Energy Policy 38 (2010) 1415–1435

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Wavelet decomposition and regime shifts: Assessing the effects of crude oil shocks on stock market returns

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ARTICLE INFO

Article history:
Received 8 June 2009
Accepted 9 November 2009
Available online 3 December 2009

Keywords:
Oil shocks
Â Trous Haar Wavelet transform
Regime switches

ABSTRACT

While there is a large body of empirical studies on the relationship between crude oil price changes and stock market returns, they have failed to achieve a consensus on this subject. In this paper, we combine wavelet analysis and Markov Switching Vector Autoregressive (MS-VAR) approach to explore the impact of the crude oil (CO) shocks on the stock market returns for UK, France and Japan over the period from January 1989 to December 2007. Our procedure involves the estimation of the extended MS-VAR model in order to investigate the importance of the resultant wavelet filtering series (after removing random components) in determining the behavior of the stock market volatilities. We show that CO shocks do not affect the recession stock market phases (except for Japan). However, they significantly reduce moderate and/or expansion stock market phases temporarily. Moreover, this negative relationship appears to be more pronounced during the pre-1999 period. The empirical findings will prove extremely useful to investors who need to understand the exact effect of international oil changes on certain stocks prices as well as for policy managers who need a more thorough evaluation about the efficiency of hedging policies affected by oil price changes.

1. Introduction

Oil is an essential energy source worldwide. Overall consumption is on the rise as more and more of the word use industrial technologies and start using modern machine. In 2006, the United States is the largest consumer of oil and consumes over 20 million barrels each day, followed by china (7.6) and Japan (5) (EIA, 2006). Given the importance of oil, there have been abundant studies on the role of oil shock on various macroeconomic variables such as Gross Domestic Product (GDP), labor, inflation, exchange rates, financial markets, etc. The literature on this area is extensive including, among others, Hamilton (1983, 1985, 1988), Bernanke et al. (1997, 2004), Mork (1989), Tatom (1988, 1993), Lee et al. (1995), Keane and Prasad (1996), Huntington (1998), Caruth et al. (1998), Kandil and Mirzaie (2003), Hamilton and Herrera (2004), and Cologni and Manera (2008). Therefore, if oil prices play an important role in the economy (Hamilton (1983), in particular, demonstrates that increases in oil prices are responsible for declines in real Gross National Product (GNP) for importing countries, it is reasonable to expect the existence of correlations between changes in crude oil prices and fluctuations in stock prices. The important role of oil prices in determining stock prices has prompted a fewer number of empirical studies. Generally speaking, studies to date have mainly focused on filling out the questions on whether and how oil price fluctuations impact on stock market returns. Jones and Kaul (1996), Sadorsky (1999) and Ciner (2001) found a negative relationship between stock market returns and oil price shock while Chen et al. (1986) and Huang et al. (1996) do not. Wei (2003) argued that the decline of stock prices after the 1973/74 oil crisis seems too large to be explained by the rise in oil prices. Several earlier studies also confirmed the existence of negative relationship between these variables. Aloui et al. (2008) find that changes in CO prices cause significantly the volatility of the stock market returns of six developed countries using univariate and multivariate approaches. Park and Ratti (2008) report that oil price shocks have a statistically significant impact on real stock returns for US and 13 European oil importing countries. Bittlingmayer (2005) documents that large oil price increase associated with war risk and those associated with other causes exhibit an asymmetric effect on the behavior of stock prices. Kilian and Park (2007) report that only oil price increase driven by precautionary demand for oil associated with concerns about future oil supply shortfalls, negatively affect stock prices. Although many varied studies have been applied, there is no robust consensus about the effect of the CO shocks on the stock market returns. Explaining such a relationship is not easy because it is influenced by complex economic phenomena like structural

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doi:10.1016/j.enpol.2009.11.023

changes. Earlier studies supported the changing nature of the connection between real activity and oil prices. Blanchard and Gali (2007) found that oil prices present a minor effect on GDP in recent years and they assert several reasons for the moving back of this effect, including efficiency, improved monetary policy, and a lack of shocks. Cologni and Manera (2009), by comparing alternative regime switching models, report that the role of oil shocks in explaining recessionary episodes has decreased over time in G7 countries. This change in the relationship between oil prices and real activity in recent years from earlier decades is attributed to several causes including improvements in energy efficiency with a better systematic approach to external supply and demand shocks by monetary and fiscal authorities. In line with these studies, Miller and Ratti (2009) find that the expected negative long-run relationship between stock market indices and increases in oil prices appears to disintegrate after 1999:9.[1] They argue that this change in the relationship from earlier decades support the presence possibly of several stock market and/or oil price bubbles since the turn of the century. Since linear models are not able to capture asymmetries, regimes switching models have become progressively applied. There is a number of subsequent empirical studies to confirm the relationship between concepts of changes in cyclical phases and change in regime (Krolzig, 1997, 2001; Clements and Krolzig, 1998, 2000; Diebold and Rudebusch, 1996; Kim and Nelson, 1998, 1999, among others). The main advantages of the Markov Switching processes, often advocated in the literature, is their ability to capture nonlinear phenomena, to model temporal asymmetries as well as persistence of the macroeconomic time series (Diebold, 1986; Hamilton and Susmel, 1994, and Lamoureux and Lastrapes, 1990): these features are crucial in the analysis of the dynamic linkage between oil price shocks and the stock market returns (Aloui and Jammazi, 2009).[2] The Markov Switching Autoregressive time series model has become increasingly popular since Hamilton's (1989) application of this technique to measure the US business cycle. In particular, we try to investigate the nonlinear relationship between changes in crude oil prices and the real stock returns of UK, France and Japan based on a multivariate generalization of the Markov Switching model[3] introduced by Krolzig (1997) over the period January 1989–December 2007. However, given the high noise level in financial time series, conventional models may provide us with a distorted picture of economic relationships, tending to reflect average behavior over the states of the economy, rather than their distinctive features. In this paper, we intend to illustrate an application of wavelet methodology to market data on crude oil as an efficient tool for noise reduction followed by an estimation of the dynamic relationship between both "true" (generated or de-noised series) and "noisy" (original) oil price data and the stock market returns. Our method for noise detecting is based on that applied by Popoola et al. (2004) and Mitra (2006) among others. Wavelets are practically new variety of basis decomposition functions that are used to express and approximate other functions. They combine powerful properties such as different degrees of smoothness, localization in time and scale, compact support, and fast implementation. Wavelet coefficients are capable of revealing aspects of the data that other techniques might miss, such as changes in variance, level changes, and discontinuities, sharp spikes, etc. They are perfectly suitable for outlier detection (Bilen and Huzurbazar, 2002). Our wavelet methodology involves the application of the Discrete Â Trous Haar Wavelet transform (THW) technique inspired by Murtagh et al. (2004). This technique is a multiresolution approximation based on a low and high-pass filters capable of providing a smooth estimate (coarser approximation) and a collection of details (finer approximation) when it is applied to a non-stationary time series.[4] Once the high frequency components are removed from the original series, it is possible to test for regime switching behavior of their correlations to the stock market. Although wavelet theory is an emerging field of applied mathematics, THW has been proved to be a useful tool in analyzing various problems in geosciences, medicine, engineering, image processing, geophysics and related fields.[5] However, it has not yet been fully exploited in financial and economic applications. As a result, this study can be considered as additional evidence examining the effects of CO shocks on the stock market returns. It contributes to the existing literature in the following ways. First, we decompose CO prices using the new approach "à THW". To the best of our knowledge, this study serves as the first study that adopts the wavelet technique to decompose the CO prices. Second, we examine the effects of oil price volatilities (original and resultant wavelet filtering series) on the real stock returns using the multivariate three regimes Markov Switching Vector Autoregressive model[6] (MS-VAR), where we introduce the possibility of switches in the exogenous variable, in the mean, variance and the autoregressive parameters. The main estimation results of the empirical analysis imply that changes in crude oil prices have a temporarily effects on the stock market volatility during moderate and/or expansion regimes for UK and France. However, for Japan, changes on West Texas Intermediate (WTI) have an effect on the expansion stock market phase and these effects are sufficiently strong to plunge the stock market into a recession. Overall, we believe that the findings reported in this essay should be of considerable interest to researchers, policy makers and investors. The remainder of this paper is organized as follows: in Section 2, we discuss the methodology of "â THW" approach and we illustrate its application to the CO prices. In Section 3, we investigate the linear relationship between the original/wavelet resultant CO series and the three stock market returns based on the co-integration and the impulse-response function plots. In a second subsection, we present the theoretical framework of the nonlinear MS-VAR model as well as the results of estimations along with the analysis. In Section 4, we discuss the present state of energy conservation policy used in oil importing countries in order to help supporting the declining statistical relationship between oil shocks and stock market over time. Section 5 provides concluding remarks.

