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RESEARCH ARTICLE

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Assessing the asymmetric volatility linkages of energy and agricultural commodity futures during low and high volatility regimes

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Abstract

This study investigated the volatility linkages between energy and agricultural futures, including possible causes for these comovements, such as external macroeconomic and financial shocks during low and high volatility regimes. A combination of Markov-switching regressions and quadrivariate VAR–DCC–GARCH and VAR–BEKK–GARCH modeling revealed that external shocks have an asymmetric effect on the relationship of these assets with higher cross-correlations reported during high volatility regimes. This comovement effect outweighs the substitution effect between energy and agricultural products. Furthermore, the quadrivariate VAR–BEKK–GARCH model provides strong evidence of a bidirectional price volatility spillover between the agricultural and energy markets during periods of high volatility. Overall, the results suggest that energy futures can be effectively used for hedging in a portfolio comprising agricultural futures (and vice versa), while a combination of macroeconomic and financial index futures can serve as an effective hedging tool in investment portfolios comprising both energy and agricultural commodities.

KEYWORDS

agricultural futures, energy futures, hedging strategies, Markov-switching regression, volatility

JEL CLASSIFICATION

C01, C58, Q02, Q41, Q16

1 | INTRODUCTION

Since the early 2000s, food-based biofuel production has surged in both the United States and Europe. This has been supported by policies devised to reduce the use of fossil fuels, such as the first EU biofuel directive introduced in 2003. Furthermore, many countries around the world have initiated programs promoting biofuel production with the aim of decreasing their dependence on fossil fuels.

The use of agricultural products in energy production has created extra linkages between these two sectors (in addition to their existing connection) because energy is used as input in the agricultural sector for agricultural production, food processing, and transportation. This increasing integration and interdependence between energy and agricultural commodity markets has fueled skepticism about the benefits of using food crops to produce biofuels instead of feeding the world population, particularly given the global food crisis in 2008 and the extremely high food prices in 2010–2012 and at present.

Extant literature suggests that the emergence of biofuel production might have engendered strong bidirectional linkages between these two markets (López Cabrera & Schulz, 2016) because price changes in agricultural commodities can induce a similar shift in biofuel prices—primarily due to feedstock costs constituting an increasingly high proportion of overall biofuel production costs. Additionally, a change in the price of energy can trigger similar changes in the prices of agricultural commodities by altering input costs and causing shifts in the biofuel market demand. This is due to biofuel prices affecting the price of fossil fuel by influencing demand through the substitution effect (Gilbert, 2010; Han et al., 2020; Meyers & Meyer, 2008). These bidirectional linkages may cause bidirectional price volatility spillovers between energy and agricultural commodity markets. A robust connection between these markets can significantly affect price levels and the volatility linkages between them. More importantly, increased price volatility reduces market participants' ability to accurately forecast future agricultural commodities and energy prices, thus exposing them to the risk of higher prices. Hence, it is crucial for traders, investors, and policy-makers to be aware of the degree of price correlation and volatility between energy and agricultural commodity markets so that they can adopt suitable hedging practices.

This study addresses this problem by investigating price, volatility, and correlation risk linkages between energy and agricultural commodity prices and examining their dynamics over time. It also assesses whether bidirectional volatility linkages exist between the markets under consideration, and whether the volatility linkage between energy and agricultural commodity markets is the outcome of the comovement effect caused by external macroeconomic shocks or the substitution effect induced by the biofuel industry (Gilbert, 2010; Han et al., 2020; Serra & Zilberman, 2013). López Cabrera and Schulz (2016) posited that the short-run volatility linkage between energy and agricultural markets is attributable to the comovement effect, while the long-run volatility linkage is attributable to the substitution effect between energy and the biofuel market.[1] However, Han et al. (2020) question such a hypothesis as they report that bidirectional linkages between these two markets are driven by external shocks, rather than the substitution effect. Our study extends knowledge of this issue by assessing the asymmetric effect of bidirectional linkages between these two markets under low and high volatility regimes induced by external macroeconomic and financial shocks. Unlike Han et al. (2020), who investigated such interconnectedness between two ad hoc subperiods (before and after the shale gas revolution), our study enhances the accuracy and practical efficacy of the relevant hedging strategy by assessing volatility spillovers during low and high volatility regimes, as determined by the Markov chain approach. Given that external shocks are found to be inherently asymmetric across different markets and financial assets (Cologni & Manera, 2009; Hau et al., 2020; Li et al., 2016) we should expect hedging efficiency to diverge across such regimes.

Hence, the contribution of this paper is fourfold. First, we use the dynamic conditional correlation (DCC) of the multivariate generalized autoregressive conditional heteroskedasticity (MVGARCH) model to estimate dynamic conditional cross-correlations among energy and agricultural commodity prices. We consider two representative energy futures and two representative agricultural futures, over the sample period from July 3, 1996, to November 2, 2020. The DCC–MVGARCH model has been used in previous studies to measure the correlation between price volatilities but does not draw on an extensive range of volatility causality links. To address this problem, we applied Markov-switching regression models in the estimated dynamic cross-correlations obtained from the DCC–MVGARCH model to identify subperiods of high and low conditional cross-correlations. We then estimated the BEKK–MVGARCH model in each subperiod to investigate volatility causality linkages between energy and agricultural commodity prices.[2] The Markov-switching technique is known for its ability to identify not only regime states regarding high and low prices, but also the volatility of the variables examined (Wang et al., 2021). Furthermore, it can demonstrate the probability of switching among the different regimes, rendering the analysis robust. In this context, because the literature has already confirmed that different phases exist in the performance of

[1]Previous literature investigating price volatility spillovers between energy and agricultural commodity markets is rather scarce, while the literature related to price-level relations and spillovers is extensive (e.g., Ahmadi et al., 2015; López Cabrera & Schulz, 2016; Nazlioglu & Soytas, 2012).

[2]The advantage of the BEKK–MVGARCH model is that it can reveal possible bidirectional price volatility transmissions between energy and agricultural markets.

financial markets (Boroumand et al., 2016), the combination of the Markov-switching technique with the BEKK–MVGARCH can be regarded as a novel and robust method.

To the best of our knowledge, our study is the first to combine the DCC–MVGARCH, the Markov-switching regression approach, and the BEKK–MVGARCH in a single framework to detect subperiods of low and high conditional cross-correlations between energy and agricultural futures returns. In our view, this is a more accurate approach towards examining the underlying determinants of low and high conditional cross-correlation states and for investigating volatility causality linkages between energy and agricultural commodity markets in each subperiod.

Second, we estimated a Markov-switching regression model for each of the estimated dynamic conditional cross-correlations among energy and agricultural commodity prices obtained from the estimation of the DCC–MVGARCH. Contrary to extant literature (e.g., Han et al., 2020; Nazlioglu et al., 2013), which breaks the period of examination into subperiods according to an economic or political event, or employs state space approaches, the use of a Markov-switching technique enabled us to identify volatility regime-shifts from the data without the need to prespecify structural breaks. As such, our modeling approach is more forward-looking and appropriate for forecasting purposes. The Markov-switching regression model also allowed us to investigate the effect of macroeconomic factors on the volatility regime levels. We accounted for increasingly volatile conditional cross-correlations among energy and agricultural commodity prices and changing economic conditions over the sample period under consideration (July 3, 1996–November 2, 2020). Common (macroeconomic and financial) factors relating to world GDP growth, monetary expansion, and exchange rate changes are likely to be the key factors inducing energy and agricultural prices level changes. The modeling superiority of the discrete Markov-switching model in our multidimensional approach was evidenced by the fact that volatility regimes were found to play a role in the effect of external shocks and the substitution effect, a result that is reported for the first time in the literature.

Third, to study the volatility linkages and transmission between energy and agricultural commodity prices, our study is one of the few to estimate a quadrivariate VAR–BEKK–GARCH model for each of the subperiods obtained in the previous step. Thus, all the variables under consideration were included in a quadrivariate Baba, Engle, Kraft, and Kroner (BEKK) model, facilitating a simultaneous analysis of all energy and agricultural commodity variables. Previous literature (e.g., Du et al., 2011; Han et al., 2020; Trujillo-Barrera et al., 2012) primarily estimated bivariate BEKK models between energy and agricultural commodities. However, such an approach fails to account for the simultaneous effect of all the energy and commodity prices.[3] We overcame this problem by performing Granger-style causality tests (i.e., exogeneity tests) to investigate spillovers in the conditional variance–covariance matrix of the BEKK model; in other words, we tested whether a set of coefficients on other (control) variables were zero.[4]

Finally, we made appropriate provisions for portfolio management and hedging activities associated with energy and agricultural commodities for the whole period under consideration and the three subperiods derived from the implementation of the Markov switch. Given that critical macroeconomic factors play an essential role in determining the comovement of energy and agricultural prices, we demonstrated how futures contracts related to key macroeconomic and financial factors can be used as hedging instruments for portfolios involving energy and agricultural commodities. Hence, we extend relevant literature that investigates hedging activities and portfolio management between main macroeconomic factors, energy, and agricultural prices, including the period at the start of the COVID-19 pandemic.

The remainder of the paper is organized as follows. Section 2 presents and discusses existing literature. Section 3 details the empirical models, following which Section 4 describes the data. Section 5 reports the empirical results. Hedging strategies are presented in Section 6 and concluding remarks are made in Section 7.

2 | LITERATURE REVIEW

In contrast to literature investigating price-level linkages between energy and agricultural commodities, research on price volatility interdependences between these types of assets is rather scarce.[5] More importantly, although most of those studies suggest the existence of such a relationship, the possible causes of such an effect are rather diverse. For

[3]The main difficulty when estimating a multivariate BEKK model is the high number of unknown parameters. Consequently, this model is rarely used when the number of series is greater than 3. Furthermore, a key weakness of this modeling approach is that its parameters do not directly represent the impact of the different lagged terms on the conditional variance–covariance matrix elements (Bauwens et al., 2006).

[4]An advantage of the BEKK model is that it is flexible enough to allow volatility causality links to move in any direction (Serra & Zilberman, 2013).

[5]In this study, we present a brief overview of the literature related to price transmission and volatility in biofuel markets. For an extensive coverage of relevant literature, readers are advised to consult Meyers and Meyer (2008) and Serra and Zilberman (2013).

example, a seminal study by Zhang et al. (2009) on price transmission and volatility spillovers between weekly wholesale prices of US ethanol, corn, soybeans, gasoline, and oil for the period from March 1989 to December 2007 reported no evidence of price volatility spillovers from ethanol to corn and soybeans markets. However, the converse was found regarding significant volatility price transmission from the corn and soybeans markets (agricultural commodities) to the energy market, especially during the ethanol boom period. According to the authors, such an effect can be attributed to higher incomes, particularly in Asia, leading to increased demand for meat and dairy products which, in turn, elevates demand for corn and soybeans and energy inputs. By contrast, Kaltalioglu and Soytas (2011) reported that variation in oil prices does not Granger cause the variance in food and agricultural raw material prices.

Employing stochastic volatility models to weekly crude oil, corn, and wheat futures prices, Du et al. (2011) reported volatility spillovers from oil prices to agricultural commodity prices after the autumn of 2006, identifying a stronger interdependence between crude oil and agricultural commodity markets induced by ethanol production. In a similar vein, Nazlioglu et al. (2013) employed the causality in variance test and impulse response functions to examine volatility transmission between oil prices and those of selected agricultural commodities (wheat, corn, soybeans, and sugar). Their empirical findings revealed evidence of oil price volatility spillovers on agricultural price volatility only after January 1, 2006.

With regard to the ethanol markets, Trujillo-Barrera et al. (2012) analyzed volatility spillovers from energy to agricultural markets using the daily futures prices of crude oil, ethanol, and corn. They found that spillovers from crude oil to corn and ethanol markets were similar in magnitude over time in both markets, but with a stronger effect during periods of high volatility in the crude oil market. In contrast to Zhang et al. (2009), the authors reported significant volatility spillovers from crude oil to corn and ethanol markets, and argued that the biofuel era created stronger connection between these two markets. This finding is supported by Serra (2011) for international crude oil prices and Brazilian ethanol and sugar prices. According to these authors, the volatility of ethanol prices is affected by shocks in the oil and sugar markets with the existence of a long-run equilibrium between prices—with ethanol being adjusted in line with deviations from this long-run equilibrium—whilst crude oil and sugar are exogenous in the long run. This was confirmed by a follow-up study on crude oil prices and Brazilian ethanol and sugar prices that employed a semiparametric GARCH model (Serra, 2011). In subsequent research, Du and McPhail (2012) investigated the interconnectedness between ethanol, gasoline, and corn prices in the United States using a DCC–GARCH model with structural breaks for the period from March 2005 to March 2011. They identified a structural change point in March 2008, with strengthened linkages between energy and corn markets in the second subperiod (i.e., after March 2008) when ethanol production expanded.

By contrast, a study of price and volatility linkages between energy and agricultural commodity prices by López Cabrera and Schulz (2016) reported a long-run equilibrium relationship where both rapeseed and biodiesel prices react to deviations from the long-run equilibrium. The authors found that biodiesel did not affect the price level of rapeseed and crude oil in the short run but did respond to price changes in the rapeseed and crude oil markets. The price volatility of biodiesel was only weakly linked to rapeseed and crude oil volatility, whereas the relationship between the price volatility of rapeseed and crude oil increased later in their sample period. In addition, their results do not provide any significant evidence to suggest that biodiesel is the cause of high and volatile agricultural commodity prices.

Finally, regarding the underlying causes of such an effect (volatility spillovers), Gilbert (2010) found that the causes of the correlation between agricultural and oil prices during the 2007–2008 food price rises, both in terms of levels and changes, were common factors (e.g., world GDP growth, monetary expansion, and exchange rate change), rather than market-specific factors, such as supply shocks. Furthermore, they provided weak evidence to show that the strengthened linkage between agricultural and oil prices was due to the increasing use of farm commodities in biofuel production. This is supported by Han et al. (2020), who reported a statistically significant bidirectional volatility relationship between energy and agricultural futures returns, especially after 2007. Such results indicate that this bidirectional volatility linkage is attributable to the comovement effect prompted by external macroeconomic shocks that emerged from the world economy, trade, and financial markets, rather than the substitution effect initiated by the biofuel industry.

Our study extends this stream of literature on the dynamic nature of cross-correlations among energy and agricultural commodity prices. Unlike previous studies, we performed a multistage analysis that combined the VAR–DCC–GARCH model, the Markov-switching technique, and a quadrivariate VAR–BEKK–MVGARCH model. Furthermore, our sample period covered the beginning of the COVID-19 pandemic, and hence provided more insights into these interrelationships given the evident shocks in both macroeconomic conditions and the financial markets.

3 | MODEL

In this study, we utilized the DCC and BEKK GARCH models with a Markov-switching technique in a manner that enabled us to overcome the problems that arise when using one of these techniques in isolation.[6] Specifically, using the DCC–GARCH model, we initially identified dynamic conditional cross-correlations between energy and agricultural futures for the period under investigation. Next, by applying Markov-switching regressions to the estimated dynamic conditional cross-correlations obtained from the DCC–GARCH model, we established the subperiods of low and high volatility regimes. In addition, we applied Markov-switching regressions on dynamic conditional cross-correlations obtained from the BEKK–GARCH model. However, identifying subperiods of low and high volatility was challenging because the conditional cross-correlations were highly volatile. Furthermore, the DCC–GARCH approach is unable to investigate potential causal effects. To overcome this weakness, we employed a BEKK–GARCH model for each subperiod by identifying and treating the subperiods evidenced from the DCC–GARCH model as independent periods. In this way, we were able to capture possible causality effects by utilizing the strengths of each technique.

3.1 | *VAR*(*p*)–*DCC*(1, 1)–*MVGARCH*(1, 1) model

We utilized the DCC of the MVGARCH model (Engle, 2002) to estimate dynamic conditional cross-correlations among energy and agricultural commodity prices for the entire period examined. In Section 3.2, we explain how we applied Markov-switching regression models on the estimated dynamic conditional cross-correlations to identify high and low conditional cross-correlation subperiods. This model follows a $VAR(p)$–$MVGARCH(1,1)$ structure with DCCs in the error terms. Throughout this section, i and j are used interchangeably to refer to *oil*, *ngas*, *corn*, or *soybeans* commodity futures. In particular, the $VAR(p)$–$DCC(1,1)$–$MVGARCH(1,1)$ is given by

$$Y_t = C + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \varepsilon_t, \quad t = 1, \ldots, T, \tag{1}$$

$$\varepsilon_t = H_t^{\frac{1}{2}} v_t, \tag{2}$$

$$H_t = D_t R_t D_t, \tag{3}$$

where $Y_t = \{y_{i,t}\}$ denotes a (4×1) vector of futures' price returns; $C = \{c_i\}$ is a (4×1) vector of constant terms; $\Phi_p = \left\{\varphi_{ij}^p\right\}$ indicates a (4×4) matrix of coefficients; p is the number of lags of the conditional means given by Equation (1); $\varepsilon_t = \{\varepsilon_{i,t}\}$ is a (4×1) error term vector of the conditional means, where $E(\varepsilon_t) = 0$ and $Cov(\varepsilon_t) = H_t$; H_t is a (4×4) conditional covariance matrix; R_t is a (4×4) conditional correlation matrix; D_t is a (4×4) diagonal matrix with time-varying standard deviations on the diagonal; and v_t is a (4×1) vector of iid errors such that $E(v_t) = 0$ and $E\left(v_t v_t'\right) = I$.

The elements of the diagonal matrix $D_t = diag\left(h_{oil}^{\frac{1}{2}}, h_{ngas}^{\frac{1}{2}}, h_{corn}^{\frac{1}{2}}, h_{soyb}^{\frac{1}{2}}\right)$ represent the standard deviations from univariate $GARCH(1,1)$ models

$$h_{i,t} = c_{0,i} + a_i \varepsilon_{i,t-1}^2 + b_i h_{i,t-1} \tag{4}$$

for $i =$ *oil*, *ngas*, *corn*, and *soybeans*, where a_i and b_i are nonnegative scalar parameters with $a_i + b_i < 1$, and $c_{0,i} > 0$. Furthermore, $R_t = \{\rho_{ij,t}\}$is a symmetric correlation matrix of conditional correlation coefficients. In the $DCC(1,1)$ model, R_t is decomposed into

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{5}$$

where

[6]Although not explicitly claimed, we believe this is also a methodological contribution of our paper.

$$Q_t = (1 - a - b)\bar{Q} + a\xi_{t-1}\xi'_{t-1} + bQ_{t-1}, \tag{6}$$

where $\xi_t = \varepsilon_{i,t}/\sqrt{h_{i,t}}$ is a (4×1) vector of standardized errors, $Q_t = \{q_{ij,t}\}$ is a (4×4) conditional variance–covariance matrix, and $\bar{Q} = Cov\left(\xi_t\xi'_t\right) = E\left(\xi_t\xi'_t\right)$ is the unconditional variance–covariance matrix of the standardized errors ξ_t, which can be estimated as $\bar{Q} = \frac{1}{T}\sum_{t=1}^{T}\xi_t\xi'_t$. The parameters a and b are scalars and must satisfy the conditions $a \geq 0, b \geq 0$, and $a + b < 1$, and Q_t^* is a diagonal matrix containing the square root of the diagonal elements of Q_t, that is, $Q_t^* = diag\{\sqrt{q_{ii,t}}\}$. It is also important to note that $\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}}$ is obtained by estimating Equation (6) using a maximum likelihood method (Engle, 2002).

