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Oil shock transmission to stock market returns: Wavelet-multivariate Markov switching GARCH approach

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ABSTRACT

Since oil prices are typically governed by nonlinear and chaotic behavior, it's become rather difficult to capture the dominant properties of their fluctuations. In recent years, unprecedented interest emerged on the decomposition methods in order to capture drifts or spikes relatively to this data. Together, our understanding of the nature of crude oil price shocks and their effects on the stock market returns has evolved noticeably. We accommodate these findings to investigate two issues that have been at the center of recent debates on the effect of crude oil shocks on the stock market returns of five developed countries (USA, UK, Japan, Germany and Canada). First, we analyze whether shocks and or volatility emanating from two major crude oil markets are transmitted to the equity markets. We do this by applying, the Haar A Trous Wavelet decomposition to monthly real crude oil series in a first step, and the trivariate BEKK Markov Switching GARCH model to analyze the effect of the smooth part on the degree of the stock market instability in a second step. The motivation behind the use of the former method is that noises and erratic behavior often appeared at the edge of the signal, can affect the quality of the shock and thus increase erroneous results of the shock transmission to the stock market. The proposed model is able to circumvent the path dependency problem that can influence the prediction's robustness and can provide useful information for investors and government agencies that have largely based their views on the notion that crude oil markets affect negatively stock market returns. Second, under the hypothesis of common increased volatility, we investigate whether these states happen around the identified international crises. Indeed, the results show that the A Haar Trous Wavelet decomposition method appears to be an important step toward improving accuracy of the smooth signal in detecting key real crude oil volatility features. Additionally, apart from UK and Japanese cases, the responses of the stock market to an oil shock depend on the geographic area for the main source of supply whether from the North Sea or from the North America (as we take two oil benchmarks WTI and Brent respectively).

1. Introduction

The stock market movements as contained in the stock price (among other economic indicator) send us some obvious "signals" of a country's economic strength and development. For instance, a bull stock market, i.e. a market which goes up and maintains upward trends, is associated with increasing business investment and vice versa.

However, the majority of Organization for Economic Co-operation and Development (OECD) countries has become increasingly dependent upon oil over the previous century with oil now recognized as the most essential energy source. In 2008, the US is the largest consumer of oil and consumes around 20 million barrels per day, followed by China (7.8) and Japan (4.8) (Energy Information Administration; EIA 2008). 2007–2008, marked the period with the fastest oil price change in its history. In fact, oil prices rose dramatically in dollar terms to more than 140 dollars per barrel in July 2008 (the record peak), and then sharply dropped to around 30 dollars per barrel on December 2008.[1] This (and also the other sequences of very large increases and decreases observed in the crude oil prices for the last three decades) will obviously affect very significantly companies' earnings through oil operating costs leading to a remarkable change in stock prices.

Although considerable attentions have been paid to the investigation of the relationship between changes in the price of crude oil and stock prices, conclusions on such effects cannot be drawn at

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[1] Source: Wikipedia, the free encyclopedia; http://en.wikipedia.org/wiki/Price_of_petroleum.

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present. The existing literature findings on this topic area can be categorized in four main strands[2]: The first includes papers that empirically support the existence of significant and negative relationship between oil and stock market returns (among some notorious studies, we cite for example Jones and Kaul [1], Sadorsky [2], Chiou and Lee [3] and Jammazi and Aloui [4]). On the contrary, the second strand of literature provides convincing evidences for positive interconnections between oil and stock market returns starting from the study of Chen et al. [5] to the most recent works of El-Sharif et al. [6], Narayan and Narayan [7] or Arouri and Rault [8]. The third category encircles some studies that confirm the existence of either positive or negative impacts of oil prices on stock market returns depending on various determinants. Park and Ratti [9] argued that the stock market response to an oil shock depends on whether a country is a net importer or exporter of oil. Kilian and Park [10] demonstrated that positive/negative responses of U.S. stock market returns depend on the sources of oil shocks in the global market for crude oil; on one hand, the precautionary demand shocks negatively affect the stock market returns. On the other hand, aggregate demand shocks have persistent positive effects on cumulative stock returns. The final category of studies seems to counter these findings by demonstrating that there is no significant relationship between oil shocks and stock market returns. Chen et al. [5], Wei [11], Apergis and Miller [12], Miller and Ratti [13] and Al-Janabi et al. [14] corroborate this finding.

Thus, at this stage a crucially important question emerges: whether or not there exists a stable relationship between oil price/volatility and the stock markets and if any what are the correct magnitude and sign of this relationship. Another interesting question can arise when exploring this enormously complex oil—stock markets nexus: what is the most productive technique that can be used to get unbiased, meaningful and more reliable results.

The majority of the above studies focus on the implementation of traditional time series modeling techniques largely relying on linearity and symmetry assumptions. However, several authors have discussed in detail the inadequacy of linear models in capturing asymmetries. Importantly, Hamilton [15] has settled that non-linear specifications should be seen as better candidate models than traditional linear approaches in capturing significantly much more stronger effects of oil shocks. Chiou and Lee [3] argued that most of the time series models experience structural changes that when applied to real data, determine the break locations. Whilst there is general agreement in the literature that any inferences without consideration of regime switching phenomenon may well lead to unreliable results for many financial time series, few studies have set out to investigate the relationship between crude oil and stock market returns in presence of structural changes.

Therefore, regimes switching models occurred as an alternative to standard GARCH models in allowing dynamic variables' behavior to depend on the state that takes place at any given point in time. The main advantages of the Markov Switching processes, often advocated in the literature, is their ability to handle many crucial features of time series such as nonlinear phenomena, temporal asymmetries as well as persistence of the macroeconomic times series [16].

During recent years, a very active research field based on univariate MS models has been proposed in the literature starting from Aloui and Jammazi [17] who develop a two regime Markov-switching EGARCH model to examine the relationship between crude oil shocks and stock market returns for UK, France and Japan. They demonstrate that Net Oil Price Increases (NOPI) play significant role in determining both the volatility of stock market returns and the probability of transition across regimes. Lee and Chiou [18] apply a two −step methodology in order to obtain more accurate estimations of the impact of oil price shocks on stock market returns. Hence, based upon the what they call Autoregressive Jump Intensity model (to capture the jump dynamics) coupled with the dynamic properties of the Markov switching models, they reveal that asymmetric price changes in the WTI lead to negative impact on the SP500 returns. Other recent works extend this area of research from univariate to multivariate analysis. In this sense, Fallahi [19] used Markov-switching vector autoregressive (MS-VAR) models to study the causal relationships between energy use and Gross Domestic Product (GDP) in the United States for the period 1960–2005. The results show that, in contrast to VAR and vector error correction models (VECM), which assume a stable relationship, the relationship between the variables could be different in the separate regimes. Using a Granger causality test under a Markov switching model, the author found evidence of bidirectional causality between the variables only in the first regime which includes the energy crises of 1970's, the recessions of the early 1980's, the early 1990's, and the 2001's recession. In the same way, Jammazi and Aloui [4] applied a wavelet regime switching VAR model in order to assess the impact of the crude oil (CO) shocks on the stock market returns for UK, France and Japan. An interesting finding from this analysis is that; the negative relationship appears to be more pronounced during the pre-1999 period. However, those models consider the state dependency only in the vector of the conditional means. Chang [20] confirmed that the predictability of stock market returns can be observed from the aspect of conditional variance since it is pursued as proxy for the risk in the financial and economic fields. In this regard, Soytas and Oran [21] pointed out that the lack of a causal link running from oil price changes to financial assets may be attributed to the hypothesis that the dynamic link is between the variances of the variables rather than the variables themselves. Based on this assumption, many empirical studies focus mainly on identifying structural shifts in the conditional variance. Specifically, a number of studies gave special attention to the Multivariate Markov Switching Generalized Autoregressive Conditional Heteroskedasticity models (Multivariate *MS-GARCH*) due to their importance in providing a better understanding of both volatility and co-volatility dynamics for multiple series than the univariate MS-GARCH. In this respect, a bivariate regime switching GARCH model was first established by Lee and Yoder [22] in order to estimate the hedge ratio for WTI, and has been used later by Alizadeh et al. [23] in the same research area.

Extending the previous works, Hung et al. [24] proposed a four-regime bivariate Markov-switching model to estimate the time varying minimum variance hedge ratios for daily WTI crude oil. Empirical results demonstrate that the four-regime Markov switching model significantly outperforms the other competing models (two-regime model, Constant Correlation-GARCH, Time Varying Correlation-GARCH, and OLS models) for both in- and out-of-sample hedging performance. A part from these recent works, multivariate regime switching GARCH models have never been used in attempts to provide better understandings on the oil − stock market relationship or to highlight the importance of oil price shocks as a source of stock market fluctuations in presence of structural changes. The main difficulty that arises and that one must give special attention when dealing with multivariate regime switching GARCH models is; the path dependency problem due to the recursive nature of the GARCH process, i.e. the conditional variance and conditional covariance will depend on all past information. In order to solve this problem, Gray [25] suggests a tractable formulation for the conditional variance process by using the conditional expectation of the variance without giving up GARCH terms. Recently, Haas et al. [26] or Lee [27] among others, modify Gray's approach offering more parsimonious specifications of multivariate MS-GARCH models free from the problem of path

[2] This literature classification has been proposed by Zhu et al. [99].

dependency. Based on their intuition, our model dedicates a considerable part to handle the path dependency in both variance and covariance formulas.

Undoubtedly, *GARCH* models worked well to capture leptokurtosis and volatility clustering generally observed in financial time series but they demonstrate some inaccuracies in terms of changes of time scales [28]. One major advantage afforded by wavelets analysis is the ability to perform local analysis – that is, to analyze a localized sub image area of a larger image (or signal). Therefore, wavelet analysis is capable of revealing aspects of data that other signal analysis techniques (like *GARCH* models) usually miss; aspects like trends, sharp spikes, discontinuities in higher derivatives, self-similarity…etc. Likewise, because it affords a different view of data than those presented by traditional techniques, wavelet analysis can often compress or de-noise a signal without appreciable degradation [29]**.** In their brief history within the signal processing field, wavelets have already proven themselves to be a very useful tool for data de-noising [4] and deconvolution (separation between two convolved signals namely smooth and detail).

In this paper, we restrict our attention to "the *HTW* transform", introduced by Murtagh et al. [30] and designed as well suited for outlier detection. Our choice was motivated by its two main advantages over the traditional wavelet methods (the two properties are largely introduced in Murtagh et al. [30] and briefly described in by Nguyen and Nabnay [29]) and can be summarized as follows**:** (i) the redundancy (non-decimation or translation-invariance) of the à Trous wavelet (*with holes*) that ensures zero phase filtering at each level since the down-sampling and up-sampling stages are removed. But it remains symmetric function which is problematic for handling boundary values. (ii) Preservation of the asymmetric nature of the time varying signal leads to use the Haar wavelet function. In other words, events at time t in the original series are associated with the corresponding coefficients at time t (Detail/smooth coefficients).

In short, the solution proposed by Murtagh et al. [30] is to use the two wavelet techniques (à Trous and Haar) together so as to gain the advantages of both. Thus, the redundant Haar wavelet (or HTW) provides a simple, credible and very straightforward solution to alleviate time series boundary effect problems. Such an environment would keep the length of the resultant smooth components same as that of the original time series, thus we preserve their inherent characteristics (especially at the edge of the signal) may be helpful in providing more accurate assessment of the oil shock transmission to the stock market returns at a given time step.

This paper introduces a novel insight for characterizing the relationship between crude oil market and real stock market returns. Firstly, we apply the *HTW* with 6 decomposition levels to extract the real crude oil signal's main and entire information labeled the smooth low frequency part of the original series. Secondly, we extend previous works (based on bivariate Markov Switching GARCH models) by including a more tractable trivariate *BEKK MSG* model under common two states. Henceforth, we reinforce the model's flexibility by keeping it free from the problem of path dependency in one hand and by combining it with the HTW wavelet variant in other hand. Thirdly, using this kind of models represents another main contribution to the crude oil – stock market relationship literature.

In sum, we analyze the shock and volatility transmission from crude oil market to the stock market returns for five developed countries namely US, UK, Germany, Japan and Canada over the period January 1989 to December 2007 and then construct a more generalized background to better understand the behaviors inherent to the given data in the presence of extreme events.

The rest of the paper is organized as follows: Section 2 presents the two econometric methodologies, namely *Â HTW* decomposition method and the trivariate *BEKK MSG* model. Section 3 presents the data and discusses how the smooth fluctuations of the real crude price of oil might be transmitted to the real stock market returns and Section 4 concludes the paper.

2. Econometric methodology

In this section we describe in detail the wavelet transform used for the crude oil data decomposition together with the multivariate *BEKK MSG* used in our analysis.

2.1. Signal decomposition using wavelet method: Â Trous Haar wavelet (Â HTW)

The *Â HTW* approach was performed according to Murtagh et al. [30]. Below, we present the main characteristics of the "â trous" algorithm as an alternative to the Discrete Wavelet Transform *DWT* (we briefly recall the basic notions of the discrete wavelet theory in Appendix A.1) and finally we discuss the properties of the "Â Haar Trous" wavelet decomposition approach. According to Murtagh et al., our chief considerations regarding the choice of this type of wavelet transform are (i) aliasing; implying preference for redundant wavelet transform and (ii) asymmetry; a wavelet function which respects the asymmetric nature of a time-varying signal leading to use the Haar wavelet function. Two properties are inherent in this type of wavelets, the redundancy (provided by the Trous) and the asymmetry (given by the Haar).

2.1.1. Â Trous wavelet transform[3]

A potential drawback with the application of the *DWT* in time-series analysis is that it suffers from a lack of translation invariance. This means that if we use traditional DWT we had to delete the first few values of our input time series, then the transformed (decimated) output wavelet data introduced into the proposed model would not produce desirable outcomes for the crude oil-stock market returns relationship due to the decreasing sample size especially at higher level scales. To overcome this problem, authors (Coifman and Donoho [33] among others) suggest applying redundant or non-decimated wavelet transform.

According to Zhang et al. [34], the redundant wavelet transform's advantage lies in the fact that it is shift invariant and it produces smoother approximations by filling the "gap" caused by decimation. Various studies circumvent this lack by using wavelet filter designed to discard minimum parts of MRA that are influenced by circularity (such as the MODWT combined with the LA wavelet filter). However, under the selected wavelet transform, it is easy to conserve the original dimensions of the series, i.e., n-length input has n-length resolution scale at each considered level.

The selected redundant wavelet, i.e. the so-called Trous (with holes) algorithm, to be described now, is based on a successive resolution levels which are constructed by;

(i) Smoothing the input time series with an increasingly dilated wavelet function namely B3-spline which looks like a Mexican Sombrero (central bump, symmetric, two negative side lobes).

Using the discrete scaling low-pass filter h, the smoothed signals at a given resolution j and at a position t are obtained by the following convolutions:

[3] A detailed description of the properties of the Â Trous and the Mallat algorithm is given in Mallat [31] and Shensa [32].

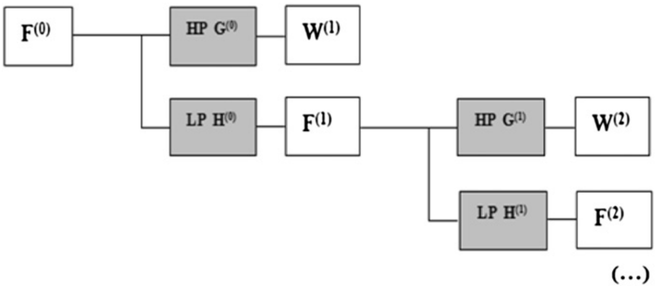

Fig. 1. Filter Bank structure of the Â Trous wavelet transform. One iteration consists of one convolution of the signal with the low-pass (LP) and a high-pass (HP) filter (H and G respectively). The low-pass filtered signal is the input for the next iteration step and so on.

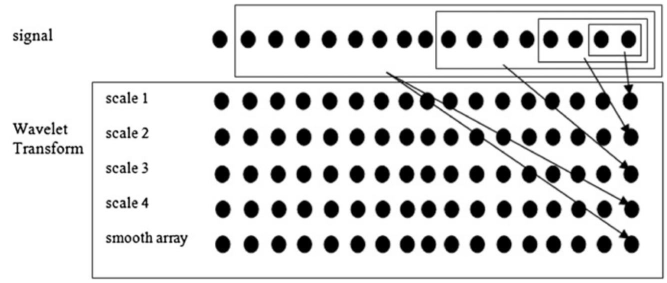

Fig. 2. The redundant Haar wavelet transform. The figure shows which time steps of the input signal are used to calculate the last wavelet coefficient in the different scales. A wavelet coefficient at a position t is calculated from the signal samples at positions less than or equal to t, but never larger.

$$s_j(t) = \sum_{l=-\infty}^{+\infty} h(l) s_{j-1}\left(t + 2^{j-1} \times l\right) \tag{1}$$

$$d_j(t) = \sum_{l=-\infty}^{+\infty} g(l) s_{j-1}\left(t + 2^{j-1} \times l\right) \tag{2}$$

Where $1 < j < J$.