2. ÂTrous Haar wavelet decomposition and its application to CO prices

In this section, we briefly present the appropriate wavelet Transform method that we use to decompose the non-stationary signal of the CO prices.

[1] They estimate a vector error correction model (VECM) with three breaks namely, May 1980, January 1988 and September 1999.

[2] As Aloui and Jammazi (2009, p, 4) underline, one advantage of the proposed MS model is its sufficient flexibility to capture regime dependence in the impact, persistence and asymmetric response to a shock.

[3] This model is simple to estimate and has become warhorse in the last two decades.

[4] Renaud et al. (2005) and Benaouda et al. (2006) provide further details on the methodology.

[5] For review of the THW uses for the analysis of complex dataset, readers are referred to Renaud et al. (2003, 2005), Guoqiang (2005), Wegner et al. (2006) and Starck et al. (2007)

[6] Boldin (1996) and Clements and Krolzig (1998) found that Hamilton (1989)'s model (for more recent sample) confirm that to realize an adequate description of the US business cycle, it is required to introduce a third regime and a regime dependent error variance.

2.1. Methodology

The analysis of non-stationary signals calls for specific tools which go beyond classical Fourier. 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 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 original signal $X(t)$ is passed through a complementary set of low- and high-pass filters as specified in Mallat (1989). The dilation and the translation of the basis functions at different resolution levels are described by the scaling function φ (or father wavelet) as follows (Strang, 1989).

$$\varphi(x) = \sum_k h_k \times \varphi(2x\text{-}k) \quad \text{or} \varphi_j(x) = \sum_k h_k \times \varphi_{j\text{-}1}(2x\text{-}k) \tag{1}$$

h_k denotes the low-pass filter coefficients which determine the characteristics of the resulting wavelet transform. The second form of Eq.1 is used to proceed from one resolution level $j-1$ to next j and ϕ results from iteration for $j \rightarrow \infty$. Furthermore, ϕ integrates to 1. Detail levels are derived from the wavelet ψ (or mother wavelet) given by:

$$\psi(x) = \sum_k g_k \times \varphi(2x\text{-}k) \tag{2}$$

g_k denotes the high-pass filter coefficients closely related to the low-pass filter (h_k) mentioned above. 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 (Heil and Walnut, 1989). these wavelets satisfy the following conditions:

$$1/2 \times \psi(x/2) = \varphi(x)\text{-}1/2 \times \varphi(x/2) \tag{3}$$

The scaling function here is a cubic B-spline. Cubic B-splines offer a mathematically elegant framework for constructing the scaling function with various good features such as smoothness and other properties. The key point of the method is that it allows a non-recursive representation of the scaling function as a piecewise polynomial (Unser, 1999; Seymour and Widrow, 2002)

$$\varphi(x) = 1/12 \times \left[|x\text{-}2|^3\text{-}4 \times |x\text{-}1|^3 + 6 \times |x|^3\text{-}4 \times |x+1|^3 + |x+2|^3\right] \tag{4}$$

In this paper, we apply a redundant wavelet transform, i.e. the so-called â trous (with holes) algorithm that yields a non-orthogonal transform, to decompose the signal (original series). Its advantage lies in the fact that it is shift invariant and it produces smoother approximations by filling the "gap" caused by decimation, i.e., it is non-decimated (it conserves the original dimensions of the series). A detailed description of the properties of the â trous and the Mallat algorithm is given in Mallat (1989) and Shensa (1992). Using the â Trous wavelet transform, the scaling coefficients, c_j, and the wavelet coefficients, d_j of $x(t)$ at different scales can be obtained as:

$$c_0(t) = x(t)$$
$$c_j(t) = \sum_{l=-\infty}^{+\infty} h(l) c_{j\text{-}1}(t + 2^{j\text{-}1} \times l) \tag{5}$$

where $1 < j < J$, h is a low-pass filter.

Implementation of the algorithm is straightforward: in each step the series is convolved with a cubic B-spline filter, h, with

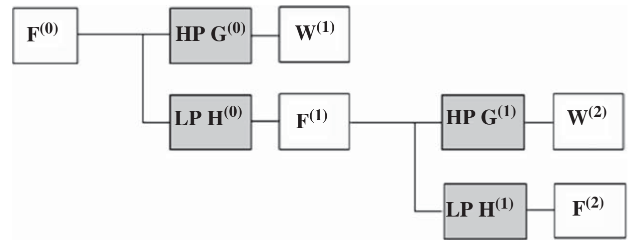

Fig. 1. Filter Bank structure of the â Trous wavelet Transform.

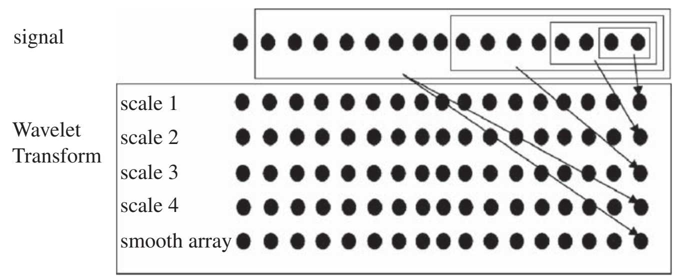

Fig. 2. the Redundant Haar wavelet Transform.

$2^{j-1} \times 1$ zeros inserted between the B-spline filter coefficients at level j, therefore the name "with holes". The convolution mask in one dimension is 1/16 [1, 4, 6, 4, 1]. Thus, we get a series of smoothed versions c_j with c_0 (the finest scale) as the normalized raw series. To obtain the wavelet coefficient (or detail signal) of $x(t)$ at level j, d_j, we take the difference between successive smoothed versions as given by:

$$d_j(t) = c_{j\text{-}1}(t)\text{-}c_j(t) \tag{6}$$

The set $d_1, d_2, \ldots d_J, c_J$ 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:

$$X(t) = c_J(t) + \sum_{j=1}^{J} \mathrm{d}_j(t) \tag{7}$$

c_J is the background or residual vector. The resolution scales are d_j and c_J.

Fig. 1 shows the architecture of the "â Trous wavelet transform" filter Bank.[7] Indeed, 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. Here, we select Haar wavelet filter to put into practice the â Trous wavelet transform. The asymmetry of the 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. (2004) develop a non-decimated or redundant version of this transform. The non-decimated algorithm is the â trous algorithm with a low-pass filter h equal to (1/2,1/2). Fig. 2 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.

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). Convolving the wavelet filter h with the original signal gives the wavelet coefficients. Then, the scaling coefficients at higher scale can be

[7] This figure is taken from the study of Wegner et al. (2006).