3.2 | Markov-switching regression

On the basis of the work of McCulloch and Tsay (1994), the next step was to estimate a Markov-switching regression model on each of the conditional cross-correlations obtained from the implementation of the $VAR(p)$–$DCC(1,1)$–$MVGARCH(1,1)$ model. Let us assume that the conditional cross-correlation between commodity returns i and j is given by $\rho_{ij,t}$. For simplicity, we drop subscripts i, j from $\rho_{ij,t}$. A two-state Markov-switching regression model is written as

$$\rho_t|\left(s_t = k, \beta_k, \sigma_k^2\right) \sim N\left(X'_t\beta_k, \sigma_k^2\right), \tag{7}$$

where $\{s_t\}$ is a Markov chain with two states $\{1, 2\}$, $X_t = (x_{1t}, \ldots, x_{it})'$ indicates a set of exogenous variables that include a constant vector of unity, $\beta_k = (\beta_1, \beta_2)'$ is a vector of regression coefficients for each state, and $\sigma_i^2 < \infty$ is the corresponding variance. The probabilities of the Markov-switching states are given by $P(s_t = 2|s_{t-1} = 1) = \varepsilon_1$ and $P(s_t = 1|s_{t-1} = 2) = \varepsilon_2$.

We then adopt Bayesian analysis to estimate the model's parameters, using a Markov chain Monte Carlo (MCMC) algorithm based on the Gibbs sampler to draw the *iid* sample from the posterior distribution of the parameters of the above model. Thus, the conjugate priors are

$$\beta_i \sim N\left(\beta_{i,0}, A_i^{-1}\right), \quad \sigma_\iota^2 \sim \frac{v_i\lambda_i}{\chi_{v_i}^2}, \quad \varepsilon_i \sim Beta(\gamma_{i,1}, \gamma_{i,2}), \quad \text{where } i = 1, 2 \tag{8}$$

deriving the full conditional posterior distribution for each parameter of the model.

If $p(w|\bullet)$ denotes the conditional posterior distribution of w, given all the other parameters and the data, we obtain the following:

(i) For $i = 1$ and 2, $p(\beta_i|\cdot) = p\left(\beta_i|\rho_i, s, \sigma_i^2\right) \sim N\left(\beta_{i,*}, A_{i,*}^{-1}\right)$, where ρ_i, $\beta_{i,*}$, and $A_{i,*}$ are defined as:

Let the observational vector be $\rho = (\rho_1, \ldots, \rho_n)'$ and the state vector be $s = (s_1, \ldots, s_n)'$. In addition, let $i_1 < i_2 < \cdots < i_{n_i}$ indicate all the time indices such that $s_{i_j} = i$. For $t = i_j$, the vector ρ_i is then defined by $\rho_i = \left(\rho_{i_1}, \rho_{i_2} \ldots, \rho_{i_n}\right)'$. Given the above, we have

$$A_{i,*} = \sigma_i^{-2}\left(\sum_{j=1}^{n_i} X_{i_j}X'_{i_j}\right) + A_i \quad \text{and} \quad \beta_{i,*} = \left(\frac{\sum_{j=1}^{n_i} X_{i_j}X'_{i_j}}{\sigma_i^2} + A_i\right)'\left(\frac{\sum_{j=1}^{n_i} X'_{i_j}\rho_{i_j}}{\sigma_i^2} + A_i\beta_{i,0}\right).$$

(ii) For $i = 1$ and 2, $p\left(\sigma_i^2|\bullet\right) \sim$ inverted χ^2 such that $\left(v_i\lambda_i + S_i^2\right)/\sigma_i^2 \sim \chi_{v_i+n_i}^2$, where $S_i^2 = \sum_{j=1}^{n_i}\left(\rho_{i_j} - X'_{i_j}\beta_i\right)^2$.

(iii) The conditional posterior distribution of ε_i depends only on s and we have $p(\varepsilon_i|s) \sim Beta(\gamma_{i,1} + k_i, \gamma_{i,2} + n_i - k_i)$ for $i = 1, 2$. It is important to note that k_1 is the number of jumps from State 1 to State 2, while k_2 indicates the number of jumps from State 2 to State 1.

(iv) The conditional posterior distribution of s is given by $p(s_{t,k}|\rho, s_{t,(-k)}, \cdot) \propto p(\rho| \cdot)p(s_{t,k}|s_{t,(-k)}, \varepsilon_1, \varepsilon_2)$ which is a discrete distribution with 2^k possible outcomes. Here, $s_{t,k}$ represents a subsection $s_{t,k} = (s_t, s_{t+1}, ..., s_{t+k-1})'$ of s with length k and $s_{t,(-k)}$ is the subset of s with $s_{t,k}$ removed. Furthermore,

$$p(\rho| \cdot) \propto p(y_t, ..., y_{t+k-1}|s_{t,k}, \cdot) = \prod_{j=t}^{t+k-1} \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_{s_j}} exp\left(\frac{-\left(\rho_j - X'_j\beta_{s_j}\right)^2}{2\sigma^2_{s_j}}\right).$$

3.3 | *VAR*(*p*)–*BEKK*(1, 1)–*MVGARCH*(1, 1) model

The *BEKK*(1, 1) of the MVGARCH model (Engle & Kroner, 1995) was employed to estimate the conditional variance–covariance matrix among energy and agricultural commodity prices for the entire sample period, as well as for the subperiod determined from the application of the Markov-switching regression model. This is because the BEKK–GARCH model permits a richer dynamic dependence between the volatility series than the DCC–GARCH model. In this case, we allowed a *VAR*(*p*) structure in the conditional mean equations but a *BEKK*(1, 1) structure in the error terms. Thus, whilst the conditional mean is given by Equations (1) and (2), the conditional variance–covariance matrix, H_t, which defines market volatility, is provided by

$$H_t = \Omega\Omega' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B, \tag{9}$$

where $\Omega = \{\omega_{ij}\}$ is a (4×4) lower triangular matrix, and $A = \{a_{ij}\}$ and $B = \{b_{ij}\}$ are general (4×4) matrices. Elements of matrix A are the coefficients of the ARCH effect, which represents the impact of shocks in the chosen market and shock spillovers from other markets on the conditional volatility of the chosen market. Conversely, elements of matrix B are the coefficients of the GARCH effect, which represents the impact of past volatility in the chosen market and past volatility spillover from the other market on the conditional volatility of a chosen market. The minimum values of Akaike Information Criterion (AIC), Schwartz Bayesian Criterion (SBC), and Hannan–Quinn information criterion (HQ) determined the goodness of fit of the models under consideration. However, the BEKK–GARCH model has a number of weaknesses. First, the parameters in the A and B matrices of the conditional variance–covariance matrix do not allow direct interpretations regarding lagged values of shocks or volatilities. Second, the number of estimated parameters increases rapidly in line with the number of variables included in the model. Because of these disadvantages, most previous studies have used a bivariate BEKK–GARCH model. In the current study, however, we employed a quadrivariate BEKK–GARCH model by including all four variables under consideration. Finally, the Ljung–Box statistics was employed to test for serial correlation in the residuals of the models under consideration. The null hypothesis of such a test is that there is no autocorrelation.

4 | DATA

4.1 | Energy and agricultural commodity future prices

The data used in this study consisted of daily returns for two energy futures (New York Mercantile Exchange [NYMEX] West Texas Intermediate [WTI] crude oil and NYMEX natural gas) and two agricultural futures (Chicago Board of Trade [CBOT] corn and the CBOT soybeans) covering the period from July 3, 1996 to November 2, 2020. These assets are major agricultural commodities (corn and soybeans) and energy (crude oil and natural gas) representatives. We used commodity futures instead of spot market prices as the former are a type of financial asset strongly influenced by market expectations, thereby allowing better price discovery and higher liquidity. Moreover, commodity future contracts provide a range of prices for the delivery of specific quantities of an underlying commodity at different maturities, unlike the commodity spot market which provides the price of a particular commodity for immediate purchase and delivery.

The data were collected from Bloomberg and we used the daily closing prices (p_t) to calculate daily price returns, $y_t = 100 \times log(p_t/p_{t-1})$. Descriptive statistics for the price returns of the energy and agricultural futures are reported in columns (1) to (4) of Table 1, and Figure 1 presents plots of the commodity futures prices.

TABLE 1 Descriptive statistics of energy futures, agricultural futures, and index returns.

	oil (1)	*ngas* (2)	*corn* (3)	*soyb* (4)	*crb* (5)	*usdx* (6)
Mean	0.0125	0.0155	0.0019	−0.0021	−0.00042	0.00057
Minimum	−28.2206 (2020:03:09)	−19.8993 (2003:02:27)	−26.8620 (2013:07:15)	−23.4109 (2008:09:15)	−11.0933 (2020:04:21)	−2.7168 (2009:03:18)
Maximum	31.9633 (2020:04:22)	32.4353 (2003:02:24)	25.0288 (2013:07:05)	20.3209 (2008:09:12)	5.8814 (2020:03:19)	2.5237 (2008:09:30)
SD	2.5180	3.3035	1.739499	1.5227	1.0261	0.4690
Skewness	0.0713	0.5358	−0.4999	−1.1430	−0.4940	−0.0652
Kurtosis	18.2525	5.6809	23.9654	21.7259	6.4887	1.8579

Notes: The table presents descriptive statistics for the returns of oil, natural gas, corn, soybeans, as well as the returns of *crb* and *usdx* indices. Dates are provided in parentheses.

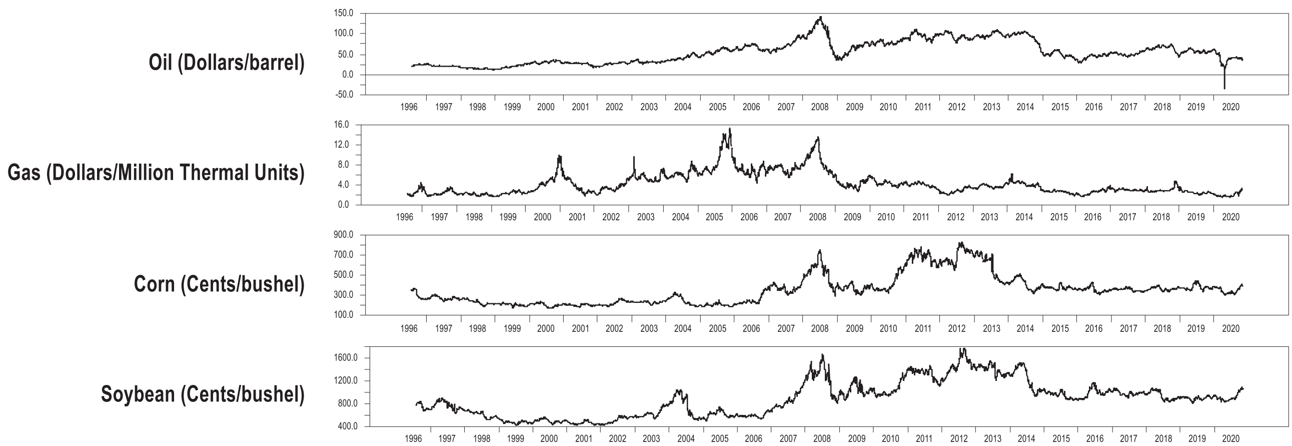

FIGURE 1 Time series of the oil, natural gas, corn, and soybeans futures prices.

We had to be extremely careful regarding the number of assets included in the multivariate VAR–BEKK–GARCH models, as these models are highly nonlinear and therefore struggle to converge to a stable solution. Hence, any increase in the number of variables makes it increasingly difficult for these models to converge. For this reason, most of the multivariate VAR–BEKK–GARCH models used in extant literature are bivariate or triradiate in nature. Our study extended this type modeling approach by estimating quadrivariate VAR–BEKK–GARCH models, further contributing to this stream of literature. Furthermore, given the nonlinear nature of the adopted quadrivariate GARCH models, we also attempted to re-estimate these models after controlling for potential seasonal effects, using dummy variables for each quarter of the year and/or month, in the conditional variance equations (and/or the conditional mean equations). However, these models failed to converge.

4.2 | Proxies for external macroeconomic factors

In this study, we employed two leading indicators to capture macroeconomic conditions: the Commodity Research Bureau index (*crb*) and the U.S. dollar index (*usdx*). The *crb* is considered an appropriate indicator of commodity price trends (Beckmann et al., 2014; Ji & Fan, 2012) because it includes the most important 19 commodities associated with energy, soft/tropical, grains/livestock, and industrial/precious metals. There are three key reasons for using the *crb* index. First, it can be utilized as a representative indicator of the worldwide commodity markets (Han et al., 2020). Second, it measures the impact of inflation on the various commodity sectors and overall commodity trades because it is computed as an unweighted geometric mean of the individual commodity prices relative to their base periods. This

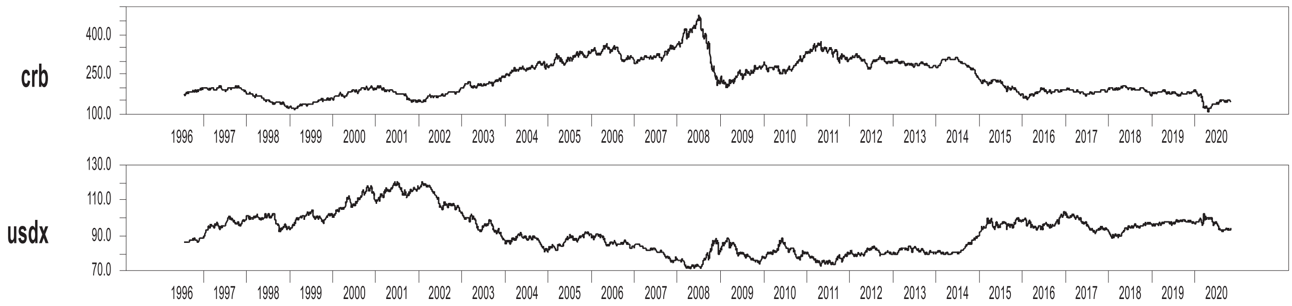

FIGURE 2 Time series of the *crb* and *usdx* indices.

TABLE 2 Unconditional pairwise Pearson correlation matrix for the full sample period.

	oil	***ngas***	***corn***	***soyb***	***crb***	***usdx***
oil	1 –	0.2116*** (7.699)	0.1450*** (5.210)	0.1223*** (4.381)	0.7500*** (40.325)	−0.1740*** (−6.282)
ngas		1 –	0.0884*** (3.155)	0.0953*** (3.402)	0.3963*** (15.348)	−0.1094*** (−3.913)
corn			1 –	0.5152 (21.373)	0.3939*** (15.240)	−0.2129*** (−7.749)
soyb				1 –	0.3568*** (13.582)	−0.1689*** (−6.094)
crb					1 –	−0.3514*** (−13.345)
usdx						1 –

Notes: This table presents the unconditional pairwise Pearson correlation coefficients for the oil, natural gas, corn, and soybeans futures returns, as well as the *crb* and *usdx* index returns. *t* Statistics are provided in parentheses.

***Indicates significance at the 1% level.

reduces the impact of extreme disturbances in individual commodity prices in the index, which may convey the wrong signals in relation to widespread inflationary pressures (Gargano & Timmermann, 2014; Han et al., 2020). Third, it can be used as an indicator of commodity prices and market access, thereby measuring the general trend of the commodity sector. The *usdx* is the ratio of the US dollar to a geometric weighted average of the six most important foreign currencies, and thus we employed it as a proxy of the world financial markets. Several studies in the literature have examined the interaction between international commodity prices (especially oil prices) and *usdx* (Benhmad, 2012; Chen et al., 2013; Harri et al., 2009; Rezitis, 2015a, 2015b; Sun et al., 2017).

Columns (5) and (6) of Table 1 report the descriptive statistics for *crb* and *usdx* index returns, while Figure 2 provides plots of both index series. As indicated in Figure 2, the *crb* and *usdx* indices exhibit opposite trends, implying that these two indices may contain substantially different information and affect the energy and agricultural markets in different ways. Table 2 also presents the Pearson correlation matrix between the energy and agricultural futures returns and the two index returns. This reveals that the return on the *crb* (*usdx*) index is positively (negatively) correlated with all the energy and agricultural futures returns at a 1% level of significance. Plots in Figures 1 and 2 support this finding, displaying similar (opposite) trends in the *crb* (*usdx*) indices and the energy and agricultural prices.

It is important to emphasize that, in general, there is no guarantee that the daily data of assets will be recorded at the same time that trades are executed as there are numerous factors that could affect the exact time a trade is recorded; for example, order procession and settlement processes, the actual exchange where the asset is traded, the time zone in which the asset is traded, and other factors. Furthermore, delays in the reporting and processing of trading information could be introduced by the various data providers. However, given that most market participants make investment decisions based on timely and accurate information, financial data providers make substantive efforts to minimize any discrepancies or delays in the data. Our study used two energy futures contracts (the NYMEX WTI crude oil and the NYMEX natural gas futures) and two agricultural futures (the CBOT corn and the CBOT soybeans futures). The time zone difference between these two exchanges (i.e., NYMEX and CBOT) is only 1 h, and minimal trading volume is recorded outside the standard exchange trading hours. Additionally, since 2006, these two exchanges have belonged to the CME Group which uses a single trading system: CME Globex. On that basis, we believe that the assets under examination in the current study are subject to minimal execution, recording, and reporting delays.