In each step the series is convolved with a cubic *B-spline* filter, h, defined as 1/16 [1,4,6,4,1], with $2^{j-1} \times l$ zeros inserted between the *B-spline* filter coefficients at level j. Thus, we get a series of smoothed versions s_j with s_0 ($s_0(t) = x(t)$ the finest scale) as the normalized raw series.

(ii) Taking the difference between the smoothed signals at two consecutive resolution levels to obtain the detailed signals, or wavelet coefficients $d(t)$ at level j, as follows:

$$d_j(t) = s_{j-1}(t) - s_j(t) \tag{3}$$

The set $d = \{d_1(t), d_2(t), \ldots d_J(t), s_J(t)\}$ represents the wavelet transform of the signal up to the scale J, and the signal can be expressed as a sum of the wavelet coefficients and the scaling coefficient:

$$x(t) = s_J(t) + \sum_{j=1}^{J} d_j(t) \tag{4}$$

Fig. 1 shows the architecture of the "Â Trous wavelet transform" filter Bank.[4]

2.1.2. The Haar Â Trous wavelet transform (HTW)

Clearly in our study, very careful attention must be given to the boundary of the crude oil signal to produce reliable estimates of its effect on the stock market returns. Indeed, most of the extreme movement in the crude oil signal occurred certainly during the Gulf war and the recent financial crisis. Henceforth, excluding boundary coefficients would discard most of the relevant data and provide spurious and misleading results. The asymmetry of the Haar wavelet function used makes it a good choice for edge detection, i.e., localized jumps. The usual Haar wavelet transform, however, is a decimated one. Consequently, Murtagh et al. [30] develop a non-decimated or redundant version of this transform. The non-decimated Haar algorithm is exactly the same as the Â trous algorithm, except that the low-pass filter h, (1/16…etc), is replaced by the simple non-symmetric filter $h = (1/2,1/2)$. Fig. 2 describes the redundant Haar wavelet transform.

By convolving the original signal with the wavelet filter h, we create the wavelet coefficients.

$$s_{j+1} = \frac{1}{2}\left(s_{j,t-2^j} + s_{j,t}\right) \tag{5}$$

Then, the scaling coefficients at higher scale can be easily obtained from the scaling coefficients at lower scale:

$$d_{j+1}(t) = c_j(t) - c_{j+1}(t) \tag{6}$$

2.2. Wavelet-Multivariate Markov Switching GARCH-BEKK model

Several studies on the transmission volatility between different financial variables are based on the estimation of multivariate *BEKK GARCH* models [36–39].

Although these models are parsimonious, they were rather based on constant shock and volatility transmissions. Multivariate Regime Switching models, which are both time varying and state dependent, are used henceforth to solve this drawback. The main advantage of Markov-switching processes, often advocated in the literature, is their ability to take into account features such as nonlinear phenomena, temporal asymmetries as well as persistence of the macroeconomic time series: these features are crucial in the analysis of the dynamic linkage between crude oil prices and stock market returns [17]. Hamilton and Susmel [40] and Cai [41] were the first to allow for regime-switches in the ARCH process. Gary [25] extended their methodology to regime switching GARCH-models. In this section, we extend the standard multivariate BEKK-GARCH model of Engle and Kroner [42] to allow for the presence of regime shifts (The generalized regime switching GARCH model with path dependent volatility is introduced in Appendix A.2). We finally discuss the trivariate wavelet *BEKK MSG* that we will use in the current analysis in order to study the transmission mechanism of shocks (volatility) originating from crude oil market to equity market returns.

To circumvent the path dependency problem, Gray [25] introduces a recombining method that collapses the conditional variances in each regime by taking the conditional expectation of h_t^2 based on the regime probabilities.[5] As a consequence, the conditional variance and the residual depend only on the current regime,

[4] This figure is taken from the study of Wegner [35].

[5] Gray [25] proposes a recombining method for the univariate Markov Switching volatility model. For a detail description of the path-dependence problem and its solution for the univariate MS GARCH process case, see Lee and Yoder [22].

not on the entire past history of the process. Based on the Gray [25]'s recombining method, we analyze in the following section how this path dependence problem may be resolved in our trivariate MS-G model case.

2.2.1. Path dependency problem circumvention: case of a trivariate Markov switching BEKK GARCH (trivariate BEKK MSG)

Since three equations considerably complicate the estimation, we have to make some choices in terms of the required number of volatility states and parameters involved in the estimation procedure. We restrict our study to the case of three equations and two states. Thus, the state-dependent crude oil and stock market returns are specified as:

$$\begin{aligned} r_{s,t} &= \mu_{s,s_t} + e_{s,t,s_t} \\ r_{w,t} &= \mu_{w,s_t} + e_{w,t,s_t} \\ r_{b,t} &= \mu_{b,s_t} + e_{b,t,s_t} \end{aligned} \tag{7}$$

Where subscribers s, w, and b denote real stock market returns, WTI and Brent real crude oil volatilities (the smooth part, see Eq. (5)) respectively, μ is a constant where $\Phi = (\mu_{s,s_t}\mu_{w,s_t}\mu_{b,s_t})'$. e_{s,t,s_t}, e_{w,t,s_t} and e_{b,t,s_t} are state dependent residual terms. The unobserved state variable $s_t = \{1,2\}$ is interpreted as the market state or regime when the process is at time t, which follows a first-order, 2-dimensional state Markov process.

The conditional variances are specified as:

$$E_{t,s_t}/\psi_{t-1} = \begin{bmatrix} e_{s,t,s_t} \\ e_{w,t,s_t} \\ e_{b,t,s_t} \end{bmatrix} \Big/ \psi_{t-1} \rightarrow \mathrm{TN}(0, H_{t,s_t}) \tag{8}$$

TN denotes the trivariate normal. H_{t,s_t} is a state-dependent conditional variance-covariance matrix of each return.

The time-varying 3×3 positive definite conditional covariance matrix, H_{t,s_t}, is specified as (where $p = q = 1$):

$$\begin{aligned} H_{t,s_t} &= \begin{bmatrix} h^2_{s,t,s_t} & 0 & 0 \\ 0 & h^2_{w,t,s_t} & 0 \\ 0 & 0 & h^2_{b,t,s_t} \end{bmatrix} \\ &= \begin{bmatrix} \gamma_{ss,s_t} & 0 & 0 \\ 0 & \gamma_{ww,s_t} & 0 \\ 0 & 0 & \gamma_{bb,s_t} \end{bmatrix} \begin{bmatrix} \gamma_{ss,s_t} & 0 & 0 \\ 0 & \gamma_{ww,s_t} & 0 \\ 0 & 0 & \gamma_{bb,s_t} \end{bmatrix}' + \begin{bmatrix} \alpha_{ss,s_t} & \alpha_{sw,s_t} & \alpha_{sb,s_t} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}' \begin{bmatrix} e^2_{ss,t-1} & e_{s,t-1}e_{w,t-1} & e_{s,t-1}e_{b,t-1} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \alpha_{ss,s_t} & \alpha_{sw,s_t} & \alpha_{sb,s_t} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \\ &+ \begin{bmatrix} \beta_{ss,s_t} & \beta_{sw,s_t} & \beta_{sb,s_t} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}' \begin{bmatrix} h^2_{s,t-1} & h_{sw,t-1} & h_{sb,t-1} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \beta_{ss,s_t} & \beta_{sw,s_t} & \beta_{sb,s_t} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \\ &= \Gamma_{s_t}\Gamma'_{s_t} + A_{s_t}E_{t-1}A'_{s_t} + B_{s_t}H_{t-1}B'_{s_t} \end{aligned} \tag{9}$$

Where Γ_{s_t} is a 3×3 diagonal matrix of state dependent coefficients, A_{s_t} and B_{s_t} are 3×3 state dependent coefficient matrices restricted to be of 1×3 dimension for further simplifications.

h_{sw,t,s_t} and h_{sb,t,s_t} are conditional covariance at time t given s_t, and h^2_{s,t,s_t}, h^2_{w,t,s_t} and h^2_{b,t,s_t} are conditional variances at time t given s_t. The matrices Γ_{s_t}, A_{s_t} and B_{s_t} and E_{t-1} are compact representations of the state-dependent coefficients γ, α, β and e respectively.

We will refer to the model defined by Eq. (9) as a trivariate BEKK Markov-switching *GARCH*(1,1;2) process or, in short triavariate *BEKK-MSG*(1,1;2). Since we are interested in providing the results related to the shock and volatility transmission only from the crude oil market to the stock market in presence of regime switching, we assume that only $h^2{}_{s,t}$ follows a *BEKK-MSG (*1,1*)* process under two volatility states (high volatility and low volatility) and each of $h^2{}_{w,t}$ and $h^2{}_{b,t}$ follow a constant.[6] We allow for the vectors of mean and variance parameters to switch across two regimes.

As in the univariate regime switching GARCH model, The recursive nature of the GARCH process makes the basic form of the model intractable due to the dependence of the conditional variance on the entire past history of the data. Indeed, only the first equation i.e., $h^2_{s,t}$, of the proposed trivariate GARCH model is subject to the path-dependency problem. Hence, it depends directly on the state variable s_t and $h^2_{s,t-1}$, which itself depends on s_{t-1} and $h^2_{s,t-2}$ and so on. The computation of the likelihood function for a sample of length T requires the integration over all 2^T possible (unobserved) regime path, rendering estimation of the model infeasible in practice. This is the well-known path dependency problem in the regime switching literature [41,40,25]. Furthermore, this problem is present not only in variances and residuals, but also in the covariance between crude oil and stock market returns $h_{sw,t}$ and $h_{sb,t}$.

In Appendix A.3, we derive the following path independent *conditional variance* as described by Lee and Yoder [22] (Appendix A.3 also provides expressions of the probabilities p_{1t} and p_{12}.

3. Methodology results and discussions

3.1. Data

Our analysis deals with two variables; (1) real stock returns of five major industrial countries, namely; US (DJIA), UK, (FTSE 100), Germany (Dax30), Japan (NIKKEI 225) and Canada (TSX) and (2) real prices of two major crude oil products, defined as the US price of West Texas Intermediate Cushing (WTI) and the Europe Brent which are quoted in Dollars per barrel. Crude oil prices were extracted from the US Department of Energy (Energy Information Administration), while stock market prices were taken from the International Financial Statistics databases (IFS). The use of Brent and WTI crude oil prices lead us to distinguish between two geographical areas that encompass a group of crude oil producing countries. Indeed, Brent oil is, by definition, produced from Europe (UK), Africa and the Middle East (Brent North Sea crude). However WTI oil is produced from North America (North America crude such as Canada).

Given this classification, in what follows, we denote WTI oil shock as "External oil shock", i.e. extra-North sea oil shock, for European country like Germany and as "Domestic oil shock" for American countries like Canada and US. In the same way, we denote Brent oil shock by "External oil shock", i.e. extra-American oil shock

[6] Henceforth, the conditional covariances $h_{ws,t-1,s_t}$ and $h_{bs,t-1,s_t}$ and the variances $h^2_{w,t-1,s_t}$ and $h^2_{b,t-1,s_t}$ were fixed to be zero.

Table 1
Top 10 U.S. imports of crude oil by country of origin.

United States	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Canada	3 (14.1)	3 (13.2)	3 (14.7)	3 (14.3)	2 (15.7)	2 (15.9)	1 (15.8)	1 (15.9)	1 (17.6)	1 (18.6)
Saudi-Arabia	2 (16.3)	2 (16.1)	2 (16.9)	1 (17.3)	1 (16.6)	1 (17.9)	3 (14.9)	3 (14.3)	3 (14.1)	2 (14.5)
Venezuela	1 (19.8)	1 (17.2)	1 (17.0)	2 (16.5)	3 (15.2)	4 (14.1)	2 (15.4)	2 (15.0)	4 (13.8)	3 (13.4)
Mexico	4 (13.0)	4 (12.3)	4 (11.3)	4 (12.5)	4 (14.1)	3 (14.5)	4 (14.5)	4 (13.8)	2 (14.4)	4 (12.5)
Iraq	8 (3.9)	5 (8.4)	6 (6.9)	6 (8.5)	6 (5.0)	NA	6 (6.5)	6 (5.2)	6 (5.5)	7 (4.8)
Nigeria	5 (8.0)	6 (7.2)	5 (9.7)	5 (9.0)	5 (6.5)	5 (8.6)	5 (10.7)	5 (10.7)	5 (10.3)	5 (10.8)
Angola	6 (5.4)	8 (4.2)	8 (3.3)	7 (3.5)	7 (3.6)	6 (3.8)	7 (3.1)	7 (4.7)	7 (5.3)	6 (5.1)
Kuwait	9 (3.5)	9 (2.9)	9 (2.9)	9 (2.5)	9 (2.4)	7 (2.2)	8 (2.4)	10 (2.2)	10 (1.8)	10 (1.6)
Colombia	7 (4.1)	7 (5.2)	7 (3.5)	8 (2.8)	8 (2.6)	8 (1.7)	..	..	..	..
Equador	10 (1.1)	10 (1.3)	10 (1.4)	10 (1.2)	10 (1.1)	9 (1.4)	9 (2.3)	8 (2.7)	9 (2.7)	9 (2.0)
Algeria	..	..	..	..	..	10 (1.2)	10 (2.1)	9 (2.3)	8 (3.6)	8 (4.4)

Note**:** Numbers in curly brackets denote the share (%) of total US crude oil imports measured in thousands of tones per year. ..: more than 10%, NA = missing values. Source: US Energy Information Administration.

Table 2
Top 10 German crude oil imports by country of origin.

Germany	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Russia	1 (24.5)	1 (26.5)	1 (28.7)	1 (28.8)	1 (30.1)	1 (31.5)	1 (33.6)	1 (35.0)	1 (33.7)	1 (31.7)
Norway	2 (20.3)	2 (20.0)	2 (18.0)	2 (19.9)	2 (21.3)	2 (20.9)	2 (19.8)	2 (15.4)	2 (16.9)	2 (15.6)
UK	3 (17.9)	4 (13.4)	3 (12.6)	3 (14.6)	3 (10.9)	3 (10.9)	3 (11.8)	3 (13.1)	3 (12.3)	3 (13.0)
Lybia	4 (12.2)	3 (13.7)	4 (11.4)	4 (9.5)	4 (8.3)	4 (8.4)	4 (11.6)	4 (11.5)	4 (11.3)	4 (10.2)
Syria	7 (4.7)	5 (5.8)	5 (6.8)	5 (7.0)	5 (6.9)	6 (5.9)	7 (3.6)	8 (3.0)	7 (3.1)	6 (2.9)
Algeria	5 (5.4)	7 (4.0)	6 (6.3)	8 (3.8)	7 (4.0)	8 (3.5)	8 (2.6)	6 (4.1)	9 (2.1)	8 (2.3)
Kazakhstan	10 (1.2)	8 (2.7)	8 (3.3)	6 (4.4)	6 (5.3)	5 (6.2)	5 (6.8)	5 (6.6)	5 (6.9)	5 (7.4)
Saudi-Arabia	6 (4.8)	6 (4.3)	7 (4.4)	7 (3.9)	8 (3.4)	7 (3.6)	6 (3.8)	7 (3.7)	6 (3.2)	9 (2.2)
Venezuela	8 (2.2)	9 (2.0)	10 (1.8)	10 (1.6)	..	..	..	..	..	10 (2.1)
Nigeria	9 (1.9)	10 (1.1)	9 (1.9)	9 (2.9)	9 (2.7)	9 (2.7)	..	9 (1.9)	8 (2.8)	..
Denmark	..	..	..	..	10 (1.6)	10 (1.8)	9 (1.8)	10 (1.7)	..	..
Azerbaïdjan	..	..	..	..	..	..	10 (1.3)	..	10 (1.7)	7 (2.7)

Note: Numbers in curly brackets denote the share (%) of total German crude oil imports measured in Annual-Thousands Barrels per Day, ..: more than 10%. Source: Eurostat.

(North America as well as South America), for American countries and as "Domestic oil shock" for European countries. Henceforth we observe, from Table 2,[7] that the top three sources of German crude oil imports were Russia, Norway and UK. Furthermore, Canada is both an exporter and an importer of crude oil. From Stats Canada for 2005, domestic crude accounts for only about 45% of Canada's oil consumption. Imports represent the remaining 55%, mostly coming from North Sea Countries (UK and Norway) or the Middle East (Algeria, Saudi Arabia…etc) (see Table 3). On the other hand, USA is the world's largest net importer of crude oil. It imported 10,984 thousand barrels per day, followed by Japan (4652) and China (3858) (EIA, 2008). According to Table 1, North and South American countries particularly Canada, Mexico, Venezuela, Colombia and Ecuador (they had no more than 52 percent of the total imports) supplied much more crude oil to the USA. The other less than 50% of the US oil supply were from foreign sources; However, Middle East countries (Saudi Arabia, Iraq, Kuwait and Algeria) provided no more than 30 percent of USA oil imports, no more than 16% by African countries (Nigeria, Angola), and no less than 2% by European countries (UK, Russia, Norway).

As it is well known, WTI and Brent have long been recognized as main global benchmarks, i.e. they serve as guidelines for other crude oil grades (also known as oil markers).

