The dynamic dependence between the major US indices and the meat commodities indices

Abdelkader Derbali
Department of Administrative and Financial Sciences and Techniques, Community College, Taibah University, Medinah, Saudi Arabia and Institut Superieur d'Informatique et de Gestion de Kairouan, Universite de Kairouan, Kairouan, Tunisia, and

Houssam Bouzgarrou
Département de Finance, Comptabilité et Gestion, Institut Supérieur de Finances et de Fiscalité, Université de Sousse, Sousse, Tunisie

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Abstract

Purpose – The purpose of this study is to examine empirically the conditional correlation between the major US indices (S&P500 index and Dow Jones Industrial index) and three selected meat commodities as: Feeder Cattle, Leen Hogs and Live Cattle during the period from July 22, 2010 to June 30, 2017.

Design/methodology/approach – In this study, the authors use for the first time the GARCH-DECO (1,1) to examine empirically the conditional nexus between the major US indices (S&P500 index and Dow Jones Industrial index) and three selected meat commodities as; Feeder Cattle, Leen Hogs and Live Cattle during the period from July 22, 2010 to June 30, 2017.

Findings – From the empirical findings, the authors conclude the existence of a highly significance of conditional heteroscedasticity parameters can demonstrate us to distinguish the nature of the volatility dependency between S&P500 index and Dow Jones Industrial index and three selected meat commodities indices.

Originality/value – This can find clear the significance of relationship in the process of financialization of the major US index and meat commodities indices in the case of this paper.

Keywords Financialization, Deco-garch, Dynamic dependence, Meat commodities, US indices

Paper type Research paper

Introduction

The successive dropping-off of international stock markets has contributed to increased investor mistrust on the stock markets. This is an indirect consequence of the subprime

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crisis, which began in the USA in August 2007. The ensuing European debt crisis makes it possible to envisage a special relationship between the main countries of the Economic and Monetary Union. The bonds that unite these countries can be seen on the stock markets and are then likely to reveal the warning signs of a systemic risk.

Thus, De Bandt and Hartmann (2000) detail the possible impacts of contagion effects on systemic risk. As the onsets of the sovereign debt crisis in Europe, instability in the financial markets and systemic risk have led public authorities to put in place numerous bailout plans. In developing these, they must consider the impact of a decision on all financial markets.

Commodity indices trade on the relationship between supply and demand. Such as developing countries, for example, China and India require important investment in commodities such as steel and oil to construct their infrastructures, cotton and metals to produce manufacturing products and food-related commodities to nourish their progressively more middle-class populations. These trends have produced significant demand and higher volatilities of prices for commodities indices. Additionally, the high level of demand has also paying attention of investors, who previously invested in only stocks and bonds markets, to take benefit of commodity markets force and its normal inverse dynamic correlation to the movement of the stock market indices coincided with the 2007-2008 booms in commodity prices (Henderson *et al.*, 2015; Roll, 2013; Erb and Harvey, 2006; Cheng and Xiong, 2013; Gorton and Rouwenhorst, 2006; Liu and Tang, 2011; Szymanowska *et al.*, 2014).

In large-system conditional covariance modeling, we can find the existence of contrast of factor autoregressive conditional heteroskedasticity (ARCH) and composite likelihood highlights a fundamental tradeoff. Engle and Kelly (2012) suggest a solution to this tradeoff that selectively combines simplifying structural assumptions and composite likelihood adaptability. They use a system in which all pairs of returns have the same correlation on a given day, but this dependence varies over time.

The model, called generalized autoregressive conditional heteroskedasticity-dynamic equicorrelation (GARCH-DECO), eliminates the computational and presentational difficulties of high-dimension systems. In addition, because equicorrelated matrices have simple analytic inverses and determinants, likelihood computation is dramatically simplified and optimization becomes feasible for vast numbers of financial time series returns and volatilities.

Then, the main purpose of our study is to examine empirically the conditional correlation between the major US indices (S&P500 index and Dow Jones Industrial index) and three selected meat commodities as; Feeder Cattle, Leen Hogs and Live Cattle during the period from July 22, 2010 to June 30, 2017. Methodologically, we use the GARCH-DECO (1,1) to investigate the dynamic equicorrelation (DECO) between S&P500 index and Dow Jones Industrial index and three selected meat commodities indices.

This paper expands its own importance and giving from the detail that it using of GARCH-DECO (1,1) for the first time on the investigation of the conditional volatility and the time-varying variance of DECO between S&P500 index and Dow Jones Industrial index and three selected meat commodities indices. The GARCH-DECO specifications, although significant, have become a standard and popular modelling framework for financial time series.

The main findings of our paper show the presence of a highly significance of conditional heteroscedasticity parameters can demonstrate us to distinguish the nature of the volatility dependency between S&P500 index and Dow Jones Industrial index and three selected meat commodities indices. This can find clear the significance of relationship in the process of financialization of the major US index and meat commodities indices in the case of this paper.

In addition, the sum of the two parameters ($\alpha + \beta$) for the chosen conditional heteroscedasticity specification (GARCH-DECO (1,1) model) is close to 1 which confirms the persistence of volatility in the conditional dependency between the major US index and meat commodities indices. There is one important justification which makes that such persistence goes along with the financialization of US stock market indices and meat commodities.

The rest of this paper is structured as follow: in Section 2, we present literature review. Section 3 presents the econometric methodology used in this paper. Section 4 indicates data characteristics. In Section 5, we report the empirical finding. Section 6 concludes and remarks. Finally, Section 7 presents the policy implications of our study.

Literature review

The previous works focus on the co-movements and dependencies among commodity markets typically concentrates on specific commodity prices and describes the co-movements by using both economic and financial channels. A first part of the literature focuses on the nexus among energy and agriculture commodities, focusing the price co-movements and volatility spillovers. In positions of price co-movements, experimental works use linear cointegration methods (Avalos, 2014; Baumeister and Kilian, 2014; Nazlioglu and Soytas, 2012; Saghaian, 2010; Rezitis, 2015; Liu *et al.*, 2019) or multivariate linear regressions (Hassouneh *et al.*, 2012) and indicate the presence of long-run co-movements or volatility spillovers (Du *et al.*, 2011; Fasanya and Akinbowale, 2019; Ji and Fan, 2012; Serra, 2011; Nazlioglu *et al.*, 2013; Mensi *et al.*, 2014; Zhang and Qu, 2015; Ji *et al.*, 2018a).

Studies that are more current concentrate on the non-linearity describing this link (Chen *et al.*, 2010; De Nicola *et al.*, 2016; Lucotte, 2016; Natanelov *et al.*, 2011; Pal and Mitra, 2017; Su *et al.*, 2019) and describe improved co-movements among energy and agricultural commodity prices, in the wake of the latest food crisis and the increase of environmental worries. In contrast, Fowowe (2016) uses cointegration tests including structural breaks and nonlinear causality tests and finds that agriculture commodity prices do not react to oil price surprises in South Africa.

A second part of the literature focus on the co-movement and volatility spillover among energy and metal markets (Aguilera and Radetzki, 2017; Behmiri and Manera, 2015; Bildirici and Turkmen, 2015; Choi and Hammoudeh, 2010; Ewing and Malik, 2013; Hammoudeh and Yuan, 2008; Ji *et al.*, 2018b, Ji *et al.*, 2019). Then, Choi and Hammoudeh (2010) examine the volatility spread among oil and industrial commodities using a regime switching methodology, although Bildirici and Turkmen (2015) investigate the cointegration and causality link between oil and precious metals using a nonlinear ARDL cointegration context and nonlinear causality tests.

Chebbi and Derbali (2016a) investigate empirically the importance of the dynamics of the correlations between commodities and Islamic indices. They use the EC-GARCH model which allows us to assess the causality and the dynamic correlations between commodities and Islamic indices. Their empirical findings support the view that volatilities of commodities returns are strongly correlated to those of Islamic indices.

Chebbi and Derbali (2016b) examine empirically the dynamics of the correlations among the Qatar Exchange Al Rayan Islamic index and crude oil and natural gas by including structural breaks in the DCC-GARCH model. Their empirical findings show that the volatility of commodity returns is strongly correlated to that of the Al Rayan Islamic index and the volatility persistence decreases by its lowest amount after incorporating structural breaks.