5 | EMPIRICAL RESULTS

5.1 | $VAR(5)$–$DCC(1,1)$–$MVGARCH(1,1)$ results

Table 3 presents the estimated coefficients for the $VAR(5)$–$DCC(1,1)$–$MVGARCH(1,1)$ model for the entire sample period (i.e., 1996:07:03–2020:11:02). The results of the conditional mean equations (Equation 1) are presented in Panel A, while the empirical results of the conditional variance (Equation 4) and the DCC (Equation 6) are provided in Panels B and C, respectively. All the estimated GARCH and DCC parameters of Panels B and C are positive and statistically significant at the 1% level, supporting the validity of the modeling specification. The values of the estimated coefficients of the GARCH term b_i are close to 1, indicating persistent volatility within the examined return time series. For the DCC model, the sum of the estimated coefficients, a and b, is less than 1, suggesting that the DCCs among these assets are reverting to the mean. Hence, although the relationship between these commodities can experience significant short-term volatility, the results from Panel C indicate a move back towards historical averages. This renders the movement of those assets more predictable, at least in terms of their correlation patterns. In addition, such a result also has significant implications for portfolio management as it implies that the potential diversification benefits can vary over time with periods of high (low) correlations among those assets leading to decreased (increased) effectiveness in portfolio diversification. Overall, we argue that this mean-reversion effect will provide a sense of stability and confidence in long-term investment strategies.

The HQ criterion, given in Panel D, determines the optimal lagged number in the mean equations (Equation 1). Panel D details the model diagnostics, while Panel E shows that the model residuals are free from autocorrelation.

Panel F presents the Wald test results, testing the null hypothesis that the conditional mean equations (Equation 1) should be modeled as having separate autoregressions on each variable. The results reject the null hypothesis at all conventional levels of significance and thus support the $VAR(5)$ representation in the conditional mean model. The conditional cross-correlations for the entire sample period (i.e., 1996:07:03–2020:11:02) were obtained from the estimation of the $VAR(5)$–$DCC(1,1)$–$MVGARCH(1,1)$ model. We continued our analysis by applying Markov-switching regression models to identify subperiods of high and low conditional cross-correlations.

5.2 | Markov-switching regression results

The Gibbs sampler generated $M + N = 2000 + 5000$ iterations for each of the conditional cross-correlations obtained from the estimation of the $VAR(5)$–$DCC(1,1)$–$MVGARCH(1,1)$ model. Table 4 presents the empirical results of the estimation of the two-state Markov-switching regression model (Equation 7), while Figure 3 presents the conditional cross-correlations obtained from the estimation of the $VAR(5)$–$DCC(1,1)$–$MVGARCH(1,1)$ model and the corresponding posterior probabilities of the high mean regime (i.e., State 2) obtained from the estimation of the Markov-switching regression.

As depicted in Table 4, all estimated coefficients are statistically significant at the 1% level. The mean and variance of each of the conditional cross-correlations for State 1 (i.e., μ_1 and σ_1^2, respectively) are lower than the corresponding mean and variance for State 2 (i.e., μ_2 and σ_2^2, respectively). Thus, we can consider State 1 the lower conditional cross-correlation state and State 2 the higher conditional cross-correlation state. Moreover, the impact of the Commodity Research Bureau Index (*crb*) and the US dollar index *(usdx)* on the conditional cross-correlations has the expected sign in that the impact of *crb* is positive while that of *usdx* is negative. However, the impact of these variables is stronger in State 2 than that in State 1.

It is also evident that both states are highly persistent with State 1 exhibiting slightly higher persistence than State 2 in four out of the six conditional cross-correlations. Moreover, the probability that the conditional cross-correlation will

TABLE 3 Coefficient estimation for $VAR(5)$–$DCC(1,1)$–$MVGARCH(1,1)$ for the whole period (1996:07:03–2020:11:02).

y_{oil}		y_{ngas}		y_{corn}		y_{soyb}	
Panel A: Mean estimators from Equation (1)							
c_{oil}	0.040** (0.021)	c_{ngas}	0.043 (0.047)	c_{corn}	0.019 (0.021)	c_{soyb}	0.014 (0.014)
$\varphi^1_{oil,oil}$	−0.005 (0.015)	$\varphi^1_{ngas,oil}$	−0.031** (0.015)	$\varphi^1_{corn,oil}$	−0.027*** (0.007)	$\varphi^1_{soyb,oil}$	−0.016*** (0.005)
$\varphi^1_{oil,ngas}$	0.006 (0.005)	$\varphi^1_{ngas,ngas}$	−0.031** (0.014)	$\varphi^1_{corn,ngas}$	0.006 (0.005)	$\varphi^1_{soyb,ngas}$	0.005** (0.002)
$\varphi^1_{oil,corn}$	−0.008 (0.011)	$\varphi^1_{ngas,corn}$	0.012 (0.020)	$\varphi^1_{corn,corn}$	0.046** (0.019)	$\varphi^1_{soyb,corn}$	0.014* (0.011)
$\varphi^1_{oil,soyb}$	0.013 (0.013)	$\varphi^1_{ngas,soyb}$	0.024 (0.024)	$\varphi^1_{corn,soyb}$	−0.015 (0.020)	$\varphi^1_{soyb,soyb}$	−0.019* (0.013)
$\varphi^2_{oil,oil}$	−0.027*** (0.010)	$\varphi^2_{ngas,oil}$	0.014 (0.013)	$\varphi^2_{corn,oil}$	0.015** (0.006)	$\varphi^2_{soyb,oil}$	0.001 (0.004)
$\varphi^2_{oil,ngas}$	0.003 (0.005)	$\varphi^2_{ngas,ngas}$	−0.025** (0.011)	$\varphi^2_{corn,ngas}$	0.0003 (0.005)	$\varphi^2_{soyb,ngas}$	0.005* (0.003)
$\varphi^2_{oil,corn}$	−0.006 (0.012)	$\varphi^2_{ngas,corn}$	0.002 (0.021)	$\varphi^2_{corn,corn}$	−0.044*** (0.016)	$\varphi^2_{soyb,corn}$	0.002 (0.011)
$\varphi^2_{oil,soyb}$	0.029* (0.016)	$\varphi^2_{ngas,soyb}$	0.026 (0.026)	$\varphi^2_{corn,soyb}$	0.021* (0.017)	$\varphi^2_{soyb,soyb}$	0.009 (0.014)
$\varphi^3_{oil,oil}$	−0.023** (0.009)	$\varphi^3_{ngas,oil}$	−0.009 (0.012)	$\varphi^3_{corn,oil}$	−0.005 (0.007)	$\varphi^3_{soyb,oil}$	0.003 (0.005)
$\varphi^3_{oil,ngas}$	0.006 (0.006)	$\varphi^3_{ngas,ngas}$	−0.012* (0.008)	$\varphi^3_{corn,ngas}$	−0.007* (0.005)	$\varphi^3_{soyb,ngas}$	−0.013*** (0.004)
$\varphi^3_{oil,corn}$	0.008 (0.011)	$\varphi^3_{ngas,corn}$	−0.019 (0.020)	$\varphi^3_{corn,corn}$	−0.002 (0.011)	$\varphi^3_{soyb,corn}$	0.003 (0.007)
$\varphi^3_{oil,soyb}$	−0.0002 (0.014)	$\varphi^3_{ngas,soyb}$	0.053** (0.023)	$\varphi^3_{corn,soyb}$	−0.003 (0.011)	$\varphi^3_{soyb,soyb}$	−0.003 (0.008)
$\varphi^4_{oil,oil}$	0.015* (0.007	$\varphi^4_{ngas,oil}$	0.003 (0.016)	$\varphi^4_{ngas,oil}$	−0.004 (0.007)	$\varphi^4_{soyb,oil}$	−0.007* (0.005)
$\varphi^4_{oil,ngas}$	−0.002 (0.005)	$\varphi^4_{ngas,ngas}$	0.010 (0.009)	$\varphi^4_{corn,ngas}$	−0.0001 (0.005)	$\varphi^4_{soyb,ngas}$	0.0004 (0.004)
$\varphi^4_{oil,corn}$	−0.016* (0.011)	$\varphi^4_{ngas,corn}$	−0.016 (0.020)	$\varphi^4_{corn,corn}$	−0.016** (0.009)	$\varphi^4_{soyb,corn}$	0.012* (0.006)
$\varphi^4_{oil,soyb}$	0.004 (0.012)	$\varphi^4_{ngas,soyb}$	0.042* (0.026)	$\varphi^4_{corn,soyb}$	0.021* (0.012)	$\varphi^4_{soyb,soyb}$	−0.008 (0.012)
$\varphi^5_{oil,oil}$	−0.004 (0.006)	$\varphi^5_{ngas,oil}$	0.004 (0.015)	$\varphi^5_{corn,oil}$	0.008* (0.006)	$\varphi^5_{soyb,oil}$	0.010** (0.005)
$\varphi^5_{oil,ngas}$	−0.0008 (0.005)	$\varphi^5_{ngas,ngas}$	−0.030*** (0.009)	$\varphi^5_{corn,ngas}$	−0.005 (0.005)	$\varphi^5_{soyb,ngas}$	0.001 (0.003)
$\varphi^5_{oil,corn}$	0.015* (0.011)	$\varphi^5_{ngas,corn}$	0.017 (0.019)	$\varphi^5_{corn,corn}$	−0.023* (0.017)	$\varphi^5_{soyb,corn}$	−0.010 (0.012)
$\varphi^5_{oil,soyb}$	−0.020* (0.015)	$\varphi^5_{ngas,soyb}$	−0.003 (0.023)	$\varphi^5_{corn,soyb}$	−0.012 (0.021)	$\varphi^5_{soyb,soyb}$	−0.026* (0.015)
Panel B: Variance estimators from Equation (4)							
$c_{0,oil}$	0.095*** (0.028)	$c_{0,ngas}$	0.150*** (0.037)	$c_{0,corn}$	0.117* (0.071)	$c_{0,soyb}$	0.029*** (0.008)
a_{oil}	0.093*** (0.017)	a_{ngas}	0.082*** (0.009)	a_{corn}	0.114** (0.054)	a_{soyb}	0.075*** (0.010)
b_{oil}	0.891*** (0.018)	b_{ngas}	0.908*** (0.009)	b_{corn}	0.850*** (0.068)	b_{soyb}	0.912*** (0.010)
Panel C: $D(1,1)$ estimators from Equation (6)							
a	0.012*** (0.004)	b	0.978*** (0.009)				

Panel D: Model diagnostics
Log likelihood: −50,907.2868
AIC: 16.118
SBC: 16.223
HQ: 16.154
Usable observations: 6329

Panel E: Residual diagnostics
$Q(10)$ statistic: 127.2643; significance level: 0.9735
$Q(20)$ statistic: 308.3814; significance level: 0.6695

(Continues)

TABLE 3 (Continued)

y_{oil}	y_{ngas}	y_{corn}	y_{soyb}
$Q(30)$ statistic: 483.1493; significance level: 0.4511			
$Q(40)$ statistic: 655.9261; significance level: 0.3227			
Panel F: Exogeneity test in the mean Equation (1)			
Test of exogeneity in the mean of all variables:			
$H_0: \varphi_{i,j}^{P} = 0$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$			
$H_1: \varphi_{i,j}^{P} \neq 0$ for at least one $\varphi_{i,j}^{P}$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$			
$\chi^2(60) = 151.8926$ or $F(60, *) = 2.5315$ with significance level 0.0000			

Notes: This table presents the estimated coefficients based on Equations (1), (4), and (6). Standard errors are in parentheses. $Q(10)$, $Q(20)$, $Q(30)$, and $Q(40)$ are the Ljung–Box statistics for serial correlation in the model residuals computed with 10, 20, 30, and 40 lags, respectively.

Abbreviations: AIC, Akaike Information Criterion; DCC, dynamic conditional correlation; HQ, Hannan–Quinn information criterion; MVGARCH, multivariate generalized autoregressive conditional heteroskedasticity; SBC, Schwartz Bayesian Criterion; VAR, vector autoregressive.

***, **, and * indicate significance at the 1%, 5%, and 10% levels.

TABLE 4 Coefficient estimation for Markov-switching regression for the whole period (1996:07:03–2020:11:02).

	$\rho_{oil,corn}$	$\rho_{oil,soyb}$	$\rho_{ngas,corn}$	$\rho_{ngas,soyb}$
$\beta_{1,0}$	0.115*** (0.003)	0.106*** (0.004)	0.045*** (0.003)	0.025*** (0.004)
$\beta_{1,usdx}$	−0.006*** (0.001)	−0.016*** (0.002)	−0.008*** (0.001	−0.008*** (0.002)
$\beta_{1,crb}$	0.005*** (0.001)	0.013*** (0.002)	0.006*** (0.001)	0.007*** (0.001)
$\beta_{2,0}$	0.275*** (0.010)	0.278*** (0.009)	0.142*** (0.006)	0.125*** (0.004)
$\beta_{2,usdx}$	−0.049*** (0.004)	−0.052*** (0.004)	−0.014*** (0.003)	−0.022*** (0.002)
$\beta_{2,crb}$	0.034*** (0.003)	0.037*** (0.003)	0.011*** (0.002)	0.017*** (0.001)
μ_1	0.114*** (0.003)	0.105*** (0.004)	0.044*** (0.003)	0.025*** (0.004)
μ_2	0.271*** (0.009)	0.274*** (0.008)	0.141*** (0.006)	0.124*** (0.004)
σ_1^2	0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
σ_2^2	0.007*** (0.000)	0.005*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
$p(1,1)$	0.993*** (0.001)	0.996*** (0.001)	0.990*** (0.002)	0.986*** (0.002)
$p(2,1)$	0.007*** (0.001)	0.004*** (0.001)	0.010*** (0.002)	0.014*** (0.002)
$p(1,2)$	0.011*** (0.002)	0.007*** (0.002)	0.016*** (0.003)	0.012*** (0.002)
$p(2,2)$	0.989*** (0.002)	0.993*** (0.002)	0.984*** (0.003)	0.988*** (0.002)

Notes: This table presents the estimated coefficients of the Markov-switching regression (7). Standard errors are in parentheses.

***Indicates significance at the 1% level.

switch from State 1 to State 2 is lower than the probability of switching from State 2 to State 1 in four out of the six conditional cross-correlations. It is also clear that the intercept of State 1 is smaller than that of State 2, and both are statistically significant, indicating that each state is also affected by additional external shocks associated with the world economy and these are accumulated in the intercept term beyond those captured by the *crb* and *usdx* variables.

Contrary to previous literature (e.g., Han et al., 2020; Nazlioglu et al., 2013), the Markov-switching regression enabled us to identify regime-shifts from the data without needing to prespecify structural breaks. Table 5 displays the percentage of total observations for which the probability that the conditional cross-correlations in the low mean state exceeds 0.5, and thus the corresponding conditional cross-correlation is deemed to be in State 1. The results indicate that we can consider three subperiods: subperiod I (1996:07:03–2006:12:29) and subperiod III (2013:01:01–2020:11:02) where State 1 dominates, except in the case of $\rho_{ngas,soyb}$ where both states are equivalent, and subperiod II

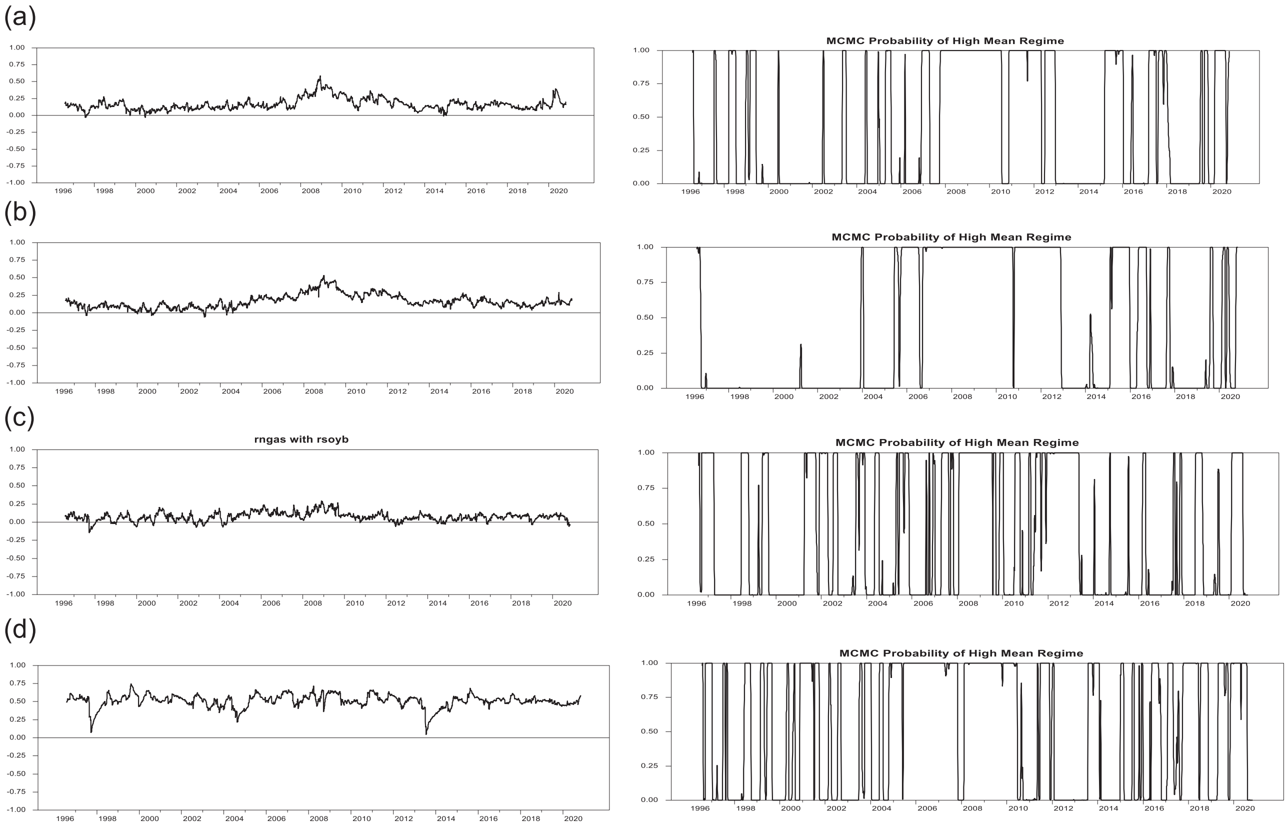

FIGURE 3 Conditional correlations from $VAR(5)$–$DCC(1, 1)$–$MVGARCH(1, 1)$ and corresponding MCMC probability of the high mean regime (State 2) of the Markov-switching regression. (a) Oil and corn conditional correlation (left graph) and the corresponding MCMC probability of the high mean regime (State 2) of the Markov-switching regression (right graph). (b) Oil and soybeans conditional correlation (left graph) and the corresponding MCMC probability of the high mean regime of the Markov-switching regression (right graph). (c) Natural gas and corn conditional correlation (left graph) and the corresponding MCMC probability of the high mean regime of the Markov-switching regression (right graph). (d) Natural gas and soybeans conditional correlation (left graph) and the corresponding MCMC probability of the high mean regime of the Markov-switching regression (right graph). DCC, dynamic conditional correlation; MCMC, Markov chain Monte Carlo; MVGARCH, multivariate generalized autoregressive conditional heteroskedasticity; VAR, vector autoregressive.

