



“De-financialization” of commodities? Evidence from stock, crude oil and natural gas markets



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ABSTRACT

In order to investigate whether the crude oil and natural gas market volatility is influenced by the volatility in the stock market or whether these different variables move all together, we introduce the Volatility Threshold Dynamic Conditional Correlations (VT-DCC) approach to investigate the spillover effect of stock market volatility index (VIX, VSTOXX) on crude oil and natural gas markets during 1999–2015, and make the correlation dynamics dependent on conditional variance values through a threshold grid search algorithm. By detecting one endogenous break point in the raw series, we identify two clusters: one in 2008 and another in 2014, due to the financial crisis and the structural low oil prices linked to changing fundamentals, respectively. Also, the U.S. Henry Hub gas seems to be associated with the stock market volatility indexes, contrary to the European NBP gas, which is linked to the Brent. Besides, regarding the volatility behaviors of our series, the four energy variables violate their thresholds at similar moments, and the stock market VIX and VSTOXX exhibit logically similarities. Co-movements are detectable as well between the VIX and crude oil series, when investigating the volatility extracted from the GARCH model. In addition, the Block-DCC estimates provide ample evidence of similarities in the correlation dynamics between the crude oil and stock volatility series. It should be noted that the modeling framework proposed in this paper represents a useful tool for the study of cross-market contagion.

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1. Introduction

After the equity market collapsed in 2000, many institutions considered commodities a new asset class after the widely publicized discovery of a negative correlation between commodity returns and stock returns by Gorton and Rouwenhorst (2006) and Erb and Harvey (2006). As a result, billions of investment dollars flowed into commodity markets from financial institutions, insurance companies, pension funds, foundations, hedge funds, and wealthy individuals (Wang et al., 2015; Mi et al., 2017). A sharp increase in the popularity of commodity investing in the past decade has triggered an unprecedented inflow of institutional funds into commodity futures markets, referred to as the financialization of commodities (Basak and Pavlova, 2016). In recent years, many experts have noticed the

influence of financialization on commodity markets or the correlation between commodity markets and financial markets.

As stated by Tang and Xiong (2012), the large index investment flow precipitated a fundamental process of financialization among commodity markets, and the vast inflows led to a process of integration of commodity futures markets with other financial markets in which portfolio rebalancing of index investors can cause volatility spillovers from outside to commodity markets. Specifically, they document that the co-movement between oil and other commodities has risen dramatically following the inflow of institutional investors starting from 2004.

Recently, Adams and Glück (2015) show that large inflows into commodity investments, i.e., financialization, has changed the behavior and dependence structure between commodities and the general stock market, and predict that the spillovers between commodities and the stock market to remain high in the future, given that institutional investors continue to target funds into commodities. Basak and Pavlova (2016) find that with financialization, i.e., in the presence of institutional investors, the prices and volatilities of all commodity futures go up, but more so for the index futures than for non-index ones. Meanwhile, the correlations among commodity futures as well as in equity-

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commodity correlations also increase, with higher increase for index commodities.

Some authors focus on the financialization related with oil markets. Based on the empirical results, Juvenal and Petrella (2015) support the view that the recent oil price increase is mainly driven by the strength of global demand but that the financialization process of commodity markets also plays a role. Yin and Yang (2016) confirm that the predictive power of technical indicators outperforms the well-known macroeconomic variables, and their ability to predict the oil price stems in part from its ability to predict changes in sentiment, suggesting the financialization of oil markets.

Besides, stronger investor interest in commodities may create closer integration with conventional asset markets (Babcock, 2012; Silvennoinen and Thorp, 2013; Yao et al., 2017); as a result, the financialization process also enhances the correlation between commodity markets and financial markets. In order to assess how commodities and financial markets are inter-related during 1983–2013, Aboura and Chevallier (2015) introduce a ‘volatility surprise’ component into the asymmetric DCC with one exogenous variable (ADCCX) framework, and find that return and volatility spillovers do exist between commodity and financial markets and that in turn, their relative impact on each other is very substantial. Silvennoinen and Thorp (2013) estimate sudden and gradual changes in correlation among stocks, bonds and commodity futures returns, and find that most correlations begin the 1990s near zero but closer integration emerges around the early 2000s and reaches peaks during the recent crisis, and higher volatility index (VIX) also increases commodity returns correlation with equity returns for about half the pairs, indicating closer integration.

Due to the wide openness and free movement for investment funds in the U.S. stock market, international crude oil and natural gas markets, a large number of investment funds can swarm into and out of these markets with limited restrictions and the dynamics of stock market volatility becomes a crucial impetus for crude oil and natural gas price fluctuations and investment decisions. Meanwhile, crude oil and natural gas play strategic roles in social economic development around the world, and the extreme volatility of crude oil and natural gas prices tends to significantly affect the economic situation and stock market returns (Aboura and Chevallier, 2016). As a result, there can be found close interaction among these markets; in particular, the influence of stock market instability on crude oil and natural gas markets has received extensive attention from academics, practitioners and government (Zhang and Wei, 2011; Mohanty et al., 2011; Broadstock and Filis, 2014; Bianconi and Yoshino, 2014).¹

Moreover, the degree of investor risk appetite has proven to affect the volatility of stock market returns (Kim et al., 2014), and caused the fluctuations of crude oil and natural gas markets. Consequently, some authors find that stock market investment risk appetite may have significant influence on crude oil and natural gas markets (Sari et al., 2011). The volatility index (VIX) of stock markets is often regarded as a proxy for risk aversion or investor sentiment (Bekaert et al., 2011; Silvennoinen and Thorp, 2013). Specifically, the higher of the VIX becomes, the more uneasy investors would feel about the stock markets. Conversely, the lower the VIX appears, the smoother the changes of stock market index will be. Among the empirical studies, Kurov (2010) shows that the market investors’ sentiment (using VIX as one of the proxies) plays a significant role in the impact of the

monetary policies on the stock markets, and monetary policy shocks have strong impact on investors’ sentiment in bear markets.

To dig further on this analysis, we study the relationship and correlation dynamics between crude oil, natural gas and stock market risk aversion or investor sentiment as captured by the VIX and VSTOXX indexes in this paper. Namely, we investigate whether the crude oil and natural gas market volatility is influenced by the VIX in the stock market or whether these different variables move all together. Our objective lies in answering the following research questions: What are the interactions between crude oil, natural gas and stock market VIX? Do some of these markets move together over time? Whether the de-financialization in energy commodities occurs after the 2008 global financial crisis? These questions are essential to understand whether crude oil and natural gas markets are driven only by their fundamentals, or whether there is also a systemic component influenced by the volatility present within the stock markets. The empirical results indicate that the turbulent periods coincide with an increase in cross-market co-movements. Our findings support the existence of contagion from stock market panic on crude oil and natural gas markets, and show that the financialization of crude oil and natural gas markets remains after the 2008 financial crisis, while there is no de-financialization after all.

The rest of the paper is structured as follows. Section 2 presents the relevant literature review. Section 3 gives research methods and data descriptions in this paper. Section 4 provides the empirical results and analyses, and Section 5 concludes.

2. Relevant literature review

The VIX is a volatility index quoted on the Chicago Board of Option exchange since 1990 and uses the call and put option of different maturities with the S&P 500 index as an underlying. It is computed as the weighted average on the price of these options (call and put) and represents the annualized volatility of the last 30 days of the S&P 500 with percentage. The VIX has often been called the “investor fear” index. In fact, it is deducted from the price of the option. A high option price means a high price for uncertainty. This is why the VIX has often been used as a proxy for market sentiment or as an “investor fear gauge” by practitioners (as mentioned by Whaley, 2000). **More generally, it is often used by traders and studies as an index for global risk perception on the financial markets** (Sari et al., 2011).

A growing number of studies argue that there exists obvious impact of stock market VIX on crude oil and natural gas markets. For example, Broadstock and Filis (2014) argue that stock market return is affected by the VIX and there is significant time-varying linkage between crude oil price and stock returns. In particular, since the VIX implies the market risk perception of investors, Sari et al. (2011) find the long-run equilibrium relationship between global risk perception and world crude oil price, and oil price may be affected by the short-term negative impact of the shocks on global investors risk perception.