Unfortunately, the recent fallen in the production of Brent, like WTI has put some doubts on their leadership and benchmark positions, hence the notion of the "broken" benchmark phenomenon [43].

In this respect, it might be necessary to assess the relationship between crude oil and stock market returns based on prices of each country's primary oil import sources instead of just two predetermined crude oil price series in order to obtain more robust results and make inferences more credible.[8] In other words, we might focus on the impact of each regional crude price markers since it is an indicator of what is happening in the regional crude oil market. However, we might still feel that this may not be accurately gauged for the following main reasons;

Firstly, abundant recent literatures confirm that various crude oil types do not have the leadership prominence as Brent and WTI: Indeed, given the growing criticism about the use of WTI and Brent as benchmarks, understanding the price relationship between crude oils, over the last few years, has become the focus of an increasing number of economists. Montepeque [44] gives more support to Brent and WTI crude oil prices as leaderships over the Russian Urals and Mars respectively. Using the Granger Causality tests, HagstrÄomer et al. [45] examine the dependence structure between 32 crude oils based on different market segments (quality segments, geographical segments and segments for OPEC and non-OPEC products). The results indicate that the well-established benchmarks WTI and Brent still lead the market but two other significant crude oils (Russian Urals and Iran Serir Kerir) may also play the role of price setters. Hammoudeh et al. [46] examined the asymmetric adjustment process between four varieties of crude

[7] As the results are insignificant, we do not report the importer shares of total Japanese and UK crude oil imports.

[8] We thank an anonymous referee for drawing our attention to this point. Although, our regression model can be extended to include at least the three major individual oil prices for each country, we decide not to report these results for the reasons evoked here after. However, an extension of our work by including the top major regional crude oil prices within more recent and higher frequency data (as required) turns out to be possible once we take a preliminary step of analysis. Indeed, it is preferable to test the long-run relationship between the selected crude oil markers before analyzing the stock-crude oils relationship as we may again be asked to identify good crude oil benchmarks.

Table 3
Top 10 Canadian crude oil imports by country of origin.

Canada	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Norway	1 (26.1)	1 (31.6)	2 (29.1)	2 (26.6)	1 (29.1)	1 (27.4)	1 (26.9)	1 (26.0)	1 (21.7)	1 (21.4)
UK	2 (15.7)	2 (20.5)	1 (29.4)	1 (30.7)	2 (24.2)	2 (21.1)	2 (20.6)	2 (15.7)	3 (15.3)	3 (16.4)
Algeria	6 (9.1)	4 (8.0)	4 (8.1)	5 (8.0)	3 (11.6)	3 (15.2)	3 (14.6)	3 (17.6)	2 (20.7)	2 (20.9)
Saudi-Arabia	5 (10.9)	5 (7.5)	5 (6.4)	6 (6.2)	6 (6.1)	5 (6.9)	4 (8.1)	4 (8.2)	5 (8.0)	4 (8.6)
US	4 (11.9)	6 (6.6)	8 (2.6)	7 (3.4)	9 (1.7)	10 (2.1)	9 (2.6)	10 (2.3)	..	..
Venezuela	3 (13.5)	3 (12.5)	3 (10.0)	3 (8.8)	5 (6.8)	9 (2.9)	6 (5.2)	6 (5.2)	9 (3.6)	7 (4.6)
Iraq	10 (1.8)	7 (3.4)	6 (5.2)	4 (8.4)	4 (9.6)	4 (8.5)	5 (7.8)	5 (7.1)	4 (8.1)	5 (7.3)
Nigeria	8 (3.0)	9 (3.1)	9 (2.3)	9 (1.8)	8 (2.0)	7 (3.5)	8 (2.8)	8 (2.7)	8 (3.9)	10 (2.6)
Mexico	7 (4.2)	10 (2.9)	7 (2.9)	8 (2.6)	7 (2.4)	8 (3.0)	7 (3.2)	7 (4.0)	7 (4.3)	9 (2.9)
Russia	9 (2.2)	8 (3.3)	10 (1.3)	..	..	6 (3.6)	10 (2.2)	9 (2.3)	6 (4.4)	8 (2.9)
Angola	..	..	..	10 (0.5)	..	..	..	..	10 (2.6)	6 (5.3)
Ecuador	NA	NA	NA	..	10 (0.8)	..	..	..	..	..

Note: Numbers in curly brackets denote the share (%) of total Canadian crude oil imports measured in Thousands cubic meters per year. ..: more than 10%, NA = missing values. Source: Statistics Canada.

oils; two grades (Dubai and Mexican Maya) and two benchmarks (WTI and Brent) and their results indicate that the latter are much more liquid and have stronger leadership stature than the former. Importantly, they declare that even if they show temporal unusual price spread between each others, they adjust to equilibrium in the long run. This finding is corroborated by Chang et al. [47] and Bentzen [48]. They claim that their result may tend to prove the hypothesis of the world crude oil market integration. In this regard, Nordhaus [49] provides arguments supporting this hypothesis, including the low costs of oil transporting and the interchangeability/fungibility of different regional crude oils. Indeed, based on the rolling five-year regressions over the period from 1994 to 2009, he examines 31 regional crude categories worldwide (among them the Russian Urals) and found that both premiums are relatively stable over the period as a whole.

Additionally, Miller et al. [50] argue that although the existence of 161 different grades of crude oils,[9] North Sea' Brent and North America's WTI remain the two most widely used and very actively traded that they still serve as global benchmarks in terms of pricing, quality, and location for the other grades consumed in their own local and regional markets. They attribute their declining relevance to several reasons such as; the move among increased number of refiners toward using heavier and sourer crude oil productions and possible short-term manipulation of benchmark crude oil prices. At the same time, several authors declare that the choice of crude oil prices would not affect their impact on the stock market empirically [17,51] since they move together in the long run [52].

Secondly, some existent statistical/mathematical tools have proved unable to prevent potential confusion regarding the understanding of the differentials (spread) between the crude oil prices: for instance Hammoudeh et al. [46] declare that forecasting models that do not account for significant asymmetry in the adjustment process are particularly misleading. Finally, possible misrepresentation of the historic, current and future crude oil market conditions can occur and because of this we cannot be confident that the analysis will be more accurate. Henceforth, comparing historical, current, and future global oil production provides some surprising results. On one hand, the current/traditional oil production share of the top exporter nations, intended for the traditional importers (or to meet local demand) is expected to fall. In fact, although Russia and Saudi Arabia (among others) are the world's current oil production leaders, EIA (2011) projects that their future contributions to the global new production will decline. On the other hand, the current less promising producers such as Brazil, Canada and Kazakhstan begin to appear as the most new interesting (more than just marginal) world's leading non-OPEC contributors to global new production [53]. Together, Hammoudeh et al. [46] declare that the recent collapses in the WTI-Brent spread occur in response to natural disasters (like Hurricane), shutdowns in the refining capacity and unplanned refinery outages in the United States but also synchronized with Oil peaking in some North Sea oil fields, new strike action at the Fos container terminals near Marseilles and the geopolitical pressures in Nigeria and Iran.

These conditions can be reflected in the recent unprecedented levels of spread between WTI and Brent. Indeed, while WTI has historically traded at a dollar or two premium over the Brent, the discount between them has reached a record-high level (exceeded $15 a barrel) since the unrest in Middle east and North Africa (EIA; 2011). Meanwhile, the differential between the two benchmarks and the other grades is widening too (Urals, Dubai, Mars, LLS…). Table 1 through 3 aim to illustrate the aforementioned facts. They present the shares of total US, German and Canadian crude oil imports respectively from the top 10 countries of origin during the period 1998–2007. A closer look at Tables 1 and 3 shows that Venezuelan oil exports to US (or Canada) records an accelerating drop, becoming the 4th major oil supplier in 2003 and 2006 (5th to 9th in 2002–07) when compared with the other higher ranks all over the period which inevitably led to heavy spending increases (focused on building more complex refineries) in more remote and less promising regions or economies, including Mexico (such as Algeria) [53]. This leads us to corroborate the claims of [46] who suggested that the fundamental changes in the Mexican Maya – WTI spread may be due to a higher-than-expected falling in the Mexican oil production which perhaps resulted from the fact that the refineries are located in a very active Hurricane area. Interestingly, they confirm that the split between two benchmarks is just a transitory phenomenon that can still occur sporadically due to several factors such as; temporary infrastructure and logistics issues, reduced capacity utilization of the domestic refinery due to maintenance especially during the shoulder season and limited level of crude oil inventories. Additionally, from the Table 2, Russia is the Germany's biggest supplier. However, in next few years the oil production level from super-giant fields in the Kazakh is expected to rise strongly over Russian exports.[10] This fact might be responsible for most of the changes in global crude oil markets through the fundamental gap between Russian Urals and North Sea Brent crude driven by a sustained rise in marginal oil production

[9] Source: The International Crude Oil Market Handbook, 2004, published by the Energy Intelligence Group.

[10] Kazakhstan has the second largest oil reserves as well as the second largest oil production in the Caspian region after Russia (EIA, 2011); and it has set itself the goal of becoming one of world's largest oil producers next year.

capacity provided by Caspian region against a slowdown in Russian and North Sea production [53]. In sum, the evolution of world oil production (the current significant share of heavier and sourer crude oil production – about 50% – is expected to further increase according to Montepeque [44] behavior accompanied with the current highly uncertain[11] situation generated from the recent structural changes (not included in our study) will prompt further debate on whether or not WTI and Brent crude should continue to be used as crude oil benchmarks but also choosing the best indicator may be more complicated than it seems.

Therefore, to get sufficient precision, many input variables (top three or more regional crude oil prices) must be involved in the model specification for each country what may unfortunately complicate the estimation leading to badly biased results caused by spurious serial correlations (between the crude oil prices), and especially path dependency problems.

More specifically, taken just the top individual crude oil markets do not provide useful generalization for their long term response on the stock markets because they offer little information about the general reaction to evolutionary changes in the global market conditions and therefore not useful as guidelines for practitioners and energy economists.

In order to avoid any possible omission or misrepresentation, the Brent and WTI remain the best-known and more credible of either of the individual crude oil prices to look at as they have long been considered as hedging mechanisms for a great number of companies and refiners (especially all over the period considered in our study) due to their very higher quality over their various less desirable (more expensive to refine) composites. Consequently, in what follows, we assume that WTI and Brent are ideals enough to be consumed in large quantities by US and Europe respectively and their prices suffice to conduct well the results of their impact on the stock market returns.

All the data are measured on a monthly basis. The sample covers the period from January 1989 to December 2007, for a total of 228 observations.

The reasons behind the use of data with monthly sampling frequency (not higher) are as follows:

i) In the final part of the wavelet decomposition step, our goal is to determine whether there is a coincidence between the oil price shock and the recession episodes identified for each country. As is well-known, the Economic Cycle Research Institute (ECRI) (or the National Bureau of Economic Research (NBER)) provides only monthly or annual dates for peaks and troughs of business cycles. Thus, to ensure accordance with the ECRI recession dates, we restrict our attention to the monthly frequency basis.

ii) Of course daily data may content more information, but more data do not necessarily imply gathering more right information about the time series, so getting better results, then making more accurate interpretation as the studies of Ramchand and Susmel [55] and Aloui and Jammazi [17] imply. The other type of problem that we may encounter when dealing with daily datasets is what it is called "time misalignment" or "difference problems with international markets" which is clearly explained by Arouri et al. [56]. They assert that time discrepancy between the opening and closing periods of the stock markets would generate great different missing daily values. For example, the U.S. stock exchange has different far fewer days of closure throughout the year compared to those in Europe or Asian countries. According to these authors, the use of either weekly or daily data may lead to biased estimates caused by the increased impact of the market microstructure effect such as the daily bid/ask bounce, non-synchronous trading days, and the illiquidity impacts on asset pricing. Additionally, in that follows we demonstrate that for our simulation study, monthly data may offer several advantages over the daily or weekly data.

Indeed, the wavelet, on one hand, can provide better resolution and smoothness for input monthly data than those for weekly or daily basis as they can help to reduce its sensitivity to noise. In other words, it is well known that monthly data have much less noise than daily or weekly data. These latter suffer from much more drifts, various missing observations for non-trading days…etc.

Moreover, to study the multi-scale behavior of the time series, the decomposition of data with daily or weekly frequency at six levels will extract components that are dominated by only short term feature of the signal's behavior as the sixth time-scale corresponds to 64–128 days (i.e. approximately 2–4 months) period dynamics. However, it is important to distinguish between different time horizons (short-term – less than 1 year, medium-term – 1–3 years, and long-term – 5 years or more) given that investors usually focus on both short and long-term price movements. In this respect, Candelon et al. [57] argue that investors with short term profit goals focus on the price relationship at higher frequencies (short term price reactions) whereas investors looking for long term gains are interested in the price interactions at lower frequencies (long term price reactions). In his study, Lehkonen [58] emphasizes the importance of wavelet in differentiating between the time-varying short and long term behavior of the stock market integrations.

Given that the maximum decomposition level is given by log2 (*T*), the multi-scale decomposition of monthly data is efficient enough to predict far more variation in returns with different time horizons. By contrast, using daily or weekly data, 14 and 9 decomposition levels are required to obtain satisfactory results (either for the smoothness or for the distinction between the different time horizons).

On the other hand, the general limitation of MS models lies in the fact that the number of parameters grows with the number of regimes, especially when large sample sizes are involved. In fact, the Maximum Likelihood estimation of Markov switching models achieves fast convergence with small samples and small numbers of regimes. Another important matter of concern is that regime switching models have become increasingly well-known tool for detecting and forecasting the turning points in the data. In this sense, recent works like Kulkarni and Haidar [59] indicate that more data points generally increase the ability of the prediction model to generalize, but nonetheless this is not necessary the case for financial or economical time series. In light of the significant changes in the economic environment that affect the time series, the forecasting of future values based on historical data becomes questionable. Incomplete as well as noisy data can have, depending upon the amount of the missing data and the importance of the piece of information that contain, a major influence on the final results (estimates parameters or the timely detection of turning points) and on the certainty with which conclusions can be drawn. Henceforth, in contrast to daily or weekly data, the use of monthly returns reduces the impact of market microstructure effect and improves the forecast performance of Markov switching models and the detection of the stylized facts (see for example Ismail and Isa [60]). In particular, Park and Ratti [9] study the impact of oil price shocks on the stock markets of US and 13 European countries

[11] Amrita Sen, an Oil Analyst at Barclays Capital said "*Indeed, currently…spreads are so far away from any sustainable equilibrium that they imply a mounting degree of market breakdown*" (source: Tom [54]; p.2).

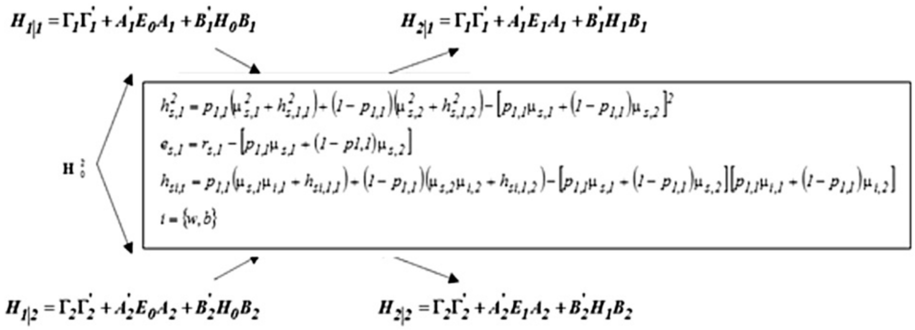

Fig. 3. Path-independent conditional variance of a trivariate BEKK-MSG model.

by constructing a measure of monthly oil price volatility using daily spot or future crude oil prices. They argue that this measure has extreme values related to major political events concerning the Middle East and may reflect uncertainty about future oil supplies. Their results show that this indicator is effective at accurately predicting the moments of future oil supply uncertainty where the volatility hits its highest point during the first Gulf War (January 1991) and the Iraqi disarmament crisis of 2003.

iii) Several recent studies point out that the significance of results is not influenced by the choice of expected frequency. More importantly, they consider that low frequency data are more appropriate than the higher frequency ones. Indeed, Sadorsky and basher [61] explore the impact of oil price risk on the stock returns based on daily, weekly and monthly data. They reach the same conclusions for daily and monthly data, in one hand and for weekly and monthly data, in the other hand. Interestingly, they find that the systematic risk (beta) affects significantly and positively the excess stock returns in that oil price shocks were both positive and negative. Henceforth, the authors declare that the similarity in results imply the impossibility of attributing the large changes in crude oil prices to the choice of data frequency but rather to the confluence of supply and demand factors, responses to geopolitical events, changes in institutional arrangements and the price dynamics of the crude oil futures market [62].

In order to determine which type of data frequency have more influence on the estimation performance, Longo et al. [63] use several kind of econometric forecasting models and four different WTI datasets on daily, weekly, monthly and quarterly basis (obtained by the arithmetic mean aggregation of the daily observations). Generally speaking, their results show that more accurate WTI forecasts are achieved with the financial models for all the frequencies, but also monthly and quarterly data frequencies in particular are considered far more preferable. Furthermore, Nanda [64] aiming to study the Chinese stock market's sensitivity to short and long run oil price shocks, finds that longer period returns (particularly, half yearly) are considerably more better in capturing the oil price sensitivity of Chinese stock returns. According to him, the high levels of noise or the more long term nature of the link is the susceptible causes that can make the underlying relationship undetectable by shorter sampling intervals (weekly data set for his case study).