TABLE 5 Percentage of total observations in regime 1.

	$\rho_{oil,corn}$ (%)	$\rho_{oil,soyb}$ (%)	$\rho_{ngas,corn}$ (%)	$\rho_{ngas,soyb}$ (%)
Subperiod I (1996:07:03–2006:12:29)	84.14	83.82	65.43	49.23
Subperiod II (2007:01:01–2012:12:31)	16.03	2.43	31.67	36.60
Subperiod III (2013:01:01–2020:11:02)	67.11	74.47	77.56	50.17

(2007:01:01–2012:12:31) where State 2 clearly dominates. Figure 3 depicts these states of high conditional cross-correlation.

The Markov-switching regression results suggest a stronger impact of the external shocks associated with common macroeconomic factors, as captured by the intercept term and the *crb* and *usdx* variables on the conditional cross-correlations between energy and agricultural commodity prices when the high volatility regime dominates. This indicates that volatility links between energy and agricultural commodities are mainly initiated by common macroeconomic factors rather than the substitution effect between energy and agricultural commodities. This is because the substitution between energy and agricultural commodities was anticipated to weaken, especially from 2006, as shale gas production increased (Han et al., 2020). Shale gas was expected to diminish the volatility links among energy and agricultural commodity markets because it provides a more cost-effective alternative for a lower-carbon economy (Middleton et al., 2017). Our findings indicate that during subperiod II (subperiod I), when shale gas production was high (low), conditional cross-volatility between energy and agricultural commodities was high (low), which was induced by the strong (weak) effect of common macroeconomic factors on the conditional cross-volatilities.

5.3 | *VAR*(5)–*BEKK*(1, 1)–*MVGARCH*(1, 1) results

We estimated a quadrivariate *VAR*(5)–*BEKK*(1, 1)–*MVGARCH*(1, 1) model for the whole period as well as for the three subperiods identified by the Markov-switching regression.[7] The empirical results are presented in Tables 6–9. The estimated parameters of the mean equations (Equation 1) are provided in Panel A of the corresponding tables, while the estimated coefficients of the conditional variance–covariance matrix (Equation 9) are given in Panel B. The AIC, SBC, and HQ criteria reported in Panel C determine the optimal lagged number in the mean equations. Panel C presents the model diagnostics, while Panel D indicates that the model residuals are free from autocorrelation.

We performed exogeneity tests to examine the dynamic dependencies in the conditional mean (Equation 1) of the *VAR*(5)–*BEKK*(1, 1) model for the whole period as well as for the three subperiods.[8] Our results reveal that prices behave differently across the three subperiods. During the second subperiod all prices are endogenous, while in the other two subperiods some prices are exogenous. In the first subperiod energy prices are exogenous, while in the third subperiod *corn* prices are exogenous. The bidirectional linkage between energy and agricultural commodity prices in the high volatility regime subperiod (subperiod II) could be attributed to the comovement effect induced by external shocks associated with the world economy rather than by the substitution effect caused by the biofuel industry. Our findings support those of several studies addressing price-level links between energy and agricultural commodity markets (Cha & Bae, 2011; Chang & Su, 2010; Gilbert, 2010; Wixson & Katchova, 2012). Thus, external shocks associated with the world economy play a role in influencing the prices of energy and agricultural commodities, while futures markets, especially those tied to these sectors, may be more sensitive to global economic events, such as financial crises or geopolitical developments. Furthermore, the comovement effect between energy and agricultural commodity prices is influenced more by external shocks than the biofuel industry. Therefore, traders focusing on the biofuel sector may find that its impact on agricultural commodity prices is less significant than broader economic factors. Finally, the volatility and bidirectional linkage that exists confirms that there may be short- to medium-term trading opportunities in both energy and agricultural commodity futures markets. Therefore, traders skilled in technical and fundamental analysis may find opportunities to profit from price movements.

Tables 6–9 present the results of several exogeneity tests conducted to examine the dynamic dependencies in the conditional variance–covariance matrix given by (Equation9) for the full period as well as for the three subperiods. Short-run endogeneity tests affirmed the higher degree of bidirectional price volatility spillovers between energy and agricultural commodity markets during the high volatility regime subperiod (i.e., subperiod II) compared with the low volatility regime subperiods (i.e., subperiods I and III).[9] The main finding of the log-run exogeneity tests is the exogeneity of *oil*, indicating that supply and demand shocks (e.g., the substitution effect) do not support price volatility spillovers from the agricultural commodity markets to the crude oil market; however, there is some evidence for price volatility spillovers from the agricultural commodity markets to the natural gas market. The finding that *oil* remained long-run exogenous in the second and third subperiods indicates that the substitution effect between energy and agricultural commodities might have been weakened by the "shale gas revolution" (Han et al., 2020).

[7]The lag selection was based on criteria, such as the AIC, SBC, and HQ, with an optimal lag of 5 chosen using the AIC. The vector autoregressive model examines the impact of lagged values in parallel equations, while the GARCH process models imply volatility. Despite some insignificant parameters in the mean equations, the VAR model remained suitable, as significant parameters were reported for lag 5 and other smaller lags (first, second, third, and fourth). Further exogeneity tests rejected the null hypothesis for most cases, confirming the validity of our model's results for lag selection.

[8]The first test is presented in Panel F and examines the exogeneity of all variables in the conditional mean Equation (1). The Wald test results supported the *VAR*(5) representation in the conditional mean model for the whole period (Table 6) as well as for the three subperiods (Tables 7–9). We also performed exogeneity tests for specific variables for the whole period and for the three subperiods under consideration.

[9]More specifically, Panels F and G of Tables 6–9 present exogeneity tests based on each of the *A* and *B* matrices. In particular, the exogeneity tests based on matrix *A* are related to short-run exogeneity (i.e., external shocks associated with the world economy), while those based on matrix *B* are connected to long-run exogeneity (i.e., supply and demand shocks associated with the energy and agricultural commodity markets).

TABLE 6 Coefficient estimation for $VAR(5)$–$BEKK(1,1)$–$MVGARCH(1,1)$ for the whole period (1996:07:03–2020:11:02).

y_{oil}		y_{ngas}		y_{corn}		y_{soyb}	
Panel A: Mean estimators from Equation (1)							
c_{oil}	0.031 (0.022)	c_{ngas}	0.047 (0.037)	c_{corn}	0.011 (0.014)	c_{soyb}	0.003 (0.012)
$\varphi^1_{oil,oil}$	−0.006 (0.010)	$\varphi^1_{ngas,oil}$	−0.040*** (0.015)	$\varphi^1_{corn,oil}$	−0.021*** (0.005)	$\varphi^1_{soyb,oil}$	−0.012*** (0.004)
$\varphi^1_{oil,ngas}$	0.010 (0.007)	$\varphi^1_{ngas,ngas}$	−0.031** (0.013)	$\varphi^1_{corn,ngas}$	0.006** (0.003)	$\varphi^1_{soyb,ngas}$	0.006** (0.003)
$\varphi^1_{oil,corn}$	−0.014 (0.013)	$\varphi^1_{ngas,corn}$	0.011 (0.018)	$\varphi^1_{corn,corn}$	0.037*** (0.014)	$\varphi^1_{soyb,corn}$	0.0005 (0.009)
$\varphi^1_{oil,soyb}$	0.019* (0.011)	$\varphi^1_{ngas,soyb}$	0.022 (0.020)	$\varphi^1_{corn,soyb}$	−0.018* (0.010)	$\varphi^1_{soyb,soyb}$	−0.012 (0.011)
$\varphi^2_{oil,oil}$	−0.027** (0.011)	$\varphi^2_{ngas,oil}$	0.014 (0.011)	$\varphi^2_{corn,oil}$	0.009* (0.005)	$\varphi^2_{soyb,oil}$	0.0002 (0.004)
$\varphi^2_{oil,ngas}$	0.006 (0.006)	$\varphi^2_{ngas,ngas}$	−0.023** (0.010)	$\varphi^2_{corn,ngas}$	−0.001 (0.004)	$\varphi^2_{soyb,ngas}$	0.005* (0.003)
$\varphi^2_{oil,corn}$	−0.003 (0.012)	$\varphi^2_{ngas,corn}$	−0.002 (0.018)	$\varphi^2_{corn,corn}$	−0.038*** (0.014)	$\varphi^2_{soyb,corn}$	0.007 (0.009)
$\varphi^2_{oil,soyb}$	0.023* (0.013)	$\varphi^2_{ngas,soyb}$	0.023 (0.021)	$\varphi^2_{corn,soyb}$	0.015 (0.013)	$\varphi^2_{soyb,soyb}$	0.006 (0.011)
$\varphi^3_{oil,oil}$	−0.015 (0.011)	$\varphi^3_{ngas,oil}$	−0.007 (0.013)	$\varphi^3_{corn,oil}$	−0.002 (0.005)	$\varphi^3_{soyb,oil}$	0.004 (0.004)
$\varphi^3_{oil,ngas}$	0.007 (0.007)	$\varphi^3_{ngas,ngas}$	−0.009 (0.009)	$\varphi^3_{corn,ngas}$	−0.006** (0.003)	$\varphi^3_{soyb,ngas}$	−0.011*** (0.003)
$\varphi^3_{oil,corn}$	0.002 (0.011)	$\varphi^3_{ngas,corn}$	−0.020 (0.020)	$\varphi^3_{corn,corn}$	−0.006 (0.010)	$\varphi^3_{soyb,corn}$	0.006 (0.007)
$\varphi^3_{oil,soyb}$	−0.011 (0.014)	$\varphi^3_{ngas,soyb}$	0.038 (0.021)	$\varphi^3_{corn,soyb}$	−0.007 (0.010)	$\varphi^3_{soyb,soyb}$	−0.007 (0.009)
$\varphi^4_{oil,oil}$	0.015 (0.012)	$\varphi^4_{ngas,oil}$	0.003 (0.014)	$\varphi^4_{ngas,oil}$	−0.005 (0.005)	$\varphi^4_{soyb,oil}$	−0.008** (0.004)
$\varphi^4_{oil,ngas}$	−0.003 (0.007)	$\varphi^4_{ngas,ngas}$	0.010 (0.009)	$\varphi^4_{corn,ngas}$	−0.0004 (0.004)	$\varphi^4_{soyb,ngas}$	0.001 (0.003)
$\varphi^4_{oil,corn}$	−0.012 (0.011)	$\varphi^4_{ngas,corn}$	−0.015 (0.017)	$\varphi^4_{corn,corn}$	−0.026*** (0.008)	$\varphi^4_{soyb,corn}$	0.015*** (0.005)
$\varphi^4_{oil,soyb}$	0.008 (0.013)	$\varphi^4_{ngas,soyb}$	0.045** (0.020)	$\varphi^4_{corn,soyb}$	0.013 (0.009)	$\varphi^4_{soyb,soyb}$	−0.008 (0.007)
$\varphi^5_{oil,oil}$	−0.014 (0.010)	$\varphi^5_{ngas,oil}$	0.008 (0.012)	$\varphi^5_{corn,oil}$	0.007 (0.005)	$\varphi^5_{soyb,oil}$	0.010** (0.004)
$\varphi^5_{oil,ngas}$	0.003 (0.006)	$\varphi^5_{ngas,ngas}$	−0.027*** (0.008)	$\varphi^5_{corn,ngas}$	−0.002 (0.003)	$\varphi^5_{soyb,ngas}$	0.002 (0.003)
$\varphi^5_{oil,corn}$	0.015 (0.012)	$\varphi^5_{ngas,corn}$	0.012 (0.019)	$\varphi^5_{corn,corn}$	−0.021** (0.010)	$\varphi^5_{soyb,corn}$	−0.012* (0.007)
$\varphi^5_{oil,soyb}$	−0.028* (0.016)	$\varphi^5_{ngas,soyb}$	−0.014 (0.021)	$\varphi^5_{corn,soyb}$	−0.009 (0.011)	$\varphi^5_{soyb,soyb}$	−0.018** (0.009)
Panel B: Variance estimators from Equation (9)							
$\omega_{oil,oil}$	0.260*** (0.017)						
$\omega_{ngas,oil}$	−0.094* (0.049)	$\omega_{ngas,ngas}$	0.371*** (0.036)				
$\omega_{corn,oil}$	−0.017 (0.039)	$\omega_{corn,ngas}$	−0.007 (0.045)	$\omega_{corn,corn}$	0.427*** (0.105)		
$\omega_{soyb,oil}$	0.010 (0.019)	$\omega_{soyb,ngas}$	0.0008 (0.015)	$\omega_{soyb,corn}$	−0.028 (0.054)	$\omega_{soyb,soyb}$	0.194*** (0.032)
$a_{oil,oil}$	0.228*** (0.009)	$a_{oil,ngas}$	−0.065*** (0.018)	$a_{oil,corn}$	−0.014** (0.007)	$a_{oil,soyb}$	0.002 (0.004)
$a_{ngas,oil}$	0.012** (0.006)	$a_{ngas,ngas}$	0.222*** (0.013)	$a_{ngas,corn}$	0.013*** (0.004)	$a_{ngas,soyb}$	−0.004 (0.004)
$a_{corn,oil}$	−0.006 (0.015)	$a_{corn,ngas}$	−0.037** (0.016)	$a_{corn,corn}$	0.342*** (0.067)	$a_{corn,soyb}$	−0.039* (0.023)
$a_{soyb,oil}$	0.016 (0.018)	$a_{soyb,ngas}$	0.025 (0.023)	$a_{soyb,corn}$	−0.144*** (0.043)	$a_{soyb,soyb}$	0.266*** (0.032)
$b_{oil,oil}$	0.967*** (0.002)	$b_{oil,ngas}$	0.022*** (0.005)	$b_{oil,corn}$	0.006*** (0.002)	$b_{oil,soyb}$	−0.0009 (0.001)
$b_{ngas,oil}$	−0.001 (0.001)	$b_{ngas,ngas}$	0.966*** (0.003)	$b_{ngas,corn}$	−0.003 (0.002)	$b_{ngas,soyb}$	0.001 (0.001)
$b_{corn,oil}$	0.004 (0.007)	$b_{corn,ngas}$	0.016* (0.009)	$b_{corn,corn}$	0.889*** (0.042)	$b_{corn,soyb}$	0.026* (0.014)
$b_{soyb,oil}$	−0.004 (0.007)	$b_{soyb,ngas}$	−0.014 (0.009)	$b_{soyb,corn}$	0.070*** (0.027)	$b_{soyb,soyb}$	0.944*** (0.016)

(Continues)

TABLE 6 (Continued)

y_{oil}	y_{ngas}	y_{corn}	y_{soyb}

Panel C: Model diagnostics
Log likelihood: −51,111.0268
AIC: 16.191
SBC: 16.326
HQ: 16.238
Usable observations: 6329

Panel D: Residual diagnostics
$Q(10)$ statistic: 197.5853; significance level: 0.0232
$Q(20)$ statistic: 355.9640; significance level: 0.0811
$Q(30)$ statistic: 517.3367; significance level: 0.1157
$Q(40)$ statistic: 673.9620; significance level: 0.1707

Panel E: Exogeneity test in the mean Equation (1)
Test of exogeneity of all variables in the mean:
$H_0 : \varphi^P_{i,j} = 0$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$
$H_1 : \varphi^P_{i,j} \neq 0$ for at least one $\varphi^P_{i,j}$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$
$\chi^2(60) = 144.8485$ or $F(60, *) = 2.4141$ with significance level 0.0000
Test of exogeneity in the mean equation of *oil*:
$H_0 : \varphi^P_{oil,j} = 0$, where $j = ngas, corn, soybeans$, and $P = 1, ..., 5$
$H_1 : \varphi^P_{oil,j} \neq 0$ for at least one $\varphi^P_{oil,j}$, where $j = ngas, corn, soybeans$, and $P = 1, ..., 5$
$\chi^2(15) = 18.2296$ or $F(15, *) = 1.2153$ with significance level 0.2507
Test of exogeneity in the mean equation of *ngas*:
$H_0 : \varphi^P_{ngas,j} = 0$, where $j = oil, corn, soybeans$, and $P = 1, ..., 5$
$H_1 : \varphi^P_{ngas,j} \neq 0$ for at least one $\varphi^P_{oil,j}$, where $j = oil, corn, soybeans$, and $P = 1, ..., 5$
$\chi^2(15) = 24.4800$ or $F(15, *) = 1.6320$ with significance level 0.0573
Test of exogeneity in the mean equation of *corn*:
$H_0 : \varphi^P_{corn,j} = 0$, where $j = oil, ngas, soybeans$, and $P = 1, ..., 5$
$H_1 : \varphi^P_{corn,j} \neq 0$ for at least one $\varphi^P_{corn,j}$, where $j = oil, ngas, soybeans$, and $P = 1, ..., 5$
$\chi^2(15) = 28.9725$ or $F(15, *) = 1.9315$ with significance level 0.0162
Test of exogeneity in the mean equation of *soybeans*:
$H_0 : \varphi^P_{soyb,j} = 0$, where $j = oil, ngas, corn$, and $P = 1, ..., 5$
$H_1 : \varphi^P_{soyb,j} \neq 0$ for at least one $\varphi^P_{soyb,j}$, where $j = oil, ngas, corn$, and $P = 1, ..., 5$
$\chi^2(15) = 43.9584$ or $F(15, *) = 2.9305$ with significance level 0.0001

Panel F: Exogeneity test in the variance Equation (9) based on A matrix: ARCH effect test
Block exclusion test based on A matrix for *oil*
$H_0 : a_{ngas,oil} = a_{corn,oil} = a_{soyb,oil} = 0$
H_1: at least one of the coefficients in H_0 is different than 0
$\chi^2(3) = 4.7581$ or $F(3, *) = 1.5860$ with significance level 0.1903
Block exclusion test based on A matrix for *ngas*
$H_0 : a_{oil,ngas} = a_{corn,ngas} = a_{soyb,ngas} = 0$
H_1: at least one of the coefficients in H_0 is different than 0
$\chi^2(3) = 19.6101$ or $F(3, *) = 6.5367$ with significance level 0.0002
Block exclusion test based on A matrix for *corn*
$H_0 : a_{oil,corn} = a_{ngas,corn} = a_{soyb,corn} = 0$
H_1: at least one of the coefficients in H_0 is different than 0
$\chi^2(3) = 12.3560$ or $F(3, *) = 4.1186$ with significance level 0.0062
Block exclusion test based on A matrix for *soyb*
$H_0 : a_{oil,soyb} = a_{ngas,soyb} = 0$
H_1: at least one of the coefficients in H_0 is different than 0
$\chi^2(3) = 3.2674$ or $F(3, *) = 1.0891$ with significance level 0.3521