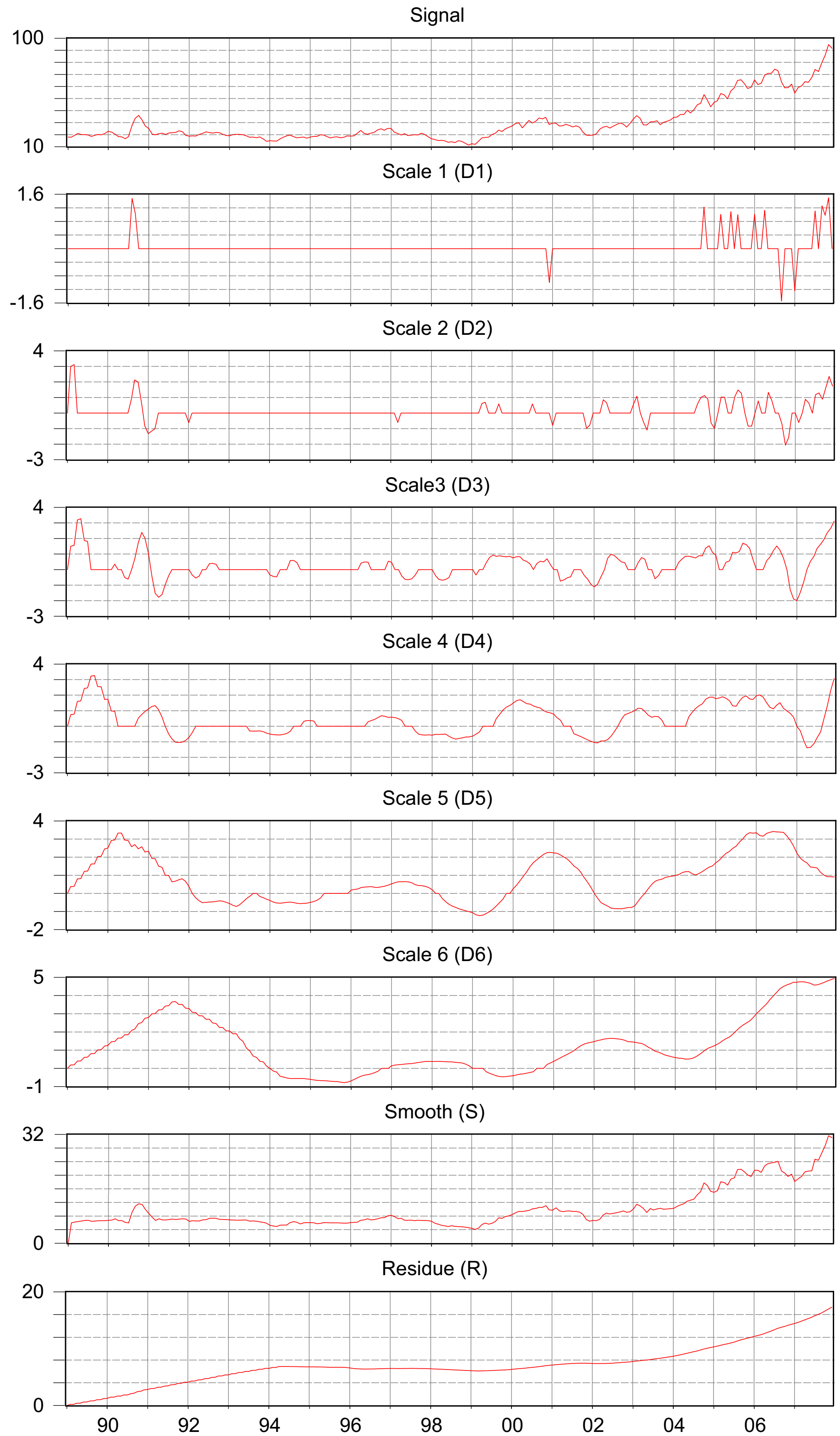

Fig. 3. Â Trous Haar Wavelet decomposition of the WTI Signal.

easily obtained from the scaling coefficients at lower scale:

$$c_{j+1} = \frac{1}{2}(c_{j,t\text{-}2^j} + c_{j,t}) \tag{8}$$

and

$$d_{j+1}(t) = c_j(t) \text{-} c_{j+1}(t) \tag{9}$$

2.2. Application

The input data consists of historical monthly west Texas Intermediate (WTI) and the Europe Brent spot prices (they are expressed in \$/bbl) for the period January 1989–December 2007. These data stem from the website of US Department of Energy. In

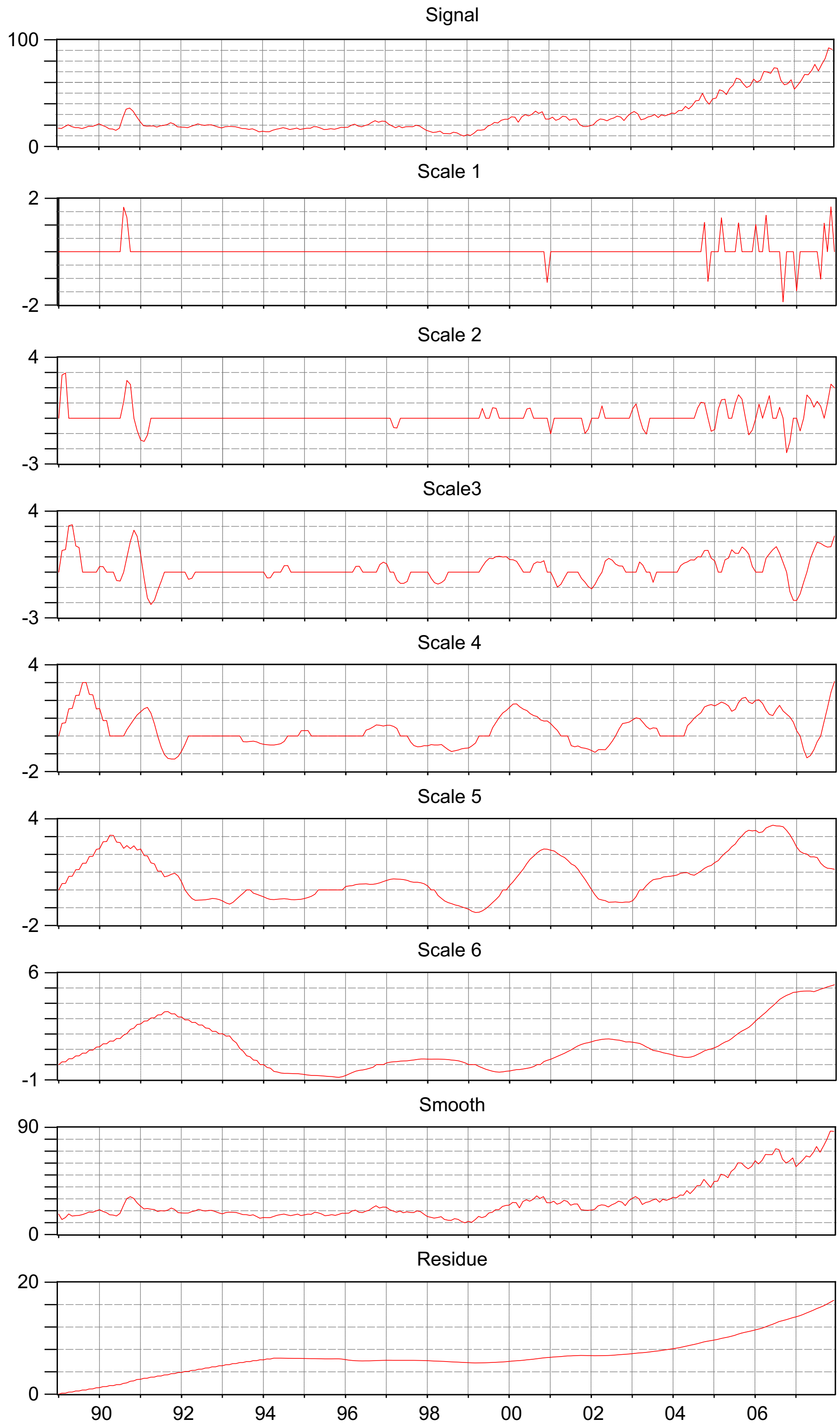

Fig. 4. Â Trous Haar Wavelet decomposition of the Brent Signal.

this section, we start decomposing the CO price series based on the THW transform with the aim of providing the true series that we will use to analyze their relationship to the stock market indices.