Besides, González-Pedraz *et al.* (2015) evaluate oil, gold and equity correlation and show evidence for tail dynamic correlation between commodities and equities. In this context, Wen *et al.* (2012) examine the dynamics of the dependencies among energy and stock markets via time-varying copulas and Creti *et al.* (2013) study time-varying dependence between commodity and equity markets via dynamic conditional correlation analysis.

On the same context, Delatte and Lopez (2013) present a thorough survey on equity and commodity correlation and find stylized facts of both asset classes by applying competing copula approaches. The authors provide time-varying relationship among commodity and stock markets and find different correlation regimes after the outbreak of financial crisis in 2008.

Methods

In our study, we use the GARCH-DECO models to test the DECO between the major US indices (S&P500 index and Dow Jones Industrial index) and three selected meat commodities as; Feeder Cattle, Leen Hogs and Live Cattle during the period from July 22, 2010 to June 30, 2017.

The dynamic conditional correlation framework is a practical modeling tool, however, when the number of test stock market indices become large the estimation can becomes unreliable and even breakdown finally. The DECO model group of correlation models is considered to overcome some of these computational difficulties issued by the dynamic conditional correlation models. As such, the documentation for DECO models will be formulated for many stock market return series (Engle and Kelly, 2012).

Consider a vector of n different stock market return series $r_t = [r_{1,t}, \ldots, r_{N,t}]$ where all series have been demeaned. Further, define the conditional covariance matrix of all stock market return series as $\mathrm{E}_{t-1}\left[r_t r_t'\right] = H_t$. Then, we can decompose H_t into the following:

$$H_t = D_t R_t D_t \tag{1}$$

where $H_t = diag(\sigma_{i,t})$ for $i = (1,2)$. $\sigma_{i,t}$ denotes the conditional volatility of return series i and is the ith diagonal entry of H_t. Finally, R_t denotes the conditional correlation matrix for the two return series. The GARCH-DECO model puts specific parametric assumptions on the evolution of D_t and R_t separately.

The conditional variance of each individual return series is modeled as a standard GARCH process:

$$\mathrm{E}_{t-1}\left[r_{i,t}^2\right] = \sigma_{i,t}^2 \tag{2}$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3}$$

By using the standard GARCH model, we can proceed to the estimation of the residuals for each return series after we have fit the univariate GARCH model. Formally, these are defined as:

$$\varepsilon_{i,t} = \frac{r_{i,t}}{\sigma_{i,t}} \tag{4}$$

Besides, the volatility residual vector $\varepsilon_t = [\varepsilon_{1,t}, \ldots, \varepsilon_{N,t}]'$ will accede to the same correlation structure as the original two return series.

The GARCH-DECO model assumes a specific parametric for the conditional correlation matrix R_t. Then, on a given day the GARCH-DECO model supposes that all pairwise correlations are identical. Also, it turns out that despite this seemingly strong restriction, the DECO model can provide consistent estimates of dynamic conditional correlation parameters in large systems. The correlation matrix R_t is, thus, defined as an equicorrelation matrix and evolves as:

$$R_t = (1 - \rho_t)I_N + \rho_t J_N \tag{5}$$

$$\rho_t = \frac{2}{N(N-1)} \sum_{i>j} \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}\, q_{j,j,t}}} \tag{6}$$

$$\overline{q}_{i,j,t} = \rho_{i,j} + \alpha_{DECO}\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \overline{\rho}_{i,j}\right) + \beta_{DECO}\left(q_{i,j,t-1} - \overline{\rho}_{i,j}\right) \tag{7}$$

where $\overline{\rho}_{i,j}$ denotes the unconditional correlation between $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$. The complete GARCH-DECO (1,1) specification is obtained after the modeling of the univariate return series as individual GARCH processes and their standardized residual series as a DECO process.

All the parameters ($\omega_{i=1,2}$; α_{DECO}; β_{DECO}) of the GARCH-DECO are estimated by using the system vie quasi maximum likelihood.

To implement maximum likelihood, we suppose the stacked return series $r_t = [r_{1,t}, r_{2,t}]'$ is multivariate normal with a conditional covariance H_t as defined above. Then, we assume that $r_t \rightarrow N(0, H_t)$ which leads to the natural definition of the likelihood function.

In addition, it can be revealed that the likelihood function can be decomposed into a volatility component and a correlation component, which naturally leads to a two step estimation procedure. First, we estimate univariate GARCH models to each return series. Next, using the stacked residuals$\varepsilon_t = \left[\varepsilon_{1,t}, \varepsilon_{2,t}\right]' = D_t^{-1} r_t$, we estimate the correlation parameters α_{DECO} and β_{DECO} by maximizing the following function:

$$L_c(\alpha_{DECO}, \beta_{DECO}) = -\frac{1}{2} \sum_t \left(\log|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t - \varepsilon_t' \varepsilon_t'\right) \tag{8}$$

As is similar with the GARCH, the single correlation ρ_t will be stable and mean-reverting so long as $\alpha_{DECO} > 0$, $\beta_{DECO} > 0$, $\alpha_{DECO} + \beta_{DECO} < 1$. The standard restrictions and properties of the univariate GARCH models that are used to model each individual return series' volatilities also naturally still hold.

Descriptive results

In this paper, we use the GARCH-DECO models to test the DECO among the major US indices (S&P500 index and Dow Jones Industrial index) and three selected meat commodities indices as: Feeder Cattle, Leen Hogs and Live Cattle.

The US financial market is among the most dynamic and represents a real barometer for the global economy. To evaluate its performance, several US stock indices have been set up. Institutional investors in the US and around the world can experience the dynamism and trend of the US market through a number of stock market indices.

The principle US indices are:

- *S&P500*: one of the main indicators is the S&P500 index, which includes the 500 largest US companies that make up more than 70% of the market capitalization of Wall Street. The values of these companies are used in the calculation of the index, with regard to their size and their free float.
- *DJIA (Dow Jones Industrial average)*: next to it is the Dow Jones Industrial average, which is an equally weighted index. It covers 30 companies of which 28 are listed on the NYSE market in addition to Microsoft and Intel which are listed on the NASDAQ.
- *NASDAQ 100*: for the latter market specialized in quotations of technology stocks, it has two indices, namely, the NASDAQ 100 and the NASDAQ composite. The first is made up of Nasdaq's 100 largest non-financial caps. This is an index that is used more on the derivatives market such as futures, warrants and EFT.
- NASDAQ composite: while the Nasdaq composite includes all US and foreign companies. A total of nearly 3,200 companies listed on its equity market. The weight of each company is proportional to its market capitalization.
- *AMEX composite*: The AMEX composite index is one of the references of the American Stock Exchange, the third largest financial market in the USA.
- *Value line index*: the value line index, for its part, consists of 1,700 securities accounting for 95% of the market capitalization, all markets combined.
- *Willshire 5000*: on the other hand, the Willshire 5000 contains all the securities listed on the NYSE and the AMEX, in addition to a fairly large portion of the securities of the "NASDAQ National Market."
- *Russel 1000*: the Russel 1000 is based on its calculation of the first 1,000 US stocks.
- *Russel 3000*: while the Russel 3000 brings together the 3,000 companies with the largest cap stocks and 98% of the US stock market.

The US stock market indices are characterized by their diversity and representativeness of the various sectors and sizes of companies operating in the US market. Moreover, they are the most closely monitored by stock market analysts and observers, given their strong influence on international financial markets.

Table 1 summarizes the descriptive statistics of the returns of the major US indices and meat commodities indices. From this table, we can remark that in average the higher return

Table 1. Descriptive statistics of the returns of the major US indices and meat commodities indices over the period from July 22, 2010 to June 30, 2017

Statistics	Leen Hogs	Live Cattle	Feeder Cattle	S&P500	Dow Jones Industrial
Mean	−0.000175	0.000567	−0.000662	0.000389	0.000421
Median	0.000000	0.000973	−0.000302	0.000541	0.000511
Maximum	0.033548	0.032626	0.064792	0.045630	0.041218
Minimum	−0.028073	−0.037850	−0.063029	−0.068208	−0.056127
SD	0.008444	0.006840	0.011880	0.008705	0.008416
Skewness	−0.015956	−0.615563	−0.149927	−0.514266	−0.410015
Kurtosis	4.089633	9.360980	5.417744	8.701012	7.226373
Jarque-Bera	86.54924	3,057.378	432.2947	2,444.244	1,349.942
Probability	0.000000*	0.000000*	0.000000*	0.000000*	0.000000*
Observations	1,748	1,748	1,748	1,748	1,748

Notes: This table reports the returns of the major US indices and meat commodities indices, over the period of study from July 22, 2010 through June 30, 2017. Statistical significance at the 1% level is denoted by * is for Live Cattle (0.000567) followed, respectively, by Dow Jones Industrial (0.000421), S&P500 (0.000389), Leen Hogs (−0.000175) and Feeder Cattle (−0.000662).