TABLE 6 (Continued)

y_{oil}	y_{ngas}	y_{corn}	y_{soyb}
Panel G: Exogeneity test in the variance Equation (9) based on B matrix: GARCH effect test			
Block exclusion test based on B matrix for *oil*			
$H_0: b_{ngas,oil} = b_{corn,oil} = b_{soyb,oil} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 1.0763$ or $F(3,*) = 0.3587$ with significance level 0.7827			
Block exclusion test based on B matrix for *ngas*			
$H_0: b_{oil,ngas} = b_{corn,ngas} = b_{soyb,ngas} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 29.0132$ or $F(3,*) = 9.6710$ with significance level 0.0000			
Block exclusion test based on B matrix for *corn*			
$H_0: b_{oil,corn} = b_{ngas,corn} = b_{soyb,corn} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 7.3301$ or $F(3,*) = 2.4433$ with significance level 0.0620			
Block exclusion test based on B matrix for *soyb*			
$H_0: b_{oil,soyb} = b_{ngas,soyb} = b_{corn,soyb} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 4.263886$ or $F(3,*) = 1.4213$ with significance level 0.2343			
Panel H: Exogeneity test in the variance Equation (9) based on A and B matrices			
Wald Test of Diagonal BEKK			
$\chi^2(24) = 67.2528$ or $F(24,*) = 2.8022$ with significance level 0.0000			
Block exclusion test, *oil* equation variance			
$H_0: a_{ngas,oil} = a_{corn,oil} = a_{soyb,oil} = b_{ngas,oil} = b_{corn,oil} = b_{soyb,oil} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 7.1210$ or $F(6,*) = 1.1868$ with significance level 0.3097			
Block exclusion test, *ngas* variance			
$H_0: a_{oil,ngas} = a_{corn,ngas} = a_{soyb,ngas} = b_{oil,ngas} = b_{corn,ngas} = b_{soyb,ngas} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 30.3800$ or $F(6,*) = 5.0634$ with significance level 0.0000			
Block exclusion test, corn variance			
$H_0: a_{oil,corn} = a_{ngas,corn} = a_{soyb,corn} = b_{oil,corn} = b_{ngas,corn} = b_{soyb,corn} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 14.0654$ or $F(6,*) = 2.3442$ with significance level 0.0289			
Block exclusion test, *soyb* variance			
$H_0: a_{oil,soyb} = a_{ngas,soyb} = a_{corn,soyb} = b_{oil,soyb} = b_{ngas,soyb} = b_{corn,soyb} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 4.6871$ or $F(6,*) = 0.7812$ with significance level 0.5845			

Notes: This table presents the estimated coefficients based on Equations (1) and (9). Standard errors are in parentheses. $Q(10)$, $Q(20)$, $Q(30)$, and $Q(40)$ are the Ljung–Box statistics for serial correlation in the model residuals computed with 10, 20, 30, and 40 lags, respectively.

Abbreviations: AIC, Akaike Information Criterion; BEKK, Baba, Engle, Kraft, and Kroner; HQ, Hannan–Quinn information criterion; MVGARCH, multivariate generalized autoregressive conditional heteroskedasticity; SBC, Schwartz Bayesian Criterion; VAR, vector autoregressive.

***, **, and * indicate significance at the 1%, 5%, and 10% levels.

A number of additional test results are of particular interest because they highlight the net effect of both short- and long-run exogeneity regarding energy and agricultural commodity markets.[10] These results indicate that the short-run effects (i.e., external shocks associated with the world economy) prevail over the long-run effects (i.e., the substitution effect) in the second subperiod. Furthermore, they support bidirectional price volatility spillovers between the agricultural commodities and energy markets in the high volatility regime subperiod. However, volatility spillover

[10]Panel H of Tables 6–9 presents the results of exogeneity tests conducted simultaneously on both the A and B matrices of the conditional variance–covariance matrix. The results of the first test in Panel H of Tables 6–9 reject the null hypothesis of a diagonal BEKK model for the whole period (Table 6) as well as for the three subperiods (Tables 7–9). The remainder of the Wald tests, in Panel H, test the exogeneity of each of the four variables in the conditional variance–covariance matrix.

TABLE 7 Coefficient estimation for $VAR(5)$–$BEKK(1,1)$–$MVGARCH(1,1)$ for the first subperiod (1996:07:03–2006:12:29).

y_{oil}		y_{ngas}		y_{corn}		y_{soyb}	
Panel A: Mean estimators from Equation (1)							
c_{oil}	0.077* (0.041)	c_{ngas}	0.129** (0.058)	c_{corn}	−0.007 (0.021)	c_{soyb}	−0.028 (0.019)
$\varphi^1_{oil,oil}$	0.008 (0.017)	$\varphi^1_{ngas,oil}$	−0.074*** (0.024)	$\varphi^1_{corn,oil}$	−0.022** (0.010)	$\varphi^1_{soyb,oil}$	−0.010 (0.009)
$\varphi^1_{oil,ngas}$	−0.001 (0.009)	$\varphi^1_{ngas,ngas}$	−0.023 (0.019)	$\varphi^1_{corn,ngas}$	0.004 (0.005)	$\varphi^1_{soyb,ngas}$	0.004 (0.004)
$\varphi^1_{oil,corn}$	−0.010 (0.026)	$\varphi^1_{ngas,corn}$	−0.027 (0.038)	$\varphi^1_{corn,corn}$	0.050** (0.020)	$\varphi^1_{soyb,corn}$	−0.007 (0.015)
$\varphi^1_{oil,soyb}$	0.028 (0.024)	$\varphi^1_{ngas,soyb}$	0.005 (0.037)	$\varphi^1_{corn,soyb}$	−0.054*** (0.016)	$\varphi^1_{soyb,soyb}$	−0.018 (0.020)
$\varphi^2_{oil,oil}$	−0.068*** (0.018)	$\varphi^2_{ngas,oil}$	−0.028 (0.020)	$\varphi^2_{corn,oil}$	0.014* (0.008)	$\varphi^2_{soyb,oil}$	0.005 (0.007)
$\varphi^2_{oil,ngas}$	0.019* (0.010)	$\varphi^2_{ngas,ngas}$	−0.013 (0.018)	$\varphi^2_{corn,ngas}$	0.008 (0.006)	$\varphi^2_{soyb,ngas}$	0.007 (0.005)
$\varphi^2_{oil,corn}$	−0.013 (0.024)	$\varphi^2_{ngas,corn}$	0.00009 (0.038)	$\varphi^2_{corn,corn}$	−0.017 (0.016)	$\varphi^2_{soyb,corn}$	0.011 (0.013)
$\varphi^2_{oil,soyb}$	0.005 (0.022)	$\varphi^2_{ngas,soyb}$	0.008 (0.037)	$\varphi^2_{corn,soyb}$	0.028** (0.013)	$\varphi^2_{soyb,soyb}$	0.005 (0.014)
$\varphi^3_{oil,oil}$	−0.007 (0.017)	$\varphi^3_{ngas,oil}$	−0.010 (0.023)	$\varphi^3_{corn,oil}$	0.002 (0.011)	$\varphi^3_{soyb,oil}$	0.006 (0.008)
$\varphi^3_{oil,ngas}$	0.009 (0.011)	$\varphi^3_{ngas,ngas}$	0.013 (0.016)	$\varphi^3_{corn,ngas}$	−0.014** (0.006)	$\varphi^3_{soyb,ngas}$	−0.013*** (0.005)
$\varphi^3_{oil,corn}$	−0.013 (0.024)	$\varphi^3_{ngas,corn}$	0.040 (0.040)	$\varphi^3_{corn,corn}$	−0.009 (0.015)	$\varphi^3_{soyb,corn}$	0.005 (0.012)
$\varphi^3_{oil,soyb}$	0.003 (0.024)	$\varphi^3_{ngas,soyb}$	−0.054 (0.040)	$\varphi^3_{corn,soyb}$	−0.001 (0.016)	$\varphi^3_{soyb,soyb}$	−0.004 (0.014)
$\varphi^4_{oil,oil}$	0.008 (0.016)	$\varphi^4_{ngas,oil}$	−0.015 (0.026)	$\varphi^4_{ngas,oil}$	−0.017* (0.009)	$\varphi^4_{soyb,oil}$	−0.022*** (0.008)
$\varphi^4_{oil,ngas}$	−0.006 (0.010)	$\varphi^4_{ngas,ngas}$	0.026* (0.014)	$\varphi^4_{corn,ngas}$	0.003 (0.005)	$\varphi^4_{soyb,ngas}$	0.010** (0.005)
$\varphi^4_{oil,corn}$	−0.048* (0.026)	$\varphi^4_{ngas,corn}$	−0.015 (0.034)	$\varphi^4_{corn,corn}$	−0.005 (0.015)	$\varphi^4_{soyb,corn}$	0.056*** (0.013)
$\varphi^4_{oil,soyb}$	0.035 (0.024)	$\varphi^4_{ngas,soyb}$	0.014 (0.035)	$\varphi^4_{corn,soyb}$	0.025* (0.015)	$\varphi^4_{soyb,soyb}$	−0.046*** (0.016)
$\varphi^5_{oil,oil}$	−0.028** (0.017)	$\varphi^5_{ngas,oil}$	−0.032 (0.026)	$\varphi^5_{corn,oil}$	0.007 (0.009)	$\varphi^5_{soyb,oil}$	0.003 (0.008)
$\varphi^5_{oil,ngas}$	0.012 (0.011)	$\varphi^5_{ngas,ngas}$	−0.008 (0.014)	$\varphi^5_{corn,ngas}$	−0.007 (0.006)	$\varphi^5_{soyb,ngas}$	0.005 (0.005)
$\varphi^5_{oil,corn}$	−0.012 (0.023)	$\varphi^5_{ngas,corn}$	0.005 (0.037)	$\varphi^5_{corn,corn}$	−0.030** (0.014)	$\varphi^5_{soyb,corn}$	−0.035** (0.014)
$\varphi^5_{oil,soyb}$	−0.009 (0.023)	$\varphi^5_{ngas,soyb}$	0.002 (0.038)	$\varphi^5_{corn,soyb}$	−0.007 (0.021)	$\varphi^5_{soyb,soyb}$	−0.008 (0.014)
Panel B: Variance estimators from Equation (9)							
$\omega_{oil,oil}$	1.170*** (0.212)						
$\omega_{ngas,oil}$	−0.273 (0.281)	$\omega_{ngas,ngas}$	0.146 (0.110)				
$\omega_{corn,oil}$	−0.080 (0.061)	$\omega_{corn,ngas}$	−0.439*** (0.073)	$\omega_{corn,corn}$	0.223** (0.099)		
$\omega_{soyb,oil}$	−0.042 (0.033)	$\omega_{soyb,ngas}$	−0.113*** (0.020)	$\omega_{soyb,corn}$	0.192*** (0.050)	$\omega_{soyb,soyb}$	0.034 (0.032)
$a_{oil,oil}$	0.265*** (0.035)	$a_{oil,ngas}$	0.236*** (0.075)	$a_{oil,corn}$	−0.020 (0.013)	$a_{oil,soyb}$	−0.001 (0.007)
$a_{ngas,oil}$	−0.027 (0.031)	$a_{ngas,ngas}$	0.308*** (0.060)	$a_{ngas,corn}$	0.023*** (0.007)	$a_{ngas,soyb}$	−0.0001 (0.004)
$a_{corn,oil}$	−0.062 (0.046)	$a_{corn,ngas}$	−0.066 (0.067)	$a_{corn,corn}$	0.289*** (0.068)	$a_{corn,soyb}$	0.018 (0.025)
$a_{soyb,oil}$	0.011 (0.025)	$a_{soyb,ngas}$	0.027 (0.058)	$a_{soyb,corn}$	0.016 (0.071)	$a_{soyb,soyb}$	0.237*** (0.020)
$b_{oil,oil}$	0.792*** (0.075)	$b_{oil,ngas}$	0.169* (0.096)	$b_{oil,corn}$	0.034** (0.017)	$b_{oil,soyb}$	0.013** (0.006)
$b_{ngas,oil}$	0.037 (0.033)	$b_{ngas,ngas}$	0.917*** (0.045)	$b_{ngas,corn}$	−0.009* (0.005)	$b_{ngas,soyb}$	−0.002 (0.002)
$b_{corn,oil}$	0.045 (0.040)	$b_{corn,ngas}$	0.008 (0.046)	$b_{corn,corn}$	0.892*** (0.047)	$b_{corn,soyb}$	−0.011 (0.020)
$b_{soyb,oil}$	−0.010 (0.014)	$b_{soyb,ngas}$	−0.004 (0.026)	$b_{soyb,corn}$	−0.007 (0.027)	$b_{soyb,soyb}$	0.962*** (0.006)

TABLE 7 (Continued)

y_{oil}	y_{ngas}	y_{corn}	y_{soyb}
Panel C: Model diagnostics			
Log likelihood: −22,025.7151			
AIC: 16.294			
SBC: 16.568			
HQ: 16.393			
Usable observations: 2719			
Panel D: Residual diagnostics			
$Q(10)$ statistic: 156.8450; significance level: 0.5557			
$Q(20)$ statistic: 326.6775; significance level: 0.3865			
$Q(30)$ statistic: 485.8224; significance level: 0.4174			
$Q(40)$ statistic: 651.1402; significance level: 0.3714			
Panel E: Exogeneity test in the mean Equation (1)			
Test of exogeneity of all variables in the mean:			
$H_0: \varphi^P_{i,j} = 0$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$			
$H_1: \varphi^P_{i,j} \neq 0$ for at least one $\varphi^P_{i,j}$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$			
$\chi^2(60) = 145.3231$ or $F(60, *) = 2.4220$ with significance level 0.0000			
Test of exogeneity in the mean equation of *oil*:			
$H_0: \varphi^P_{oil,j} = 0$, where $j = ngas, corn, soybeans$, and $P = 1, ..., 5$			
$H_1: \varphi^P_{oil,j} \neq 0$ for at least one $\varphi^P_{oil,j}$, where $j = ngas, corn, soybeans$, and $P = 1, ..., 5$			
$\chi^2(15) = 14.3324$ or $F(15, *) = 0.9555$ with significance level 0.5004			
Test of exogeneity in the mean equation of *ngas*:			
$H_0: \varphi^P_{ngas,j} = 0$, where $j = oil, corn, soybeans$, and $P = 1, ..., 5$			
$H_1: \varphi^P_{ngas,j} \neq 0$ for at least one $\varphi^P_{oil,j}$, where $j =$oil, $corn, soybeans$, and $P = 1, ..., 5$			
$\chi^2(15) = 19.0198$ or $F(15, *) = 1.2679$ with significance level 0.2128			
Test of exogeneity in the mean equation of *corn*:			
$H_0: \varphi^P_{corn,j} = 0$, where $j = oil, ngas, soybeans$, and $P = 1, ..., 5$			
$H_1: \varphi^P_{corn,j} \neq 0$ for at least one $\varphi^P_{corn,j}$, where $j = oil, ngas, soybeans$, and $P = 1, ..., 5$			
$\chi^2(15) = 47.2746$ or $F(15, *) = 3.1516$ with significance level 0.0000			
Test of exogeneity in the mean equation of *soybeans*:			
$H_0: \varphi^P_{soyb,j} = 0$, where $j = oil, ngas, corn$, and $P = 1, ..., 5$			
$H_1: \varphi^P_{soyb,j} \neq 0$ for at least one $\varphi^P_{soyb,j}$, where $j = oil, ngas, corn$, and $P = 1, ..., 5$			
$\chi^2(15) = 58.3069$ or $F(15, *) = 3.8871$ with significance level 0.0000			
Panel F: Exogeneity test in the variance Equation (9) based on A matrix: ARCH effect test			
Block exclusion test based on A matrix for *oil*			
$H_0: a_{ngas,oil} = a_{corn,oil} = a_{soyb,oil} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 3.0527$ or $F(3, *) = 1.0175$ with significance level 0.3835			
Block exclusion test based on A matrix for *ngas*			
$H_0: a_{oil,ngas} = a_{corn,ngas} = a_{soyb,ngas} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 16.8631$ or $F(3, *) = 5.6210$ with significance level 0.0007			
Block exclusion test based on A matrix for *corn*			
$H_0: a_{oil,corn} = a_{ngas,corn} = a_{soyb,corn} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 10.8948$ or $F(3, *) = 2.3343$ with significance level 0.0123			
Block exclusion test based on A matrix for *soyb*			
$H_0: a_{oil,soyb} = a_{ngas,soyb} = a_{corn,soyb} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 0.6832$ or $F(3, *) = 1.0339$ with significance level 0.8771			

(Continues)

TABLE 7 (Continued)

y_{oil}	y_{ngas}	y_{corn}	y_{soyb}
Panel G: Exogeneity test in the variance Equation (9) based on B matrix: GARCH effect test			
Block exclusion test based on B matrix for *oil*			
$H_0 : b_{ngas,oil} = b_{corn,oil} = b_{soyb,oil} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 4.8440$ or $F(3, *) = 1.6147$ with significance level 0.1835			
Block exclusion test based on B matrix for *ngas*			
$H_0 : b_{oil,ngas} = b_{corn,ngas} = b_{soyb,ngas} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 9.0745$ or $F(3, *) = 3.0248$ with significance level 0.0283			
Block exclusion test based on B matrix for *corn*			
$H_0 : b_{oil,corn} = b_{ngas,corn} = b_{soyb,corn} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 3.8617$ or $F(3, *) = 1.2872$ with significance level 0.2767			
Block exclusion test based on B matrix for *soyb*			
$H_0 : b_{oil,soyb} = b_{ngas,soyb} = b_{corn,soyb} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 3.8972$ or $F(3, *) = 1.299$ with significance level 0.2727			
Panel H: Exogeneity test in the variance Equation (9) based on A and B matrices			
Wald Test of Diagonal BEKK			
$\chi^2(24) = 75.3748$ or $F(24, *) = 3.1406$ with significance level 0.0000			
Block exclusion test, *oil* equation variance			
$H_0 : a_{ngas,oil} = a_{corn,oil} = a_{soyb,oil} = b_{ngas,oil} = b_{corn,oil} = b_{soyb,oil} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 5.9062$ or $F(6, *) = 0.9843$ with significance level 0.4337			
Block exclusion test, *ngas* variance			
$H_0 : a_{oil,ngas} = a_{corn,ngas} = a_{soyb,ngas} = b_{oil,ngas} = b_{corn,ngas} = b_{soyb,ngas} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 25.9250$ or $F(6, *) = 4.3208$ with significance level 0.0002			
Block exclusion test, corn variance			
$H_0 : a_{oil,corn} = a_{ngas,corn} = a_{soyb,corn} = b_{oil,corn} = b_{ngas,corn} = b_{soyb,corn} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 14.0063$ or $F(6, *) = 2.3343$ with significance level 0.0295			
Block exclusion test, *soyb* variance			
$H_0 : a_{oil,soyb} = a_{ngas,soyb} = a_{corn,soyb} = b_{oil,soyb} = b_{ngas,soyb} = b_{corn,soyb} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 6.2034$ or $F(6, *) = 1.0339$ with significance level 0.4007			

Notes: This table presents the estimated coefficients based on Equations (1) and (9). Standard errors are in parentheses. $Q(10)$, $Q(20)$, $Q(30)$, and $Q(40)$ are the Ljung–Box statistics for serial correlation in the model residuals computed with 10, 20, 30, and 40 lags, respectively.