2.2.1. Wavelet decompositions:

The wavelet transform technique has been largely applied on non-stationary signals (Nason and Von Sachs, 1999). It is used to decompose non-stationary time series into different time scales and it provides useful information for the interpretation of the series structure and the analysis of its history. Crude oil price series are highly volatile and non-stationary in nature. In this work, initially monthly CO prices were used to assess the performance of the THW algorithm in getting a smooth component without losing the underlying characteristics of the respective series. The two given

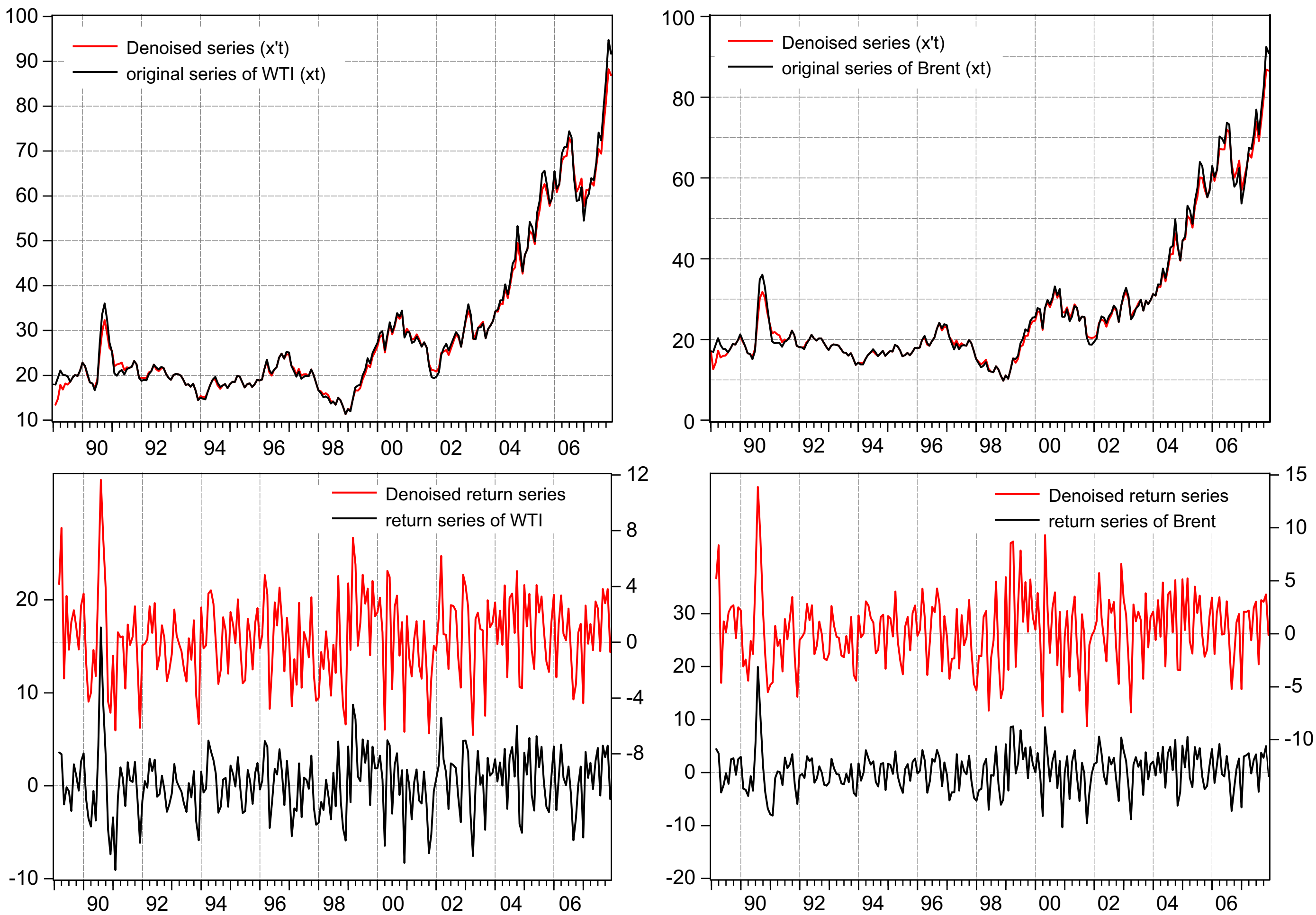

Fig. 5. Original and de-noised crude oil series: the vertical axes correspond respectively to the level of oil prices in US dollar per barrel (for the first raw panel) and their return rate (for the second raw panel).

Table 1
Descriptive statistics and unit root tests of de-noised and original series.

Variables	Mean	Standard dev.	ADF	KPSS
Original series:				
WTI	29.77	17.12	−0.47	0.417
Brent	28.24	16.92	−0.57	0.415
Diff. series:	0.358	3.384	−11.92***	0.221***
WTI Brent	0.369	3.835	−12.41***	0.203***
De-noised series:				
WTI	29.47	16.61	0.42	0.414
Brent	27.99	16.75	0.17	0.411
Diff. series:	0.313	2.990	−12.79***	0.158***
WTI Brent	0.323	3.390	−13.41***	0.156***

Notes: Number of observations is 228. ADF denotes the augmented Dickey-Fuller (1979) statistic for testing the null hypothesis that the series contains a unit root. KPSS denotes the Kwiatkowski et al. (1992) statistic for testing the null hypothesis that the series is stationary. Tests at the level of the series include intercept and linear trend while tests on first differences do not. Both tests indicate that all the series (original and de-noised) are non-stationary in levels but their log differences are stationary. *** indicate significance at 1% level.

series of the CO prices (x_t) are decomposed into their different time scales using the THW which is redundant or non-decimated decomposition method. The wavelet filter used in the decomposition is the discrete low-pass filter (B_1) of length, L=6.[8] The sifting processes produce six level details which are captured by $D_1 \dots D_6$ and one residue (R) plus the smooth part (S). At each scale, the corresponding component is reconstituted according to Eqs. 8–9. The THW decompositions of the monthly CO prices (the original signal) are shown in Figs. 3 and 4, in which the vertical axis represents the amplitude of scaling coefficient (in HERTZ) for the scale 1–6, and oil prices in US dollar per barrel for the signal and the smooth series. The multi-resolution analysis contains 6 scales each containing 228 samples. Cycles are not necessarily regular as the details can have various amplitudes over time. The standard deviations (SD) of each detail are not uniform across the series but proportional to the SD of the underlying signal. The residue (R) is slowly varying around the long-term average. Since we use monthly data, the first level of details represent the variations within a month or two, while the next levels 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 D_1 and D_2, and some in the third 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. These details exhibit very low correlation coefficients with the observed data and account for less than five percent of the total variance. This means that these scales do not have serious effect on crude oil prices. This latter feature allows to remove series noise and to retain significant coefficients on all wavelet levels as explained in the next section. However, the variance became higher at scales 4–6

[8] It has been observed that for improving decomposition accuracy using wavelet transform, the THW of order six gives the best performance.

suggesting that we were facing medium and long-term shocks to CO prices. 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 (Bilen and Huzurbazar (2002) and Tommi (2005)). Details 4, 5 and 6 show four major peaks or spikes. Indeed, during the studied period, there are four major peaks in crude oil prices in line with specific events in world history. The first most serious event which strongly affected crude oil market occurred in September 1991 due to the Persian Gulf War. The next two oil price peaks are accompanied respectively with the East Asian economic crisis (mid-1997) and the US terrorists attack (on September 11, 2001) whose effects appear to be far more serious and shorter lived than the previous event. In addition, the war in Afghanistan, the subsequent problems in Russia, the 2003 Iraq war and the 2006 Lebanon conflict have had some impacts. Another major factor cited is the accelerating Asian economic growth particularly China and India which have had a significant effect on the high demand for oil. The US subprime crisis has also driven-up oil prices leading to the emergence of an oil peak in 2008. Our findings are consistent with those of Alexandridis et al. (2008) who use the continuous wavelet transform and the Debauchies wavelet family at level 3 in order to decompose oil price returns. Indeed, these dramatic shifts are helpful to look at because of their impact upon the economy. A long line of empirical work confirms that declines in output follow increases in oil prices.[9] If oil price changes affect real activity, increase in oil price depress aggregate stock prices by lowering expected earnings. This suggests that oil price shocks should be associated with stock market returns.