All the data were used in real terms. For each country, real stock returns are defined as the difference between the continuously compounded return on stock price index and the inflation rate given by the log-difference in the consumer price index. Consumer price indices are from OECD databases. On the other hand, the most accurate measure of an oil shock is the real oil price. So that the world oil prices were deflated by the consumer price index (CPI) of each country. Put it differently, we take the world price of oil in US $ and divide by the CPI of each country. This choice of variables may be crucial for an ultimate comparison purposes. Indeed, many of the recent studies have shown that net oil prices have predictive content for determining stock market turning points [17]. In contrast to some work, we would like to show that the real oil prices are also useful predictor of turning points in stock markets. Fig. 5 (left panel) plot the real equity returns and the smooth part of the real crude oil returns.[12] It is likely that time series include structural changes in the mean during the investigated period. For instance, real DJIA return series increases especially around 1992 and 2007. However, for the other countries, real equity returns experience several jumps throughout most of the period that roughly coincide with the major conventional crises.

The results from Fig. 5 (left panel) provide some preliminary evidence of (roughly) coincidental market volatility switches between real stock returns and the smoothed real crude oil volatility during the study period. In the following sections, we explore this issue further by applying the trivariate wavelet-BEKK MSG model. Let us start with the extraction of the smoothed series for the crude oil volatility index based on the new wavelet decomposition method described above.

3.2. Haar A Trous Wavelet decomposition: application to the real crude oil volatility

Oil prices traditionally have been more volatile than many other commodity or asset prices [65]. Recently, it has been claimed that "*Wavelet filtering is particularly relevant to volatile and time-varying characteristics of real world time series.*" [66], p. 803.

To verify this, monthly real crude oil price volatilities were used to assess the performance of the *Â HTW* algorithm in getting a smooth component without losing the underlying characteristics of the respective series. Indeed, the input data consists of the monthly real crude oil price volatility of the West Texas Intermediate Cushing (WTI) and the Europe Brent real oil returns (expressed in $/bbl) for the period January 1989–December 2007. The real crude oil market volatility R_{it} is taken as the log difference of real crude oil price P:

$$R_{it} = LogP_t - LogP_{t-1}$$

Where P_t is the real crude oil price at date t.

The two transformed series are decomposed into their time scale components using *Â HTW* which is redundant or non-

[12] We first decompose the original signal (monthly real crude oil returns) using the HTW transform. We then extract the smooth part from the signal. We will discuss this in more details in the following section.

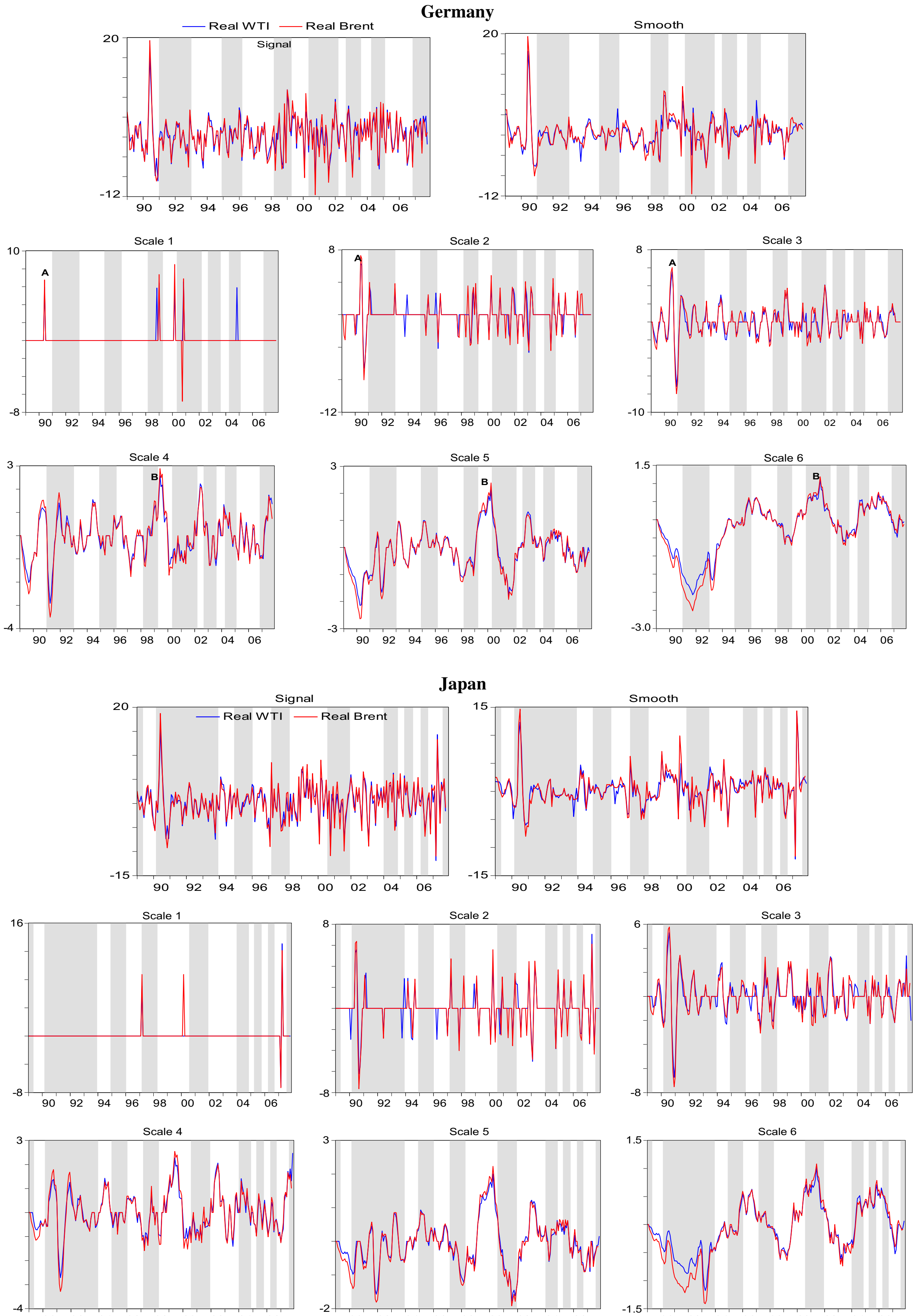

Fig. 4. Haar Â Trous Wavelet decomposition of the real crude oil volatilities. The top panel: the original series (signal) and the smoothed series (smooth). The six panels namely scale 1 to scale 6: the wavelet components (vertical axis represents the amplitude of scaling coefficients (in Hertz). The shaded vertical bars indicate growth cycle recessions as dated by ECRI "Economic Cycle Research Institute." The sample period is January 1989 to December 2007, a total of 228 observations.

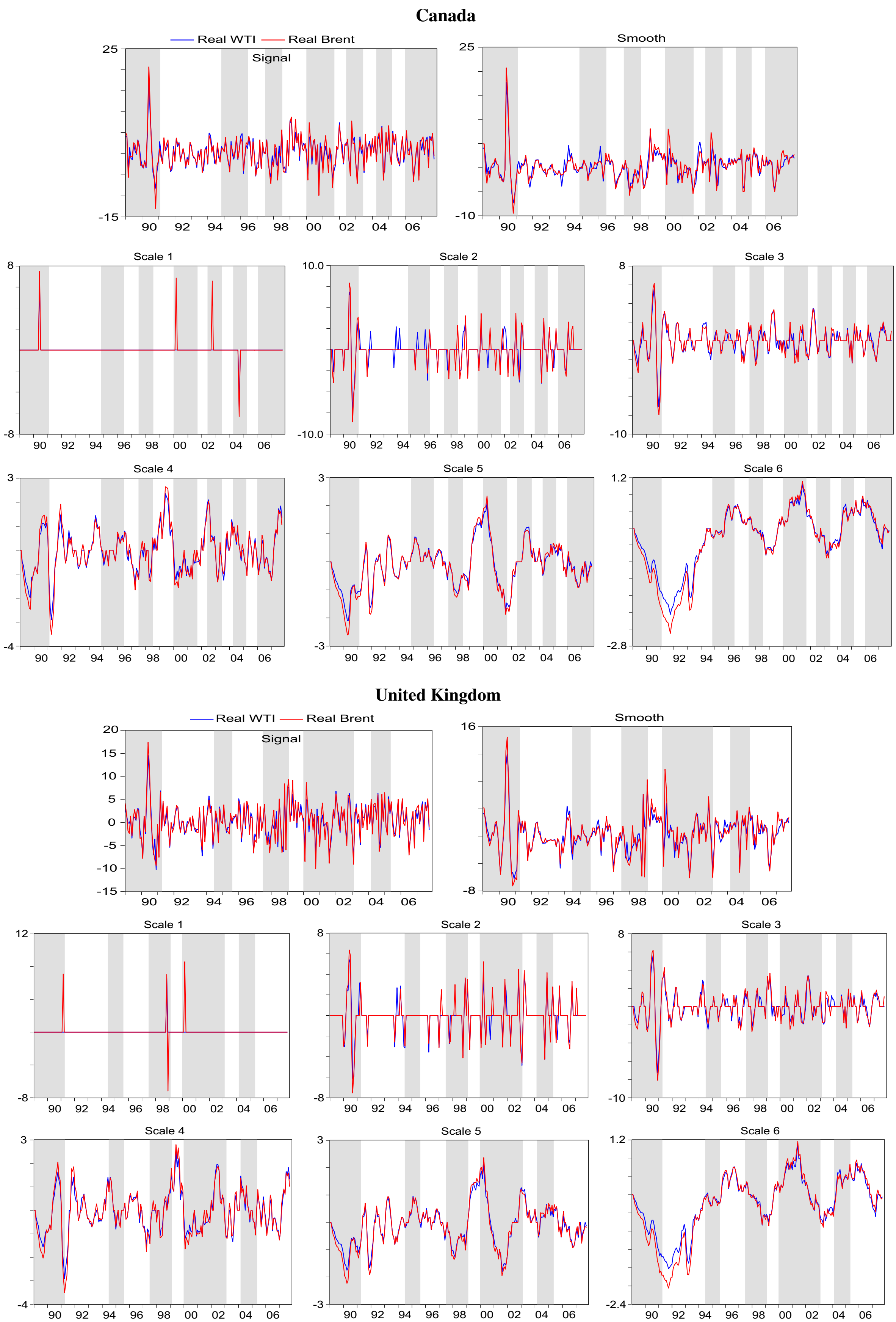

Fig. 4. (*continued*).

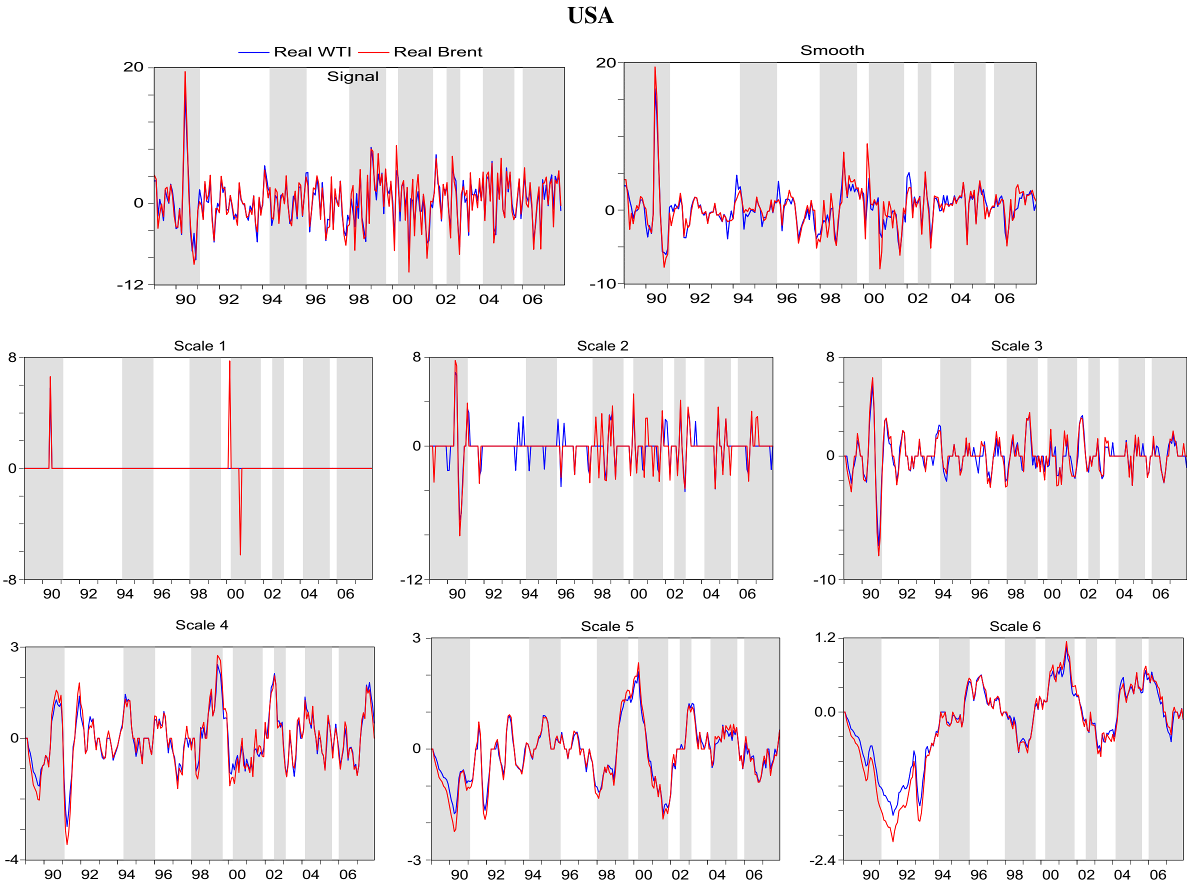

Fig. 4. (*continued*).

decimated method. The wavelet filter used is the discrete low pass filter (G) of length, $L = 6$. The sifting processes produce six level details which are captured by *scale* 1, *scale* 2, ..., *scale* 6 plus the smoothed series (*Smooth*) each containing 228 samples. At each scale, the corresponding component is reconstituted according to Eqs. (5) and (6). Fig. 4 plot the original series (*signal*), the details (*scale* 1–6) and, the smoothed series (*smooth*) for the real crude oil volatilities of US, UK, Germany, Canada and Japan. The standard deviations (*SD*) of each detail are not uniform across the series but proportional to the *SD* of the underlying signal. Since, we use monthly data, the level of details represent the variations within 2^i months horizon which correspond to 4–8, 8–16, 16–32, 32–64 and 64–128 month dynamics, respectively. All the details are listed from the highest frequency to the lowest frequency. The most short-run fluctuations are observed in the two finest components scales 1, and 2 and some in scale 3 which contain the high frequency content, so that they are extremely sensitive to non-smooth data characteristics such as noise, jumps, and spikes in the data. However, scales 4–6 depict medium and long-term fluctuations of the series. As the wavelet resolution level increases, the corresponding coefficients become smoother and the smooth trend (the coarsest approximation series) contains the lower frequency movements.

One of the advantages of the wavelet transform is to analyze stylized facts in a time series such as revealing structural break at different time scales [67].

As noted in his article, Hamilton [68] argues that, during the post-World War II period, nine of the last ten recessions in the US were preceded by large increases in oil prices. Suppose, instead, that we believe large oil shocks are followed by sharp recessions. To do so, we are going first to look at the recession history with a particular focus on how each recession is preceded by a specific oil shock.[13] Henceforth, shaded bars in Fig. 4 indicate recessionary periods in months, as identified by ECRI from 1989 to 2007 (see Table 6 (second column)). According to ECRI dating, recession periods show some similarities and differences in the growth of business cycles. All the countries experienced six (single or double adjacent) recessions in the period studied (except for UK). The first deep recession took place during times of two crises known as the mid-1990's Gulf war and 1991 Iraq War and Soviet Union's Collapse. The second recession occurred during the 1994 economic crisis in Mexico (Mexican Peso crisis) followed by another one (1997–1998) that might be triggered by two conjugated crises namely Asian and Russian Financial Crises. The Figures also depict a recession in the period 2000–2001 that seems coupled with three consecutive extreme events namely the 1999's big cut in OPEC oil production, the 2000's Housing Market Boom and the 2001 Terrorist Attack. Additionally, a period of double-Dip recession seems closely associated with a succession of several crises namely; 2002 Argentine crisis, the PdVSA workers strike, 2003 Iraq War and the 2004's Argentine energy crisis. Finally, the timing of the last recession (or double recessions appeared since 2006) perfectly coincide with the recent financial crisis, called the 2006–2010's US subprime crisis).

[13] It is important to note that we do not attempt to analyze the causality between the crude oil spike volatility and recessions but we are just trying to examine graphically the correlation between them at different time scale.