Abbreviations: AIC, Akaike Information Criterion; BEKK, Baba, Engle, Kraft, and Kroner; HQ, Hannan–Quinn information criterion; MVGARCH, multivariate generalized autoregressive conditional heteroskedasticity; SBC, Schwartz Bayesian Criterion; VAR, vector autoregressive.

***, **, and * indicate significance at the 1%, 5%, and 10% levels.

effects between agricultural commodities and energy markets are weaker in the first and third subperiods. In general, our volatility spillover results are in line with previous literature as volatility transmission has been evidenced between agricultural and energy markets (Du et al., 2011; Du & McPhail, 2012; Gilbert, 2010; Han et al., 2020; Nazlioglu et al., 2013; Trujillo-Barrera et al., 2012; Zhang et al., 2009). Our approach extends these results, demonstrating the presence of volatility spillovers for specific subperiods (based on the regimes evidenced from the Markov-switching technique).

This study contributes to the literature by demonstrating price-level links and price volatility interactions between energy and agricultural commodity markets for an extended period and its subperiods, and that these correspond to high and low volatility regimes. It further identifies that the primary source of volatility linkages is the comovement of

TABLE 8 Coefficient estimation for $VAR(5)–BEKK(1,1)–MVGARCH(1,1)$ for the second subperiod (2007:01:01–2012:12:31).

y_{oil}		y_{ngas}		y_{corn}		y_{soyb}	
Panel A: Mean estimators from Equation (1)							
c_{oil}	0.059 (0.048)	c_{ngas}	−0.006 (0.082)	c_{corn}	0.081* (0.044)	c_{soyb}	0.082*** (0.030)
$\varphi^1_{oil,oil}$	−0.065*** (0.024)	$\varphi^1_{ngas,oil}$	−0.006 (0.028)	$\varphi^1_{corn,oil}$	−0.053** (0.021)	$\varphi^1_{soyb,oil}$	−0.068*** (0.015)
$\varphi^1_{oil,ngas}$	0.021 (0.014)	$\varphi^1_{ngas,ngas}$	−0.065*** (0.021)	$\varphi^1_{corn,ngas}$	0.030** (0.012)	$\varphi^1_{soyb,ngas}$	0.017* (0.009)
$\varphi^1_{oil,corn}$	0.020 (0.022)	$\varphi^1_{ngas,corn}$	0.045 (0.029)	$\varphi^1_{corn,corn}$	0.045* (0.024)	$\varphi^1_{soyb,corn}$	0.0008 (0.017)
$\varphi^1_{oil,soyb}$	0.043 (0.029)	$\varphi^1_{ngas,soyb}$	0.010 (0.040)	$\varphi^1_{corn,soyb}$	0.033 (0.034)	$\varphi^1_{soyb,soyb}$	0.026 (0.026)
$\varphi^2_{oil,oil}$	0.011 (0.023)	$\varphi^2_{ngas,oil}$	0.040* (0.025)	$\varphi^2_{corn,oil}$	0.028 (0.020)	$\varphi^2_{soyb,oil}$	0.017 (0.018)
$\varphi^2_{oil,ngas}$	0.026* (0.014)	$\varphi^2_{ngas,ngas}$	−0.0004 (0.021)	$\varphi^2_{corn,ngas}$	−0.025* (0.014)	$\varphi^2_{soyb,ngas}$	−0.023** (0.011)
$\varphi^2_{oil,corn}$	0.007 (0.023)	$\varphi^2_{ngas,corn}$	0.027 (0.030)	$\varphi^2_{corn,corn}$	0.001 (0.021)	$\varphi^2_{soyb,corn}$	0.035** (0.017)
$\varphi^2_{oil,soyb}$	−0.043 (0.033)	$\varphi^2_{ngas,soyb}$	−0.042 (0.033)	$\varphi^2_{corn,soyb}$	−0.077** (0.032)	$\varphi^2_{soyb,soyb}$	−0.039 (0.027)
$\varphi^3_{oil,oil}$	−0.033 (0.021)	$\varphi^3_{ngas,oil}$	−0.014 (0.020)	$\varphi^3_{corn,oil}$	−0.008 (0.015)	$\varphi^3_{soyb,oil}$	−0.018* (0.011)
$\varphi^3_{oil,ngas}$	0.004 (0.015)	$\varphi^3_{ngas,ngas}$	−0.046*** (0.018)	$\varphi^3_{corn,ngas}$	0.012 (0.012)	$\varphi^3_{soyb,ngas}$	−0.003 (0.010)
$\varphi^3_{oil,corn}$	0.014 (0.021)	$\varphi^3_{ngas,corn}$	−0.037 (0.028)	$\varphi^3_{corn,corn}$	−0.034* (0.020)	$\varphi^3_{soyb,corn}$	0.008 (0.016)
$\varphi^3_{oil,soyb}$	0.011 (0.030)	$\varphi^3_{ngas,soyb}$	0.135*** (0.031)	$\varphi^3_{corn,soyb}$	0.045* (0.025)	$\varphi^3_{soyb,soyb}$	0.027 (0.019)
$\varphi^4_{oil,oil}$	0.025 (0.021)	$\varphi^4_{ngas,oil}$	0.004 (0.026)	$\varphi^4_{ngas,oil}$	0.031* (0.016)	$\varphi^4_{soyb,oil}$	0.003 (0.011)
$\varphi^4_{oil,ngas}$	−0.026* (0.014)	$\varphi^4_{ngas,ngas}$	−0.034** (0.017)	$\varphi^4_{corn,ngas}$	−0.011 (0.012)	$\varphi^4_{soyb,ngas}$	−0.012 (0.009)
$\varphi^4_{oil,corn}$	0.035* (0.021)	$\varphi^4_{ngas,corn}$	0.008 (0.029)	$\varphi^4_{corn,corn}$	0.0003 (0.019)	$\varphi^4_{soyb,corn}$	0.008 (0.015)
$\varphi^4_{oil,soyb}$	−0.028 (0.029)	$\varphi^4_{ngas,soyb}$	0.050 (0.036)	$\varphi^4_{corn,soyb}$	−0.047* (0.026)	$\varphi^4_{soyb,soyb}$	−0.002 (0.025)
$\varphi^5_{oil,oil}$	−0.032 (0.022)	$\varphi^5_{ngas,oil}$	0.016 (0.024)	$\varphi^5_{corn,oil}$	−0.040*** (0.015)	$\varphi^5_{soyb,oil}$	−0.001 (0.012)
$\varphi^5_{oil,ngas}$	−0.022 (0.014)	$\varphi^5_{ngas,ngas}$	−0.079*** (0.021)	$\varphi^5_{corn,ngas}$	0.003 (0.013)	$\varphi^5_{soyb,ngas}$	−0.004 (0.009)
$\varphi^5_{oil,corn}$	0.073*** (0.025)	$\varphi^5_{ngas,corn}$	0.034 (0.031)	$\varphi^5_{corn,corn}$	0.001 (0.022)	$\varphi^5_{soyb,corn}$	0.035* (0.018)
$\varphi^5_{oil,soyb}$	−0.057 (0.037)	$\varphi^5_{ngas,soyb}$	−0.015 (0.035)	$\varphi^5_{corn,soyb}$	0.006 (0.025)	$\varphi^5_{soyb,soyb}$	−0.036 (0.026)
Panel B: Variance estimators from Equation (9)							
$\omega_{oil,oil}$	0.213*** (0.070)						
$\omega_{ngas,oil}$	0.068 (0.073)	$\omega_{ngas,ngas}$	0.167*** (0.063)				
$\omega_{corn,oil}$	0.148 (0.280)	$\omega_{corn,ngas}$	−0.379 (0.358)	$\omega_{corn,corn}$	0.603** (0.300)		
$\omega_{soyb,oil}$	−0.105 (0.084)	$\omega_{soyb,ngas}$	−0.232** (0.116)	$\omega_{soyb,corn}$	−0.172 (0.192)	$\omega_{soyb,soyb}$	−0.00001 (0.124)
$a_{oil,oil}$	0.224*** (0.038)	$a_{oil,ngas}$	0.011 (0.024)	$a_{oil,corn}$	0.059* (0.035)	$a_{oil,soyb}$	−0.0002 (0.036)
$a_{ngas,oil}$	−0.021* (0.012)	$a_{ngas,ngas}$	0.129*** (0.024)	$a_{ngas,corn}$	0.059** (0.028)	$a_{ngas,soyb}$	0.001 (0.012)
$a_{corn,oil}$	−0.078** (0.036)	$a_{corn,ngas}$	0.044 (0.033)	$a_{corn,corn}$	0.237*** (0.051)	$a_{corn,soyb}$	−0.124*** (0.030)
$a_{soyb,oil}$	0.081** (0.040)	$a_{soyb,ngas}$	−0.022 (0.040)	$a_{soyb,corn}$	−0.087** (0.044)	$a_{soyb,soyb}$	0.418*** (0.071)
$b_{oil,oil}$	0.961*** (0.012)	$b_{oil,ngas}$	−0.021*** (0.005)	$b_{oil,corn}$	−0.013 (0.010)	$b_{oil,soyb}$	−0.004 (0.014)
$b_{ngas,oil}$	0.001 (0.003)	$b_{ngas,ngas}$	0.984*** (0.004)	$b_{ngas,corn}$	−0.012* (0.007)	$b_{ngas,soyb}$	−0.006** (0.003)
$b_{corn,oil}$	0.029 (0.029)	$b_{corn,ngas}$	0.053* (0.028)	$b_{corn,corn}$	0.860*** (0.040)	$b_{corn,soyb}$	0.073*** (0.026)
$b_{soyb,oil}$	−0.009 (0.026)	$b_{soyb,ngas}$	0.016 (0.024)	$b_{soyb,corn}$	0.100*** (0.029)	$b_{soyb,soyb}$	0.872*** (0.033)

(Continues)

TABLE 8 (Continued)

y_{oil}	y_{ngas}	y_{corn}	y_{soyb}
Panel C: Model diagnostics			
Log likelihood: −13047.5075			
AIC: 16.878			
SBC: 17.310			
HQ: 17.039			
Usable observations: 1561			
Panel D: Residual diagnostics			
$Q(10)$ statistic: 150.9944; significance level: 0.6829			
$Q(20)$ statistic: 337.8491; significance level: 0.2360			
$Q(30)$ statistic: 483.9069; significance level: 0.4415			
$Q(40)$ statistic: 627.4317; significance level: 0.6312			
Panel E: Exogeneity test in the mean Equation (1)			
Test of exogeneity of all variables in the mean:			
$H_0 : \varphi^P_{i,j} = 0$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$			
$H_1 : \varphi^P_{i,j} \neq 0$ for at least one $\varphi^P_{i,j}$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$			
$\chi^2(60) = 227.1733$ or $F(60, *) = 3.7862$ with significance level 0.0000			
Test of exogeneity in the mean equation of *oil*:			
$H_0 : \varphi^P_{oil,j} = 0$, where $j = ngas, corn, soybeans$, and $P = 1, ..., 5$			
$H_1 : \varphi^P_{oil,j} \neq 0$ for at least one $\varphi^P_{oil,j}$, where $j = ngas, corn, soybeans$, and $P = 1, ..., 5$			
$\chi^2(15) = 30.8284$ or $F(15, *) = 2.0552$ with significance level 0.0092			
Test of exogeneity in the mean equation of *ngas*:			
$H_0 : \varphi^P_{ngas,j} = 0$, where $j = oil, corn, soybeans$, and $P = 1, ..., 5$			
$H_1 : \varphi^P_{ngas,j} \neq 0$ for at least one $\varphi^P_{oil,j}$, where $j = oil, corn, soybeans$, and $P = 1, ..., 5$			
$\chi^2(15) = 29.8879$ or $F(15, *) = 1.9925$ with significance level 0.0123			
Test of exogeneity in the mean equation of *corn*:			
$H_0 : \varphi^P_{corn,j} = 0$, where $j = oil, ngas, soybeans$, and $P = 1, ..., 5$			
$H_1 : \varphi^P_{corn,j} \neq 0$ for at least one $\varphi^P_{corn,j}$, where $j = oil, ngas, soybeans$, and $P = 1, ..., 5$			
$\chi^2(15) = 40.8945$ or $F(15, *) = 2.7263$ with significance level 0.0003			
Test of exogeneity in the mean equation of *soybeans*:			
$H_0 : \varphi^P_{soyb,j} = 0$, where $j = oil, ngas, corn$, and $P = 1, ..., 5$			
$H_1 : \varphi^P_{soyb,j} \neq 0$ for at least one $\varphi^P_{soyb,j}$, where $j = oil, ngas, corn$, and $P = 1, ..., 5$			
$\chi^2(15) = 49.8654$ or $F(15, *) = 3.3243$ with significance level 0.0000			
Panel F: Exogeneity test in the variance Equation (9) based on A matrix: ARCH effect test			
Block exclusion test, *oil* equation variance			
$H_0 : a_{ngas,oil} = a_{corn,oil} = a_{soyb,oil} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 6.6654$ or $F(3, *) = 2.2218$ with significance level 0.0833			
Block exclusion test, *ngas* variance			
$H_0 : a_{oil,ngas} = a_{corn,ngas} = a_{soyb,ngas} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 4.0883$ or $F(3, *) = 1.3628$ with significance level 0.2520			
Block exclusion test, corn variance			
$H_0 : a_{oil,corn} = a_{ngas,corn} = a_{soyb,corn} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 13.6790$ or $F(3, *) = 4.5596$ with significance level 0.0033			
Block exclusion test, *soyb* variance			
$H_0 : a_{oil,soyb} = a_{ngas,soyb} = a_{corn,soyb} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 17.8002$ or $F(3, *) = 5.9334$ with significance level 0.0004			

TABLE 8 (Continued)

y_{oil}	y_{ngas}	y_{corn}	y_{soyb}

Panel G: Exogeneity test in the variance Equation (9) based on B matrix: GARCH effect test

Block exclusion test based on B matrix for *oil*

$H_0: b_{ngas,oil} = b_{corn,oil} = b_{soyb,oil} = 0$

H_1: at least one of the coefficients in H_0 is different than 0

$\chi^2(3) = 3.1963$ or $F(3,*) = 1.0654$ with significance level 0.3623

Block exclusion test based on B matrix for *ngas*

$H_0: b_{oil,ngas} = b_{corn,ngas} = b_{soyb,ngas} = 0$

H_1: at least one of the coefficients in H_0 is different than 0

$\chi^2(3) = 50.8275$ or $F(3,*) = 16.9425$ with significance level 0.0000

Block exclusion test based on B matrix for *corn*

$H_0: b_{oil,corn} = b_{ngas,corn} = b_{soyb,corn} = 0$

H_1: at least one of the coefficients in H_0 is different than 0

$\chi^2(3) = 18.3994$ or $F(3,*) = 6.1331$ with significance level 0.0003

Block exclusion test based on B matrix for *soyb*

$H_0: b_{oil,soyb} = b_{ngas,soyb} = b_{corn,soyb} = 0$

H_1: at least one of the coefficients in H_0 is different than 0

$\chi^2(3) = 9.7441$ or $F(3,*) = 3.3333$ with significance level 0.0208

Panel H: Exogeneity test in the variance Equation (9) based on A and B matrices

Wald Test of Diagonal BEKK

$\chi^2(24) = 171.7885$ or $F(24,*) = 7.1578$ with significance level 0.0000

Block exclusion test, *oil* equation variance

$H_0: a_{ngas,oil} = a_{corn,oil} = a_{soyb,oil} = b_{ngas,oil} = b_{corn,oil} = b_{soyb,oil} = 0$

H_1: at least one of the coefficients in H_0 is different than 0

$\chi^2(6) = 24.6902$ or $F(6,*) = 4.1150$ with significance level 0.0003

Block exclusion test, *ngas* variance

$H_0: a_{oil,ngas} = a_{corn,ngas} = a_{soyb,ngas} = b_{oil,ngas} = b_{corn,ngas} = b_{soyb,ngas} = 0$

H_1: at least one of the coefficients in H_0 is different than 0

$\chi^2(6) = 53.1163$ or $F(6,*) = 8.8527$ with significance level 0.0000

Block exclusion test, corn variance

$H_0: a_{oil,corn} = a_{ngas,corn} = a_{soyb,corn} = b_{oil,corn} = b_{ngas,corn} = b_{soyb,corn} = 0$

H_1: at least one of the coefficients in H_0 is different than 0

$\chi^2(6) = 22.3921$ or $F(6,*) = 3.7320$ with significance level 0.0010

Block exclusion test, *soyb* variance

$H_0: a_{oil,soyb} = a_{ngas,soyb} = a_{corn,soyb} = b_{oil,soyb} = b_{ngas,soyb} = b_{corn,soyb} = 0$

H_1: at least one of the coefficients in H_0 is different than 0

$\chi^2(6) = 20.000$ or $F(6,*) = 3.3333$ with significance level 0.0027

Notes: This table presents the estimated coefficients based on Equations (1) and (9). Standard errors are in parentheses. $Q(10)$, $Q(20)$, $Q(30)$, and $Q(40)$ are the Ljung–Box statistics for serial correlation in the model residuals computed with 10, 20, 30, and 40 lags, respectively.