The changes of stock market VIX prove to be often influenced by the uncertainties of financial and economic situation, and then exert some shocks on crude oil and natural gas markets. Some literature indicates that the interaction between the VIX and financial risk variables proves significant (Cochran et al., 2012); as a result, crude oil and natural gas prices would see significant fluctuations when financial and economic environment changes (Kolodziej et al., 2014), and then crude oil and natural gas market prices would be impacted by the increasing degree of VIX due to the uncertainty in investment environment. During the recent financial crisis, monetary policies have been adjusted meanwhile the VIX has also appeared significant changes, which is consistent with the contagion effect and interdependence between crude oil and stock markets (Wen et al., 2012); specifically, when one market is impacted by some new information, the volatility in the other market would be influenced as well (Vo, 2011).

¹ In fact, the close linkage between stock market and petroleum market has also been well recognized by practitioners and timely response tends to be seen. For instance, after June 2014, international crude oil prices have seen significant continuous decline, due to astonishingly surplus crude oil supply and sluggish oil demand from tardy economic recovery in the world. Just as the report on January 6, 2015 from *The Times*, the sinking crude oil price has sent European markets sliding further. Specifically, European markets extended their losses on that day as the price of oil slipped below \$53 to a fresh five-and-a-half-year low. All of the FTSE 100, France’s CAC, Germany’s DAX and Spain’s IBEX have fallen as Brent crude oil price continued to decline, falling as low as \$52.28. Meanwhile, it was a similar picture in Asia overnight, with Japan leading the fall.

It should be noted that a body of studies have shed light upon the influence of the VIX on oil returns, but fewer have been conducted on the impact of the VIX on natural gas markets. Panagiotidis and Rutledge (2007) document over a period from 1996 to 2003 that UK crude oil and natural gas markets (Brent and NBP) are strongly interrelated and cointegrated. Due to oil-formula indexation present in gas contract, to the proximity of oil and gas reserves and to the substitutability of these two markets, it is often admitted that these both markets were strongly interconnected. However, they have different pricing mechanisms; therefore, it is imperative to examine the impact of stock market VIX on natural gas markets.

To sum up, the stock market VIX reflects the complexity of investors' psychological process, and is influenced by various factors simultaneously. Meanwhile, it has significant time-varying property, which causes the spillover effect of the VIX on crude oil and natural gas markets to be also time-varying. However, little literature has shed light upon the time-varying spillover effect of stock market VIX (or VSTOXX from the European side) on crude oil and natural gas markets. Besides, unexpected events are very common in stock markets to affect investors' returns, but little literature investigates its influence and considers the threshold volatility spillover between stock market VIX and crude oil and natural gas markets. In fact, the results based on the volatility spillover will be helpful to foresee crude oil and natural gas market fluctuations, so as to effectively design investment portfolios and address market extreme risks.

3. Methods and data

3.1. Methods

In order to highlight the spillover effect between stock markets VIX on commodities, multivariate GARCH-type models have mostly been used in the literature on volatility transmission as they allow for the joint modeling of variances and covariances between different variables. Among the different specifications of multivariate GARCH models, (i.e., CCC, DCC, VEC and BEKK),² we propose to use the methodological framework of the Volatility-Threshold Dynamical Conditional Correlation (VT-DCC) put forward by Kasch and Caporin (2013) in this paper. The econometric procedures unfold for six daily time series taken from the American and European markets. Specifically, WTI crude oil, Henry Hub natural gas, and the stock market VIX composes the U.S. markets, while Brent price, Natural Gas Balancing Point and the VSTOXX form the European markets. In order to determine which variables behave similarly, we first apply the Zivot and Andrews (2002) unit root test with endogenous break detection on the raw series. This test constitutes our first attempt to understand the interactions at stake among these variables, and to detect clusters. Then, we proceed with a GARCH analysis to extract the conditional volatility from the return series. After running a threshold search in the quantile of the conditional volatility series, we analyze violations with respect to their thresholds. More precisely, we analyze whether each conditional volatility series violates its own threshold at the same date as another series. Finally, we run a DCC analysis for all the pairs ($n = 6$, and $[n * (n - 1)] / 2 = 15$ in total), and determine whether the correlation peaks occur at the same moment for different pairs. Our objective is then to cluster the pairs that are the mostly correlated into blocks, and to run a Block-DCC type tests considering these blocks in order to check the robustness of these relationships, and to understand more deeply the correlation dynamics and volatility peaks.

² CCC: Constant Conditional Correlation of Bollerslev (1990); DCC: Dynamic Conditional Correlation of Engle (2002); VEC: Multivariate GARCH with time-varying covariances of Bollerslev et al. (1988); BEKK: Multivariate GARCH of Baba et al. (1991).

The VT-GDCC model is the extension of the DCC model proposed by Engle (2002) and the Asymmetric DCC (ADCC) by Cappiello et al. (2006). In the VT-GDCC model, the dynamic correlation depends on variance values through a threshold structure. Specifically, according to Kasch and Caporin (2013), we consider an n -variate conditional process ε_t with zero mean and covariance matrix H_t as follows:

$$\varepsilon_t | F_{t-1} \sim U(0, H_t) \quad (1)$$

where ε_t indicates either a vector of zero mean returns or the vector of residuals obtained from the return mean model. F_{t-1} is the information set available up to time $t - 1$. $U(\bullet)$ denotes that ε_t is identically distributed following an unspecified density. Then the covariance matrix H_t is decomposed into volatility and correlation as Eq. (2):

$$H_t = D_t R_t D_t \quad (2)$$

where D_t is the diagonal matrix of conditional volatilities, i.e.,

$$D_t = \text{diag}(\sqrt{h_{i,t}}) \quad (3)$$

where $h_{i,t}$ is the conditional volatility of asset i at time t and obtained from the univariate GARCH model, and R_t is the dynamic conditional correlation (DCC) matrix. Then the variance standardized residual series is defined as Eq. (4):

$$\eta_t = D_t^{-1} \varepsilon_t \quad (4)$$

In the GDCC model proposed by Cappiello et al. (2006), the dynamic conditional correlation is defined as follows:

$$R_t = (\text{diag}(Q_t))^{-1/2} Q_t (\text{diag}(Q_t))^{-1/2} \quad (5)$$

$$Q_t = (\bar{Q} - A\bar{Q}A' - B\bar{Q}B') + A(h_{t-1}h'_{t-1})A' + BQ_{t-1}B' \quad (6)$$

where \bar{Q} denotes a correlation matrix of dimension n , while A and B are $n \times n$ parameter matrices. According to Cappiello et al. (2006), in order to restrict the parameter matrices to be diagonal, the individual elements of Q_t are defined as follows.

$$q_{ij,t} = (1 - \alpha_i\alpha_j - \beta_i\beta_j)\bar{q}_{ij} + \alpha_i\alpha_j\eta_{i,t-1}\eta_{j,t-1} + \beta_i\beta_jq_{ij,t-1} \quad (7)$$

where α_i and β_i are the elements of the parameter matrices A and B , and $i, j = 1, 2, \dots, n$. Then, we model a threshold structure based on the volatility levels as follows:

$$q_{ij,t} = (1 - \alpha_i\alpha_j - \beta_i\beta_j)\bar{q}_{ij} + \alpha_i\alpha_j\eta_{i,t-1}\eta_{j,t-1} + \beta_i\beta_jq_{ij,t-1} + \gamma_i\gamma_j(\nu_{ij,t} - \bar{\nu}_{ij,t}) \quad (8)$$

where $\nu_{ij,t}$ are the elements of a dummy variable matrix V , indicating the threshold violation, and $\bar{V} = E[V]$, and γ_i are the elements of the diagonal parameter matrix Γ . The general specification of the volatility threshold dummies $\nu_{ij,t}$ depends on the hypothesis to be tested. Consider two alternative designs of $\nu_{ij,t}$ as follows:

$$\nu_{ij,t} = \begin{cases} 1 & h_{i,t} > x_i, h_{j,t} > x_j \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where x_i and x_j are the volatility thresholds for assets i and j , respectively. We suggest to define the volatility threshold as $x_i = Q_i(\delta_i)$, where δ_i is the quantile level (namely, a parameter assuming values between 0 and 1) and $Q_i(\delta_i)$ denotes the empirical δ_i quantile of the conditional variance process $h_{i,t}$.