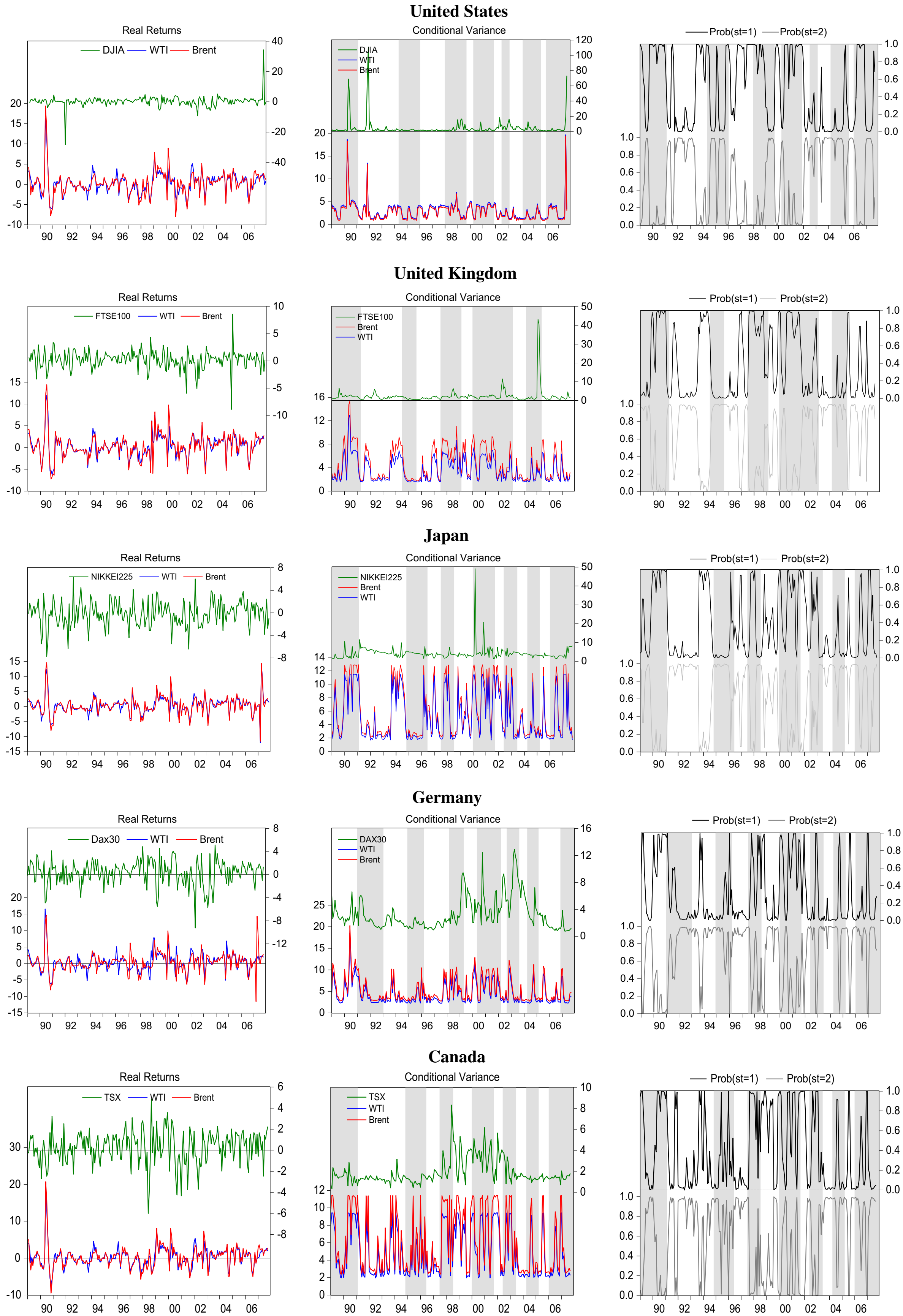

Fig. 5. The left vertical panel: monthly real stock market returns and the smoothed real crude oil volatilities. The second vertical panel: the conditional variances obtained from the trivariate RS-BEKK-GARCH model. The right vertical panel: smoothed probabilities of regime 1 and of regime 2 that the three markets are jointly in regime 1 (high volatility regime) at time *t* and in regime 2 (low volatility regime) at time *t* respectively. The shaded vertical bars indicate growth cycle recessions as dated by ECRI "Economic Cycle Research Institute." The sample period is January 1989 to December 2007, a total of 228 observations.

The 1994 recession in US, Canada lasted longer than that for UK, Germany and Japan. This result may highlight the closer economically intertwined relationship between Mexico and their northern neighbors. So any crisis that causes a sharp downturn in Mexico may be transmitted around the world showing more dramatic responses in neighboring countries than more distant ones. However the 1997–1998 recessions were longer for US and UK. The main difference in the business cycle's growth among these countries concerns the recession around 1990–1991. This later started earlier in UK, US, Canada while in Germany did not begin until two years later. On the other hand, Japan experienced double recessions during the same period. This result is relevant because it may demonstrate how the Middle Eastern oil dependence can expose the industrialized country to an economically-threatening disruption in oil supplies (in August 1990, these countries voted to impose an embargo on oil imports from Iraq and Kuwait) [69]. This may also emphasize the high costs of war and the military spending impacts on the economies of participating countries. Then, Germany and Japan who provided only financial assistance after the war instead of direct military assistance, show considerable delayed reactions to shocks compared to the other participating countries [70]. The recession in the early 2000 was long for UK, lasting about two years and shorter for Japan, whereas for US, Canada and Germany, two shorter recessions occurred close to each other during the same period. The recession of 2004 started and ended at about the same time while Japan had again two recessions during this period. In 2006, Canada, Germany and Japan sank into a recession at about the same time. However, this latter crisis did not hit UK.

The obtained wavelet coefficients were used to identify characteristics of the time-scale signal (smooth) that were not apparent from the original time domain signal. Therefore, it is shown in Fig. 4 (scale1 to scale 6) that crude oil volatility peak detections are easily perceptible in the finest scales (short-term fluctuations of the series) as well as in the coarsest scales (medium and long-term fluctuations of the series). From these plots, it is easy to see which peak features are meaningful at any specific time in world history. For example,[14] in levels 1–3, the wavelets do well in capturing the most intense volatility peak denoted by "A", which has a value of 6 or 7 and occurs on June/July 1990 for all the country cases. Essentially, this huge short-term real crude oil volatility peak leads to the 1990's recession. On the other hand, low frequency waves (scale 4–6) present fewer and thicker spikes with smaller lengths. For instance, wavelet is capable of capturing the long-term real crude oil volatility peak denoted by "B" which has a value of about 2 and occurs on 1999/2000. This one has followed the early 2000's recession. These plots highlight also the wavelet's strength of detecting pertinent information at varying decomposition levels. It can be seen that this evidence is also supported in the smooth series. Indeed, the studied period began with a huge oil shock in 1990 (Japan has a second largest oil shock which took place at the beginning of 2007). One can observe again that the spike of 1990 seems to be the historical at which the global economy can achieve a severe crisis. After this dramatic increase in real crude oil volatility, political controls try to stabilize the trend oil price to its equilibrium. The second highest real crude oil volatility, which rise and fall in a distinct series of spikes, was at the beginning of 2000 in almost all the countries. Furthermore, it is unequivocal that there exist several instances of coincidence of recessions with crude oil volatility spikes identified by the smooth series. Indeed, the initial spike volatility case was followed by a recession only for Germany and Canada[15] while the latter spike volatility case, on the other hand, was followed by a recession for all the economies. The other ECRI recession cases were preceded by rather small oil shocks.

Once we verify Hamilton's assumption, we achieve our analysis by improving further Â THW effectiveness; that is the possibility of noise level reduction while preserving the significant feature of the original signal. Indeed, although the original signal (Fig. 4 (top left panel)) presents several peaks that precede each identified international crisis, they are unfortunately noise contaminated.

It is apparent from the plot of the smooth series (Fig. 4 (top right panel)) that the noise is reduced but the peak height is also reduced slightly. Indeed, the smoothed peaks and original unsmoothed peaks are not perfectly coincident. This is not always the case as the presence of noise can shift the peak by 1–3 sample locations. The peak values after undergoing the smoothing algorithm are higher in amplitude than the noisy peak, and this agreement is typical of the better quality data. Finally, we could easily argue that the reconstructed signal has a simple and very smooth fluctuation that allows for easy interpretation.

Further examination of the figures led to the discovery that each spike in the oil volatility series was matched by transient instabilities in other economic indicator, including stock market returns [71]. Our interest lies whether oil price changes affect the stock market returns. Fig. 5 (left panels) plot real stock returns and the smooth real crude oil returns for each country. The relationships shown in this graph were correlative. Care thus has to be taken since correlation in time does not imply causation. Bearing this in mind, the hypothesis posed was that these recurring spikes of volatility in oil price destabilized the stock market returns.

3.3. Estimation results of the multivariate Markov switching model

Having the true real crude oil volatility signal in hand, in the analysis that follows, we are interested in investigating whether switches in this signal have a trend toward higher stock market volatility in the five developed countries. In particular, we assume that high volatility states coincide across the two markets and we use our data set to inquire whether these states coincide with the main international crises.

The estimation of our trivariate *BEKK* MSG (1,1; 2) as specified in Eq. (9) already gives us five three-market combinations where each one contains three variables: WTI real returns, Brent real returns and the respective individual real developed-country stock market returns (i.e., U.S., U.K., Germany, Japan, and Canada). We refer to the crude oil markets as "potential originators" and the stock markets as "potential recipient markets" because we want to explore whether shocks and volatilities originating from these markets are related with shocks and volatilities of the stock markets as in the following pairs of markets[16]:

In order to reduce the computational burden, we allow the triple markets, i.e. the recipient market (the stock market) and the two originator markets (WTI and Brent crude oil markets) to share the same volatility state. In this trivariate formulation, the number of states is six. For instance, for USA, we have the following six primitive states for each country case:

$s_t = 1$: DJIA real stock return – low volatility, WTI – low volatility, Brent – low volatility.

[14] This example is only illustrated in the case of Germany. The rest of figures generally report the same behavior.

[15] A potential explanation of this result is that a prolonged recession occurred in the beginning of 1988 (not included in our data set) were rather preceded by successive oil shocks and reaching the one of 1990 for US, UK and Canada.

[16] This idea has been inspired by that of Edwards and Susmel [72] who analyze the behavior of the stock market volatilities for a group of Latin America countries using both univariate and bivariate switching models.

Table 4
The likelihood ratio test.

	Ln_{MMSG}	Ln_{MS}	LR statistic
USA	−833.7	−898.9	130.4***
UK	−750.1	−782.7	65.2***
Germany	−842.9	−889.4	93***
Japan	−867.8	−886.7	37.8***
Canada	−785.7	−833.4	95.4***

Note: The LR test statistic approximately follows a χ2 distribution with three degree of freedom. Ln_{MMSG} denotes the log maximum Likelihood value of the Trivariate Markov Switching GARCH-BEKK model and Ln_{MG} designates the log maximum likelihood value of the Multivariate GARCH-BEKK model. ***, ** denotes significance at the 1 percent level.

$s_t = 2$: DJIA real stock return − high volatility, WTI − high volatility, Brent − high volatility

The conditional variance H is specified as a *BEKK* representation where the first element (h^2_{s,s_t}) of the diagonal matrix follows a *BEKK* MSG(1,1; 2) process and the two other elements (h^2_{w,s_t} and h^2_{b,s_t}) follow a constant. Regime switching is allowed through the conditional mean intercepts and all the conditional variance parameters.

These choices allows us to refine our aim which consists essentially in finding out whether shocks and/or volatilities originating from crude oil markets are transmitted to stock markets under a jointly “high−high” volatility state or “low−low” volatility state. Edward and Sumel [72] call the behavior under this hypothesis “high volatility synchronization” which signifies that when the “originator market” is in high (or low) volatility state, the “recipient market” is always in the high (or low) volatility state. Furthermore, we are interested in determining whether these identified transmissions happen around the time of the conventional international crises.

Therefore, it is important to use the best possible model specification. According to this idea, assuming a *BEKK* structure, we consider two different models: (1) a standard Trivariate GARCH model with $p = q = 1$ which we denote MG(1,1) and, (2) our trivariate MSG (1,1; 2).

In order to pick the most likely model, Table 4 summarizes the critical values of Likelihood Ratio (LR) test, suggested by Garcia and Perron [73]. The log maximum likelihood values for the MMSG (1,1,2) models are higher than for the case where no regime switching is allowed. Notice that the former performs much better than the single regime model. Additionally, one can directly see that the MMSG ranks better than the MS model according to the SIC, HQC and AIC criteria (not reported here).[17]

The results of estimating multivariate Markov Switching GARCH model with BEKK parameterization for each conditional mean and conditional volatility equation are reported in Table 5. Five triple-wise models are estimated and several interesting findings merit attention. It can be seen from the results that the three markets can be separated into two regimes. It is easy to interpret these two regimes. The first regime (labeled $s_t = 1$) indicates that all the real returns are at the same time in a “crash” state with low mean (a_S, a_W, a_B) and high variance (c_{11}, c_{22}, c_{33}). Conversely, regime 2 (labeled $s_t = 2$) captures the behavior of the real returns in the recovery state with high mean and low variance. These states can differ substantially in durations.

We derived the transition probability matrix for the “originator” and “recipient” markets. As it was assumed, the probability law that causes the market to switch among states is given by a $K = 2$ states Markov chain, P, with a typical element given by Prob ($s_t = j$/ $s_{t-1} = i) = p_{ij}$. From the estimated transition probabilities P_{11} and P_{22}, we can calculate the duration of being in each regime.[18] In the case of USA, the average expected durations of being in regime 1 and 2 are roughly equal (6.5 months). The expected durations of being in regime 2 for the rest of country cases are approximately twice as high as for those of being in regime 1. Thus, high variance states are less stable for UK, Germany, Japan and Canada. It is expected to persist as long as for the low volatility state in the case of USA.

One of the study’s key objectives is to find out whether the originator and the recipient market states, assumed to be in a joint high−high volatility states, occur around the identified international crises episodes. Put it differently, we verify whether the “volatility synchronization” between the cycles of stock market and the crude oil market happen around the conventional economic recessions.

To verify this hypothesis graphically, we plot the smoothed probability for the two states $s_t = j$ ($j = 1,2$) in the right panels of Fig. 5. These figures display both the probability that crude oil market and stock markets are jointly in a high-volatility state or state 1 (black line) and the probability that the two markets are jointly in a low-volatility state or state 2 (gray line). The observations are classified following Hamilton’s [74] proposed method for dating regime switches. According to this procedure, an observation belongs to state i if the smoothed probability $\Pr(s_t = i|\psi_t)$ is higher than 0.5.

These figures show that regimes are seen to change frequently although the states are quite persistent. Table 6 compares the ECRI turning points for the five developed countries and the joint high − high volatility periods obtained from our regime switching models. In order to concentrate on the transmission of high volatility from crude oil market to stock market, in the discussion that follows, we focus mostly on the upper line of the bottom panel. As regard to the dating results of the joint high − volatility regime, the model is able to delineate all the identified international crises. Additionally, the figures show that around each of the identified ECRI crises, crude oil and stock market jointly experience high volatility states. Importantly, we should bear in mind that there might be other factors, apart from crude oil volatility, such as bad economic news that could help explain the past behavior of the stock market. Specifically, the official announcement about whether the economy had entered into a recession can have an impact on the performance of the stock market since the majority of investors become more fearful of a reversion to recession. We cite for example the study conducted by McQueen and Roley [75] who found that stock prices respond strongly to macroeconomic news announcements.

The common contraction periods differ in length and severity. The duration of the 5 or 6 contractions are ranged from 6 to 27 months for USA, from 5 to 24 months for UK, from 2 to 33 months for Germany, from 3 to 44 months for Canada and from 2 to 23 months for Japan (see Table 6). The longest joint recession probability (a range of two or more successive recessions occurred close to each other) is associated with the 1996 East Asian crisis for USA and UK, the economic recession of 2000 for Canada and Japan and the 1990’s Gulf war for Germany. Furthermore, it is obvious that the oil shock of 1990 induces the longest joint recovery period lasting about three years for Canada and Japan. In contrast, the oil shock of 2000 provokes the longest common recovery period for USA, UK and Germany.

The estimations of the econometric models are reported in Table 5. we first consider matrix Ö in the mean equation (Eq. (7)), captured by the parameters ì$_{ij}$ in Table 5, to see the link in terms of

[17] Diagnostic tests for the MG model are available upon request.

[18] The average duration of being in state 1 as suggested by Hamilton [74] can be calculated as: $D_i = (1 - P_{ii})^{-1}$.

Table 5
Estimates of the trivariate BEKK-MSG model.