Abbreviations: AIC, Akaike Information Criterion; BEKK, Baba, Engle, Kraft, and Kroner; HQ, Hannan–Quinn information criterion; MVGARCH, multivariate generalized autoregressive conditional heteroskedasticity; SBC, Schwartz Bayesian Criterion; VAR, vector autoregressive.

***, **, and * indicate significance at the 1%, 5%, and 10% levels.

common macroeconomic factors rather than the substitution effect between energy and agricultural commodity markets, corroborating the results of Han et al. (2020).

Currently, there is an ongoing debate concerning two main hypotheses. The first states that the comovement between agricultural and energy commodities is due to the substitution effect induced by the biofuel industry, while the second suggests that macrofactors are the primary cause. Our empirical approach examined both hypotheses by determining which one dominates and in which subperiod this happens during the period under investigation. The empirical findings indicate that during the period of high volatility (i.e., subperiod II) the macroeconomic factors dominate, while in the rest of the period (i.e., subperiods I and III), which is characterized by low volatility, the substitution effect is stronger than the macroeconomic shocks.

TABLE 9 Coefficient estimation for $VAR(5)$–$BEKK(1,1)$–$MVGARCH(1,1)$ for the third subperiod (2013:01:01–2020:11:02).

y_{oil}		y_{ngas}		y_{corn}		y_{soyb}	
Panel A: Mean estimators from Equation (1)							
c_{oil}	0.006 (0.036)	c_{ngas}	0.020 (0.068)	c_{corn}	−0.010 (0.022)	c_{soyb}	−0.003 (0.018)
$\varphi^1_{oil,oil}$	−0.016 (0.019)	$\varphi^1_{ngas,oil}$	−0.032* (0.017)	$\varphi^1_{corn,oil}$	−0.019** (0.008)	$\varphi^1_{soyb,oil}$	−0.005 (0.006)
$\varphi^1_{oil,ngas}$	0.027* (0.014)	$\varphi^1_{ngas,ngas}$	−0.029 (0.022)	$\varphi^1_{corn,ngas}$	−0.001 (0.007)	$\varphi^1_{soyb,ngas}$	0.006 (0.006)
$\varphi^1_{oil,corn}$	−0.028* (0.017)	$\varphi^1_{ngas,corn}$	0.002 (0.033)	$\varphi^1_{corn,corn}$	0.054 (0.048)	$\varphi^1_{soyb,corn}$	0.032** (0.016)
$\varphi^1_{oil,soyb}$	0.032 (0.030)	$\varphi^1_{ngas,soyb}$	0.031 (0.049)	$\varphi^1_{corn,soyb}$	0.002 (0.036)	$\varphi^1_{soyb,soyb}$	−0.020 (0.022)
$\varphi^2_{oil,oil}$	−0.026 (0.023)	$\varphi^2_{ngas,oil}$	0.044*** (0.017)	$\varphi^2_{corn,oil}$	0.014* (0.008)	$\varphi^2_{soyb,oil}$	−0.003 (0.006)
$\varphi^2_{oil,ngas}$	−0.025** (0.012)	$\varphi^2_{ngas,ngas}$	−0.055*** (0.019)	$\varphi^2_{corn,ngas}$	0.001 (0.006)	$\varphi^2_{soyb,ngas}$	0.009 (0.006)
$\varphi^2_{oil,corn}$	−0.011 (0.017)	$\varphi^2_{ngas,corn}$	−0.029 (0.031)	$\varphi^2_{corn,corn}$	−0.074*** (0.023)	$\varphi^2_{soyb,corn}$	−0.013 (0.011)
$\varphi^2_{oil,soyb}$	0.053* (0.028)	$\varphi^2_{ngas,soyb}$	0.065 (0.050)	$\varphi^2_{corn,soyb}$	0.057** (0.026)	$\varphi^2_{soyb,soyb}$	0.015 (0.019)
$\varphi^3_{oil,oil}$	−0.0006 (0.023)	$\varphi^3_{ngas,oil}$	−0.012 (0.018)	$\varphi^3_{corn,oil}$	−0.006 (0.008)	$\varphi^3_{soyb,oil}$	0.007 (0.007)
$\varphi^3_{oil,ngas}$	0.001 (0.013)	$\varphi^3_{ngas,ngas}$	−0.014 (0.019)	$\varphi^3_{corn,ngas}$	−0.007 (0.005)	$\varphi^3_{soyb,ngas}$	−0.013* (0.007)
$\varphi^3_{oil,corn}$	−0.013 (0.020)	$\varphi^3_{ngas,corn}$	−0.057* (0.035)	$\varphi^3_{corn,corn}$	0.013 (0.025)	$\varphi^3_{soyb,corn}$	0.010 (0.013)
$\varphi^3_{oil,soyb}$	−0.021 (0.032)	$\varphi^3_{ngas,soyb}$	0.083 (0.054)	$\varphi^3_{corn,soyb}$	−0.016 (0.026)	$\varphi^3_{soyb,soyb}$	−0.039** (0.019)
$\varphi^4_{oil,oil}$	0.008 (0.025)	$\varphi^4_{ngas,oil}$	0.003 (0.015)	$\varphi^4_{ngas,oil}$	−0.004 (0.006)	$\varphi^4_{soyb,oil}$	−0.002 (0.006)
$\varphi^4_{oil,ngas}$	0.009 (0.013)	$\varphi^4_{ngas,ngas}$	0.017 (0.015)	$\varphi^4_{corn,ngas}$	−0.001 (0.007)	$\varphi^4_{soyb,ngas}$	−0.005 (0.006)
$\varphi^4_{oil,corn}$	−0.035** (0.016)	$\varphi^4_{ngas,corn}$	−0.036 (0.026)	$\varphi^4_{corn,corn}$	−0.058** (0.025)	$\varphi^4_{soyb,corn}$	−0.009 (0.014)
$\varphi^4_{oil,soyb}$	−0.004 (0.029)	$\varphi^4_{ngas,soyb}$	0.075 (0.053)	$\varphi^4_{corn,soyb}$	0.007 (0.027)	$\varphi^4_{soyb,soyb}$	−0.013 (0.021)
$\varphi^5_{oil,oil}$	0.009 (0.017)	$\varphi^5_{ngas,oil}$	0.019 (0.015)	$\varphi^5_{corn,oil}$	0.013* (0.007)	$\varphi^5_{soyb,oil}$	0.014** (0.006)
$\varphi^5_{oil,ngas}$	0.006 (0.012)	$\varphi^5_{ngas,ngas}$	−0.017 (0.015)	$\varphi^5_{corn,ngas}$	0.001 (0.007)	$\varphi^5_{soyb,ngas}$	0.002 (0.007)
$\varphi^5_{oil,corn}$	0.003 (0.019)	$\varphi^5_{ngas,corn}$	−0.007 (0.030)	$\varphi^5_{corn,corn}$	0.023 (0.026)	$\varphi^5_{soyb,corn}$	−0.025* (0.015)
$\varphi^5_{oil,soyb}$	−0.052** (0.021)	$\varphi^5_{ngas,soyb}$	0.017 (0.046)	$\varphi^5_{corn,soyb}$	−0.047 (0.045)	$\varphi^5_{soyb,soyb}$	−0.012 (0.021)
Panel B: Variance estimators from Equation (9)							
$\omega_{oil,oil}$	0.261*** (0.041)						
$\omega_{ngas,oil}$	−0.064 (0.0730)	$\omega_{ngas,ngas}$	0.386*** (0.043)				
$\omega_{corn,oil}$	0.007 (0.059)	$\omega_{corn,ngas}$	0.079 (0.066)	$\omega_{corn,corn}$	0.500*** (0.076)		
$\omega_{soyb,oil}$	−0.009 (0.033)	$\omega_{soyb,ngas}$	0.039 (0.028)	$\omega_{soyb,corn}$	0.029 (0.057)	$\omega_{soyb,soyb}$	0.133* (0.025)
$a_{oil,oil}$	0.303*** (0.031)	$a_{oil,ngas}$	−0.065** (0.030)	$a_{oil,corn}$	−0.014** (0.007)	$a_{oil,soyb}$	−0.001 (0.006)
$a_{ngas,oil}$	0.016 (0.012)	$a_{ngas,ngas}$	0.219*** (0.024)	$a_{ngas,corn}$	−0.002 (0.007)	$a_{ngas,soyb}$	−0.0008 (0.005)
$a_{corn,oil}$	0.010 (0.012)	$a_{corn,ngas}$	−0.030 (0.019)	$a_{corn,corn}$	0.470*** (0.088)	$a_{corn,soyb}$	0.032** (0.016)
$a_{soyb,oil}$	−0.0002 (0.028)	$a_{soyb,ngas}$	−0.004 (0.035)	$a_{soyb,corn}$	−0.257*** (0.099)	$a_{soyb,soyb}$	0.143*** (0.033)
$b_{oil,oil}$	0.951*** (0.009)	$b_{oil,ngas}$	0.025*** (0.006)	$b_{oil,corn}$	0.007*** (0.002)	$b_{oil,soyb}$	0.001 (0.001)
$b_{ngas,oil}$	−0.004 (0.003)	$b_{ngas,ngas}$	0.963*** (0.005)	$b_{ngas,corn}$	−0.0007 (0.003)	$b_{ngas,soyb}$	−0.0003 (0.001)
$b_{corn,oil}$	−0.007 (0.007)	$b_{corn,ngas}$	0.008 (0.008)	$b_{corn,corn}$	0.810*** (0.033)	$b_{corn,soyb}$	−0.032*** (0.011)
$b_{soyb,oil}$	0.008 (0.007)	$b_{soyb,ngas}$	−0.009 (0.010)	$b_{soyb,corn}$	0.128*** (0.040)	$b_{soyb,soyb}$	0.996*** (0.009)

TABLE 9 (Continued)

y_{oil}	y_{ngas}	y_{corn}	y_{soyb}
Panel C: Model diagnostics Log likelihood: −15,659.3333 AIC: 15.476 SBC: 15.823 HQ: 15.603 Usable observations: 2040			
Panel D: Residual diagnostics Q(10) statistic: 168.9456; significance level: 0.2987 Q(20) statistic: 341.2501; significance level: 0.1981 Q(30) statistic: 508.9873; significance level: 0.1739 Q(40) statistic: 692.4959; significance level: 0.0739			
Panel E: Exogeneity test in the mean Equation (1) Test of exogeneity of all variables in the mean: $H_0 : \varphi_{i,j}^{P} = 0$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$ $H_1 : \varphi_{i,j}^{P} \neq 0$ for at least one $\varphi_{i,j}^{P}$, where $i \neq j = oil, ngas, corn, soybeans$, and $P = 1, ..., 5$ $\chi^2(60) = 117.3482$ or $F(60, *) = 1.9558$ with significance level 0.0000 Test of exogeneity in the mean equation of *oil*: $H_0 : \varphi_{oil,j}^{P} = 0$, where $j = ngas, corn, soybeans$, and $P = 1, ..., 5$ $H_1 : \varphi_{oil,j}^{P} \neq 0$ for at least one $\varphi_{oil,j}^{P}$, where $j = ngas, corn, soybeans$, and $P = 1, ..., 5$ $\chi^2(15) = 35.9517$ or $F(15, *) = 2.3967$ with significance level 0.0017 Test of exogeneity in the mean equation of *ngas*: $H_0 : \varphi_{ngas,j}^{P} = 0$, where $j = oil, corn, soybeans$, and $P = 1, ..., 5$ $H_1 : \varphi_{ngas,j}^{P} \neq 0$ for at least one $\varphi_{oil,j}^{P}$, where $j = oil, corn, soybeans$, and $P = 1, ..., 5$ $\chi^2(15) = 24.5242$ or $F(15, *) = 1.6349$ with significance level 0.0567 Test of exogeneity in the mean equation of *corn*: $H_0 : \varphi_{corn,j}^{P} = 0$, where $j = oil, ngas, soybeans$, and $P = 1, ..., 5$ $H_1 : \varphi_{corn,j}^{P} \neq 0$ for at least one $\varphi_{corn,j}^{P}$, where $j = oil, ngas, soybeans$, and $P = 1, ..., 5$ $\chi^2(15) = 21.3235$ or $F(15, *) = 1.4215$ with significance level 0.1268 Test of exogeneity in the mean equation of *soybeans*: $H_0 : \varphi_{soyb,j}^{P} = 0$, where $j = oil, ngas, corn$, and $P = 1, ..., 5$ $H_1 : \varphi_{soyb,j}^{P} \neq 0$ for at least one $\varphi_{soyb,j}^{P}$, where $j = oil, ngas, corn$, and $P = 1, ..., 5$ $\chi^2(15) = 24.2285$ or $F(15, *) = 1.6152$ with significance level 0.0613			
Panel F: Exogeneity test in the variance Equation (9) based on A matrix: ARCH effect test Block exclusion test based on A matrix for *oil* $H_0 : a_{ngas,oil} = a_{corn,oil} = a_{soyb,oil} = 0$ H_1: at least one of the coefficients in H_0 is different than 0 $\chi^2(3) = 2.3240$ or $F(3, *) = 0.7746$ with significance level 0.5079 Block exclusion test based on A matrix for *ngas* $H_0 : a_{oil,ngas} = a_{corn,ngas} = a_{soyb,ngas} = 0$ H_1: at least one of the coefficients in H_0 is different than 0 $\chi^2(3) = 6.7204$ or $F(3, *) = 2.2401$ with significance level 0.0813 Block exclusion test based on A matrix for *corn* $H_0 : a_{oil,corn} = a_{ngas,corn} = a_{soyb,corn} = 0$ H_1: at least one of the coefficients in H_0 is different than 0 $\chi^2(3) = 7.4214$ or $F(3, *) = 2.4738$ with significance level 0.0596 Block exclusion test based on A matrix for *soyb* $H_0 : a_{oil,soyb} = a_{ngas,soyb} = a_{corn,soyb} = 0$ H_1: at least one of the coefficients in H_0 is different than 0 $\chi^2(3) = 3.9560$ or $F(3, *) = 1.3186$ with significance level 0.2662			

(Continues)

TABLE 9 (Continued)

y_{oil}	y_{ngas}	y_{corn}	y_{soyb}
Panel G: Exogeneity test in the variance Equation (9) based on B matrix: GARCH effect test			
Block exclusion test based on B matrix for *oil*			
$H_0 : b_{ngas,oil} = b_{corn,oil} = b_{soyb,oil} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 3.5796$ or $F(3,*) = 1.1932$ with significance level 0.3105			
Block exclusion test based on B matrix for *ngas*			
$H_0 : b_{oil,ngas} = b_{corn,ngas} = b_{soyb,ngas} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 14.8419$ or $F(3,*) = 4.9473$ with significance level 0.0019			
Block exclusion test based on B matrix for *corn*			
$H_0 : b_{oil,corn} = b_{ngas,corn} = b_{soyb,corn} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 14.69750$ or $F(3,*) = 4.8991$ with significance level 0.0020			
Block exclusion test based on B matrix for *soyb*			
$H_0 : b_{oil,soyb} = b_{ngas,soyb} = b_{corn,soyb} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(3) = 8.6935$ or $F(3,*) = 2.8978$ with significance level 0.0336			
Panel H: Exogeneity test in the variance Equation (9) based on A and B matrices			
Wald Test of Diagonal BEKK			
$\chi^2(24) = 54.7212$ or $F(24,*) = 2.2800$ with significance level 0.0003			
Block exclusion test, *oil* equation variance			
$H_0 : a_{ngas,oil} = a_{corn,oil} = a_{soyb,oil} = b_{ngas,oil} = b_{corn,oil} = b_{soyb,oil} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 5.2874$ or $F(6,*) = 0.8812$ with significance level 0.5075			
Block exclusion test, *ngas* variance			
$H_0 : a_{oil,ngas} = a_{corn,ngas} = a_{soyb,ngas} = b_{oil,ngas} = b_{corn,ngas} = b_{soyb,ngas} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 21.3280$ or $F(6,*) = 3.5546$ with significance level 0.0016			
Block exclusion test, corn variance			
$H_0 : a_{oil,corn} = a_{ngas,corn} = a_{soyb,corn} = b_{oil,corn} = b_{ngas,corn} = b_{soyb,corn} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 15.0427$ or $F(6,*) = 2.5071$ with significance level 0.0199			
Block exclusion test, *soyb* variance			
$H_0 : a_{oil,soyb} = a_{ngas,soyb} = a_{corn,soyb} = b_{oil,soyb} = b_{ngas,soyb} = b_{corn,soyb} = 0$			
H_1: at least one of the coefficients in H_0 is different than 0			
$\chi^2(6) = 8.9104$ or $F(6,*) = 1.4850$ with significance level 0.1786			

Notes: This table presents the estimated coefficients based on Equations (1) and (9). Standard errors are in parentheses. $Q(10)$, $Q(20)$, $Q(30)$, and $Q(40)$ are the Ljung–Box statistics for serial correlation in the model residuals computed with 10, 20, 30, and 40 lags, respectively.

Abbreviations: AIC, Akaike Information Criterion; BEKK, Baba, Engle, Kraft, and Kroner; HQ, Hannan–Quinn information criterion; MVGARCH, multivariate generalized autoregressive conditional heteroskedasticity; SBC, Schwartz Bayesian Criterion; VAR, vector autoregressive.

***, **, and * indicate significance at the 1%, 5%, and 10% levels.

In this regard, our work not only follows the literature but also significantly extends it. Han et al. (2020) assert that robust bidirectional volatility linkages exist between agricultural and energy futures, particularly following the shale gas revolution. Such findings contradict the substitution effect, indicating that it may be overshadowed by a comovement effect resulting from various shared external shocks. These findings align with our work but only for certain volatility regimes. Employing the Markov-switching MVGARCH model as a method for identifying subperiods of high and low volatility, we add further clarity to the "substitution versus external shocks" academic debate. The results presented not only validate the variability in the relationship between agricultural and energy futures but also confirm the superiority of the comovement effect between these two types of derivative instruments over specific volatility regimes rather than across the entire testing period.

6 | HEDGING

Following Kroner and Sultan (1993), we constructed optimal hedge ratios using the conditional volatility estimates obtained from Equation (9). Given a portfolio of two commodities i and j, a long position of one dollar in commodity i can be hedged with a short position in commodity j, such that the risk of the portfolio is minimized without reducing returns. The optimal hedge ratio between commodity i and commodity j can be computed as

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}}, \tag{10}$$

where $h_{ij,t}$ is the estimated conditional covariance between commodities i and j, and $h_{jj,t}$ is the estimated conditional variance of commodity j, both of which are obtained through the estimation of Equation (9). A dynamic hedging strategy consists of a long position of one dollar in commodity i and a short position of β dollars in commodity j.