For the two statistics of skewness (asymmetry) and kurtosis (leptokurtic), we can remark that the two variables used in our study are characterized by non-normal distribution. The negative sign of the skewness coefficients indicate that the variable is skewed to the left and it is far from being symmetric for all variables. Also, the Kurtosis coefficients confirm that the leptokurtic for all variables used in this paper show the existence of a high peak or a fat-tailed in their volatilities.

Based on the positive sign of estimate Jarque-Bera coefficients, we can reject the null hypothesis of normal distribution of the variables used in our study. Then, the high value of Jarque-Bera coefficients reflects that the series is not normally distributed at the level of 1%.

Additionally, Table 2 reports the descriptive statistics of the conditional volatility of the major US indices and meat commodities indices over the period from July 22, 2010 to June 30, 2017. Then, we can observe that in mean the higher conditional volatility is for Feeder Cattle (0.014585) followed, respectively, by Leen Hogs (0.008990), S&P500 (0.007611), Dow Jones Industrial (0.007125) and Live Cattle (0.005973).

For the conditional volatility prediction by the GARCH (1,1) model, we can show that the biggest weekly, monthly and yearly prediction is for the energy commodities followed by the agriculture commodities, the precious metals commodities and the livestock commodities.

Figures 1 to 10 present the evolution of the returns and the conditional volatility prediction by GARCH (1,1) specification of the major US indices; S&P500 index and Dow Jones Industrial index and three selected meat commodities indices as: Feeder Cattle, Leen Hogs and Live Cattle.

According to these figures, we can observe that the conditional volatility prediction of the chosen series returns attained their maximum in the start of period of study and in the end of the same period. This period is coinciding with the presence of an international financial instability followed by an international liquidity and banking crisis in developing and developed countries.

Findings

In this section, we investigate empirically the DECO between the major US indices (S&P500 index and Dow Jones Industrial index) and three selected meat commodities indices as:

Statistics	Leen Hogs	Live Cattle	Feeder Cattle	S&P500	Dow Jones Industrial
Mean	0.008990	0.005973	0.014585	0.007611	0.007125
Median	0.007682	0.002541	0.010684	0.006252	0.005955
Maximum	0.061803	0.049529	0.105262	0.059740	0.052388
Minimum	0.000356	0.000222	0.000727	0.000618	0.000320
SD	0.006197	0.005844	0.013692	0.005380	0.004998
Skewness	2.692822	2.395880	2.962528	2.481286	2.252905
Kurtosis	16.75917	11.11653	14.22448	15.79008	13.46311
Jarque-Bera	15,900.97	6,470.438	11,733.10	13,708.20	9,452.236
Probability	0.000000*	0.000000*	0.000000*	0.000000*	0.000000*
Observations	1,748	1,748	1,748	1,748	1,748

Notes: This table reports the conditional volatility of the major US indices and meat commodities indices, over the period of study from July 22, 2010 through June 30, 2017. Statistical significance at the 1% level is denoted by *

Table 2. Descriptive statistics of the conditional volatility of the major US indices and meat commodities indices over the period from July 22, 2010 to June 30, 2017

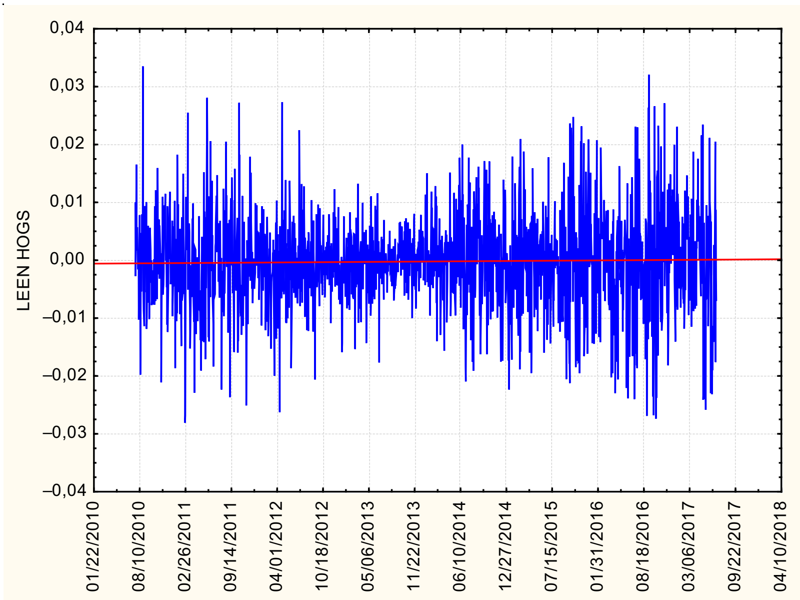

Figure 1.
The return of Leen Hogs index over the period from July 22, 2010 to June 30, 2017

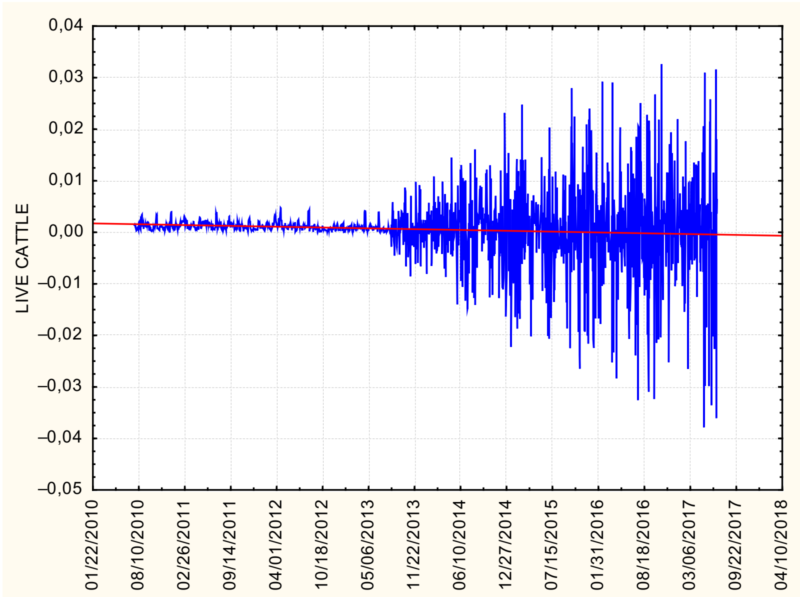

Figure 2.
The return of Live Cattle index over the period from July 22, 2010 to June 30, 2017

Feeder Cattle, Leen Hogs and Live Cattle during the period of study from July 22, 2010 to June 30, 2017.

So, we use a data set composed by daily series returns of the whole selected indices. In the empirical investigation, we use the GARCH-DECO (1,1) to study the DECO between

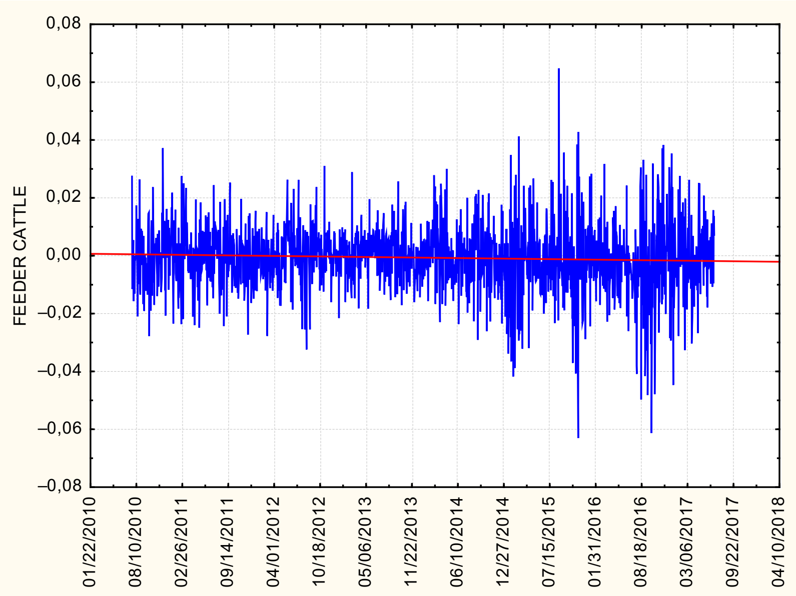

Figure 3.
The return of Feeder Cattle index over the period from July 22, 2010 to June 30, 2017