Param.	USA	UK	Japan	Germany	Canada
Mean equation					
$\mu_{ss,s_t=1}$	0.43723***	0.0667	−0.05047	0.41293	0.37441*
	(2.533)	(0.157)	(−0.063)	(1.094)	(1.378)
$\mu_{ww,s_t=1}$	−0.86701***	−1.16371	−0.57928	−0.47747	−0.23688
	(−2.336)	(−0.69)	(−0.123)	(−0.656)	(−0.462)
$\mu_{bb,s_t=1}$	−0.81018***	−1.10085	−0.64003	−0.7421	−0.38566
	(−4.234)	(−0.598)	(−0.127)	(−0.971)	(−0.557)
$\mu_{ss,s_t=2}$	0.8655***	0.53434***	0.06613	0.69504***	0.41688*
	(4.122)	(2.786)	(0.151)	(4.57)	(1.791)
$\mu_{ww,s_t=2}$	0.753669***	0.71245*	0.60213	0.64799***	0.48967*
	(4.14)	(1.558)	(0.66)	(2.697)	(1.747)
$\mu_{bb,s_t=2}$	0.81946***	0.76233*	0.67792	0.71545***	0.54541*
	(4.234)	(1.56)	(0.683)	(2.86)	(1.604)
Variance equation					
$\gamma_{ss,s_t=1}$	1.01169***	1.21839***	1.08123***	1.09181***	0.72372***
	(9.3243)	(9.802)	(2.761)	(7.126)	(5.453)
$\gamma_{ww,s_t=1}$	1.38159***	1.58813***	1.84192***	1.70612***	1.75198***
	(14.069)	(3.002)	(8.559)	(7.316)	(13.123)
$\gamma_{bb,s_t=1}$	1.41483***	1.71815***	1.89504***	1.7876***	1.83818***
	(12.920)	(3.153)	(11.273)	(7.357)	(12.053)
$\gamma_{ss,s_t=2}$	0.82333***	0.79844***	0.64524***	0.24226	0.65601
	(5.2642)	(3.956)	(3.164)	(0.7963)	(1.226)
$\gamma_{ww,s_t=2}$	0.96959***	1.10553***	1.14041***	1.20845***	1.18165***
	(17.407)	(11.223)	(3.760)	(16.091)	(12.373)
$\gamma_{bb,s_t=2}$	1.0292***	1.13841***	1.19702***	1.27353***	1.23767***
	(15.981)	(10.396)	(3.110)	(15.761)	(11.523)
$\alpha_{ss,s_t=1}$	−0.08768	0.04765	0.35916	−0.16367*	−0.4012***
	(−1.287)	(0.053)	(1.032)	(−1.472)	(−3.828)
$\alpha_{sw,s_t=1}$	0.10004	−0.05232	−1.1248	0.56081*	−0.50581***
	(0.638)	(−0.804)	(−1.151)	(1.776)	(−2.642)
$\alpha_{sb,s_t=1}$	−0.08387	0.01302	1.05857	−0.57145***	0.32392*
	(−0.603)	(0.074)	(1.113)	(−2.108)	(1.894)
$\beta_{ss,s_t=1}$	−0.09402	−0.39355	0.0000	0.60485***	0.67594***
	(−0.093)	(−0.132)	(0.000)	(3.616)	(5.661)
$\beta_{sw,s_t=1}$	−4.84532	−1.15252	−0.61242	−0.03723	1.12084
	(−1.104)	(−0.166)	(−0.001)	(−0.045)	(0.07)
$\beta_{sb,s_t=1}$	5.96062	1.01243	−0.02393	0.21019	−0.81552
	(1.198)	(0.163)	(0.000)	(0.298)	(−0.064)
$\alpha_{ss,s_t=2}$	0.8655***	−0.67316***	0.05621	0.21307***	0.23979***
	(4.122)	(−2.327)	(0.647)	(2.617)	(3.5347)
$\alpha_{sw,s_t=2}$	0.89084*	0.02779	−0.34526	−0.11484	0.16314
	(1.795)	(0.048)	(−1.185)	(−1.296)	(1.116)
$\alpha_{sb,s_t=2}$	−0.27778	−0.06521	0.22148	0.15617*	−0.07771
	(−0.739)	(−0.303)	(0.981)	(1.81)	(−0.58)
$\beta_{ss,s_t=2}$	0.19619***	0.55125***	0.98334***	0.76459***	0.95601***
	(3.125)	(2.855)	(64.439)	(10.22)	(74.63)
$\beta_{sw,s_t=2}$	4.99591*	−1.02577	3.86618	0.68817	−1.28347
	(1.703)	(−0.155)	(0.026)	(0.186)	(−0.005)
$\beta_{sb,s_t=2}$	−7.89867***	0.71428	−2.97633	0.1982	0.84935
	(−2.389)	(0.14)	(−0.032)	(0.055)	(0.004)
Transition probabilities					
P_{11}	0.84493	0.78607	0.74283	0.66801	0.71520
P_{22}	0.84671	0.87895	0.85757	0.85954	0.81371
Residuals diagnostics					
Log-L	−833.757	−750.196	−867.844	−842.985	−785.767
SIC	−923.123	−839.488	−957.283	−932.351	−875.132
HQC	−889.507	−805.918	−923.62	−898.735	−841.516
AIC	−866.757	−783.196	−900.844	−875.985	−818.767

Notes: The regime dependent covariance matrices H evolves according to a trivariate RS-GARCH(1,1) equation with a BEKK representation. The diagonal elements "μ" in matrix Φ represent the constant mean coefficients. While the diagonal elements "γ" in matrix Γ represent the constant variance coefficients. Elements "α" in matrix A captures own and cross-market ARCH effects. Elements "β" in matrix B measure own and cross-market GARCH effects. Subscribers: *s*, *w*, and *b* denote real stock market returns, WTI and Brent real crude oil returns. Student-*t* statistics of parameters are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%.

returns across the markets in each triple case. The diagonal parameters $\grave{\imath}_{11,st=2}$, $\grave{\imath}_{22,st=2}$ and $\grave{\imath}_{33,st=2}$ for all the modeled triples equations are positively significant (except for Japan) and approximately equal during expansion phases, suggesting that financial markets and crude oil markets tend to become more stable and predictable during expansion regime. For instance, the average mean of the real DJIA return is 0.69% while for the real crude oil returns are 0.64% and 0.71% (respectively for the WTI and the Brent). In contrast, during high volatility states, these diagonal parameters are significant only for USA and Canada (for Canada, only one of the three parameters is significant; $\grave{\imath}_{11,st=1}$). However, as it is shown while stock market returns appear to be positive, crude oil markets are characterized by negative returns during recession states. This can demonstrate that high volatility regime in crude oil markets are on average more severe whereas American and Canadian stock markets seem to be more resistant to an economic slowdown. An equal plausible explanation is that: since the economy is oil-based (oil and natural gas are the energy sources for

Table 6
Reference and estimated recession periods extracted from the trivariate MS-GARCH model.

Country	Reference*	Regime 1 (recession)	Regime 2 (expansion)
USA	1.1989M01–1991M02 (26 months)	1. 1989M04–1989M09 (5 months)	a. 1989M10–1989M12 (3 months)
	2.1994M05–1996M01 (21 months)	1990M01–1991M05 (17 months)	1991M06–1991M09 (4 months)
	3.1998M01–1999M09 (21 months)	1991M10–1991M12 (3 months)	1992M01–1993M08 (20 months)
	4.2000M04–2001M11 (20 months)	2. 1993M09–1994M10 (14 months)	b. 1994M11–1995M04 (6 months)
	2002M07–2003M02 (8 months)	1995M05–1995M06 (2 months)	1995M07–1996M01 (7 months)
	5.2004M03–2005M08 (18 months)	1996M02–1996M06 (5 months)	1996M07–1996M11 (3 months)
	6.2006M01–2007M12 (24 months)	3. 1996M12–1997M07 (8 months)	c. 1997M08 (1 month)
		1997M09–1999M03 (19 months)	1999M04–1999M12 (9 months)
		4. 2000M01–2000M05 (5 months)	d. 2000M06–2000M09 (4 months)
		2000M10–2001M01 (4 months)	2001M02 (1 month)
		2001M03–2002M04 (14 months)	2002M05–2003M08 (16 months)
		2003M09 (1 month)	2003M10–2005M06 (21 months)
		5. 2005M05–2005M10 (6 months)	e. 2005M11–2006M06 (8 months)
		6. 2006M07–2007M02 (8 months)	f. 2007M03–2007M10 (10 months)
		2007M11–2007M12 (2 months)	
UK	1. 1989M01–1991M04 (28 months)	1. 1990M03–1990M05 (3 months)	a. 1990M06–1990M07 (2 months)
	2. 1994M07–1995M08 (14 months)	1990M08–1992M03 (20 months)	1992M04–1993M11 (20 months)
	3. 1997M07–1999M02 (20 months)	2. 1993M12–1994M11 (12 months)	b. 1994M12–1997M02 (28 months)
	4. 2000M01–2003M02 (38 months)	3. 1997M03–1997M07 (5 months)	c. 1997M08–1997M11 (4 months)
	5. 2004M03–2005M05 (15 months)	1997M12–1999M02 (15 months)	1999M03–1999M06 (4 months)
		1999M07–1999M10 (4 months)	1999M11–2000M03 (5 months)
		4. 2000M04–2000M06 (3 months)	d. 2000M07–2000M11 (5 months)
		2000M12–2002M01 (14 months)	2002M02–2003M02 (13 months)
		2003M03–2003M04 (2 months)	2003M05–2005M09 (29 months)
		5. 2005M10–2005M11 (2 months)	e. 2005M12–2006M08 (9 months)
		2006M09–2006M10 (2 months)	2006M11–2007M03 (5 months)
		2007M04 (1 month)	2007M05–2007M12 (8 months)
Germany	1. 1991M01–1993M01 (25 months)	1. 1989M03–1989M07 (5 months)	a. 1989M08–1990M03 (8 months)
	2. 1994M12–1996M03 (16 months)	1990M04–1990M06 (3 months)	1990M07 (1 month)
	3. 1998M03–1999M04 (14 months)	1990M08–1991M05 (10 months)	1991M06–1991M09 (4 months)
	4. 2000M05–2002M03 (23 months)	1991M10–1992M12 (15 months)	1993M01–1993M11 (11 months)
	2002M09–2003M08 (12 months)	2. 1994M12–1995M02 (3 months)	b. 1995M03–1995M11 (9 months)
	5. 2004M04–2005M02 (11 months)	1995M12 (1 month)	1996M01–1996M03 (3 months)
	6. 2006M11–2007M12 (14 months)	1996M04 (1 month)	1996M05–1997M11 (19 months)
		1997M12–1998M03 (4 months)	1998M04–1998M06 (3 months)
		3. 1998M07–1998M09 (3 months)	c. 1989M10 (1 month)
		1998M11–1999M01 (3 months)	1998M02–1999M03 (15 months)
		4. 2000M04–2000M07 (4 months)	d. 2000M08–2000M11 (4 months)
		2000M12–2001M01 (2 months)	2001M02 (1 month)
		2001M03–2001M07 (5 months)	2001M08–2001M09 (2 months)
		2001M10–2001M12 (2 months)	2002M01 (1 month)
		2002M02–2002M03 (2 months)	2002M04–2003M01 (10 months)
		2003M02–2003M04 (3 months)	2003M05–2004M11 (19 months)
		5. 2004M12–2005M01 (2 months)	e. 2005M02–2005M09 (8 months)
		2005M10–2005M11 (2 months)	2005M12–2006M02 (3 months)
		6. 2007M03–2007M04 (2 months)	f. 2007M05–2007M12 (8 months)
Canada	1. 1989M01–1991M02 (26 months)	1. 1989M04–1989M08 (5 months)	a. 1989M09–1990M07 (11 months)
	2. 1994M11–1996M06 (20 months)	1990M08–1991M06 (11 months)	1991M07–1991M12 (6 months)
	3. 1997M07–1998M07 (13 months)	1992M01–1992M03 (3 months)	1992M04–1993M11 (20 months)
	4. 2000M01–2001M09 (21 months)	1993M12–1994M02 (3 months)	1994M03–1994M04 (2 months)
	2002M06–2003M06 (13 months)	2. 1994M05–1994M06 (2 months)	b. 1994M07–1995M08 (14 months)
	5. 2004M04–2005M03 (12 months)	1995M09 (1 month)	1995M10–1996M02 (5 months)
	6. 2006M01–2007M12 (24 months)	1996M03–1996M04 (2 months)	1996M05–1996M07 (3 months)
		1996M08 (1 month)	1996M09–1997M11 (3 months)
		3. 1997M12–1998M07 (8 months)	c. 1998M08/M10 (2 months)
		1998M09 (1 month)	1999M06 (1 month)
		1998M11–1999M05 (7 months)	1999M11–2000M02 (4 months)
		1999M07–1999M10 (4 months)	d. 2000M07–2000M11 (5 months)
		4. 2000M03–2000M06 (4 months)	2001M03–2001M04 (2 months)
		2000M12–2001M02 (3 months)	2001M08–2001M09 (2 months)
		2001M05–2001M07 (3 months)	2002M06–2002M10 (5 months)
		2001M10–2002M05 (8 months)	2003M06–2004M10 (17 months)
		2002M11–2003M05 (26 months)	e. 2005M01–2005M09 (9 months)
		5. 2004M11–2004M12 (2 months)	2005M12–2006M09 (10 months)
		2005M10–2005M11 (2 months)	f. 2006M11–2007M02 (4 months)
		6. 2006M10 (1 month)	2007M05–2007M12 (8 months)
		2007M03–2007M04 (2 months)	

Table 6 (*continued*)

Country	Reference*	Regime 1 (recession)	Regime 2 (expansion)
Japan	1. 1989M01–1989M05 (5 months) 1990M03–1993M12 (46 months) 2. 1994M12–1996M01 (14 months) 3. 1997M03–1998M04 (14 months) 4. 2000M08–2001M12 (17 months) 5. 2004M01–2004M11 (11 months) 2005M04–2005M10 (7 months) 6. 2006M04–2006M09 (6 months) 2007M08–2007M12 (5 months)	1. 1989M05–1989M06 (2 months) 1990M02–1991M04 (15 months) 2. 1993M11–1994M10 (12 months) 1996M05 (1 month) 3. 1997M02–1997M03 (2 months) 1997M12–1998M04 (5 months) 1999M01/09 (2 months) 2000M02–2000M05 (4 months) 4. 2000M11–2001M06 (8 months) 2001M09–2002M05 (9 months) 2002M10 (1 month) 2002M12–2003M04 (5 months) 5. 2004M11 (1 month) 2005M09 (1 month) 6. 2006M08–2006M10 (3 months) 2007M04–2007M06 (3 months) 2007M08 (1 month)	a. 1989M07–1990M01 (7 months) 1991M05–1993M10 (30 months) b. 1994M11–1996M04 (18 months) 1996M06–1997M01 (8 months) c. 1997M04–1997M11 (8 months) 1998M05–1998M12 (8 months) 1999M02–1999M08 (7 months) 1999M10–2000M01 (4 months) 2000M06–2000M10 (5 months) d. 2001M07–2001M08 (2 months) 2002M06–2002M09 (4 months) 2002M11 (1 month) 2003M05–2004M10 (18 months) e. 2004M12–2005M08 (9 months) 2005M10–2006M07 (10 months) f. 2006M11–2007M03 (5 months) 2007M07 (1 month) 2007M09–2007M12 (4 months)

Note: *Growth rate cycle peak and trough dates from 1989 to 2007 (source: Economic Cycle Research Institute (ECRI)). Figures in parentheses indicate the average length of the period in month.

most processes, including transportation and electricity. Petroleum is a raw material for many chemical products as well), cheaper oil prices could reflect more reduced oil companies' spending bringing increased investment and driving stock prices up.

Japanese case clearly distinguishes itself compared to the rest of countries. It shows no significant effects on the means of any of the parameters studied either during recessions or during expansions phases.

Results from the constant parameters of the variance equations show that all the intercept terms except $\gamma_{11,st=2}$ for Germany and Canada, are positively significant. However the amplitude of these parameters is slightly reduced when volatilities switch simultaneously from state 1 to state 2. Interestingly, we observe that the variances of changes in stock prices are lower than those of changes in CO prices in both states, indicating that changes in CO market are more volatile. In other words, the crude oil market returns are much more uncertain (they have higher risk investment) than those of the stock market.

To demonstrate the stock market's response to crude oil market movement, Table 5 shows the estimated interaction parameters between the degrees of turbulence or stability emanating from real crude oil volatility series to real stock market returns.

We find that almost two stock markets utilized in our analysis are affected by news ($\acute{a}_{ss,st=1/2}$) and volatility ($\hat{a}_{ss,st=2}$) generated from their own markets, namely Dax30 and TSX during joint recession state. However, almost all the markets are affected by news (except for Japan) and volatility generated from their own markets during the joint expansion state. Moreover, the responses of the stock market volatility to news arrival in recessions and expansions are quite different. On average, the parameters are shown to be positive during expansions and negative during recessions (except for Japan). Thus stock market volatility usually increases on bad news (such as rising unemployment, rising oil prices) in good times. It follows that rising oil prices which is a bad news for the economy since it prompt concerns about inflation pressures are supposed to increase the stock market volatility during expansion phases. These findings are consistent with those of other studies such as Boyd et al. [76].

Table 5 provides results from estimating the model using equity markets and WTI, Brent crude oil markets subscribed by the letters *s*, *w* and *b* respectively.