Besides, we can impose block structures on the parameter matrices to reduce the parameter space dimension. For instance, we cluster the n variables into $m < n$ non-overlapping groups, and the elements of Q_t are shown as Eqs. (10) and (11), i.e., the Block-VT-GDCC model (Kasch and Caporin, 2013).

$$q_{ij,t} = (1 - \alpha_l \alpha_k - \beta_l \beta_k) \bar{q}_{ij} + \alpha_l \alpha_k \eta_{i,t-1} \eta_{j,t-1} + \beta_l \beta_k q_{ij,t-1} + \gamma_l \gamma_k (\nu_{ij,t} - \bar{\nu}_{ij}), \quad (10)$$

where $i \in l, j \in k, l, k = 1, 2, \dots, m, l \neq k$, and

$$q_{ij,t} = (1 - \alpha_l^2 - \beta_l^2) \bar{q}_{ij} + \alpha_l^2 \eta_{i,t-1} \eta_{j,t-1} + \beta_l^2 q_{ij,t-1} + \gamma_l^2 (\nu_{ij,t} - \bar{\nu}_{ij}), \quad (11)$$

where $i, j \in l, l = 1, 2, \dots, m$, and l and k are the groups including assets i and/or j . Based on the equations of the Block-VT-GDCC model, we can deduce the simple VT-DCC specification as Eq. (12):

$$q_{ij,t} = (1 - \alpha - \beta) \bar{q}_{ij} + \alpha \eta_{i,t-1} \eta_{j,t-1} + \beta q_{ij,t-1} + \gamma (\nu_{ij,t} - \bar{\nu}_{ij}), \quad (12)$$

(where) $i, j = 1, 2, \dots, n$.

3.2. Data description

In order to examine the spillover effect of stock market volatility index (the VIX of CBOE for the U.S. stock market while the VSTOXX for European stock market) on crude oil prices (WTI and Brent) and natural gas prices (Henry Hub and NBP), six time series are retrieved from Thomson Financial Datastream from 01/04/1999 to 01/02/2015, totaling 4175 daily observations: (1) CBOEVIX is the CBOE SPX VOLATILITY **VIX** (NEW) - PRICE INDEX, (2) **VSTOXX** is the EURO STOXX 50 Volatility, (3) OILBREN is the Crude Oil **Brent** Cur. Month FOB US\$/BBL, (4) CRUDWTC is the Crude Oil **WTI** FOB Cushing US\$/BBL, (5) NATGHEN is the Natural Gas, **Henry Hub** US\$/MMBTU, and (6) TRGBNBD is the TR Natural Gas **NBP** UK 1st Fut. Day - Settlement price. As for the VSTOXX, we begin our sample on January 4, 1999, because this volatility index is listed only since that date. When necessary, the time series have been transformed into USD using the bilateral exchange rate from the Fed.

The descriptive statistics of all-time series can be found in Table 1, which indicate that all of them show the typical non-normality of financial time series and most of the series are positively skewed and display excess kurtosis.

Regarding the volatility series, taken in returns form, the average and standard deviation are really close. The shape of the distribution is also similar between these two series. There exists non-Gaussianity with a positive asymmetry and a relatively high kurtosis for both series. This kurtosis can be seen diagnosed graphically with the presence of relatively frequent extreme moves. The crude oil series highlight the heteroskedasticity phenomenon. For both series, we notice high volatility regimes in 2002 or 2008, with subsequent low volatility regimes in 2013 for instance. Their standard deviations in returns forms are very close. We can also remark that these two series are very close to the Gaussian distribution (Skewness of 0 and Kurtosis of 3).

The gas series share some common characteristics, such as low volatility regimes since 2010 and the relatively high frequency of extreme price movements. Through the high Kurtosis coefficients (respectively 27.99 for the European gas and 12.19 for the American one, in returns), we record spikes that can be explained by sudden events such as a disruption of a pipeline or a sudden increase in temperature.

4. Results and analyses

In this section, we resort to the VT-DCC method by Kasch and Caporin (2013) to capture the dynamic spillovers of stock market VIX and VSTOXX on crude oil and natural gas markets.³

4.1. Volatility thresholds

We now turn to the estimation of the Volatility Threshold (VT) specifications for the spillovers of stock markets VIX and VSTOXX on crude oil and natural gas markets. In the empirical implementation below, we follow the threshold calibration approach discussed in Section 3.1, i.e., the estimation of Eq. (8) employing the VT component defined in Eq. (9).

Various computational steps are required. First, we calculate the quantile $sq = 0.50$ to 0.99 of the conditional variance for each series. Next, we perform a non-linear threshold grid search in the conditional variance of each series, as detailed by Kasch and Caporin (2013).

As shown in Table 2, the threshold identified by the grid search algorithm for the VIX is equal to 0.0826, which corresponds to the 93% series specific variance quantile. The results are broadly similar for the remaining time series, with thresholds detected above the 90th quantile of the conditional variance.

The last step consists in computing the threshold violations, for instance whenever the VIX historical volatility is above the 93% quantile. This should enable us to understand if some variables co-move together, and if abnormal volatility spikes occur at the same time.

The historical volatilities of GARCH(1,1) models are shown in Fig. 1 (top panel for each sub-figure). These plots enable us take into account the leptokurtic characteristic of the distribution of each series. Besides, the conditional volatilities are needed as an input in the next step of the VT-DCC methodology, which aims at detecting the threshold violations. Further GARCH(1,1) historical volatilities are displayed in Fig. 1 during the respective sub-periods. We clearly identify the pattern of time-varying conditional volatilities during each sub-period.

4.1.1. Stock markets variances

We examine the conditional volatility of VIX and VSTOXX (see Fig. 1, bottom panels of (a1), (a2), (b1) and (b2)). For both volatility series, the density of threshold violations is higher after the 2008 crisis than before. That validates the argument by González-Hermosillo and Hesse (2011) that the VIX behavior has changed since the global crisis.

4.1.2. Crude oil variances

In the threshold violation figures (see Fig. 1, bottom panels of (c1), (c2), (d1) and (d2)), we can find that Brent and WTI violate their thresholds in a very similar way. Except few differences around the financial crisis period, there is significant overlap between these two series in terms of threshold violations. Therefore, the historical volatilities seem to be interconnected between two crude oil markets, and to spread on each other.

4.1.3. Natural gas variances

For the natural gas series, the European NBP (bottom panels of (f1) and (f2)) seems to have similarities with the two oil series. In fact, the density of threshold violations is relatively high before 2010 before diminishing, which is similar to both oil series. Their volatility may answer the same common indicators. For the U.S. Henry Hub gas (bottom panels of (e1) and (e2)), the analysis is different as there exists a strong

³ Unconditional cross-correlations among the VIX, VSTOXX, crude oil and natural gas prices reveal that the volatility series are basically negatively correlated with energy variables. Cross-correlation levels did not indicate multicollinearity (including both the raw series and returns). Not displayed to save space, the inspection of the unconditional cross-correlation tables is available upon request to the authors.

Table 1
Descriptive statistics for VIX, VSTOXX, oil and gas series.