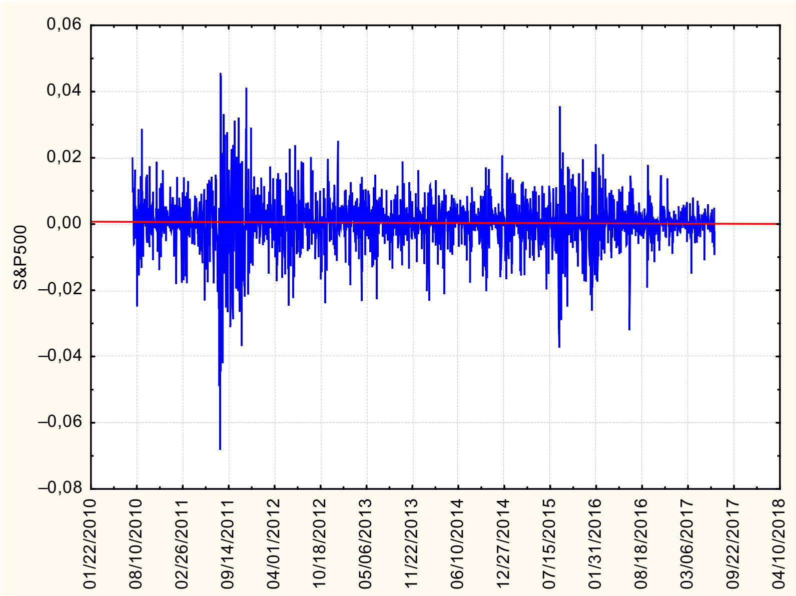

Figure 4.
The return of S&P500 index over the period from July 22, 2010 to June 30, 2017

S&P500 index and Dow Jones Industrial index and three selected meat commodities indices as: Feeder Cattle, Leen Hogs and Live Cattle.

Figures 11 to 16 report the progress of the DECO among S&P500 index and Dow Jones Industrial index and three selected meat commodities indices as: Feeder Cattle,

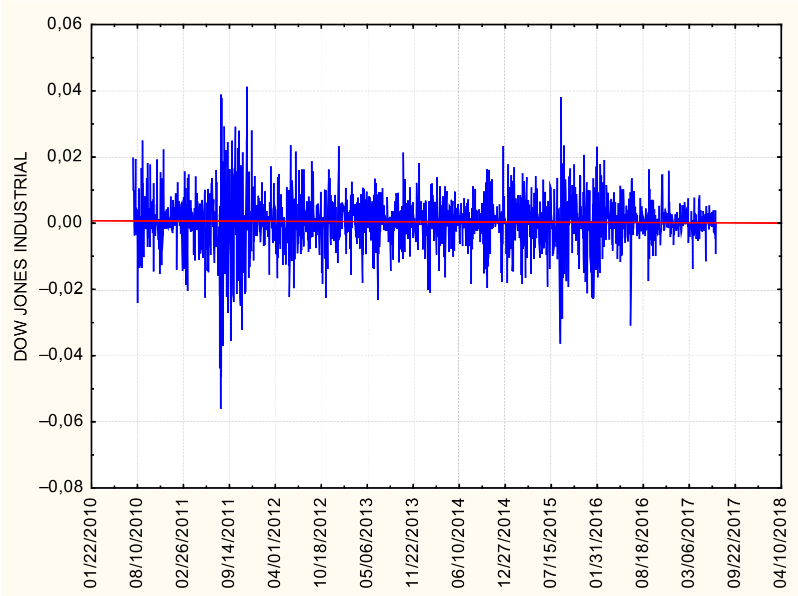

Figure 5.
The return of Dow Jones Industrial index over the period from July 22, 2010 to June 30, 2017

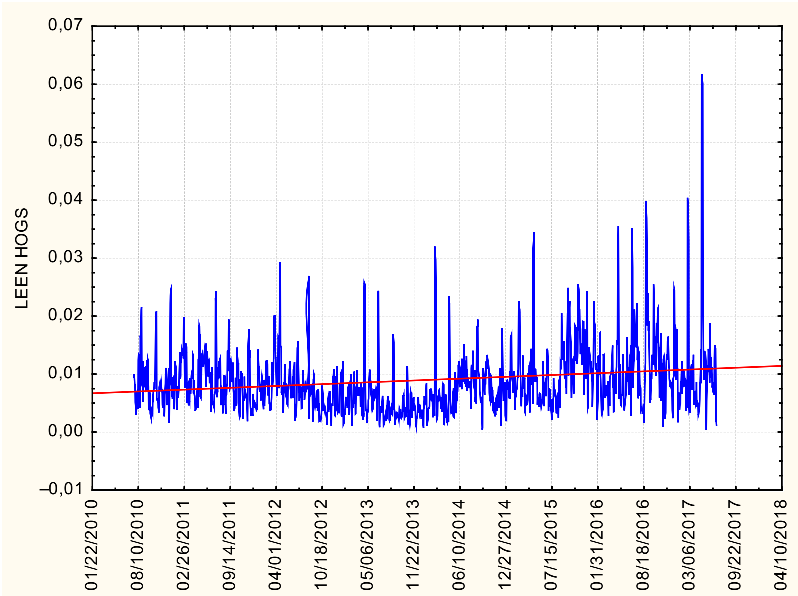

Figure 6.
The conditional volatility of Leen Hogs index over the period from July 22, 2010 to June 30, 2017

Leen Hogs and Live Cattle. According to these figures, we can observe that the DECO among the S&P500 index and Dow Jones Industrial index and three selected meat commodities estimated by the GARCH-DECO (1,1) reach their greatest in the beginning and the end of the period of study. Both periods are corresponding to the

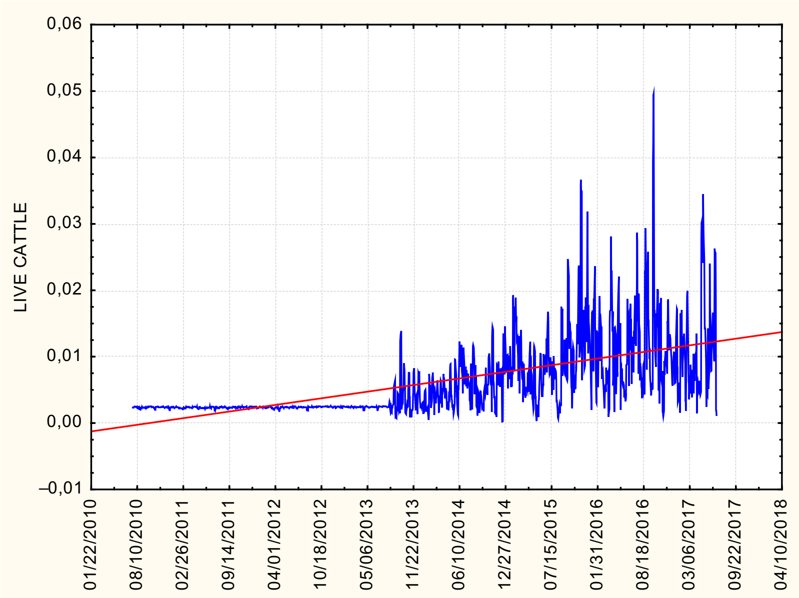

Figure 7. The conditional volatility of Live Cattle index over the period from July 22, 2010 to June 30, 2017

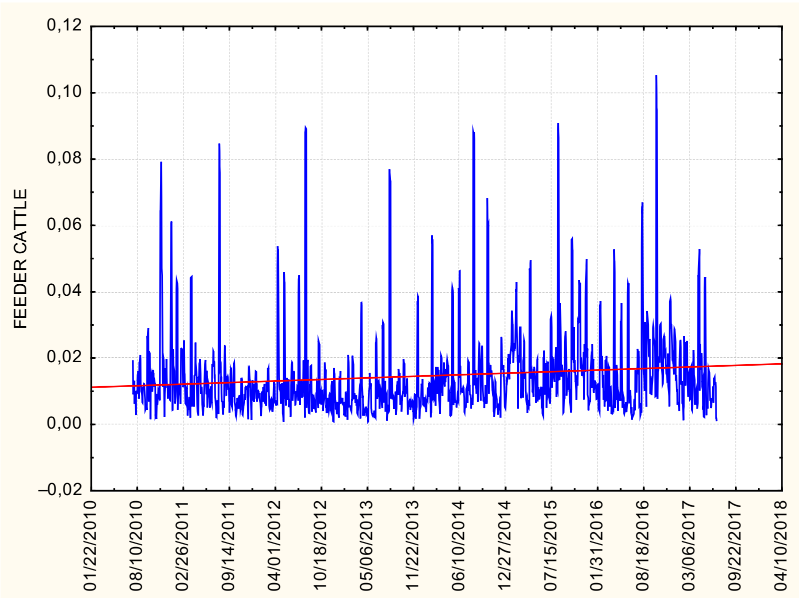

Figure 8. The conditional volatility of Feeder Cattle index over the period from July 22, 2010 to June 30, 2017

presence of an international liquidity and banking instability in developing and developed countries.