Overall, we find that three out of five stock market returns (Dax30, DJIA and TSX) are indirectly affected by 'news' ($\acute{a}_{sw,st=1/2}$ and $\acute{a}_{sb,st=1/2}$) and/or volatility ($\hat{a}_{sw,st=1/2}$ and $\hat{a}_{sb,st=1/2}$) originated from WTI and/or Brent crude oil markets.

Fundamentally, the oil market is directly influenced by basic economic concepts of supply and demand which in turn are affected by a number of factors including; the OPEC petroleum policies, weather conditions, both production and the refining capacity, political events, rapid growth in the demand for oil by developing countries,…etc [39].

The results apparently indicate that FTSE 100 and NIKKEI 225 stock market returns do not receive significant shocks/volatility originating from crude oil markets either during joint high volatility state or during joint low volatility state.

Therefore the biggest danger to financial stability does not seem to have come from high increases in crude oil market volatility.

As shown in the second column panel of Fig. 5, excepting the abnormally increase (during the beginning of 2000 and 2005 for Japan and UK respectively),[19] UK and Japanese stock market volatilities still static all over the period although the presence of large spikes in the volatility of crude oil markets. Henceforth, despite the large dependency on oil,[20] UK and Japanese equity market returns are not interrelated during the last twenty years. This may indicate the important role that improvement in energy efficiency play in reducing oil shock transmission to the volatility of the stock market. Indeed, by the data of EIA (2009), UK and Japan have the lowest primary energy intensities of any countries since the oil shock of 1970's, indicating a higher efficiency compared to the other developed countries. Together, high volatility states in stock markets may be affected by diverse factors other than oil shocks such as interest rates or exchange rates [12].

Table 5 shows that the recessionary WTI (Brent) oil price shock ($\alpha_{sw,st=1}$ and $\alpha_{sb,st=1}$) are positively (negatively) and significantly transmitted to the high volatility state of the German Dax30 stock market. Then this transmission intensity switches to the joint

[19] Britain and Japanese stock market volatilities saw an unprecedented rise of about 50% (in 2005 and 2000 respectively) followed by rapid reversals. These meteoric rises may not be explained by any change in oil (or fundamentals), which barely changed during this period but may be indicative of explosive bubbles (including UK bubble of 2004-05 in asset market particularly housing market (OECD (2005) suggested that house prices were overvalued by 30% or more in 2003–04) and the IT-bubble when only the electronic sector was hit hard).

[20] Japan imports all of its oil. It is considered as the third largest oil consumer in the world (behind US and China) and the second largest net importer of oil (behind US) in spite of its limited domestic oil reserves and production. U.K. is largest producer of oil and natural gas in the European Union but it cannot produce enough oil to meet its domestic demand (EIA, 2008).

recovery state and becomes negative (positive) and insignificant (significant) with an amplitude of 5 times lower ($\alpha_{sw,st=2}$ and $\alpha_{sb,st=2}$). The finding for Canada can be interpreted in a similar way as for Germany with a difference in the amplitude and the sign of the coefficients $\alpha_{sw,st=1}$ and $\alpha_{sb,st=2}$ where the oil shock transmission switches from negative (positive) and significant during simultaneous high volatility state to positive (negative) and insignificant with an amplitude of 3 times lower during simultaneous low volatility state. However, there is no evidence of volatility transmission running from crude oil market to stock market.

This finding suggests that recessionary "external oil shocks" (WTI) affect the German and Canadian (Brent) stock markets by increasing their volatilities. On the other hand, reaching the expansion regime, the underlying shocks negatively affect the stock market volatility and their transmission intensities become much less pronounced or even insignificant. In contrast, the opposite happens for "domestic oil shocks". Indeed, they rather stabilize the underlying stock markets by decreasing their volatilities during the joint recessionary state. This may highlight the decreased role that hedging policy efficiency play in order to neutralize any potential oil price impact (particularly "external oil shocks") on the volatility of the stock market. Decision makers are advised to drive domestic oil production and seek renewable energy technologies in order to reduce its reliance on foreign oil.

It should be emphasized, as shown in Fig. 5 (second column panels) for Canadian and German cases, that these transmissions were concentrated during 1999–2004 the period of severe worldwide economic contractions (the bursting of the equity bubble of 1990, the US terrorist attack and the Enron scandals in 2001, the Argentine energy crisis, the Iraq disarmament crisis). They were opposite and weaker than that observed before and after those crises periods. Indeed, as clearly illustrated in these figures, the conditional variances of TSX and Dax30 varied dramatically over the period 2000–03 which coincides with the sharp increases in oil volatility. Together, as previously demonstrated in Section 3.2, these respective low frequency component of crude oil volatility shock take longer period to stabilize. Moreover, especially in the case of Canada, real Brent is more volatile and therefore far more vulnerable to the real TSX than do the real WTI.

The US stock market response differs systematically from that of other oil-importing countries. Table 5 shows that crude oil markets do not transmit any signals (shock or volatility) to the DJIA stock market return during common recession state. The significant coefficient on $\alpha_{12,st=1}$ shows that shocks of WTI arising during simultaneous low volatility states are transmitted positively and significantly to the DJIA stock market. There is also evidence of positive (negative) volatility transmission from WTI (Brent) oil market ($\beta_{12,st=2}$ and $\beta_{13,st=2}$) to the US stock market during those same periods. In addition, the DJIA stock market volatility is considerably sensitive to volatility coming from crude oil returns (4.9 and 7.8), underlying the major role that the crude oil plays in this country as the largest oil importer.

The positive transmission of the WTI's shock/volatility to the expansion phase of the USA stock market may underline the more vulnerability of this latter to shocks/volatilities coming from American sources of crude oil prices than those coming from the North Sea crude oil prices but not a level to lead to a stock market crash. These findings lead one to conclude that the increased dependence on American crude oil supplies and the decreased dependence on North Sea crude oil supplies as well as other policies undertaken by US may be viewed as a welcome prosperity in the stock market.

Gallo et al., 2010 [77] reveal, from their causality tests, that supply factors have more direct impact on oil prices (especially the recent fluctuations from 2001 to 2008) than consumption ones. Consequently, the more dependent an economy on foreign oil imports, the more it is exposed to supply disruptions, caused by unintentional or intentional acts;

(i) Intentional acts: the government of the producing country may undertake intentional forces illustrated by the so called "Resource nationalism" on a potential predominant importer of oil resulting in lower exports, either directly or indirectly. Luciani [78], among others, defines "the resource nationalism" as; "*the voluntary adoption of policies by national government of the producing country that restricts access to domestic crude oil resources to a subset of potential players, or create separation between domestic and international market, or directly impose quantitative limitations to production and exports*".

The reasons behind the resort to resource nationalism may be the exploitation, war, civil strife, terrorism…etc.

One of the most prominent examples of geopolitical developments that help illustrate this strategic action is the embargo on oil exports to the United States declared by the Arab members of the Organization of the Petroleum Exporting Countries (OPEC) in response to the US support for Israel in the war against Egypt and Syria (the fourth Arab-Israeli war of 1973).

(ii) unintentional forces i.e., involuntary reduction in production arising from incentive accidents and extraneous developments such as weather and natural disasters (hurricanes, earthquakes, volcano,…), labor disruption, sabotage and other unanticipated technical problems at the refineries. For example, since the recent war in 2003, oil Iraqi pipelines and installations have been frequently sabotaged eventually resulting in reduced export and domestic distribution of oil. The EIA (2006) estimated 315 attacks on Iraqi energy infrastructure between April 2003 and June 2006.

Consequently, greater reliance on foreign oil may pose a serious and increasing threat to the U.S. economy or even to the U.S. national security [79].

Hence, the less sensitivity of the DJIA stock market to the Brent crude oil shock may highlight the adequate strategic and economic protection undertaken by US to hedge against a threatening disruption in foreign crude oil supplies in times of wars, crisis, or natural catastrophe. We present some known hedging strategies and policies generally adopted by US in an effort to reduce its vulnerability to uncertain oil supplies and oil price shocks (for further discussion of policies see Parry and Daemstadlter [80].

(i) The US Strategic petroleum reserve (SPR): Major events in several Arab nations (such as 1974–74 oil embargo and the Persian Gulf War of 1990) underscored the importance of a strategic oil reserve in preventing future critical disruptions.

US created the largest SPR to store emergency supplies of crude oil owned by the US department of Energy. Major oil supply disruptions caused by unforeseen and geopolitical events had led to several calls for releasing oil from SPR (US department of Energy).

(ii) Increase its dependence on friendly and neighboring countries: Many authors declare that great dependence of a country on non-secure sources will result in ongoing threats to its national energy security [69].

Then, to provide stable and secure sources of oil, US is seeking to renewal their supply chains by moving them near-shoring close to it; in Canada, Mexico or somewhere in Latin America.

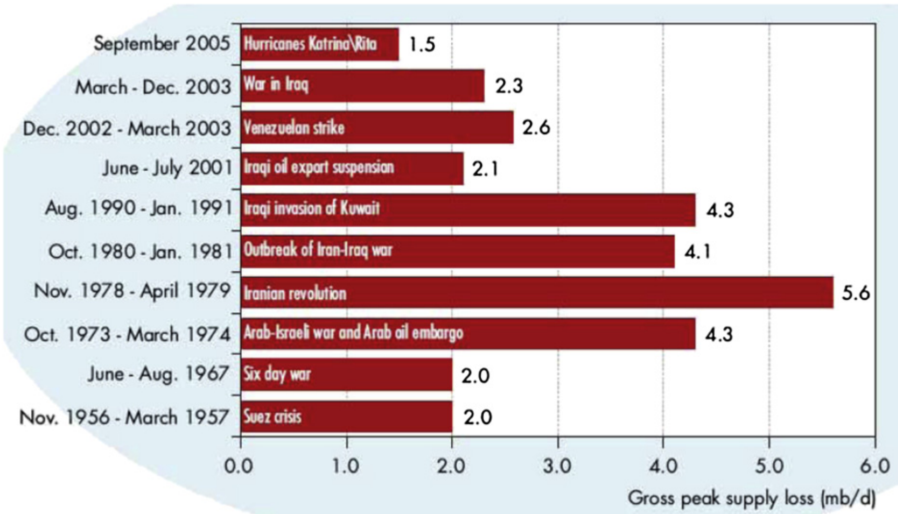

Fig. 6. Historical world oil supply disruptions: Magnitude of supply shortfall is the peak supply peak loss excluding supply increases of other oil producing countries. Source: IEA (2011).

As we can observe from Table 1, the majority of oil imported into the U.S. is from safe, friendly and neighboring countries, like Canada, the leading oil supplier since 2004. A bit less than 40% of US oil imports are, however, from countries always regarded as the world's most politically unstable and hostile to the U.S. interests (or have the potential to be) [81].

Foreign sources of oil are becoming less secure against supply chain disruptions caused by many external uncontrollable factors such as civil wars and terrorism in particular [82]. This does not mean that critical infrastructure in the US, Canada, Mexico or Latin America is immune, but they are generally more secured and protected from intentional incidents such as war and intrastate violence than comparable infrastructure in the Middle East and Nigeria. And it can deal more easily with the disruptions if they occur.

The IEA (2011) presents a background of major past oil supply disruptions (see Fig. 6). We can clearly observe that significant and larger oil supply disruptions have occurred in the Middle East and African countries such as the Iraq-Iran war, the Iraqi invasion of Kuwait, the supply hiccups caused by the third Gulf war, the political and economic turmoil in Nigeria and Russia and the civil wars in Angola, Sudan and Algeria (not included in the IEA list for more information see [78]) and more recently the Libyan revolution. Also, the U.S. suffered disruptions from political instability in Venezuela (general strike of 2002–03) as well as the natural disasters in Mexico (Hurricane Katrina of 2005).

Henceforth, although the vulnerability of DJIA to domestic and neighboring oil sources seem also inevitable, it still face less risk from short term supply disruptions as U.S. oil production area has suffered from a minor and transient geopolitical instabilities compared to the Middle East.

At the same time, although, Latin America holds the third position among the most politically unstable regions in the world during the post-war era (1955–2003) [83], Venezuela and Colombia (among the top 10 oil exporter to US) have lower average instability than Middle East and Sub-Saharan regions as they were consistently democratic [84].

Indeed, the overall threats caused by Latin America's instability and violence are not persuade as risk factor for US energy security since according to Dunning [85], Latin America's oil producer appear to be immune to the effects of the so called "oil curse" while petroleum wealth in the rest of the world has encouraged violent conflicts due to the hindrance to democracy.

Under such evidence, U.S. and its closest neighboring oil producing countries can usually handle conflicts in an amicable and equitable manner by negotiation given the mutual longstanding economic interests to both nations [86]. For example, while Venezuelan foreign policy has repeatedly conflicted with US interests since 1999, "*US patronizes Venezuela for its convenient and cost effective location*"[21] (Diebold [87], p.20). By way of illustration, Table 1 would appear to demonstrate that despite the abrupt curtailment in Venezuela's oil exports to U.S. caused by the general strike of 2002–2003 (the rate has fallen from 16.5% in 2001 to 15 and 14 in 2002 and 2003 respectively), U.S. continued access to this important source of oil making Venezuela the 2nd largest U.S.'s oil exporter in 2004 and 2005 respectively. On the other hand, the U.S. remains Venezuela's largest trading partner. In 2009, 42% of total Venezuelan exports went to the US, and 24.2% of total Venezuelan imports came from the U.S. (US department of state).

(iii) "US Middle East oil independence" program[22] [88]

The predictions about the decline in the existing world production volume of oil fields, and the relentless growth of oil demand particularly in China and India[23] may both contribute to a continuing drop in the U.S. foreign oil consumption [90].

Practically, many American politicians (George W. Bush, among others) had worked toward reducing the dangerous dependence on Middle Eastern suppliers to get long term immunity to the risks of any future oil supply disruption, to cut the risk "premium" for oil and to ensure national security (by stopping enriching the sponsors of terrorism which are financed by the oil wealth). For instance, following the attacks of 11/09, George W. Bush(among others) said in his 2006 State of the Union Address, that "*Breakthroughs on this and other new technologies will help us reach another great goal: to replace more than 75 percent of our oil imports from the Middle East by 2025*" (ENS).

[21] Venezuela has the least expensive petrol in the world because the consumer price of petrol is so heavily subsidized.

[22] For more information see the articles "US energy independence" (Wikipedia), "Journey for energy independence" (AEI) and "future of oil" (IAGS).

[23] In 2008, Chinese crude oil imports, largely concentrated in the volatile Middle East, was roughly 4 times higher than in 1978 (Leung [89]).

Then the growing gap between consumption and domestic production may help address the U.S. strategic interests in the Middle East region given its oil reserve and its position as an energy-rich region [91].

Indeed, over 63% of proven world oil reserves are controlled by Middle Eastern regimes that restrict access to large quantities of oil, (Saudi Arabia (22%), Iran(11.4%), Iran(10%), UAE (8.5%), Kuwait(8.4%), and Libya(3.1%)). However, less than 37% of the world's known oil reserves are shared between North America (5.5%), central and Latin America (9%), Europe and Eurasia (9.2%), Africa (9%), Asia Pacific (4.2%) and Former Soviet Union (7.6%) (BP SRWE, 2003). Additionally, for 19 year projection (2002-base year), they will control 83% of global oil reserves while oil production in the non-Middle Eastern countries (such as Russia, Mexico, U.S., Norway, China and Brazil) is projected to fall in less than two decades and where production is becoming increasingly cost prohibitive. Together, the demand for oil in China and India is expected to rise by reaching that of US and overtaking that of Europe (WOO, 2010).

(iv) Diversification of oil supply' sources.

From Table 1, we observe that U.S. stay focused on the goal of preserving a stable access to geographically and politically diversified sources of oil in order to minimize the likelihood of severe disruptions. Apart from South America, West Africa such as Nigeria and Angola remain important sources of diversity in the US oil supply.

Indeed, US relies mainly on oil imports from these "*safe zones*" because the production is profitable only if prices remain very high while the extraction costs in North America and the North Sea continue to climb [92].

(v) Reduce the nation's dependence on oil:

Cologni and Manera [71], among others, report that oil prices seem to have lost their ability to shock macroeconomics, in recent years. Importantly, Miller and Ratti [13] declare that improvements in energy efficiency may play a particularly important role in reducing the vulnerability of the stock market to oil shocks. U.S. energy intensity-the amount of energy consumed per unit of output- registered a decline of 27% from 1990 to 2008.

However, the U.S. currently imports more than half of the oil consumed, 69% of which is used by the transportation sector (EERE). Over 70% of petroleum and petroleum-related products will be imported from volatile oil-rich countries between 2007 and 2030 (AEO, 2007).

To neutralize the inflationary effects of oil shocks and to reduce global warming pollution, the U.S. administration is planning to cut dependence on oil imports by one third by 2025. To reach this goal, policy makers should focus on the consumption side of oil, especially in the transportation sector by developing new fuel-efficient vehicles of all kinds, encouraging renewable energy technology…etc.

In sum, all these policies may help making the stock market more resilient to crude oil supply disruptions especially those from the North Sea oil supplies (among them the Middle East often considered as the most unstable countries in the world).