2.2.2. *De-noised series*

Noises in financial data can lead to biased estimation of parameter, erroneous or invalid inference and poor volatility forecasts. Therefore their detection should be taken seriously in order to reduce their effects. According to Mitra (2006), in analyzing the long-run equilibrium relationships among macro-economic variables, one can focus his attention to the low frequency content of the data series ignoring the high frequency fluctuations, which might distort the series. Such a low frequency content of the data, without losing the basic characteristics of the original series is capable of capturing the correct long-run dynamic relationship among the considered macroeconomic time series. Consequently, the small wavelet time scales are contaminated by noise and this may cause convergence failure. Therefore, we propose a noise reduction technique that consists of the elimination of random components[10] D_1, D_2 and D_3 from the signal. These series have abundant economic meanings and reveal some new features of CO prices. The generated series are then de-noised x_t', transformed into their equivalent return series r_t' (Fig. 5) and compared to the original series. The stationarity of these transformed time series is tested and confirmed by the augmented Dickey-Fuller test and KPSS test (Kwiatkowski et al., 1992) (Table 1). Table 1 presents some descriptive statistics of de-noised series compared with raw series and Fig. 5 shows plots of these two series (in levels and returns). These figures allow the qualitative appreciation of the de-noising technique on the signal. Note that the generated series are less noisy but still sharp, suggesting no resolution loss. The first two columns of Table 1 indicate the values of the mean and the standard deviations of the wavelet generated series (for the series in level or in log difference) which look a bit different than those of the original series. There was a remarkable consistency of the results among the de-noised series indicating a consistent reduction of the variability of about 3% for series in levels and 13% for the series in log differences. The mean values are quite low throughout the generated series indicating a decrease of 1% from the original series in levels and of 12.5% from the series in log differences. Finally, it is interesting to note that the movement of the original and de-noised series are perfectly correlated (the correlations (not reported) are around 0.98 for the WTI and 0.99 for the Brent). The generated and the original series are used in the next sections to allow quantitative evaluation and explain the movement of the stock market returns.

3. Testing for the relationship between CO shocks and stock market returns

We start our analysis by estimating the linear vector autoregressive (VAR) model to examine whether or not there exists a relationship between the original/generated CO series and real stock prices. This would require stationary form of variables to be added to the VAR model. Then even the series appear non-stationary, we may be able to transform them such as taking their first difference. The analysis was also conducted using three monthly equity prices of UK, France and Japan[11].

3.1. *Tests under linear relationships:*

To check if any of the CO volatility variables present an impact on the stock market return, it is recommended in a preliminary analysis to determine the presence of co-integration using some standard tests.

3.1.1. *Stationarity tests*

Before examining the co-integration between the series, it is necessary to test whether the three return series and the CO de-noised series are stationary in level or in first difference.[12] To do so, we jointly use the unit-root test based on the traditional augmented Dickey and Fuller (1979, ADF) and the KPSS

[9] Hamilton (1983) finds that oil shocks were contributing factors in at least some of the US recessions prior to 1972. The related empirical studies such as Mork (1989), Mork et al. (1994), Lee et al. (2001), Cologni and Manera (2008) found a negative relationship between oil prices and real activity in oil importing countries.

[10] We have applied the Markov Switching models to the wavelet smooth series and to the de-noised series as defined above. The results show that the proposed MS models outperform CO indices using de-noised series and provide more accurate results than those using wavelet smooth series. This approach has been successfully applied by several authors such as Mitra (2006) and Popoola et al. (2004) to noise reduction and fault feature extracting of baring signals.

[11] Our choice of countries was thus for two reasons: First, we have examined the impact of the crude oil returns on the Japanese, European, French and American stock market returns but the first non-US market fails to share any evidence of regime dependent with the US stock market. However, we find significant results only when we consider the first set of variables. Second, this panel of countries is quite robust and plausible because France and UK are among the European Union nations and any global shock like oil shock would shake up these two markets at the same time. In addition, Japan (according to Energy Information Administration (EIA, 2008), represents the third largest petroleum consumer in the world in 2007, after United States and China), France and UK are among the worl six biggest economies (United States, Japan, China, Germany, France and United Kingdom (IMF, 2009) which are all members of the International Energy Agency) which could have seen their economies greatly affected by a possible crude oil shock. This approach can be extended to examine CO shocks across other sets of countries, which is left for future work.

[12] The CO series are analyzed in return, which is the first difference of natural logarithms multiplied by 100. For the stock market variable, we use the real stock return defined as the difference between the compounded return and the inflation given by the log difference in the consumer price index. Consumer price indices are taken from the OECD databases.

Table 2
Co-integration rank test.

Trace test					
Series*	Original WTI & RSP[a]	Generated WTI & RSP	Original Brent & RSP	Generated Brent & RSP	Critical value
None	49.44	48.94	48.33	48.66	63.66
At most 1	29.17	29.33	27.12	30.56	42.77
At most 2	14.89	15.58	14.61	16.26	25.73

Notes: *We define two groups of series: (1) Original CO prices and the three real stock prices, (2) Generated CO prices and the three real stock prices.Trace tests indicate 0 co-integrating relationship(s).

stationarity test (Kwiatkowski et al., 1992).[13] In this paper, we employ these tests to investigate the stationarity of FTSE 100 (United Kingdom), CAC40 (France), NIKKEI 225 (Japan) indexes and the CO prices examined above. Monthly stock market indices are collected from the International Financial Statistics database (IFS) and cover the same period as CO prices. We allow the intercept and trend in the unit-root test regression for the level data, but we only permit the intercept in regression for differentiated data. The results indicate that each level series is integrated of order one, I(1), but their first difference is stationary. Having established the order of integration, we next move to test the co-integrating relationships among the series using multivariate VAR approach as performed by Johansen (1988).[14]