	CBOEVIX		VSTOXX		OILBREN		CRUDWTC		NATGHEN		TRGBNBD	
	Raw	Returns	Raw	Returns	Raw	Returns	Raw	Returns	Raw	Returns	Raw	Returns
Mean	21.3554	0.0000	25.2640	0.0017	58.2015	0.0002	56.3159	0.0002	4.6534	0.0001	20.1669	0.0002
Median	19.9800	−0.0014	23.1400	−0.0034	52.7300	0.0002	53.9600	0.0000	4.1500	0.0000	15.8562	0.0000
Max	80.8600	0.4960	87.5130	0.6313	145.6100	0.1350	145.3100	0.1641	15.3000	0.3781	84.7116	0.9928
Min	9.8900	−0.3506	11.6000	−0.2205	9.5500	−0.1363	10.8200	−0.1709	1.6100	−0.2890	1.9759	−1.1046
Std. dev	8.4835	0.0618	9.8741	0.0583	36.0763	0.0215	31.8522	0.0240	2.3184	0.0412	12.2956	0.0861
Skewness	1.9094	0.5865	1.5560	1.4859	0.4022	−0.0542	0.3198	−0.1859	1.3844	0.4505	0.6193	−0.4682
Kurtosis	9.4121	6.9186	3.1065	8.6614	1.7420	6.2124	1.8166	8.2602	5.5351	12.1915	2.3198	27.9977

Note: The time series are retrieved from the Datastream from 01/04/1999 to 01/02/2015, totaling 4175 daily observations. CBOEVIX is the CBOE SPX VOLATILITY VIX (NEW) - PRICE INDEX. VSTOXX is the EURO STOXX 50 Volatility. OILBREN is the Crude Oil-Brent Cur. Month FOB US\$/BBL. CRUDWTC is the Crude Oil WTI FOB Cushing US\$/BBL. NATGHEN denotes the Natural Gas, Henry Hub US\$/MMBTU. TRGBNBD denotes the TR Natural Gas NBP UK 1st Fut. Day - SETT. PRICE.

phase of threshold violations in 2014, which does not occur for the three other series (Brent, WTI, NBP). In 2012 and 2013, none of the gas or oil series' conditional volatilities exceeds their threshold values at any time. Hence, the volatilities of these four energy series share some common characteristics. Even if the Henry Hub conditional volatility evolves a bit apart, energy series seem in a certain way to be intertwined.

4.1.4. Co-movements

What can look surprising is that the abnormal volatility of the VIX and VSTOXX does not co-move with the energy series. In contrast, the very high density of threshold violations for the VIX after the crisis is absolutely not visible for the energy series, where the conditional volatility nearly never violates their threshold (except two peaks in 2010 and 2014 for the Henry Hub gas). After the crisis, higher than expected volatility levels for the VIX and VSTOXX move in an opposite way to the oil and gas series.

Before the crisis, the similarities are not obvious either. For the VIX, we get a relatively high density of threshold violations, which seems in a certain way to be matched with the high density of threshold violation of the energy series, so the volatility co-movement between these four series may change after the crisis.

For the VSTOXX, however, the density of volatility spikes is not consistent with the volatility of oil series. Graphically, we may have the impression that the volatility of the VSTOXX and the gas series co-move together, which would be surprising particularly between European volatility index and American gas index, where the volatility connection seems to be dubious. When we look closer at the bottom panels (b) for the VSTOXX and (e)–(f) for both gas series in Fig. 1, it appears that the dates of the threshold violations are not overlapping in most cases.

To sum up, the co-movement of abnormal high level of volatility among the stock, oil and gas markets reveals several interesting findings. First, the conditional volatilities of Brent and WTI evolve in a very similar way, as judged by their variance quantile threshold violations. Oil markets being highly connected and integrated, these variables answer the same common indicator or information.

Second, for the gas series, the threshold violations allow us to identify that their conditional volatilities share globally the same

characteristics as crude oil. Thus, we could build a block of the four energy variables. Given that their conditional volatilities behave similarly, it is possible to suggest that these four series co-move together.

This statement seems accurate, as energy markets are nowadays strongly connected to each other.⁴ Consider for instance that these four series answer together the same events such as a major geopolitical event. When a war explodes in an area of the Middle East, both oil and gas markets are affected. This is a reason why their conditional volatility seems to co-move together. This finding confirms the previous results by Malik and Ewing (2009), who document significant connections between the volatility series of oil and gas.

For the VIX and VSTOXX, their co-movement is less evident to identify. If there are some similarities between these two series, there are very few between the VIX and energy series, and nearly none between the VSTOXX and energy series. Further cross-market linkages between stock and energy markets are to be investigated in the correlation structures.

4.2. The DCC analysis

4.2.1. The DCC estimates

We now proceed with the next step of the VT-DCC, as presented in Section 3. Our aim is to identify similar behaviors between series in terms of correlation, and more precisely to understand whether for some pairs, the peaks of correlation occur at the same time. To be able to proceed with this analysis, we run a DCC analysis on every existing pair, i.e., $[n * (n - 1) / 2] = 15$ pairs in total. After the identification of the correlation similarities between pairs, we run the block-DCCs with more than two series in case of strong common dynamic in the correlation of the series.

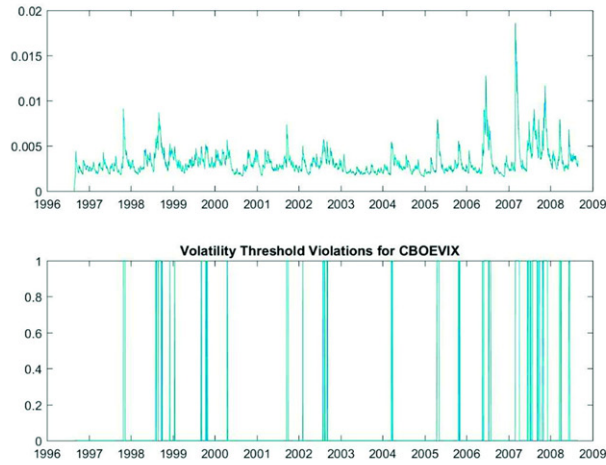
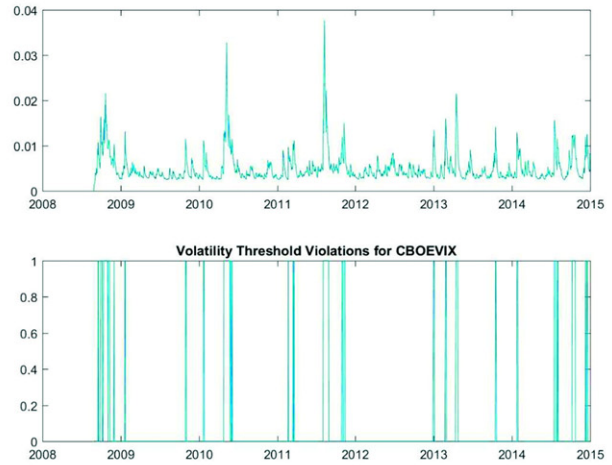
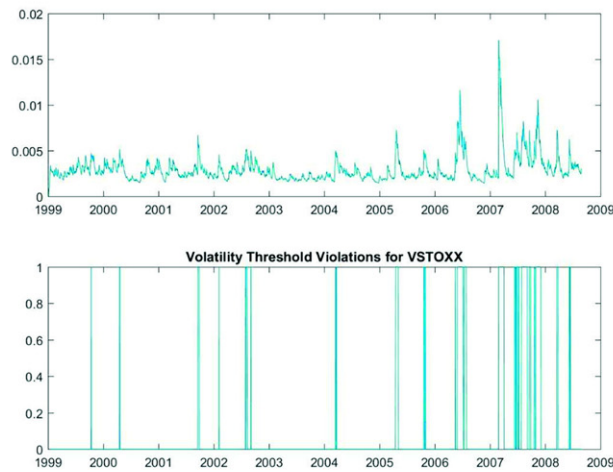
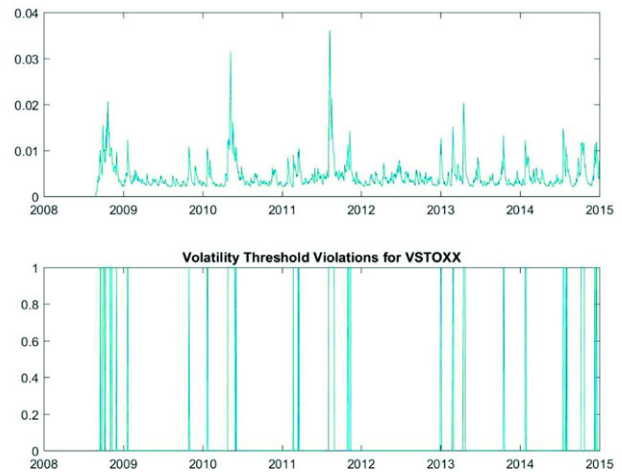
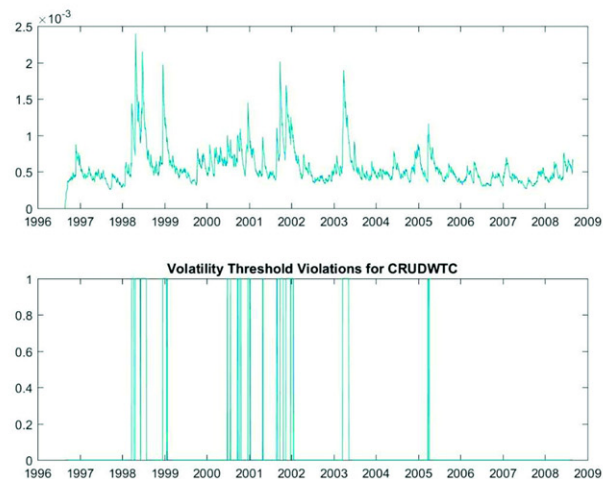
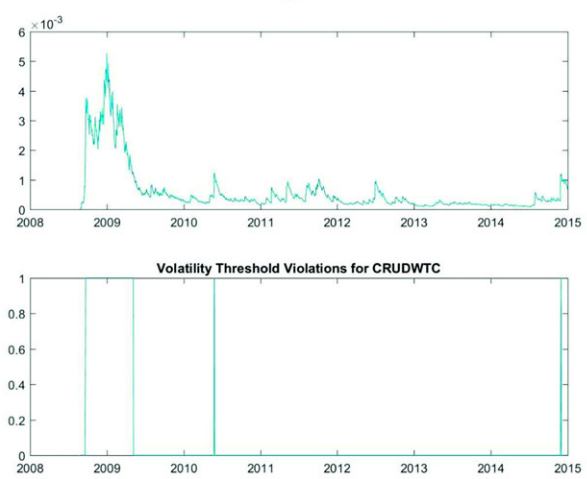
The DCC(1,1) coefficients are reproduced in Table A1 of Appendix A, whereas the time-varying correlations are not displayed to save space, but can be accessed upon request to the authors. The DCC models are correctly specified for every pair run (when we look at the alpha and beta coefficient for each pair, we can remark that their sum never exceeds one). Besides, the coefficients are statistically significant and positive.