In addition, we can remark the importance of the meat commodities indices in the US financial market especially, after the outbreak of the sovereign debt.

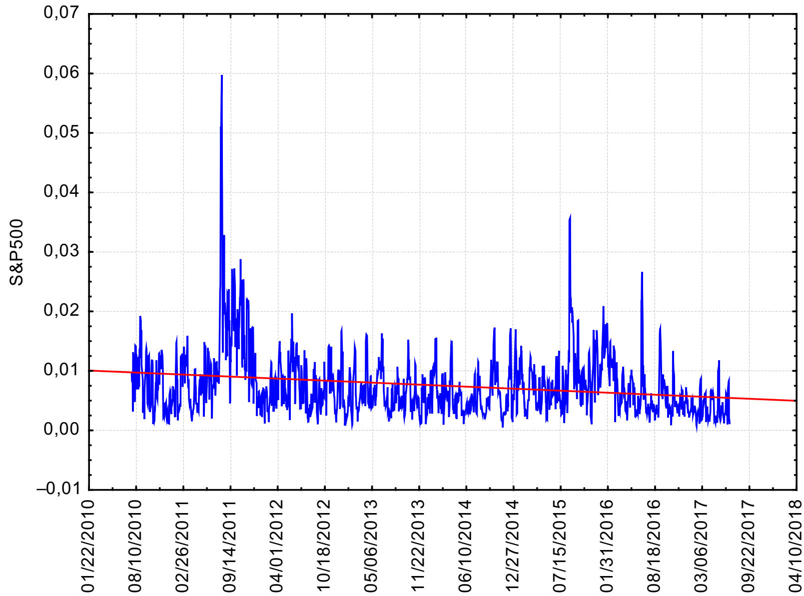

Figure 9.
The conditional volatility of S&P500 index over the period from July 22, 2010 to June 30, 2017

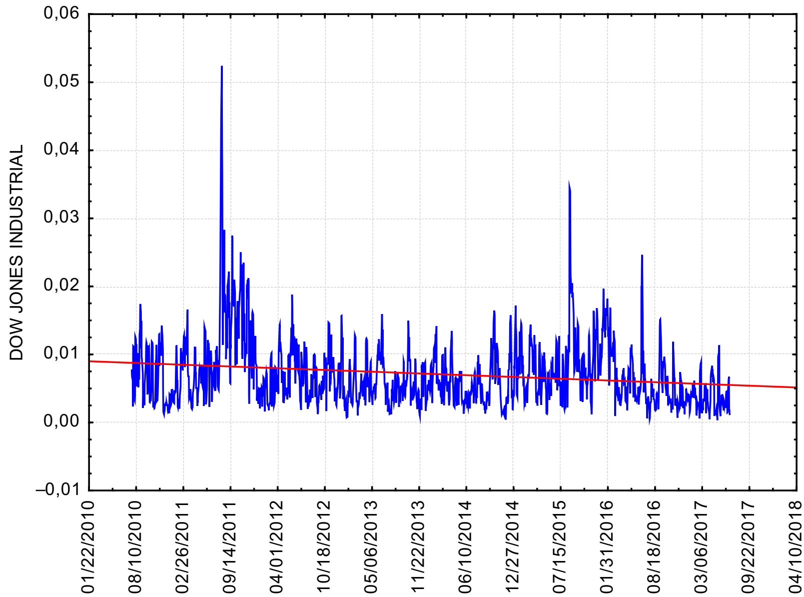

Figure 10.
The conditional volatility of Dow Jones Industrial index over the period from July 22, 2010 to June 30, 2017

Table 3 summarizes the descriptive statistics of the DECO between the major US indices and meat commodities indices over the period from July 22, 2010 to June 30, 2017. Then, we can find that in mean the higher DECO is for Dow Jones Industrial/Leen Hogs (0.635721) followed, respectively, by Dow Jones Industrial/Feeder Cattle (0.580194), S&P500/Live Cattle

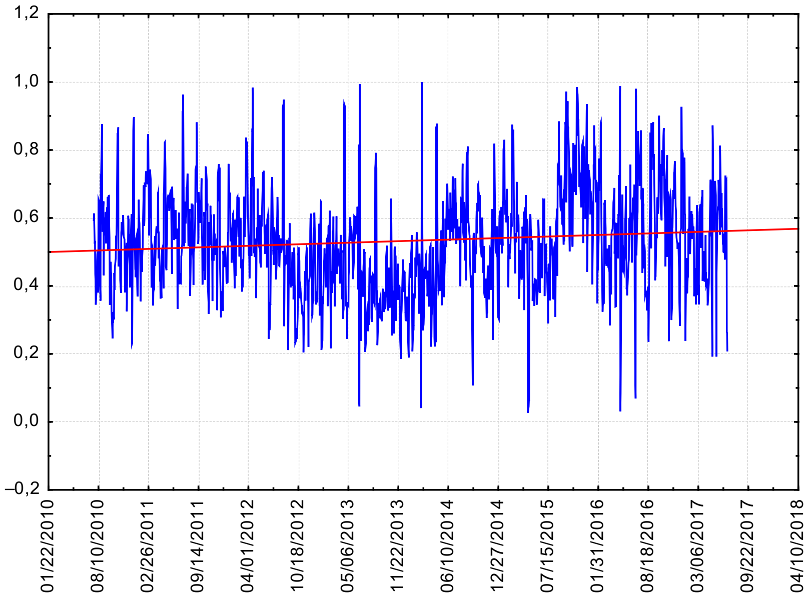

Figure 11.
The DECO between S&P500 and Leen Hogs indices over the period from July 22, 2010 to June 30, 2017

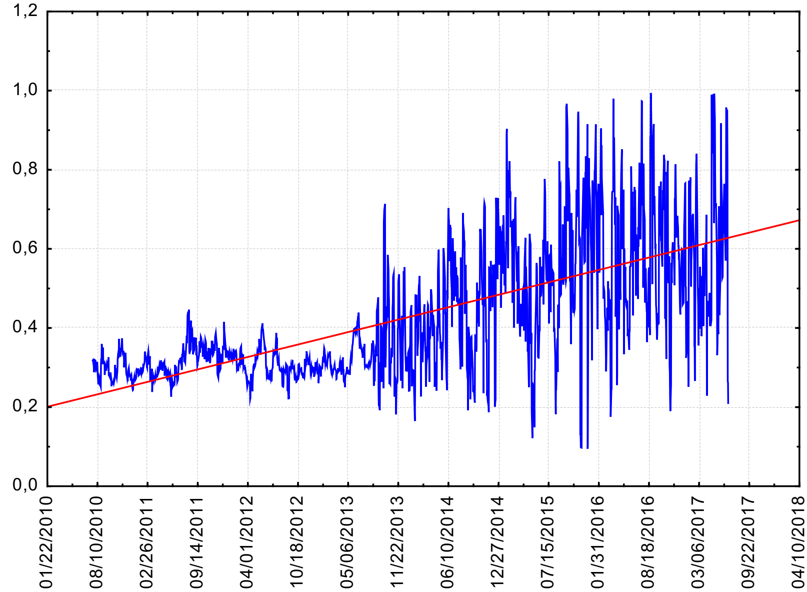

Figure 12.
The DECO between S&P500 and Live Cattle indices over the period from July 22, 2010 to June 30, 2017