3.1.2. Integration and Co-integration properties of the data

In this subsection, we present the co-integration analysis by exploring possibility of co-integrating long-run equilibrium relationships among the resultant wavelet filtered CO series and Real Stock Prices (RSP) of FTSE 100, CAC40 and NIKKEI 225. Following the general procedure proposed by Johansen (1988), the co-integration relation (the statistical equilibrium) between variables can be modeled by a Vector Error Correction (VEC) model with Gaussian errors ε_t as follows:

$$\Delta Y_t = \mu + \mathbf{\Pi} Y_{t\text{-}1} + \sum_{i=1}^{k\text{-}1} \Gamma_i \Delta Y_{t\text{-}i} + \varepsilon_t \tag{10}$$

where Y is the (original CO price of WTI or Brent/their generated series and real stock prices of Japan, France and UK) $(n \times 1)$ vector of variables, μ is a vector of constant terms. The matrix Π conveys information about the long-run relationship between the Y variables, it is $(n \times n)$ of unknown variables parameters. From Eq. (10), it can be concluded that, while the Y_t is stationary and the variables are not, the existence of Y_{t-k} depends on the existence of linear combination(s) which is (are) defined by Y_{t-k}. The rank of Π is the number of linearly independent and stationary linear combinations of the variables. The VEC shows how the variables come back to the equilibrium after suffering a shock. In order to obtain the optimal VEC model, we select a model with 1 length. We apply the Johansen method based on the maximum likelihood to identify the co-integrating rank in nonstationary time series. The trace test and eigenvalue tests are designed to test the null of no co-integration against the alternative of co-integration in the variables. The estimation procedure assumes unrestricted intercepts, trends and seasonal dummies in the VAR model. As shown in Table 2, both tests do not reject the null hypothesis of zero co-integrating vectors between the original/generated CO prices and the three real stock prices (Maximum Eigenvalue test not reported) at 5% level. Thus we conclude that there is no evidence of long-run equilibrium relationship among the original/generated series for the CO prices and the three real stock prices. The evidence of co-integration would imply that variables can be modeled using VAR augmented by including error correction term(s) because of the possibility of omitted variable bias. However, as no evidence of co-integration is detected then we estimate a standard vector autoregressive model. With regard to the analysis of our co-integration test results, we proceed to the observation of the Impulse Response Functions.

3.1.3. Impulse response functions

Having tested co-integrating VAR relations among the studied variables, we carry out the Impulse Response Functions (IRF) plots which trace out the responses of the real stock variables in the VAR(5) system to CO shocks and we consider all the variables up to the second lag. We adopt the usual approach of injecting one standard error (S.E.) shock in each of the VAR equations and observing the effect of such a shock on the other variables involved in the VAR system. Fig. 6 displays the IRF of all the three stock returns to a positive shock in CO prices. From the IRF plots, we observe that original oil price shocks have larger effects on the stock market prices than those of the generated oil price shocks (the magnitude of impacts of original oil price shock is about twice that of the generated series). Cleaning the data of noises reduces the magnitude of impacts and allows for more accurate results compared to the ones obtained when ignoring the existence of noises. In addition, the effect on real stock prices of Japan is considerably larger as compared with that on the real stock prices of UK and France. Moreover, the results suggest that after an oil shock, the effects fall for about 10 months for UK and France (and no more than 5 months for Japan) but they quickly recover and become positive for about 70 or 90 months (for UK, the effect reaches its peak after almost 20 months and declines steadily following the shock over almost 80 months) and finally erode. In summary, the responses of stock prices to oil shocks look rational. Indeed, since UK and France have lower and proximate oil consumption, their reaction would be correspondingly smaller if compared to Japan which consumes about five times more than UK and France. Furthermore, the IRF plots reveal the asymmetric stock market's behavior in response to the oil shock but this relationship seems to disperse rapidly after about 100 months which is matched with the period forward 1999 IT bubble. This may indicate that structural breaks may be responsible for the major changes in these time series. For this purpose, we turn to the examination of the vector autoregressive process of real stock market returns with Markovian regime shifts.

3.1.4. Estimation Results of the VAR model

Having verified that variables are not cointegrated, the next step involves the estimation of the vector autoregressive (VAR) model in real stock returns of the three developed countries.[15]

[13] The ADF and KPSS tests results for the CO series are presented in Table 1. In order to save space, we do not report the stationarity test results of the stock market series.

[14] This test was then discussed extensively in Johansen and Juselius (1990).

[15] The estimation of this linear model is required before moving to the MS model.

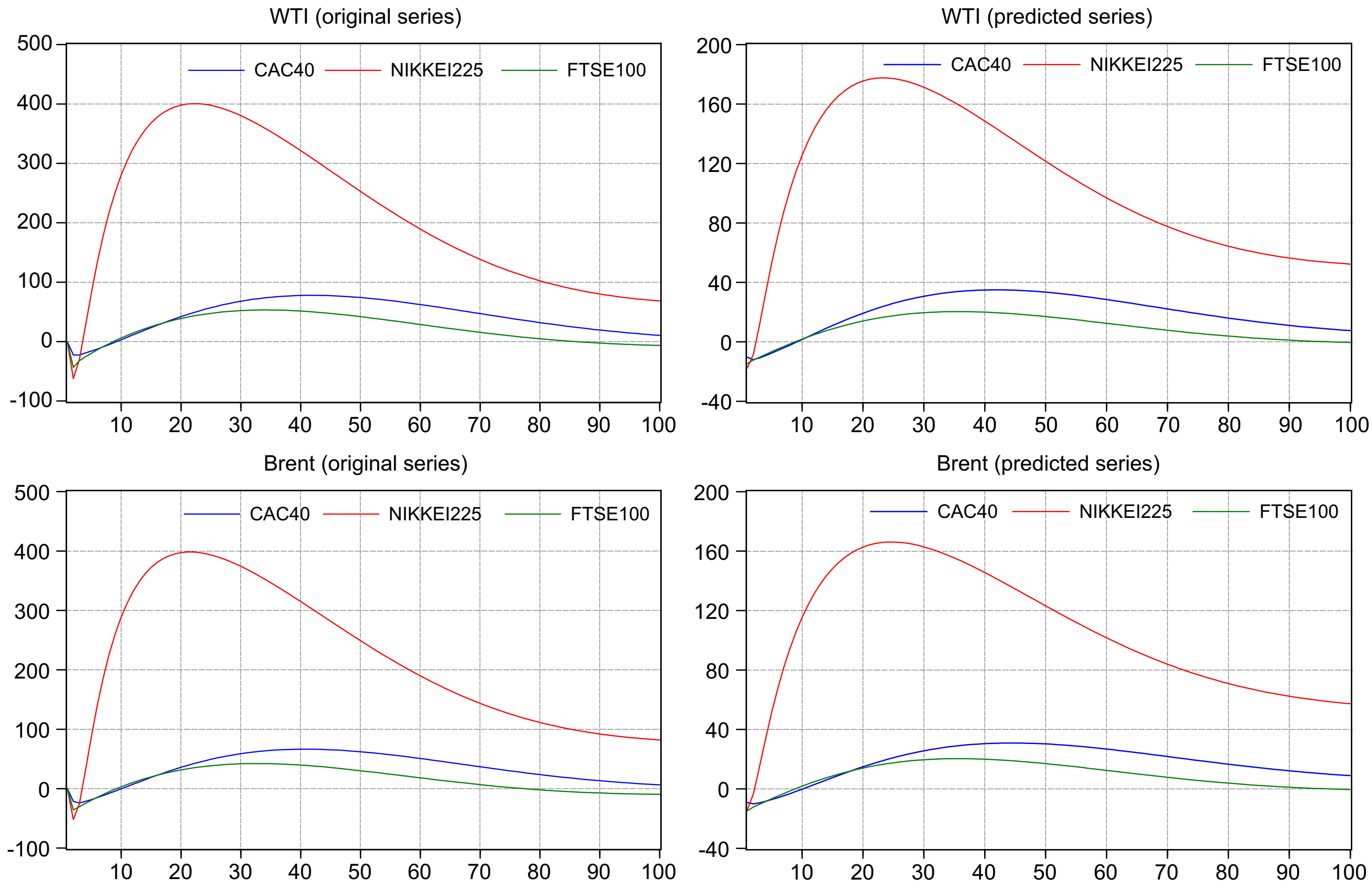

Fig. 6. Impulse-response functions of the three real stock prices to a positive shock in CO prices; on the horizontal axis: the horizon in months. On the vertical axis: the impact of a shock of one standard deviation of the residuals of the corresponding equation in the VAR system.