Thanks to the analysis of the fifteen pairs, we are able to detect the main trends in the correlation dynamics. First, in the line of the threshold violations, the conditional correlations of the four energy variables are behaving globally in a similar way. In all the energy pairs (BRENT/WTI, BRENT/NBP, BRENT/HH, WTI/NBP, WTI/HH and NBP/HH), we capture a common feature in the correlation structure. Indeed, there is a clear change in the correlation dynamics after 2010, with a peak in correlation between 2008 and 2010, which corresponds respectively to the dramatic oil price swing and the progressive

⁴ Particularly crude oil and gas markets, because of the presence of gas when new oil fields are discovered and the persistence of oil-indexation formulae in the gas long-term contracts.

Table 2
Volatility thresholds in the quantiles of the conditional variance.

	1999–2015		1999–2008		2008–2015	
	Value	Quantile	Value	Quantile	Value	Quantile
CBOEVIX	0.0826	93%	0.0048	91%	0.0094	92%
VSTOXX	0.0642	92%	0.0041	92%	0.0066	92%
OILBREN	0.0301	92%	0.0008	90%	0.0007	90%
CRUDWTC	0.0309	91%	0.0009	92%	0.0012	90%
NATGHEN	0.0683	93%	0.0037	92%	0.0028	92%
TRGBNBD	0.1551	93%	0.0296	92%	0.0050	92%

(a1) CBOEVIX GARCH(1,1) historical volatility during 1999–2008**(a2) CBOEVIX GARCH(1,1) historical volatility during 2008–2015****(b1) VSTOXX GARCH(1,1) historical volatility during 1999–2008****(b2) VSTOXX GARCH(1,1) historical volatility during 2008–2015****(c1) CRUDWTC GARCH(1,1) historical volatility during 1999–2008****(c2) CRUDWTC GARCH(1,1) historical volatility during 2008–2015****Fig. 1.** GARCH(1,1) historical volatility (top) and volatility threshold violations (bottom).

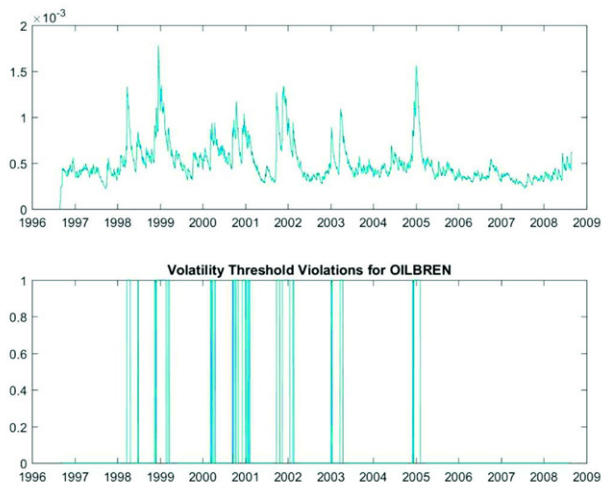
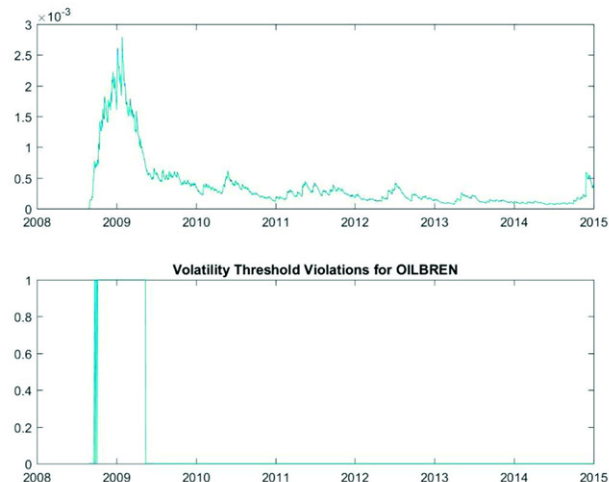
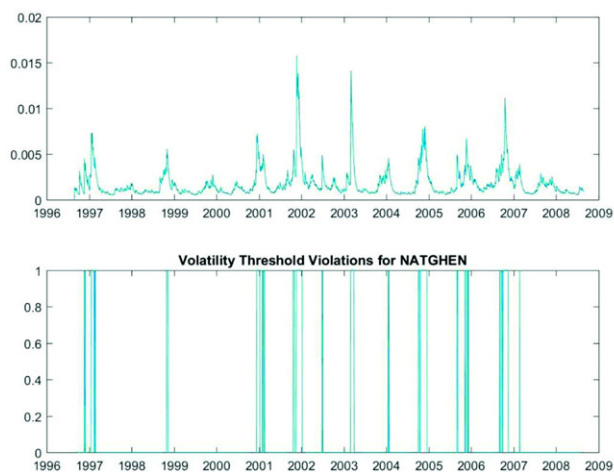
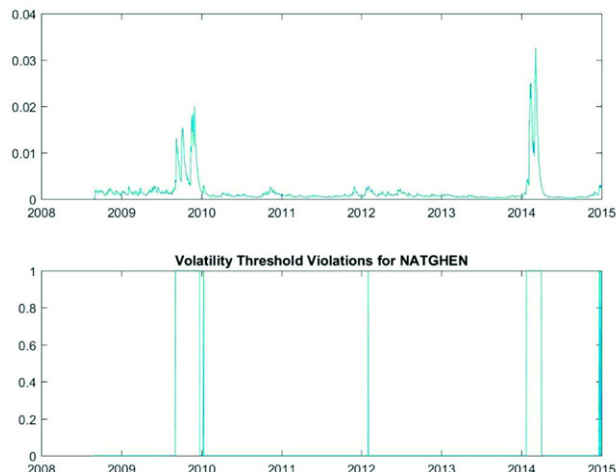
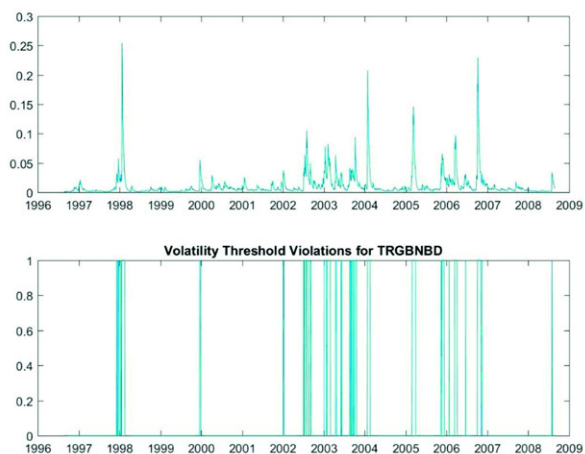
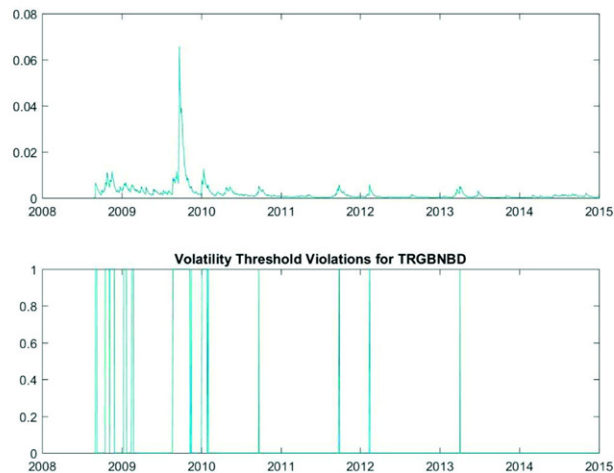
(d1) OILBREN GARCH(1,1) historical volatility during 1999–2008**(d2) OILBREN GARCH(1,1) historical volatility during 2008–2015****(e1) NATHGEN GARCH(1,1) historical volatility during 1999–2008****(e2) NATHGEN GARCH(1,1) historical volatility during 2008–2015****(f1) TRGBNBD GARCH(1,1) historical volatility during 1999–2008****(f2) TRGBNBD GARCH(1,1) historical volatility during 2008–2015****Fig. 1 (continued).**