Furthermore, we constructed the optimal portfolio weight to determine the optimal amount of each commodity to be included in the one-dollar investment portfolio. On the basis of Kroner and Ng (1998), the optimal portfolio weight of commodity i is given by

$$,w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}} \quad \text{with} \quad w_{ij,t} = \left\{ \begin{matrix} 0 & \text{if } w_{ij,t} < 0, \\ w_{ij,t} & \text{if } 0 \le w_{ij,t} \le 1, \\ 1 & \text{if } w_{ij,t} > 1, \end{matrix} \right\}, \tag{11}$$

where $w_{ij,t}$ is the weight of commodity i in a dollar portfolio of two commodities (i.e., commodity i and commodity j) at time t; $h_{ij,t}$ is the estimated conditional covariance between commodities i and j; and $h_{jj,t}$ is the estimated conditional variance of commodity j. (Note that the weight of the second commodity is $1 - w_{ij,t}$).

Panel A of Table 10 presents the optimal hedge ratios between agriculture and energy for the whole period as well as for the three subperiods. Comparing these values across subperiods reveals that the hedging values of the second subperiod are higher than those of the first and third subperiods as well as those of the full period. Thus, it is much more expensive to hedge during the second subperiod and much cheaper to hedge during the first subperiod.

TABLE 10 Optimal hedge ratios (long/short) and optimal portfolio weights between agriculture and energy.

	Full sample	Subperiod I	Subperiod II	Subperiod III
Panel A: Hedge ratio (long/short) between agriculture and energy; means (standard deviations)				
oil/corn	0.11 (0.13)	0.05 (0.07)	0.31 (0.14)	0.07 (0.15)
corn/oil	0.23 (0.36)	0.13 (0.16)	0.35 (0.23)	0.24 (0.60)
oil/soyb	0.10 (0.14)	0.02 (0.07)	0.30 (0.19)	0.07 (0.09)
soyb/oil	0.25 (0.37)	0.07 (0.18)	0.50 (0.29)	0.28 (0.45)
ngas/corn	0.04 (0.10)	0.02 (0.06)	0.12 (0.10)	0.02 (0.16)
corn/ngas	0.16 (0.27)	0.14 (0.37)	0.22 (0.16)	0.12 (0.28)
ngas/soyb	0.04 (0.08)	0.03 (0.08)	0.07 (0.10)	0.02 (0.05)
soyb/ngas	0.16 (0.35)	0.17 (0.45)	0.19 (0.23)	0.10 (0.28)
Panel B: Portfolio weights; means (standard deviations)				
oil/corn	0.35 (0.17)	0.28 (0.09)	0.48 (0.18)	0.34 (0.19)
oil/soyb	0.28 (0.16)	0.28 (0.13)	0.33 (0.19)	0.23 (0.17)
ngas/corn	0.22 (0.13)	0.15 (0.09)	0.32 (0.10)	0.24 (0.15)
ngas/soyb	0.17 (0.13)	0.14 (0.12)	0.32 (0.10)	0.16 (0.11)

Notes: Standard errors are in parentheses.

The cheapest hedges are: for the first subperiod, long *oil*–short *soyb*, and long *ngas*–short *corn*; for the second subperiod, long *ngas*–short soyb; and for the third subperiod, long ngas–short soyb, and long ngas–short *corn*. The results also suggest that during the second and third subperiods (i.e., after 2007) the average optimal ratio for agricultural futures (i.e., *oil* and *soyb*) to hedge against gas futures (i.e., *ngas*) is smaller than the ratio used to hedge against oil futures (i.e., *oil*). This finding is in line with Han et al. (2020), indicating that in recent years, hedging against a long position in the oil market has been more expensive than hedging against a long position in the gas market.

Summary statistics for portfolio weights are reported in Panel B of Table 10. Here, it is important to note that the average weights of the second subperiod are much higher than those of the other two subperiod and for the full period. The results show that the average optimal weight for energy futures (i.e., *oil* and *ngas*) is smaller than that of agricultural commodity futures (i.e., *corn* and *soyb*) for the three subperiods and the entire period. This suggests that portfolio investors should place greater weight on agricultural commodity futures in a portfolio involving energy and agricultural futures, which is in accordance with the results of Han et al. (2020).

Panels A and B of Table 11 display the optimal hedge ratios between macroeconomic index futures (i.e., *crb* or *usdx*) and energy-agricultural portfolios for the whole period as well as for the three subperiods. (The energy-agricultural portfolios were created using the optimal portfolio weights provided in Panel B of Table 10.) Panel A of Table 11 reveals that the average values of the hedge ratios between energy-agricultural portfolios (i.e., *oil&corn, oil&soyb, ngas&corn*, or *ngas&soyb*) and *crb* are lower than the corresponding average hedge ratio values between *crb* and energy-agricultural portfolios for the whole period as well as for the three subperiods. Thus, the strategy of hedging long in energy-agricultural portfolios and short in *crb* is cheaper than the strategy of hedging long in *crb* and short in energy-agricultural portfolios.

Moreover, a comparison of the optimal hedging values across subperiods indicates that the hedging values of the second subperiod are higher than those of the first and third subperiods as well as those of the full period.

Panel B of Table 11 shows that the average values of the hedge ratios between *usdx* and energy-agricultural portfolios are negative for the full period as well as for the three subperiods. Negative values for a hedge indicate that a short position should be taken in the first asset and a long position in the second asset. The average values of the hedge

TABLE 11 Optimal hedge ratios between *crb* (*usdx*) and energy-agriculture portfolio.

	Full sample	Subperiod I	Subperiod II	Subperiod III
Panel A: Hedge ratios between crb and energy-agriculture portfolio; means (standard deviations)				
oil&cron/crb	0.52 (0.17)	0.49 (0.13)	0.59 (0.09)	0.49 (0.24)
crb/oil&corn	0.99 (0.30)	0.85 (0.22)	1.22 (0.21)	0.94 (0.34)
oil&soyb/crb	0.56 (0.19)	0.52 (0.15)	0.67 (0.15)	0.51 (0.23)
crb/oil&soyb	0.84 (0.32)	0.81 (0.28)	0.99 (0.28)	0.71 (0.30)
ngas&corn/crb	0.33 (0.19)	0.30 (0.12)	0.41 (0.16)	0.29 (0.25)
crb/ngas&corn	0.72 (0.33)	0.60 (0.26)	0.97 (0.26)	0.60 (0.30)
ngas&soyb/crb	0.37 (0.22)	0.29 (0.14)	0.54 (0.19)	0.35 (0.28)
crb/ngas&soyb	0.62 (0.34)	0.57 (0.33)	0.83 (0.31)	0.47 (0.25)
Panel B: Hedge ratios between usdx and energy-agriculture portfolio; means (standard deviations)				
oil&corn/usdx	−0.05 (0.08)	−0.02 (0.07)	−0.13 (0.06)	−0.04 (0.07)
usdx/oil&corn	−0.45 (0.72)	−0.11 (0.45)	−1.30 (0.70)	−0.27 (0.44)
oil&soyb/usdx	−0.07 (0.09)	−0.03 (0.07)	−0.15 (0.08)	−0.05 (0.08)
usdx/oil&soyb	−0.43 (0.63)	−0.18 (0.39)	−1.11 (0.73)	−0.25 (0.37)
ngas&corn/usdx	−0.04 (0.07)	−0.02 (0.06)	−0.08 (0.06)	−0.03 (0.06)
usdx/ngas&corn	−0.34 (0.64)	−0.11 (0.47)	−0.87 (0.64)	−0.20 (0.48)
ngas&soyb/usdx	−0.05 (0.08)	−0.03 (0.06)	−0.11 (0.07)	−0.04 (0.07)
usdx/ngas&soyb	−0.35 (0.54)	−0.19 (0.42)	−0.81 (0.55)	−0.20 (0.35)

Notes: Standard errors are in parentheses.

ratios between energy-agricultural portfolios and *usdx* are lower (in absolute value) than the corresponding average hedge ratio values between *usdx* and energy-agricultural portfolios for the whole period as well as for the three subperiods. Furthermore, the hedging values of the second subperiod are higher (in absolute value) than those of the first and third subperiods as well as those of the full period.

In general, the results of Table 11 indicate that *crb* and *usdx* index futures can be employed as effective risk management (hedging) instruments to mitigate risk for portfolios involving energy and agricultural commodities. The hedging strategy explained above provides insights into the different portfolio structures investors should be aware of, based on the different market phases, as demonstrated by the Markov-switching techniques. This finding makes a vital contribution to the field of portfolio management.

Asset prices are known to reflect several linkages among their underlying assets. Agricultural and energy futures are among these cases. Because the fundamental goal of numerous investors and financial professionals is to minimize the risk of their asset portfolio, it is imperative for them to diversify their portfolios across different asset classes, financial instruments, regions, and industries. Using financial futures is an integral part of such an approach, with energy and agricultural futures being commonly used assets, especially when following investment strategies, such as inter-commodity spread trading. Testing the various commodity pairs on an ex-ante basis enabled us to identify possible weak relationships for modeling purposes. Hence, potential low hedge ratios do not necessarily challenge the validity of our work, but they do question whether such assets, when combined within a fully diversifiable investment portfolio, would eliminate portfolio risk.[11]

In the next step, we calculated hedging effectiveness (HE), offering comparable information on the hedging performance of the different portfolios in line with Han et al. (2021). The HE index is algebraically formulated as follows:

$$Hedging \quad Effectiveness \ (HE) = \frac{variance_{unhedged} - variance_{hedged}}{variance_{unhedged}}. \tag{12}$$

Here, a better hedging strategy corresponds to high HE index values, suggesting significant risk reduction. Table 12 presents the HE indices between energy and agricultural futures. According to the results, the highest HE index for the entire sample period may not be the best indicator for the subsamples. More specifically, corn and soybean futures, both with a HE index of 0.02, are the best hedging instruments against oil futures for the full sample. However, corn futures are the best hedging instruments against oil futures in the first subperiod, and soybean futures are the best in the second subperiod. Corn and soybean futures are the best hedging instruments for the third subperiod. The HE indices of Table 12 indicate that hedging agricultural futures against oil futures achieves better performance than hedging against natural gas futures.

Panels A and B of Table 13 report the HE indices between energy-agricultural portfolios and *crb* and *usdx* index futures, respectively for (i) the entire period and (ii) the three subperiods separately. The results of Panel A indicate that *crb* index futures are more effective hedging instruments in the second subperiod (HE = 52% for *crb* against *oil&corn* and HE = 5 3% for *crb* against *oil&soyb*) than the first (32% and 33%) and third (31% and 24%) periods, respectively. A similar picture is presented for *crb* index futures hedging against the *ngas&corn* and *ngas&soyb* commodity pairs, albeit of a significantly lower magnitude (27% and 37%, respectively), for the second period. The results of Panel B indicate that *usdex* index futures are more effective hedging instruments in the second subperiod, results that are consistent with those of the *crb* index futures.

In general, these findings suggest that during periods of increased volatility linkage between agricultural and energy markets, such as in the second subperiod of our sample, agricultural (energy) futures could become good hedges for energy (agricultural futures). Furthermore, because agricultural and energy markets are more exposed to common macroeconomic shocks, *crb* and *usdx* index futures can be utilized as effective hedging tools against agricultural and energy portfolios in periods of high volatility. However, all these HE indicators fall considerably below what is generally considered an optimal hedge ratio (80%–120%) according to the existing literature (Bialkowski et al., 2023).

Our work is in line with, and indeed significantly extends, the current literature. For example, other recent studies confirm that volatility spillover is transmitted between the energy and agricultural sectors (Tiwari et al., 2022), but such

[11]In the same context, other studies, such as that by Han et al. (2021), utilize a wide range of similar hedging pairs, that is, oil&corn/soyabeans/wheat, and gas&corn/soyabeans/wheat, validating our commodity pairs selection approach.

TABLE 12 Hedge ratio efficiency between agriculture and energy.

	Full sample	Subperiod I	Subperiod II	Subperiod III
oil/corn	0.021	0.004	0.116	0.008
corn/oil	0.002	−0.010	0.120	−0.068
oil/soyb	0.017	0.001	0.130	0.006
soyb/oil	−0.032	−0.003	0.095	−0.321
ngas/corn	0.003	0.001	0.020	0.001
corn/ngas	−0.047	−0.085	−0.002	−0.028
ngas/soyb	0.002	0.001	0.009	0.001
soyb/ngas	−0.075	−0.118	−0.018	−0.048

TABLE 13 Hedge ratio efficiency between crb (usdx) and energy-agriculture portfolio.

	Full sample	Subperiod I	Subperiod II	Subperiod III
Panel A: Hedge ratio efficiency between crb and energy-agriculture portfolio				
oil&cron/crb	0.386	0.316	0.517	0.306
crb/oil&corn	0.067	0.090	−0.090	0.013
oil&soyb/crb	0.385	0.332	0.533	0.239
crb/oil&soyb	0.279	0.182	0.341	0.177
ngas&corn/crb	0.166	0.118	0.269	0.115
crb/ngas&corn	−0.081	−0.102	−0.237	−0.028
ngas&soyb/crb	0.188	0.111	0.374	0.116
crb/ngas&soyb	0.117	−0.064	0.268	0.090
Panel B: Hedge ratio efficiency between usdx and energy-agriculture portfolio				
oil&corn/usdx	0.007	0.001	0.032	0.002
usdx/oil&corn	−1.247	−0.057	−14.390	−0.455
oil&soyb/usdx	0.009	0.002	0.037	0.003
usdx/oil&soyb	−0.889	−0.139	−8.772	−0.273
ngas&corn/usdx	0.003	0.001	0.012	0.001
usdx/ngas&corn	−0.859	−0.076	−7.221	−0.291
ngas&soyb/usdx	0.005	0.001	0.021	0.002
usdx/ngas&soyb	−0.679	−0.222	−4.340	−0.184

spillover effects vary over time (Bonato, 2019) and across different futures (Zivkov et al., 2020). In this regard, certain combinations in the same portfolio are better than others (Yang & Awokuse, 2003). These findings are corroborated by our modeling approach as our results also suggest a lack of uniformity for the examined hedges (i.e., energy vs. agriculture, vice versa, and similarly with macroeconomic variables), even though specific pairs are better than others. Moreover, according to Narayan et al. (2015), futures markets indicate variability in the context of trading strategies as this relationship is frequency-dependent. Therefore, the dynamic nature of price volatility transmission in these industries justifies our chosen approach and its superiority in capturing such diverse dynamics.

Finally, regarding the efficiency of relevant hedging strategies, previous approaches have yielded mixed findings as their results varied between the entire period and subperiods (Han et al., 2020). By contrast, the robustness of our results is demonstrated by consistently showing that the oil/corn and oil/soybean pairs exhibit the highest hedging efficiency across all subperiods and the entire period. More importantly, hedging efficiency is significantly better in the high volatility regime than its low counterparts. Consequently, combining Markov regime switches with MVGARCH models can help investors develop optimal portfolio strategies for different market volatility phases, a finding that adds strongly to the literature on portfolio management.[12]

7 | CONCLUSION

In this paper, we investigated the volatility linkages between energy and agricultural commodity futures and examined their dynamics over time. Specifically, we tested whether bidirectional price volatility linkages exist between energy and agricultural commodity markets, and whether such volatility linkages are the result of the comovement effect caused by external macroeconomic and financial shocks stemming from the world economy, or the substitution effect induced by the biofuel industry. The contribution our study makes to the existing literature is fourfold. First, using a quadrivariate VAR–DCC–GARCH model, we estimated dynamic conditional cross-correlations between energy and agricultural futures from July 3, 1996 to November 2, 2020. Second, by performing Markov-switching regressions on the estimated dynamic conditional cross-correlations, we identified two subperiods of a low volatility regime (i.e., July 3, 1996–December 29, 2006, and January 1, 2013–November 2, 2020) and one subperiod of a high volatility regime (i.e., January 1, 2007–December 31, 2012). Markov-switching estimates revealed that common macroeconomic and financial external shocks from the world economy, as proxied by *crb* and *usdx* indices, exerted a stronger effect on conditional cross-correlations in the high volatility regime (second subperiod) than in the low volatility regime (first and third subperiods).

This finding indicates that during the second subperiod (i.e., high volatility regime), the comovement effect induced by external macroeconomic and financial shocks outweighed the weak substitution effect between energy and agricultural products caused by the development of shale gas. Therefore, whilst the shale gas revolution may weaken the volatility linkage between the energy and agricultural markets by diminishing the substitution effect between these markets, the comovement effect caused an overall increase in the volatility linkages in the second subperiod. Third, using a quadrivariate VAR–BEKK–GARCH model, we affirmed bidirectional price volatility spillovers between the agricultural commodities and energy markets in the high volatility regime subperiod. However, volatility spillover effects between agricultural commodities and energy markets were weaker in the first and third subperiods (i.e., low volatility regime subperiods). Specifically, exogeneity test results revealed that for the second subperiod, short-run effects (i.e., external shocks associated with the world economy) prevailed over the long-run effects (i.e., the substitution effect). Finally, we provided useful information for portfolio management activities associated with energy and agricultural commodities and *crb* and *usdx* index futures. For instance, we found that energy (agricultural) futures could be employed as a good hedge for agricultural (energy) futures. As such, portfolio investors should place greater weight on agricultural commodity futures in a portfolio encompassing energy and agricultural futures. Finally, *crb* and *usdx* index futures can be employed as effective hedging tools to reduce risk for portfolios entailing energy and agricultural commodities.

We also analyzed the HE of these strategies. Our results indicate that the effectiveness of hedging varied across different subperiods. In particular, *crb* index futures were more effective during the second subperiod while the *usdx* index futures were more effective in the second subperiod. This suggests that agricultural and energy futures can function as mutually effective hedging tools during periods of increased market volatility. Furthermore, due to their exposure to common macroeconomic shocks, certain index futures, such as the *crb* and *usdx*, can be utilized during those periods of high volatility as effective hedging instruments against agricultural and energy portfolios. Our work paves the way for in-depth investigations that consider alternative regime states in the various volatility phases when examining the price transmission between commodities. Future studies could expand our work by incorporating various other commodities, such as industrial/precious metals.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

[12]More recently, Liu et al. (2023) reported a similar finding with respect to the inflation-hedging ability of various commodity futures. As their study reveals, the hedging performance of the various commodities exhibits time-varying characteristics. From the large number of commodities tested, only industrial and precious metals can be effectively employed against inflation, but with smaller reliability in the case of precious metals.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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