The VAR model is estimated on a set of (endogenously determined) stationary variables. In our case, these endogenous variables are the changes in stock prices for the United Kingdom, Japan and France.[16] The three-equation VAR(m) model is shown in Eq.(11), where r is the monthly real stock returns and m represents the number of the optimum lag length which is determined empiriquely by the log Likelihood, Schwartz (1978) (SIC) and Akaike (1974) (AIC) information criteria. The general one-state VAR model consists of a system of equations that expresses each variable in the system as a linear function of its own lagged value and lagged values of all the other variables in the system. A VAR of m order that includes the three real stock returns can be written as follows:

$$\begin{aligned} r_{UKt} &= a_{10} + \sum_{i=1}^{m} a_{i1} r_{UKt\text{-}i} + \sum_{i=1}^{m} b_{i1} r_{JPt\text{-}i} + \sum_{i=1}^{m} c_{i1} r_{FRt\text{-}i} + \upsilon_{1t} \\ r_{JPt} &= a_{20} + \sum_{i=1}^{m} a_{i2} r_{UKt\text{-}i} + \sum_{i=1}^{m} b_{i2} r_{JPt\text{-}i} + \sum_{i=1}^{m} c_{i2} r_{FRt\text{-}i} + \upsilon_{2t} \\ r_{FRt} &= a_{30} + \sum_{i=1}^{m} a_{i3} r_{UKt\text{-}i} + \sum_{i=1}^{m} b_{i3} r_{JPt\text{-}i} + \sum_{i=1}^{m} c_{i3} r_{FRt\text{-}i} + \upsilon_{3t} \\ h_t &= \sigma^2 \end{aligned} \tag{11}$$

The VAR(m) model can be written compactly using matrix notation:

$$g_t = a_0 + \beta(L) g_t + v_t \tag{12}$$

Here, we let g_t be the (3×1) vector of real stock returns (i.e., r_{UK}, r_{JP} and r_{FR}, respectively), a_0 the constant term vector, and v_t be the corresponding vector (i.e., υ_{1t}, υ_{2t} and υ_{3t} are the shocks to the three real stock returns). L denotes a polynomial in the lag operator, thus, the right-hand side of Eq. (12) contains only past values of the three real stock returns as well as the constant and error terms.

The results of the estimation of the three-equation VAR model[17] are presented in Table 3. From different versions of VAR systems, we choose a conditional VAR of order 1. This appropriate order was determined based upon Likelihood Ratio test (LR), AIC and SCH criteria. Additionally, a constant term was included in each equation. Note that for each country examined the current change in real stock returns depends on its own immediate past change only. The magnitude of the estimated coefficient on this first-order autoregressive term is different across countries and it is higher for Japan. Thus, changes in real stock returns exhibit a higher degree of persistence or momentum in Japan (0.263) followed by France (0.197) and UK (0.034).

[16] To reduce complexity (models become complex when we introduce CO variables as endogenous variables, this aspect is well explained in subsection 3–2–1) we report only the model containing real stock returns as endogenous variables and the effects of exogenous CO shocks will be discussed under the regime shifts assumption in the next sections.

[17] Since our study does not include the analysis of the interrelationship between the volatility across the stock markets, we fix the interdependence parameters to zero in the succeeding VAR estimations.

Table 3
One-state VAR model estimates for each stock market.

	UK	France	Japan
r_{t-1}	0.03494 [0.75]	0.19771*** [3.94]	0.26309*** [4.446]
Constant	0.27723*** [2.664]	0.32756*** [2.080]	−0.05015 [−0.257]
σ	1.22298*** [13,945]	1.53787*** [14,787]	1.75067*** [15,74]
Log-Likelihood		−813.332	
Q(12)	4.3185	7.8025	7.5036
$Q^2(12)$	32.6871	11.6409	20.121

Notes: *t*-statistics are shown in brackets. r_{t-1}: denotes the lagged own return for each stock market. Box Pierce (1970) test (Q(12)) indicates that residuals were free of serial correlation for the first 12 order. Further diagnostic tests indicate that the residuals were normally distributed. Results of residuals diagnostic tests are available upon request. *** indicate significance at the 1% level.

3.2. Markov switching models estimation

Once the two measures of CO returns (original and generated) are fixed, a MS-VAR model is formulated to estimate the relationship among real stock returns and original/generated CO returns in the presence of structural break.

3.2.1. Methodology and structural break test

Following Hamilton (1989), y_t can be estimated by a univariate MS-AR model of order p which is subject to regime shifts in the intercept, the error variance and the autoregressive parameters;

$$y_t = \mu(S_t) + \left[\sum_{j=1}^{p} \varphi_j (y_{t\text{-}j} \text{-} \mu(S_{t\text{-}j}))\right] + \varepsilon_t \qquad (13)$$
$$\varepsilon_t / S_t \to NID(0, \sigma^2(S_t))$$

where φ_j are the autoregressive parameters. NID: Normal and identically distributed. The MS-VAR model introduced by Krolzig (1997) is a multivariate generalization of the MS-AR process proposed by Hamilton (1989) whose definition is recalled above. The model was set as a K-regimes first-order MS-VAR as follows;

$$Y_t\text{-}\rho(S_t) = \sum_{j=1}^{p} \phi_j(S_t)(Y_{t\text{-}j}\text{-}\rho(S_{t\text{-}j}\phi)) + \sum_{m=1}^{M} \delta_m X_{t\text{-}m}(S_t) + \xi_t \vartheta(S_t) \qquad (14)$$

where Y_t denotes the vector of observable real equity index (y_t) of each country, ξ_t is the innovation process with shifts in the variance–covariance matrix $\vartheta(S_t)$, ξ is an $N \times N$ coefficient matrix of a stable VAR process, for j=1…p, $\rho(S_t)$: state-dependent vector of parameters having the feature that switches occur around the conditional mean. δ_m: coefficient associated to the lagged oil variable. The unobservable discrete variable (S_t), for all t, $S_t \in \{1,\ldots,K\}$ K being the number of regimes, is supposed to follow a Markov process defined by the transition probabilities of moving from one state to the other[18] p_{ij}. That is the probability that for a value of the time series S_t (regime i) for all t depends only on the last value S_{t-1} (regime j), for ij=1,…,K. We can describe a Markov chain as follows:

$$P(S_t = j | S_{t\text{-}1} = i, S_{t\text{-}2} = i, \ldots) = P(S_t = j | S_{t\text{-}1} = i) = p_{ij}$$

where $P_{i1}+P_{i2}+\ldots P_{in}$=1. The transition matrix of the following form can be estimated:

$$\begin{pmatrix} P_{11} & P_{12} & \ldots & P_{11} \\ P_{21} & P_{22} & \ldots & P_{11} \\ \ldots & \ldots & \ldots & \ldots \\ P_{n1} & P_{n2} & \ldots & P_{nn} \end{pmatrix} \qquad (15)$$

[18] The transition probabilities provide us the expected duration of staying in a given regime. Then the expected duration of regime j is calculated from the formula; $D_j = (1\text{-}p_{jj})^{-1}$, $j = 1, \ldots K$.

Table 4
Models comparison.

	(1):linear VAR	(2):MS(2)-VAR	(3):MS(3)-VAR
lnl	−813.332	−797.165	−771.284
LR_1		32.334	84.096
LR_2			51.762

Notes: $LR_1 = 2 \times |\ln L_{\text{MS-VAR}}\text{-}\ln L_{\text{linearVAR}}|$ and $LR_2 = 2 \times |\ln L_{\text{MS(3)-VAR}}\text{-}\ln L_{\text{MS(2)-VAR}}|$, ln$L$ is the log likelihood and the critical values are based on Davies (1987)*p*-value.

We augment Eq. 13 by entering the original or generated CO volatilities as an exogenous variable (X_t), allowed to change across regimes, which may exercise an effect upon the domestic equity market. The maximum likelihood estimation method of Eq.13 is based on the Expectation-Maximization (EM) algorithm (Hamilton (1989), which has been proved to be more robust to the starting parameters values. As a by-product of the estimation step, we get the smoothed probabilities of being in the state i, for i=1,…,K, $P(S_t$=$i/Y_T,\ldots,Y_1,h)$.