(0.579981), S&P500/Feeder Cattle (0.532669), Dow Jones Industrial/Live Cattle (0.497530) and S&P500/Leen Hogs (0.428295)

In Table 4, we expose the empirical results from the GARCH-DECO (1,1) model. From Table 4, we can remark that all parameters are highly significant with a volatility

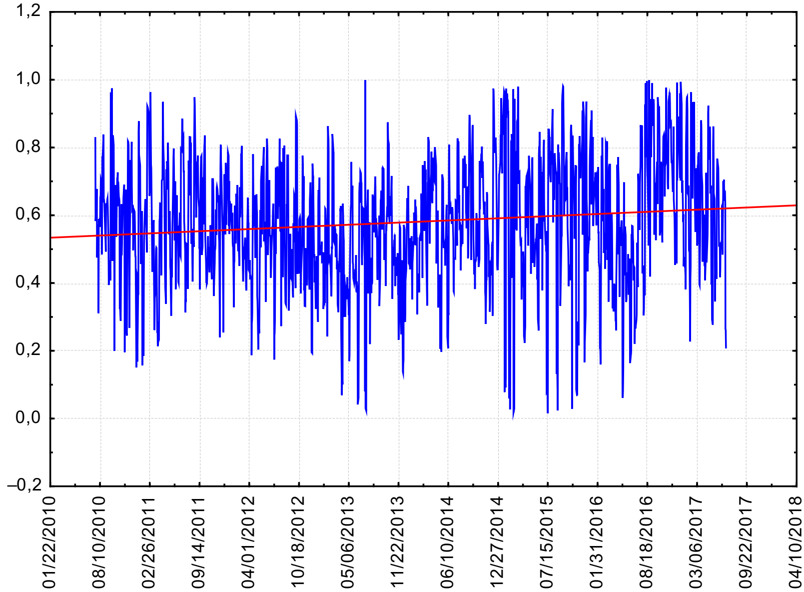

Figure 13.
The DECO between S&P500 and Feeder Cattle indices over the period from July 22, 2010 to June 30, 2017

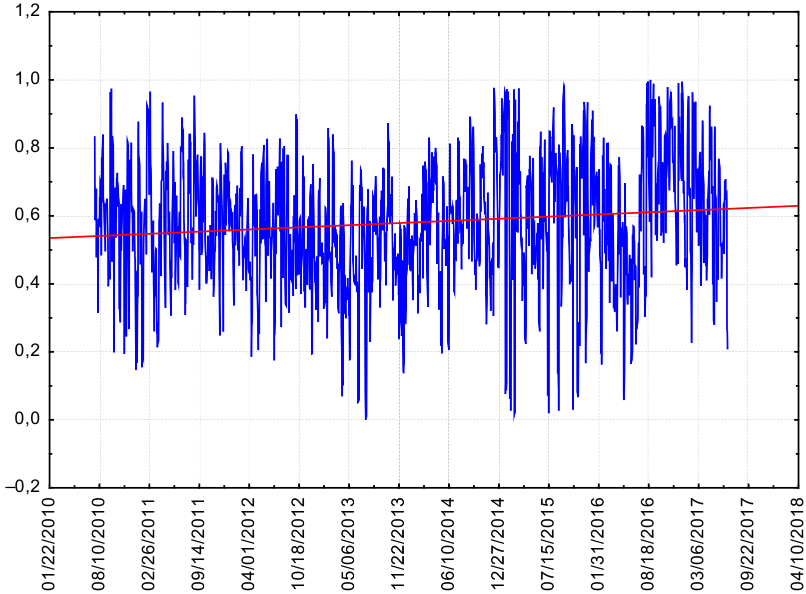

Figure 14.
The DECO between Dow Jones Industrial and Leen Hogs indices over the period from July 22, 2010 to June 30, 2017

persistence superior than 0.90 ($\alpha + \beta$) for the DECO among the major US indices (S&P500 index and Dow Jones Industrial index) and three selected meat commodities indices as: Feeder Cattle, Leen Hogs and Live Cattle. Also, the difference among the levels of volatility persistence can be just defined by the reality that commodities cannot be viewed as a

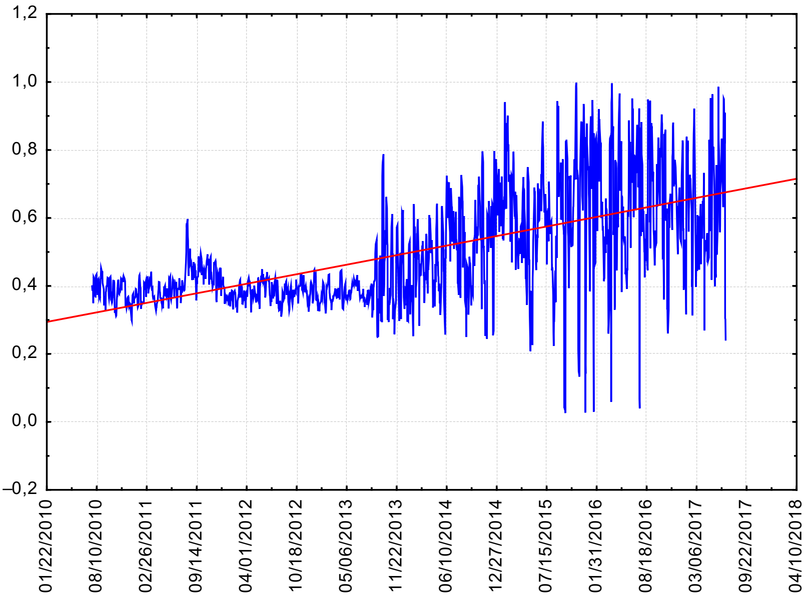

Figure 15.
The DECO between Dow Jones Industrial and Live Cattle indices over the period from July 22, 2010 to June 30, 2017

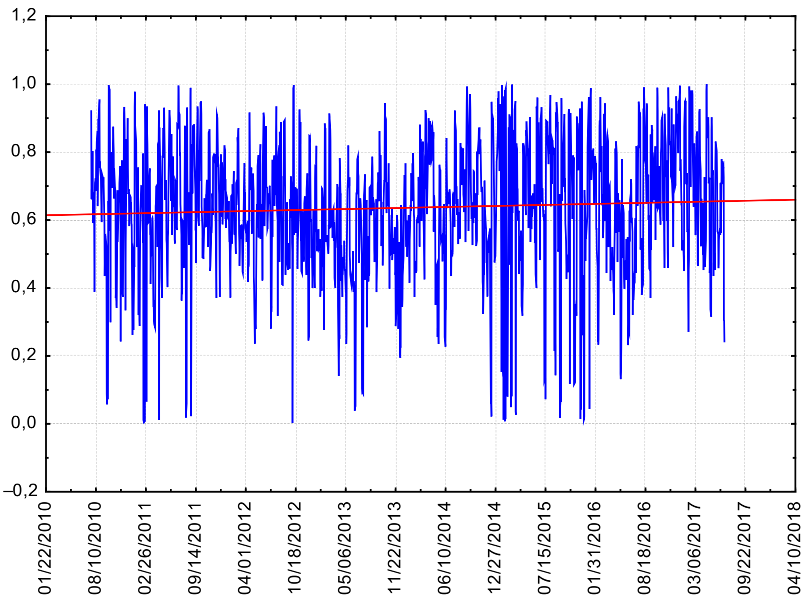

Figure 16.
The DECO between Dow Jones Industrial and Feeder Cattle indices over the period from July 22, 2010 to June 30, 2017

homogeneous asset class (Creti *et al.*, 2013; Chebbi and Derbali, 2015; Chebbi and Derbali, 2016a, 2016b).