Table 3

Block-DCC(1,1) parameter estimates for returns.

Panel A: The whole sample period							
Blocks		Constant			Alpha		Beta
CRUDWTC-OILBREN-NATGHEN-TRGBNBD	Coeff.		0.0964		0.0001		0.8745
	Std. dev.		0.0002		0.0001		0.2144
CBOEVIX-VSTOXX-CRUDWTC-OILBREN	Coeff.		0.0344		0.0062		0.8683
	Std. dev.		0.0003		0.0024		0.2117
Panel B: The two sample sub-periods							
Blocks		1999–2008			2008–2015		
		Constant	Alpha	Beta	Constant	Alpha	Beta
CRUDWTC-OILBREN-NATGHEN - TRGBNBD	Coeff.	0.0034	0.0099	0.9831	0.0593	0.0098	0.9735
	Std. dev.	0.0057	0.0032	0.0057	0.0301	0.0036	0.0229
CBOEVIX-VSTOXX-	Coeff.	0.4654	0.0104	0.9828	0.5535	0.0264	0.9363
CRUDWTC - OILBREN	Std. dev.	0.0332	0.0028	0.0046	0.0364	0.0092	0.0349
Panel C: Average of time-varying conditional correlation							
Blocks		1999–2015		1999–2008		2008–2015	
Block 1: Energy only		0.2486		0.2467		0.8825	
Block 2: Energy and stock markets		0.1725		0.2317		0.6400	

economic recovery (mainly driven by growth in emerging countries). What we observe more generally in that the conditional correlation is turbulent before 2008, all these pairs experiencing correlation peaks as it is the case for the BRENT/WTI and the WTI/NBP pairs

for example. These correlation peaks are for some energy pairs (BRENT/HH, BRENT/WTI, WTI/HH) only oriented in a positive way, whereas the remaining pairs (BRENT/NBP, WTI/NBP, HH/NBP) are characterized by both negative and positive correlation peaks. At a

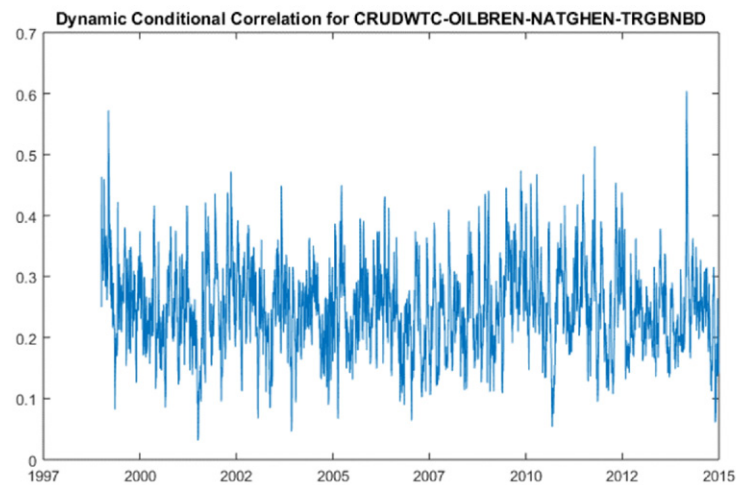
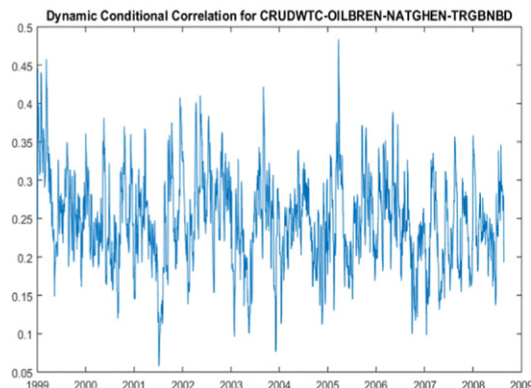
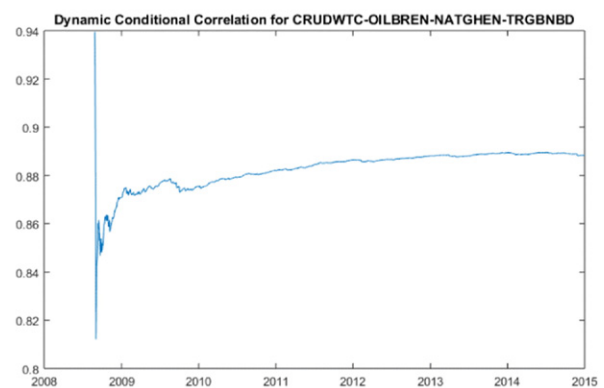
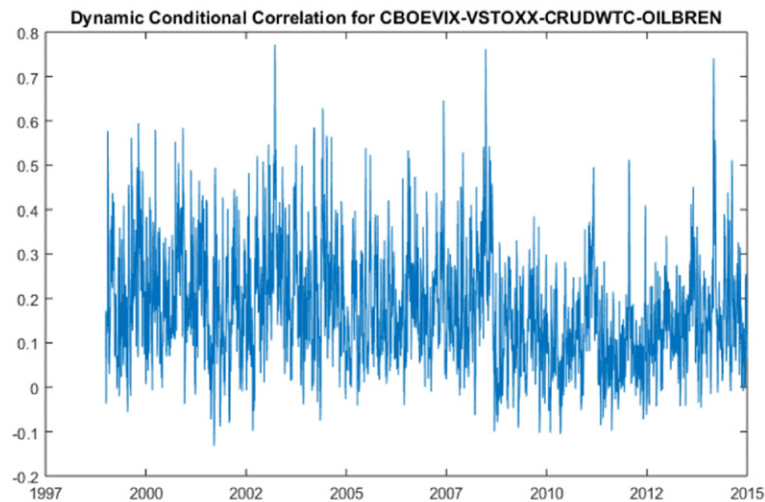
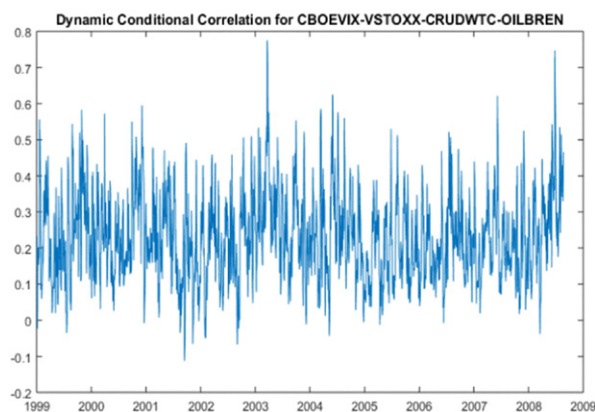
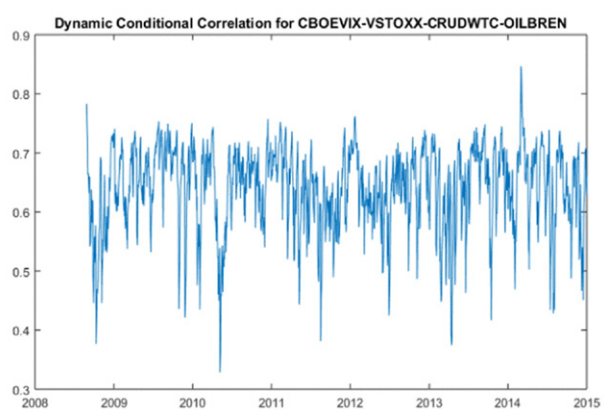
(a1) Block 1-DCC(1,1) correlation during 1999–2015**(b1) Block 1-DCC(1,1) correlation during 1999–2008****(c1) Block 1-DCC(1,1) correlation during 2008–2015**