The economic intuition for our main findings is most easily explained with reference to the second column panel of Fig. 5. In this panel the crude oil variances vary considerably over time and low spikes (state 2) are associated with very moderate investments in stocks but large spikes (1999–2004). In contrast sharp spikes (state 1), are associated especially with small stock and reduced allocations (the two subsequent high volatility periods occurred in 1990 and the other one appeared in 2007). Because regimes are persistent, short-horizon investors clearly attempt to time the market by reducing (increasing) the allocation to the riskiest assets when investment opportunities are poor (good) based on the information offered by the crude oil market volatility.

As there is no spillover effect between the stock market and crude oil market for USA during the joint high volatility sate, the potential for making riskless excess profit on the U.S. stock market, in very less time, based on information from say, WTI (for example) is limited. Except for these periods, Volatility in U.S. equity markets remained generally low.

4. Summary and concluding remarks

In this paper, we use monthly stock market prices and two crude oil data (WTI and Brent) for a group of five developed countries (USA, UK, Germany, Japan and Canada) to quantify the magnitude and time-varying nature of volatility spillovers running from the crude oil market to the equity markets (DJIA, FTSE100, Dax30, NIKKEI225 and TSX).

Under the objective of finding the most efficient way to model the behavior of crude oil price volatilities; we use wavelet filtering, particularly Trous Haar wavelet decomposition method, as it has been proved very useful in providing a better insight into the dynamics of financial time series.

Moreover, most studies assume that the relationship between variables (especially asset returns) is generated by a linear process with stable coefficients so the predictive power of state variables does not vary over time. However, there is mounting empirical evidence that spillover parameters follow a more complicated process with multiple "regimes", each of which is associated with a very different distribution of asset returns. The restricted trivariate *BEKK MSG* model used in our analysis is quite general and allows means, variances and parameters of shock/volatility transmission to vary across states. Hence assuming that the two variables are in common states, the stock market return can vary across states in response to a shock or volatility originating from the crude oil market.

The results show that the *HTW* decomposition method appears to be an important step toward obtaining more accurate results. Indeed, we find that it seems to be very important in detecting break-points, which implies that crude oil shock intensity varies significantly through time. Further, the resulting signals are smooth and give us a better approximation or reconstruction of the original signal. We also improve accuracy of this variable in detecting key real crude oil volatility features.

On the other hand, the trivariate *BEKK-MSG* estimations suggest that, the connections between the joint equity and crude oil high volatility state and international recessions is fairly close. Additionally, apart from UK and Japanese cases, the responses of the stock market to an oil shock depend on the geographic area for the main source of supply whether from the North Sea or from the North America (as we take two oil benchmarks WTI and Brent respectively). Then, for Germany and Canada, external oil sources are more helping to cause a stock market crash even if these countries import less oil from abroad (Western America for Germany and Europe for Canada). It is seen as risks that may make the stock market more vulnerable since it depends on dangerously volatile oil markets. Put it differently, for an oil importing country like Germany (Canada), higher real crude oil price shocks coming from non European countries; North America (from Europe, Africa and Middle East) destabilize more the stock market perhaps enough to plunge it into a recession. However, oil shocks coming from Eurasian or European countries (North America) appear to be far less vulnerable.

The results for the US stock market volatility response to the crude oil shock or volatility are different. Indeed, WTI crude oil volatility (American sources of oil) increases the DJIA stock market volatility whereas this latter exhibit inverse reaction to the Brent crude oil. The US stock appears to be more resilient to crude oil shocks since even they exist they do not lead to a potential stock market crash.

However, Japanese and Britain equity markets do not show any reaction to shocks and/or volatilities coming from crude oil market.

Our results might be interesting to:

(1) Investors; for example, knowing that the current crude oil market state is a persistent bear state, coincident with a potential recession period, and having positive shock/volatility transmissions reflect most risky assets and more attractive than in a bull crude oil market state where the transmissions became insignificant or smaller in magnitude.
(2) Monetary policy makers; the obtained results suggest that there are divergences between the hedging performance of WTI and Brent. For example, the presence of a positive transmission of the temporary WTI oil price shocks to the recessionary stock market phase highlights the decreased hedging policy efficiency in Germany to neutralize WTI oil price effect on the volatility of the German Dax30 stock market. Reaching the expansion phase, the opposite happens but shocks take longer period to stabilize. Here, monetary policy may play a more active role as a stabilizer absorbing the effect of the high oil prices of the Brent on German economy more than it do for the WTI.
(3) Energy policy makers; since German stock market may be more vulnerable to WTI shock than Brent shock (the inverse case for Canada), the government should import little to none oil from WTI crude main production countries by diversifying sources and promote incentive for alternative energy sources development (both in industrial and household sectors), so that it is not dependent on any one area outside the Brent crude main source countries. Conversely, the results for the U.S.'s case can be attributed to the successful efforts by American policy makers to renew efficient energy since it depend mostly on WTI often referenced in North America.

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Appendix A.1. Discrete wavelet transform

Contrary to the trigonometric functions, wavelets are defined in a finite domain and unlike the Fourier transform they are well-localized with respect to both time and scale. This behavior makes them ultimately useful to analyze non-stationary signals. The other most important property of the wavelet method is that it can be used to recreate a series without loss of information. Indeed, the wavelet transform techniques split up a signal into a large timescale approximation (coarse approximation) and a collection of "details" at different smaller time scales (finer details). The coarse image preserves the large-scale structure and the mean of the image whereas the "detail" or wavelet levels complement the coarse level and thus preserve the total image information. The first step of the wavelet de-noising method is the application of filters. The dilation and the translation of the basis functions at different resolution levels are described by the scaling function φ, the so-called *father wavelet* [93] given by:

$$\phi_{j,k}(t) = 2^{-j/2}\phi\left(2^{-j}t - k\right) \text{ or } \varphi(x) = \sum_k h_k \times \varphi(2x - k) \quad \text{(A1)}$$

h_k denotes the low-pass filter coefficients. The low pass filter is a filter that allows only low frequency signals through its output, so it can be used to reduce the amplitude of signals with high frequencies. Detail levels are generated from the single basic wavelet ψ, the so-called *mother wavelet*:

$$\psi_{j,k}(t) = 2^{-j/2}\psi\left(2^{-j}t - k\right) \text{ or } \psi(x) = \sum_k g_k \times \varphi(2x - k) \quad \text{(A2)}$$

Where $j = 1 + \ldots + J$ in a J-level decomposition. g_k is called the high-pass (or a band-pass) filter coefficients closely related to the low-pass filter (h_k) mentioned above. The high pass filter does just the opposite, by allowing only frequency components below some threshold.

The father wavelets are used to capture the smooth, low frequency nature of the data, whereas the mother wavelets are used to capture the detailed and high frequency nature of the data. The father wavelet integrates to one, and the mother wavelet integrates to zero [94]. Then, an original signal $f(t)$ in $L^2(R)$ may be expanded approximately using these two basic wavelet functions (φ and ψ):

$$\begin{aligned} f(t) &\approx \sum_j \sum_k \alpha_{j,k}\phi_{j,k}(t) \approx \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\phi_{J,k}(t) + \ldots \\ &\quad + \sum_k d_{1,k}\phi_{1,k}(t) \\ &\approx \sum_k s_{J,k}\phi_{J,k}(t) + \sum_j \sum_k d_{j,k}\psi_{j,k}(t) \end{aligned} \quad \text{(A3)}$$

Where $s_{J,k} = \langle f(t), \phi_{j,k}(t)\rangle$ and $d_{j,k} = \langle f(t), \psi_{j,k}(t)\rangle$ are the wavelet coefficients. The coefficients $s_{J,k}$ and $d_{j,k}$ are the smooth and the detail component coefficients respectively and are given by the projections:

$$s_{J,k} = \int \phi_{J,k} f(t)\mathrm{d}t \quad \text{(A4)}$$

$$d_{J,k} = \int \psi_{J,k} f(t)\mathrm{d}t \quad \text{(A5)}$$

Appendix A.2. Generalized regime switching GARCH model with path dependent volatility

According to Haas and Mittnick [95], we derive in this section, the multivariate *BEKK MSG* process. Let us suppose that the joint process for a given number of series is governed by the following set of equations:

$$\begin{aligned} R_t &= \Phi + E_t \\ e_{t,s_t} &= H^{1/2}_{\Delta_t,t}E_t \quad E_t/\Omega_{t-1} \rightarrow N(o_{M\times 1}, I_M) \end{aligned} \quad \text{(A6)}$$

Both the return R and the variance H are made regime dependent. Let R_t be the return matrix at time t, modeled as a constant plus a disturbance term. Φ constitutes the constant vector, I_M denotes the identity matrix of dimension M, The transition between the successive states is governed by a first order Markov process $\{\Delta_t\}$ with finite state space $S = \{1, 2, \ldots, k\}$ and a primitive (i.e., irreducible and aperiodic) fixed $k \times k$ transition probability matrix P,

$$P = \begin{bmatrix} p_{11} & \cdots & p_{k1} \\ \cdots & \cdots & \cdots \\ p_{1k} & \cdots & p_{kk} \end{bmatrix} \tag{A7}$$

Where the transition probabilities are given by $p_{ij} = p(\Delta_t = j/\Delta_{t-1} = i)$, $i,j = 1,\ldots,k$ The regime-dependent covariance matrix H is assumed to follow a *Multivariate Markov Switching GARCH*(p,q,k)) in Vech form as introduced by Bollerslev et al. [96];

$$h_{jt} = \gamma_{0j} + \sum_{i=1}^{q} \alpha_{ij}\eta_{t-i} + \sum_{i=1}^{p} \beta_{ij}h_{jt-i} \quad j = 1,\ldots,k \tag{A8}$$

Where $\alpha_i = [\alpha'_{i1},\ldots,\alpha'_{ik}]'$, $i = 1,\ldots,q$ and $\beta_i = [\beta'_{i1},\ldots,\beta'_{ik}]$, $i = 1,\ldots,p$ are parameter matrices of appropriate dimension. The number of the independent element of the regime-dependent conditional covariance matrices H_{jt}, is $N := M(M+1)/2$. The "squared", (ee'_t) in $h_{jt} := \text{vech}(H_{jt})$ and $\eta_t := \text{vech}(e_t e'_t)$, respectively.

One big disadvantage on using the model defined in (8) is that the positive definiteness of the estimated conditional covariance matrices is not guaranteed [97]. Every covariance matrix must be positive definite but for this model it is probably impossible to give general restrictions on parameters to insure a positive definite covariance matrix. To make the application trustworthy, parameter constraints are required. Such a parameterization is provided by the Baba et al. (1993) (BEKK) representation of Baba et al. [98] which specifies the conditional volatility as

$$H_{jt} = \gamma^*_{0j}\gamma^{*\prime}_{0j} + \sum_{l=1}^{L}\sum_{i=1}^{q} \alpha^*_{ij,l} e_{t-i} e'_{t-i} \alpha^{*\prime}_{ij,l} + \sum_{l=1}^{L}\sum_{i=1}^{p} \beta^*_{ij,l} H_{t-i} \beta^{*\prime}_{ij,l}$$
$$j = \{1,\ldots,k\}$$

Where γ^*_{0j} are $k \times k$ lower triangular matrices of state dependent coefficients, L is the lag operator. γ^*_{0j}, α^*_{ij} and β^*_{ij} are state dependent matrices. By recombining the GARCH model to regime switching and given h_0^2, recursive substitution in a univariate *MS-G* (1,1) model yields [26]:

$$h^2_{t,s_t} = \sum_{i=0}^{t-1}\left(\gamma_{s_{t-i}} + \alpha_{s_{t-i}} e^2_{t-1-i}\right)\prod_{j=0}^{i-1}\beta_{s_{t-j}} + h_0^2 \prod_{i=0}^{t-1}\beta_{s_{t-i}} \tag{A9}$$

Although the *BEKK* model involves far fewer parameters than the unrestricted *vech* form, the conditional variance as specified in Eq. (A9) suffers from the path dependence problem. Indeed, in this formulation, the state dependent conditional variances are a function of the lagged values both the lagged aggregated variances and aggregated error terms (after integrated the unobserved state variable).

Appendix A.3. The path-independent conditional variance

Using Gray [25]'s recombining method at time 1, the path-independent conditional variance, residual and covariance for the stock market variance-covariance equation are, respectively, given by:

$$\begin{aligned} h^2_{s,t} &= E\left(r^2_{s,t}|\psi_{t-1}\right) - E\left(r_{s,t}|\psi_{t-1}\right)^2 \\ &= p_{1,t}\left(\mu^2_{s,1} + h^2_{s,t,1}\right) + (1-p_{1t})\left(\mu^2_{s,2} + h^2_{s,t,2}\right) \\ &\quad -\left[p_{1t}\mu_{s,1} + (1-p_{1t})\mu_{s,2}\right]^2 \end{aligned} \tag{A10}$$

$$\begin{aligned} e_{s,t} &= r_{s,t} - E\left[r_{s,t}|\psi_{t-1}\right] \\ &= r_{s,t} - \left[p_{1t}\mu_{s,1} + (1-p_{1t})\mu_{s,2}\right] \end{aligned} \tag{A11}$$

$$\begin{aligned} h_{si,t} &= Cov(r_{s,t}, r_{i,t}|\psi_{t-1}) \\ &= E\left[r_{s,t}r_{i,t}|\psi_{t-1}\right] - E\left[r_{s,t}|\psi_{t-1}\right]E\left[r_{i,t}|\psi_{t-1}\right] \end{aligned} \quad i = \{w,b\} \tag{A12}$$

Where;

$$E\left[r_{s,t}r_{i,t}|\psi_{t-1}\right] = p_{1t}(\mu_{s,1}\mu_{i,1} + h_{si,t,1}) + (1-p_{1t})\ (\mu_{s,2}\mu_{i,2} + h_{si,2}) \tag{A13}$$

$$E\left[r_{s,t}|\psi_{t-1}\right] = p_{1t}\mu_{s,1} + (1-p_{1t})\mu_{s,2} \tag{A14}$$

$$E\left[r_{i,t}|\psi_{t-1}\right] = p_{1t}\mu_{i,1} + (1-p_{1t})\mu_{i,2} \tag{A15}$$

With this definition, the conditional covariance depends only on the current regime, not on the entire past history of the process. The model is then state-independent and tractable even with large samples. A graphical illustration for the recombining method for *BEKK* Markov Switching model is shown in Fig. 3. The regime probability of being in state 1 at time t is:

$$\begin{aligned} p_{1t} &= \Pr(s_t = 1|\psi_{t-1}) \\ &= P\left[\frac{f_{1t-1}p_{1t-1}}{f_{1t-1}p_{1t-1} + f_{2t-1}(1-p_{1t-1})}\right] \\ &\quad +(1-Q)\left[\frac{f_{2t-1}(1-p_{1t-1})}{f_{1t-1}p_{1t-1} + f_{2t-1}(1-p_{1t-1})}\right] \end{aligned} \tag{A16}$$

Where

$$\begin{aligned} P &= \Pr[s_t = 1|s_{t-1} = 1] \\ Q &= \Pr[s_t = 2|s_{t-1} = 2] \end{aligned} \tag{A17}$$

$$\begin{aligned} f_{s_t} &= f(R_t|s_t = i, \psi_{t-1}) \\ &= (2\pi)^{-1}|H_{t,i}|^{-1/2}\exp\left\{-1/2e'_{t,i}H^{-1}_{t,i}e_{t,i}\right\}, \quad \text{for } i = \{1,2\} \end{aligned} \tag{A18}$$

$R_t = [r_{s,t}\ \ r_{w,t}\ \ r_{b,t}]'$ is a vector of crude oil and stock market returns at time t. H and e are defined in Eqs. (A8) and (A9), respectively. The steady-state probabilities of s_t used as the initial start value for the recursive expression of the regime probability is:

$$\left\{\Pr(s_t = 1|\psi_0) = \frac{1-Q}{2-P-Q}\right\} \tag{A19}$$

Where P and Q are state transition probabilities assumed to follow a logistic distribution defined as in the following equations;

$$\begin{aligned} P &= \Pr[s_t = 1|s_{t-1} = 2] = \frac{\exp(p_0)}{1+\exp(p_0)} \\ Q &= \Pr[s_t = 2|s_{t-1} = 2] = \frac{\exp(q_0)}{1+\exp(q_0)} \end{aligned} \tag{A20}$$

p_0 and q_0 denote unconstrained constant terms which have to be estimated along with the regression coefficients' system. Given the path independent *BEKK MSG* model as described by Lee and Yoder [22], the unknown parameters that we seek to estimate for our trivariate case model are $\{p_0, q_0, \mu_{s,s_t}, \mu_{w,s_t}, \mu_{b,s_t}, \gamma_{ss,s_t}, \gamma_{sw,s_t}, \gamma_{sb,s_t}, \alpha_{ss,s_t}, \alpha_{sw,s_t}, \alpha_{sb,s_t}, \beta_{ss,s_t}, \beta_{sw,s_t}, \beta_{sb,s_t}\}$ for $s_t = \{1,2\}$. We obtain the estimates parameters by maximizing the following log-likelihood function.

$$LL = \sum_{t=1}^{T}\log[p_{1t}f_{1t} + (1-p_{1t})f_{2t}] \tag{A21}$$

Where f_{it} for $i = \{1,2\}$ is defined as shown in Eq. (A18).

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