The same empirical results presented in Table 4 argument the existing literature by reviewing the answer of the conditional relationship linking stock markets indices and

Table 3. Descriptive statistics of the DECO between of the major US indices and meat commodities indices over the period from July 22, 2010 to June 30, 2017

Statistics	DECO (S&P500/ Leen Hogs)	DECO (S&P500/ Live Cattle)	DECO (S&P500/ Feeder Cattle)	DECO (Dow Jones Industrial/ Leen Hogs)	DECO (Dow Jones Industrial/ Feeder Cattle)	DECO (Dow Jones Industrial/ Live Cattle)
Mean	0.428295	0.579981	0.532669	0.635721	0.580194	0.497530
Median	0.355767	0.579873	0.525151	0.650097	0.580387	0.427667
Maximum	0.993618	0.999353	0.999371	0.999256	0.999917	0.997524
Minimum	0.094348	0.016093	0.026757	0.001679	0.000137	0.026000
SD	0.172030	0.189871	0.156768	0.201170	0.189944	0.166918
Skewness	1.040993	−0.271464	0.206481	−0.707448	−0.290756	0.822395
Kurtosis	3.302705	2.945813	3.317865	3.612582	2.976643	3.140674
Jarque-Bera	322.1973	21.67053	19.76849	173.0396	24.65475	198.3662
Probability	0.000000*	0.000020	0.000051	0.000000*	0.000004*	0.000000*
Observations	1,748	1,748	1,748	1,748	1,748	1,748

Notes: This table reports the DECO between of the major US indices and meat commodities indices, over the period of study from July 22, 2010 through June 30, 2017. Statistical significance at the 1% level is denoted by *

Table 4. Estimation results of dynamic equicorrelation GARCH-DECO (1,1) between the major US indices and meat commodities indices over the period from July 22, 2010 to June 30, 2017

DECO between of US indices and meat commodities indices	Ω	α	β
DECO (S&P500/Leen Hogs)	1.11e-06 (5.56)*	0.0376748 (5.66)*	0.9352374 (41.32)*
DECO (S&P500/Live Cattle)	1.27e-06 (5.01)*	0.0256468 (5.23)*	0.9834521 (50.73)*
DECO (S&P500/Feeder Cattle)	1.09e-06 (2.22)**	0.0005374 (9.55)*	0.9734029 (60.82)*
DECO (Dow Jones Industrial/Leen Hogs)	1.32e-06 (3.09)*	0.0205372 (5.97)*	0.8735564 (40.99)*
DECO (Dow Jones Industrial/Feeder Cattle)	1.51e-06 (4.13)*	0.0214984 (8.49)*	0.9556485 (62.21)*
DECO (Dow Jones Industrial/Live Cattle)	1.41e-06 (5.32)*	0.0906653 (9.67)*	0.8435543 (53.42)*

Notes: This table reports estimated coefficients from GARCH-DECO (1,1) model. To empirically test this model, we use daily volatility series of the two major US indices (S&P500 and Dow Jones Industrial) and three meat commodities indices (Feeder Cattle, Leen Hogs and Live Cattle), over the period of study from July 22, 2010 through June 30, 2017. Statistical significance at the 1% and 5% levels is denoted by * and **; respectively. Values in parentheses represent the *t*-Student

commodities indices. Furthermore, we can find that all parameters are statistically significant confirming that the dynamic dependence between the major US indices (S&P500 index and Dow Jones Industrial index) and three selected meat commodities indices as: Feeder Cattle, Leen Hogs and Live Cattle are time-varying and extremely volatile.

In addition, there is a corroboration that the sum of the volatility coefficients ($\alpha + \beta$) is very close to unity, namely, for the case between S&P500 index and Dow Jones Industrial index and three selected meat commodities indices as exposed proving the higher persistence of volatility between the US stock market indices and commodity markets indices. There is one probable clarification which finds that such persistence goes along with the financialization of stock market indices and commodities (Creti *et al.*, 2013; Chebbi and Derbali, 2015; Chebbi and Derbali, 2016a, 2016b). Our empirical findings emphasize the importance of using GARCH-DECO (1,1) in modeling the time-varying DECOs.

The close dynamic dependence among daily co-movements of commodities and stock markets, which have persisted regularly uninterrupted as the outbreak of the financial crisis of 2007, has frayed. The daily co-movements of the S&P500 index and Dow Jones Industrial index and three selected meat commodities indices were more or less in tandem for the period from 2010 to 2017.

Concluding comments

In our paper, we examine empirically the DECO between the major US indices (S&P500 index and Dow Jones Industrial index) and three selected meat commodities as: Feeder Cattle, Leen Hogs and Live Cattle during the period from July 22, 2010 to June 30, 2017.

Then, we use a data set composed by daily series returns of the whole selected indices. For the econometric methodology, we use the GARCH-DECO (1,1) to study the DECO between S&P500 index and Dow Jones Industrial index and three selected meat commodities as: Feeder Cattle, Leen Hogs and Live Cattle.

By recording to the empirical results of the GARCH-DECO (1,1), we find the existence of a highly significance of conditional heteroscedasticity parameters can demonstrate us to distinguish the nature of the volatility dependency between S&P500 index and Dow Jones Industrial index and three selected meat commodities indices. This can find clear the significance of relationship in the process of financialization of the major US index and meat commodities indices in the case of this paper.

The GARCH-DECO (1,1) estimation has a good fit of data; it captures all the observed highly volatility in the conditional dependency of return series.

Besides, the sum of the two parameters ($\alpha + \beta$) for the chosen conditional heteroscedasticity specification (GARCH-DECO (1,1) model) is close to 1 which implies the persistence of volatility in the conditional dependency between the major US index and meat commodities indices.

Policy implications

Our study is a vital subject for policymakers and portfolio risk managers. From a policy-making perspective, having accurate estimates of the volatility spillovers during markets is an essential step in preparing profitable portfolio investment. From the perspective of portfolio risk managers, our empirical findings are reliable with the idea of cross-market hedging. There is one significant explanation which becomes that such perseverance goes along with the financialization of US stock market indices and meat commodities.

References

Aguilera, R.F. and Radetzki, M. (2017), "The synchronized and exceptional price performance of oil and gold: explanations and prospects", *Resources Policy*, Vol. 54, pp. 81-87.

Avalos, F. (2014), "Do oil prices drive food prices? The tale of a structural break", *Journal of International Money and Finance*, Vol. 42, pp. 253-271.

Baumeister, C. and Kilian, L. (2014), "Do oil price increases cause higher food prices?", *Economic Policy*, Vol. 29 No. 80, pp. 691-747.

Behmiri, N.B. and Manera, M. (2015), "The role of outliers and oil price shocks on volatility of metal prices", *Resources Policy*, Vol. 46, pp. 139-150.

Bildirici, M.E. and Turkmen, C. (2015), "Nonlinear causality between oil and precious metals", *Resources Policy*, Vol. 46, pp. 202-211.

Chebbi, T. and Derbali, A. (2015), "The dynamic correlation between energy commodities and Islamic stock market: analysis and forecasting", *International Journal of Trade and Global Markets*, Vol. 8 No. 2, pp. 112-126.

Chebbi, T. and Derbali, A. (2016a), "A dynamic conditional correlation between commodities and the Islamic stock market", *The Journal of Energy Markets*, Vol. 9 No. 1, pp. 65-90.

Chebbi, T. and Derbali, A. (2016b), "On the role of structural breaks in identifying the dynamic conditional linkages between stock and commodity markets", *The Journal of Energy Markets*, Vol. 9 No. 4, pp. 71-81.

Chen, S., Kuo, H. and Chen, C. (2010), "Modeling the relationship between the oil price and global food prices", *Applied Energy*, Vol. 87 No. 8, pp. 2517-2525.

Cheng, I.H. and Xiong, W. (2013), "The financialization of commodity markets", National Bureau of Economic Research, Working Paper No. 19642.

Choi, K. and Hammoudeh, S. (2010), "Volatility behavior of oil, industrial commodity and stock markets in a regime switching environment", *Energy Policy*, Vol. 38 No. 8, pp. 4388-4399.

Creti, A., Joëts, M. and Mignon, V. (2013), "On the links between stock and commodity markets' volatility", *Energy Economics*, Vol. 37 No. 3, pp. 16-28.

De Bandt, O. and Hartmann, P. (2000), "Systemic risk: a survey", European Central Bank, Working Paper Series, No 35.

De Nicola, F., De Pace, P. and Hernandez, M.A. (2016), "Co-movement of major energy, agricultural, and food price returns: a time-series assessment", *Energy Economics*, Vol. 57, pp. 28-41.

Delatte, A.L. and Lopez, C. (2013), "Commodity and equity markets: some stylized facts from a copula approach", *Journal of Banking and Finance*, Vol. 37 No. 12, pp. 5346-5356.