Fig. 2. Block-DCC(1,1) time-varying correlations between Blocks of returns. Note: (b1) and (c1), (b2) and (c2) both display the sub-periods time-varying dynamic correlations for the Block composed of energy variables before/after the break date of August 27, 2008.

(a2) Block 2-DCC(1,1)correlation during 1999–2015**(b2) Block 2-DCC(1,1)correlation during 1999–2008****(c2) Block 2-DCC(1,1)correlation during 2008–2015****Fig. 2** (continued).

more detailed level, we realize that, when the NBP series is involved in a pair, the correlation may be negative or positive, experiencing spikes in both ways. This singularity vanishes when NBP is not involved. We may infer that, before the crisis, the European Gas reacts negatively to some news involving the other energy series. Regarding the precise occurrence of the correlation spike, without NBP, it occurs in the midst of the financial collapse (September 2008), while for the pairs with NBP series this correlation spike occurs later in 2010. This means that the NBP may react later, or differently, to the signals or information affecting the three other energy series. Perhaps the NBP series is less responding to the global economy, but reacts more to the news directly connected to its fundamentals.

The second observation lies in the common aspects in the correlation dynamic between the pairs involving volatility series (VIX, VSTOXX) and the pairs involving oil series (BRENT, WTI). Indeed, we can remark that for the 6 pairs involving these variables (BRENT/VIX, BRENT/VSTOXX, BRENT/WTI, VIX/VSTOXX, WTI/VIX, WTI/VSTOXX), there are common behaviors in the correlation dynamics. Before the crisis, there are no correlation peaks, and the level of correlation is relatively low. In September 2008, the peak of correlation is suddenly extremely high for all the pairs. In the aftermath of the crisis, the correlation regime appears different across pairs. More scrutiny reveals that the correlation structure is highly similar among VIX/BRENT, VIX/WTI, VSTOXX/BRENT and VSTOXX/WTI. In fact, a few months before September 2008, the correlation of these four pairs slowly increases, suddenly drops and then recovers simultaneously. Between 2010 and 2012, and nearly at the

same moment, the correlation peaks recorded are successively negative, positive and negative again. This design of correlation structure is more pronounced for the pairs involving the VIX (VIX/BRENT, VIX/WTI). Contrary to the threshold violation analysis, there is here ample evidence that the VSTOXX behaves in the same fashion as the VIX. Since the global economic collapse of 2008, the correlation dynamics seems experiencing higher peaks than before. In this context of turbulent economic events spreading to equity and oil markets, this is evidence of contagion. Oil and equity markets being more and more integrated, a piece of news impacting one of these markets can affect the other one. Gas however does not experience the same correlation structure, given its decoupling from oil markets in the recent years. Gas has a regional exposure, it is thus more influenced by physical determinants such as the level of reserves, temperatures or congestions in the system.

The robustness checks of the DCC(1,1) model are conducted for the two sub-periods, i.e., 1999–2008 and 2008–2015. The detailed coefficients and correlations during the two sub-periods are not displayed for brevity, but can be accessed upon request. We find that the central results remain unchanged compared with those for the whole sample period.

4.2.2. The Block-DCC analysis

Given the discussion above, the block composed of energy variables only corresponds to Tang and Xiong's (2012) definition of the financialization of commodities, whereby correlations would increase among commodities (within the same asset class). The block composed of oil and stock market volatilities variables corresponds to the second

part of the definition, whereby correlations increase between traditional assets and the commodity sphere. We investigate whether this definition holds before and after the financial crisis based on the time-varying correlations computed for each block.

The Block-DCC estimation unfolds from Eqs. (10) to (12) as detailed in Section 3.1. Parameter estimates are reproduced in Table 3.

Given the comments above, the four energy series are globally experiencing strong similarities in terms of correlation dynamics. That is why we proceed further with the construction of a Block-DCC of CRUDWTC-OILBREN-NATGHEN-TRGBNBD, and analyze the correlation structure. The second block that we build based on the previous empirical evidence is one consisting of CBOEVIX-VSTOXX-CRUDWTC-OILBREN.

From the results of time-varying conditional correlation in Table 3, we can find that, not only the correlation between oil and gas markets, but also that between energy and stock markets has risen after the 2008 financial crisis, which corroborates the occurrence of financialization phenomenon mentioned above. Specifically, as for the first Block, i.e., energy market only, the average conditional correlation went up from 0.2467 during 1999–2008 to 0.8825 during 2008–2015. And for the second Block, we can find that the average conditional correlation increased from 0.2317 during 1999–2008 to 0.6400 during 2008–2015. These results indicate that after the 2008 financial crisis, the financialization has been strengthened, and there is no de-financialization after all, which corroborates the results proposed by Adams and Glück (2015), who predict that the spillovers between commodity and stock markets to remain high after the financial crisis. In fact, many authors such as Zhang and Li (2016) have established that the oil and equity markets have similar reactions to specific shocks, and are more and more integrated to each other over time. Besides, as for the conditional correlation during the overall sample period, we find that the correlation in energy markets outweighs that between energy and stock markets on average.

As for the time-varying correlations for the two blocks which are displayed in Fig. 2, we can also have at least two findings. On the one hand, as for the first block, before 2008, the correlation among energy variables had significant fluctuations but it kept a continual increasing trend after 2008 and the level significantly exceeded that before 2008 overall. In the second block which refers the combination of energy and stock markets, the results suggest that no matter before or after 2008, the correlation of energy and stock markets was evidently characterized by time-varying feature, but the overall correlation level was lifted across the financial crisis. That is, the interactions between energy and stock markets became closer after the crisis, and the financialization phenomena remained all the time and even got enhanced.

The robustness checks of parameter estimates for all series in the same Block are listed in Table A2 of Appendix A during the full and the two sub-periods. Besides, further graphs of the time-varying correlations for all series are displayed in Fig. 3.

