmetry and structural breaks. *International Journal of Energy Sector Management*. doi:10.1108/IJESM-07-2018-0004.

Fernado, A. 2014. Do oil prices drive food prices? The tale of a structural break. *Journal of International Money and Finance* 42: 253–71.

Fowowe, B. 2016. Do oil prices drive agricultural commodity prices? Evidence from South Africa. *Energy* 104: 149–57.

Kaltalioglu, M., and U. Soytas. 2011. Volatility Spillover from oil to food and agricultural raw material markets. *Modern Economy* 2: 71–6.

Kapusuzoglu, A., and M.K. Ulusoy. 2015. The interactions between agricultural commodity and oil prices: An empirical analysis. *Agricultural Economics* 61, no. 9: 410–21.

Katusiime, L. 2019. Investigating spillover effects between foreign exchange rate volatility and commodity price volatility in Uganda. *Economies* 7, no. 1: 1. doi:10.3390/economies7010001.

Koop, G., M.H. Pesaran, and S.M. Potter. 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Eeconometrics* 74, no. 1: 119–47.

Lütkepohl, H. 2005. *New introduction to multiple time series analys*is. Springer Science & Business Media. Berlin, Heidelberg & New York.

Mitchell, D. 2008. *A Note on rising food prices*, Policy Research Working Paper No. 4682. Washington, DC: World Bank.

Monika, P. 2014. A dynamic analysis of causality between prices of corn, crude oil and ethanol.

Nazlioglu, S. 2011. World oil and agricultural commodity prices: Evidence from nonlinear causality. *Energy Policy* 39: 2935–43.

Nazlioglu, S., C. Erdem, and S. Soytas. 2013. Volatility spillover between oil and agricultural commodity markets. *Energy Economics* 36: 658–65.

Nazlioglu, S., and U. Soytas. 2011. World oil prices and agricultural commodity prices: Evidence from an emerging market. *Energy Economics* 33: 488–96.

Nazlioglu, S., and U. Soytas. 2012. Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. *Energy Economics* 34: 1098–104.

Nwoko, I.C., G.C. Aye, and B.C. Asogwa. 2016. Oil price and food price volatility dynamics: The case of Nigeria. *Cogent Food & Agriculture* 2, no. 1: 1142413.

Olasunkanmi, O.I., and K.S. Oladele. 2018. Oil price shock and agricultural commodity prices in Nigeria: A non-linear autoregressive distributed Lag (NARDL) approach. *African Journal of Economic Review* 6, no. 2: 74–91.

Pesaran, H.H., and Y. Shin. 1998. Generalized impulse response analysis in linear multivariate models. *Economics Lletters* 58, no. 1: 17–29.
Phillips, P.C., and P. Perron. 1988. Testing for a unit root in time series regression. *Biometrika* 75, no. 2: 335–46.
Reboredo, J.C. 2012. Do food and oil prices co-move? *Energy Policy* 49: 456–67.
Rosa, F., and M. Vasciaveo. 2012. Agri-commodity price dynamics: The relationship between oil and agricultural market (No. 1007-2016-79633).
Saghaian, S.H. 2010. The impact of the oil sector on commodity prices: Correlation or causation? *Journal of Agricultural and Applied Economics* 42, no. 3: 477–85.
Salisu, A.A., O.J. Oyewole, and I.O. Fasanya. 2018. Modelling return and volatility spillovers in global foreign exchange markets. *Journal of Information and Optimization Sciences*, 39(7): 1–32.
Yu, T.E., D.A. Bessler, and S. Fuller. 2006. Cointegration and causality analysis of world vegetable oil and crude oil prices. American agricultural economics association annual meeting, Long Beach, California, July 23–26, 2006.
Zhang, Z., L. Lohr, C. Escalante, and M. Wetzstein. 2010. Food versus fuel: What do prices tell us? *Energy Policy* 38: 445–51.

Appendix

Table 1A. Summary of previous literature.

Study (Author)	Period	Methodology	Commodity	Empirical finding
Fowowe (2016)	2003–2014	Non-linear causality and cointegration estimation	Maize, sunflower, soybeans, oil	Agricultural commodities in southern Africa are neutral to global oil prices
Balcilar et al. (2014)	2005–2014	Quantile regression	Soybeans, wheat, sunflower and corn	The impact of oil on agricultural commodities fluctuates across different quantiles of conditional distribution
Monika (2014)	2007–2014	Augmented VARY, Toda-Yamamoto	Crude oil, corn, ethanol	The results reveal dependencies between the prices of energy sources and food price change over time
Fang, Lee, and Chang (2014)	2004–2012	Toda-Yamamoto Causality & impulse response analysis	Rice, flour, soybean oil, peanut oil, grape salt, white chicken meat, fuel oil price	Neutrality (no causal relation)
Kapusuzoglu and Ulusoy (2015)	1991–2014	VECM & Johansen	Wheat, corn and soybeans	Neutrality
Kaltalioglu and Soytas (2011)	1980–2008	Granger Causality	Oil prices, food production, agricultural raw material index	Neutrality
Rosa and Vasciaveo (2012)	1999–2012	Co-integration Analysis, Granger	Wheat, corn, soybeans, crude oil	Neutrality
Fernado (2014)	1986–2012	VECM, Granger Causality	Corn, soybeans, oil price	Inverse causality from crop to oil prices
Zhang et al. (2010)	1989–2008	VECM, Granger Causality	Ethanol, corn, rice, soybeans, sugar, wheat, gasoline and crude oil	No direct long-run price relations between fuel and agricultural commodity prices
Busse, Brummer, and Ihle (2010)	2002–2009	MS-VECM	Biodiesel, rapeseed oil, soya oil, crude oil	Causality exists; crude oil influence on agricultural commodity prices and rapeseed oil prices
Yu, Bessler, and Fuller (2006)	1999–2006	Granger Causality & Co-integration	Corn, soybeans, wheat, Brent oil, West Texas intermediate (WTI)	Neutrality
Nazlioglu (2011)	1994–2010	Toda-Yamamoto and DiskPanchenko Causality Analysis	Corn, soybeans and oil	The findings of Non-Linear Causality reveal causality as against the linear and soybeans
Saghaian (2010)	1996–2008	VECM, Granger Causality	Corn, soybeans and wheat	Oil price influences agricultural commodity prices
Nazlioglu, Erdem, and Soytas (2013)	1986–2011	Causality in Variance Test	Soybeans, wheat, corn, oil	Oil price influences agricultural commodity prices
Adämmer and Bohl (2015)	1993–2012	VECM, Granger Causality and MTAR	Wheat, real exchange rate, real oil price	Causality from oil to wheat

Source: Author's creation.
Note: Neutrality refers to no causal relationship among the variables under investigation.