Du, X., Yu, C.L. and Hayes, D.J. (2011), "Speculation and volatility spillover in the crude oil and agricultural commodity markets: a Bayesian analysis", *Energy Economics*, Vol. 33 No. 3, pp. 497-503.

Erb, C.B. and Harvey, C.R. (2006), "The strategic and tactical value of commodity futures", *Financial Analysts Journal*, Vol. 62 No. 2, pp. 69-97.

Engle, R. and Kelly, B. (2012), "Dynamic equicorrelation", *Journal of Business and Economic Statistics*, Vol. 30 No. 2, pp. 212-228.

Ewing, B.T. and Malik, F. (2013), "Volatility transmission between oil and gold futures under structural breaks", *International Review of Economics and Finance*, Vol. 25, pp. 113-121.

Fasanya, I. and Akinbowale, S. (2019), "Modelling the return and volatility spillovers of crude oil and food prices in Nigeria", *Energy*, Vol. 169, pp. 186-205.

Fowowe, B. (2016), "Do oil prices drive agricultural commodity prices? Evidence from Africa", *Energy*, Vol. 104, pp. 149-157.

González-Pedraz, C., Moreno, M. and Peña, J.I. (2015), "Portfolio selection with commodities under conditional copulas and skew preferences", *Quantitative Finance*, Vol. 15 No. 1, pp. 151-170.

Gorton, G. and Rouwenhorst, K.G. (2006), "Facts and fantasies about commodity futures", *Financial Analysts Journal*, Vol. 62 No. 2, pp. 47-68.

Hammoudeh, A. and Yuan, Y. (2008), "Metal volatility in presence of oil and interest rate shocks", *Energy Economics*, Vol. 30 No. 2, pp. 606-620.

Hassouneh, I., Serra, T., Goodwin, B.K. and Gil, J.M. (2012), "Non-parametric and parametric modeling of biodiesel, sunflower oil, and crude oil price relationships", *Energy Economics*, Vol. 34 No. 5, pp. 1507-1513.

Henderson, B.J., Pearson, N.D. and Wang, L. (2015), "New evidence on the financialization of commodity markets", *Review of Financial Studies*, Vol. 28 No. 5, pp. 1285-1311.

Ji, Q. and Fan, F. (2012), "How does oil price volatility affect non-energy commodity markets?", *Applied Energy*, Vol. 89 No. 1, pp. 273-280.

Ji, Q., Bouri, E. and Roubaud, D. (2018b), "Dynamic network of implied volatility transmission among US equities, strategic commodities, and BRICS equities", *International Review of Financial Analysis*, Vol. 57, pp. 1-12.

Ji, Q., Bouri, E., Roubaud, D. and Kristoufek, L. (2019), "Information interdependence among energy, cryptocurrency and major commodity markets", *Energy Economics*, Vol. 81, pp. 1042-1055.

Ji, Q., Bouri, E., Roubaud, D. and Shahzad, S.J.H. (2018a), "Risk spillover between energy and agricultural commodity markets: a dependence-switching CoVaR-copula model", *Energy Economics*, Vol. 75, pp. 14-27.

Liu, P. and Tang, K. (2011), "The stochastic behavior of commodity prices with heteroskedasticity in the convenience yield", *Journal of Empirical Finance*, Vol. 18 No. 2, pp. 211-224.

Liu, X., Pan, F., Yuan, L. and Chen, Y. (2019), "The dependence structure between crude oil futures prices and Chinese agricultural commodity futures prices: measurement based on Markov-switching GRG copula", *Energy*, Vol. 182, pp. 999-1012.

Lucotte, Y. (2016), "Co-movements between crude oil and food prices: a post-commodity boom perspective", *Economics Letters*, Vol. 147, pp. 142-147.

Mensi, W., Hammoudeh, S., Nguyen, D.K. and Yoon, S.M. (2014), "Dynamic spillovers among major energy and cereal commodity prices", *Energy Economics*, Vol. 43, pp. 225-243.

Natanelov, V., Alam, M.J., McKenzie, A.M. and Van Huylenbroeck, G. (2011), "Is there comovement of agricultural commodities futures prices and crude oil?", *Energy Policy*, Vol. 39 No. 9, pp. 4971-4984.

Nazlioglu, S. and Soytas, U. (2012), "Oil price, agricultural commodity prices, and the dollar: a panel cointegration and causality analysis", *Energy Economics*, Vol. 34 No. 4, pp. 1098-1104.

Nazlioglu, S., Erdem, C. and Soytas, U. (2013), "Volatility spillover between oil and agricultural commodity markets", *Energy Economics*, Vol. 36, pp. 658-665.

Pal, D. and Mitra, S.K. (2017), "Time-frequency contained co-movement of crude oil and world food prices: a wavelet-based analysis", *Energy Economics*, Vol. 62, pp. 230-239.

Rezitis, A.N. (2015), "The relationship between agricultural commodity prices, crude oil prices and US dollar exchange rates: a panel VAR approach and causality analysis", *International Review of Applied Economics*, Vol. 29 No. 3, pp. 403-434.

Roll, R. (2013), "Volatility, correlation, and diversification in a multi-factor world", *The Journal of Portfolio Management*, Vol. 39 No. 2, pp. 11-18.

Saghaian, S.H. (2010), "The impact of the oil sector on commodity prices: correlation or causation?", *Journal of Agricultural and Applied Economics*, Vol. 42 No. 3, pp. 477-485.

Serra, T. (2011), "Volatility spillovers between food and energy markets: a semiparametric approach", *Energy Economics*, Vol. 33 No. 6, pp. 1155-1164.

Su, C.W., Wang, X.Q., Tao, R. and Lobont, O.R. (2019), "Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context", *Energy*, Vol. 172, pp. 691-701.

Szymanowska, M., Roon, F., Nijman, T. and Goorbergh, R. (2014), "An anatomy of commodity futures risk premia", *The Journal of Finance*, Vol. 69 No. 1, pp. 453-482.

Wen, X., Wei, Y. and Huang, D. (2012), "Measuring contagion between energy market and stock market during financial crisis: a copula approach", *Energy Economics*, Vol. 34 No. 5, pp. 1435-1446.

Zhang, C. and Qu, X. (2015), "The effect of global oil price shocks on China's agricultural commodities", *Energy Economics*, Vol. 51, pp. 354-364.

Further readings

Büyükşahin, B. and Robe, M.A. (2014), "Speculators, commodities and cross-market linkages", *Journal of International Money and Finance*, Vol. 42, pp. 38-70.

Erb, C.B. and Campbell, R.H. (2006), "The strategic and tactical value of commodity futures", *Financial Analysts Journal*, Vol. 62 No. 2, pp. 69-97.

Hammoudeh, S., Nguyen, D.K., Reboredo, J.C. and Wen, X. (2014), "Dependence of stock and commodity futures markets in China: implications for portfolio investment", *Emerging Markets Review*, Vol. 21, pp. 183-200.

About the authors

Dr Abdelkader Derbali is an Associate Professor in Finance at the Community College, Taibah University, Saudi Arabia. He is one of the Editorial Board Members in the *Journal of Energy Markets, International Business Review, Cogent Economic & Finance, International Review of Applied Economics, African Journal of Accounting, Auditing and Finance, and African Journal of Economic and Sustainable Development*. His research interests include Risk Management, Systemic risk, International finance, Capital markets and institutions, Banking and market microstructure and Islamic Finance. He has published articles, among others, in *Research in International Business and Management, Cogent Business & Management, Cogent Economic & Finance, Journal of Chinese Governance, The Chinese Economy, Journal of Energy Markets, African Journal of Accounting, Auditing and Finance, International Journal of Economics and Accounting, International Journal of Critical Accounting, and International Journal of Trade and Global Markets*. Abdelkader Derbali is the corresponding author and can be contacted at: derbaliabdelkader@outlook.fr

Houssam Bouzgarrou is currently an Associate Professor of finance at Higher Institute of Finance and Taxation of Sousse, Sousse University, Tunisia. He was previously an Assistant Professor at Rennes 1 University (France). His research interests are M&A, corporate governance, financial markets and institutions. He obtained a PhD from Rennes 1 University. He has published several articles in international journals (*International Review of Financial Analysis; International Journal of Business and Finance Research; International Management; Journal of applied Business Research; Bankers, Markets and Investors; Recherches en Sciences de Gestion*). He is currently member of Executive Committee of Tunisian Society for Financial Studies.