4.2.3. The Markov-switching perspective

From a general viewpoint, the volatility threshold effects may be integrated in the different dynamic correlation specifications proposed in the literature. Therefore, the joint use of the volatility threshold structure and Markov switching dynamics may provide further richer results for stock market VIX and petroleum markets. Specifically, to further ascertain the reliability of our estimates, we run the two-regime Markov-switching process suggested by Hamilton (1989), which can be described as follows⁵:

$$(y_t - \mu(s_t)) = \phi_1(y_{t-1} - \mu(s_{t-1})) + \dots + \phi_p(y_{t-p} - \mu(s_{t-p})) + u_t \quad (13)$$

where $u_t \sim \text{IIDN}(0, \sigma^2)$ and the conditional mean, $\mu(s_t)$, switches between two states:

$$\mu(s_t) = \begin{cases} \mu_1, & \mu_1 < \mu_2 \\ \mu_2, & \end{cases} \quad (14)$$

when $s_t = 1$ and $s_t = 2$, respectively. In the business cycles context, state 1 can be associated with contractions while state 2 with expansions. In modeling asset prices, we may identify state 1 with bear markets while state 2 with bull markets. The effect of the regime s_t on the variable y_t is given by the conditional probability density function $p(y_t/s_t)$. s_t is assumed to be a discrete-valued random variable that can only assume an integer value, i.e., $\{1, 2\}$. The probability that s_t equals some particular value b depends on the past through the most recent value s_{t-1} according to the following definition:

$$P\{s_t = b/s_{t-1} = a, s_{t-2} = k, \dots\} = P\{s_t = b/s_{t-1} = a\} = p_{ab} \quad (15)$$

where p_{ab} is equal to the probability that the process moves from state a at time $t-1$ to state b at time t . As for the p_{ab} to define proper probabilities, they should be non-negative, while it should also hold $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$, which implies that $p_{12} = 1 - p_{11}$ and $p_{21} = 1 - p_{22}$. The transition probability p_{bb} can be interpreted as a regime persistence measure.

This procedure allows us to recover the dates at which the business cycle is considered in Expansion (EXP) or in Recession (REC). We run the Block-DCC analysis separately on the two regimes in order to understand whether our results are dependent on the business cycle, or invariant. To save space, we do not reproduce the full results of the MS estimates in the text, but they are available in Appendix B of the web version of this paper. The main message of the paper is robust to the Markov-Switching dynamics during expansion or recession periods only.

5. Conclusions and future work

Financial and commodity markets are increasingly connected and integrated to each other in the past decades. In this study, we aim at examining whether American and European oil, gas and stock market volatility series experience similar behaviors in their price movements and in their correlation dynamics. The central research question consists in understanding whether the energy variables are affected by stock market VIX, whether there exists volatility transmission, and whether de-financialization works out after the 2008 global financial crisis.

For these purposes, we introduce a VT-DCC model to empirically examine the spillover effect of stock markets VIX on crude oil and natural gas markets during 1999–2015, and make the correlation dynamic dependent on variance values through a threshold structure. The Zivot and Andrews (2002) test constitutes our first attempt to understand how equity volatility, crude oil and natural gas series interact with each other. By detecting one endogenous break point in the raw series, two clusters were identifiable: one in 2008, and another in 2014. The first cluster is due to the financial crisis, while the second cluster is driven by the structural low oil prices linked to changing fundamentals. The U.S. Henry Hub gas seems to be associated with the volatility indexes (VIX, VSTOXX), contrary to the European NBP gas, which is linked to the Brent. This divergence may be clarified by the regional aspect of the gas market, and the fact that these two markets can evolve relatively separately.

These findings have been further scrutinized with threshold violations in variance quantiles, which allow us to detect whether several series violate a threshold at the same time, and with correlation dynamics through the VT-DCC model run on all possible pairs/relevant blocks. Regarding the volatility behaviors of our series, the four energy variables violate their thresholds at similar moments, with again less

⁵ In fact, we also estimate the three-regime MS model, but most coefficients are not statistically significant, so we select the two-regime MS model in the end, which has significant coefficients.

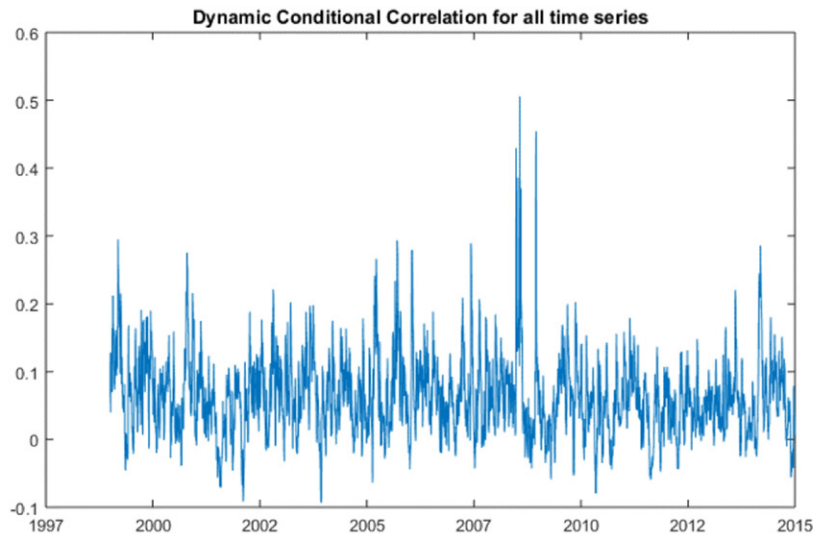
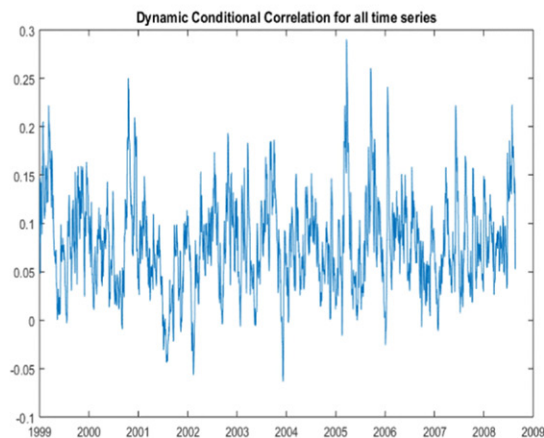
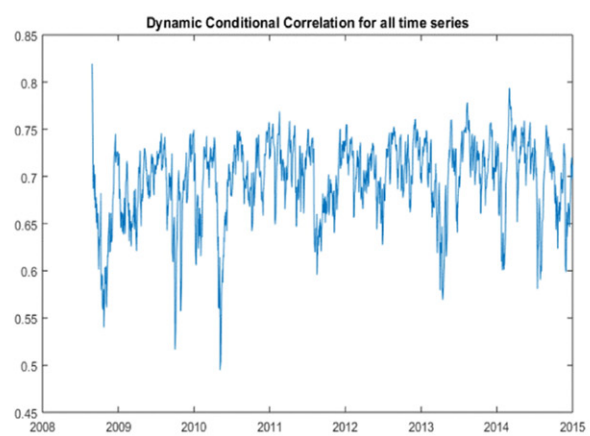
(a) Block All-DCC(1,1) correlation during 1999–2015**(b) Block All-DCC(1,1) correlation during 1999–2008****(c) Block All-DCC(1,1) correlation during 2008–2015**

Fig. 3. Block-DCC(1,1) time-varying correlations between all returns. Note: (b) and (c) displays the sub-periods time-varying dynamic correlations for the Block composed of all variables before/after the break date of August 27, 2008.

evidence for the gas series. The VIX and VSTOXX exhibit logically similarities. Co-movements are detectable as well between the VIX and oil series, when investigating the volatility extracted from the GARCH model.

The last step of the VT-DCC model, namely the estimation of pairwise DCCs, is consistent with our prior findings, particularly for the energy variables that experience correlation peaks simultaneously. The Block-DCC estimates provide ample evidence of similarities in the correlation dynamics between the oil and volatility series. Equity and oil markets are therefore found to be connected, the oil price reflecting not only its fundamentals, but also market risk aversion or investor sentiment. The VIX and VSTOXX constitute broad market indexes capable of capturing significant levels of uncertainty on financial markets. Moreover, the results indicate that the financialization of commodities remains after 2008 and the interactions between oil and gas market, as well as between energy and stock markets, become closer over time.

As for the future work, there are still many relevant research directions to be investigated. For instance, due to the extent that energy markets are an indispensable part of global economy, it is of great importance to understand how risk reallocation and information

transmission from energy markets affect real economy and global financial markets; meanwhile since 2014, with the dramatic drop of crude oil and gas prices caused by the massive extraction of shale oil and gas, we may wonder whether the interactions between energy and financial markets have changed, and whether the role of financialization in energy commodities still remain significant.

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Issues (ISEFI 2016, IPAG Business School, France), the University of Evry - Finance Seminar, the Energy and Commodity Finance Conference (2016 ECOMFIN, ESSEC Business School, France).

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.eneco.2017.09.024>.

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