The starting point is the estimation of the standard MS-VAR model that does not include CO shock. Before we further discuss the estimation model, we turn to testing for mean/variance regime dependence. To do so, we test the null hypothesis of the Markov switching model against the linear alternative and a three-regime model against a two-regime model using the likelihood ratio test (LR) suggested by Garcia and Perron (1996). The results from Table 4 imply very strong rejection of the null hypothesis of no switching at 1% or 5% critical values. Therefore it is clear that there is a strong evidence of regime switching behavior in all the return series. The test of three versus two regimes rejects the lower number of states. From these results, we can conclude that non-linear MS(3)-VAR model is better describing the data than linear VAR and MS(2)-VAR models.

3.2.2. MS-VAR model estimation results (without oils shock)

In this section, a three-regime MS-VAR model for the three real stock returns, from January 1989 to December 2007, is estimated. We allow for the vectors of intercepts, variances and the matrices of autoregressive parameters to switch across three regimes. The estimated parameters along with the *t*-statistics of the MS-VAR model are presented in Table 5. It can be seen from these results that the real stock market can be separated into three stages. The first regime (noted Regime 1) indicates that all the real stock returns are in the bear market or recession phase with lower negative sign of the expected return (cst_1) and higher variance of errors (SE_1), (the square root of the variance–covariance matrices). The second regime captures the behavior of the stock market in a moderate decrease with intermediary mean (cst_2) and variance of errors (SE_2). Conversely, regime 3 captures the behavior of the stock market in the bull market or expansion phase with higher positive sign of the expected return (cst_3) and

Table 5
Estimated parameters of the MS(3)-VAR(1).

	UK	France	Japan
Cst_1	−0.3866 (−0.981)	−0.81595* (−1.457)	−1.27926*** (−2.899)
Cst_2	−0.21078 (1.082)	0.25288 (0.85)	−0.6276* (−1.523)
Cst_3	1.68455*** (4.831)	0.95479*** (7.432)	1.34062*** (4.375)
$AR_{t-1}1$	−0.21078* (−1.43)	0.02495 (0.134)	−0.06763 (−0.345)
$AR_{t-1}2$	0.08628 (0.824)	0.25068*** (3.055)	0.33196*** (3.286)
$AR_{t-1}3$	0.03069 (0.753)	−0.09872 (−1.277)	−0.08482 (−0.519)
SE_1	1.68455*** (3,759)	2.04624*** (3,6287)	1.78656*** (3,928)
SE_2	1.437*** (11,156)	1.73091*** (11,501)	1.623*** (5,254)
SE_3	0.53495*** (4,4320)	0.70392*** (7,124)	1.42167*** (6,503)
P_{ij}	S_{t-1}=1	S_{t-2}=2	S_{t-3}=3
S_t=1	0.80963	0.0013493	0.12182
S_t=2	0.001383	0.92418	0.15631
S_t=3	0.18899	0.074469	0.72187
$D(s_t)$	5.25	13.19	3.60

Notes: Figures in the parentheses are the *t*-values, ***, ** and * indicate significance at the 1%, 5% and 10% significance levels.

lower variance of errors (SE_3). As it is shown in Table 5 all the stock market series are characterized by negative return during recession states; Japan has the lowest return (nearly −1.3% per month) but the returns of UK and France are near zero. The fall in the real return series between the normal regime and the recession regimes[19] is small for UK (less than 0.5% at monthly rate) and higher than 0.5% for France and Japan. The rise in the return series between the normal to the expansion regimes is generally around 2% for UK and Japan and it is smaller for France (0.7%). As it is apparent from Table 5, the persistence of the 3 regimes (recession, transitory and expansion) is quite high, since the probability to stay in the same regime exceeds 72% (the transition probabilities; p_{11}=0.81, p_{22}=0.92 and p_{33}=0.721). The duration of the expansion regime is shorter than for recessions (4 against 5 months), and the moderate regime is found to be the longest lasting where the duration is higher than 13 months. Fig. 7 display the three smoothed probabilities of being in each regime. As seen in the graphs, the moderate regime vanished before July 1998 indicating that, during the months subsequent to this date which may coincide with the stock market bubble of 1999/2000,[20] the stock market cannot jump to the high volatility regime directly from the low volatility regime as in the nineties. A remarkable feature of the system involving these three countries is that the expansion regime follows the recession state until 1998, but after that it almost follows the normal and not the recession. The change in the behavior of the stock market volatility around the turn of the century may be explained by the presence of the so-called "IT-bubble". Indeed, after the introduction of a speculative bubble, i.e. between 1999 and early 2000, all the stock markets were less volatile. However, stock prices nose-dived and became much more volatile for about two years. After the extremely volatile period in 2000–2002, stock markets showed temporary recovery periods where they switched to the lowest regime gradually until recent times, (Qiao et al., 2008). The change in the behavior of the stock market return since 1999 led to an overall re-examination of the expected long-run negative relationship between the stock market return and the CO volatility. In order to highlight this point, Miller and Ratti (2009) provide evidence that the negative long-run relationship between real oil price and real stock price support a conjuncture of change after September 1999 compared to earlier years, which may suggest the presence of several stock market and or oil price bubbles since the turn of the century. In order to study the effects of crude oil shocks (generated or original) in different phases of the real stock returns, MS-VAR model will be extended to include these shocks.[21]

3.2.3. Effects of oil price volatility

This subsection reports the estimation of the extended Markov-switching models to investigate the role of CO shocks in explaining the stock market shifts behavior. Therefore, we maintain the same regime dependent model as in the previous section but we allow the CO coefficients included as exogenous variables to switch between the three states.[22] In order to get a better grasp of how well MS-VAR model is able to generate the dynamics of the stock market in the presence of structural break and to fit its linkage to the generated CO data series, we compare the model including generated CO series to the one containing original series. Table 6 presents the estimation results of extended models. Models denoted 1 and 3 present the link between real stock returns and the original CO volatilities (respectively for the WTI and Brent), whereas, model 2 and 4 illustrate the link between real stock returns and the generated CO volatilities. The likelihood ratio test (LR) suggested by Garcia and Perron (1996) is also involved. The results indicate that extended models 2 and 4, compared with models 1 and 2, achieve a significant improvement in the likelihood function (the likelihood function values increase from −756.73 to −755.66 and from −762.12 to −754.21) according to conventional likelihood ratio testing. Ljung–Box statistic for the residuals model indicates no serial correlation in either the residuals (Q) or the squared residuals (Q^2), inferring that the fitted models are appropriate. It is worth noting that the estimated parameters for the mean (especially for the third regime) and the variance (in all the regimes) are statistically significant, suggesting that structural shifts have to be taken into account when modeling the volatility processes for all series. The estimated autoregressive coefficients across regimes are, in general, statistically significant (but none for regime 3) while all the estimated coefficients are different in magnitude. The obtained results also indicate a classification into three observable regimes: recession, moderate or stagnation and expansion for each stock market. Furthermore, the matrices of the transition probability are reported in Table 7. The transition probabilities signal the presence of important asymmetries in the stock markets. The results indicate that the recession regime has the highest persistence probability and the highest duration since it lasted about 5 months (except for the model 3 where the expansion regime is more persistent). The expansion regime is also persistent though it lasts around three months and the moderate regime seems to be persistent but not permanent (it lasts around two months). From the transition probabilities, findings indicate that moderate and expansion regimes are relatively short, in comparison with recessions in these economies. Figs. 8–11 plot the smoothed probabilities for the four models based on the model described in Eq. (14). For each model, we compare the dating of the estimated recessions inferred from the smoothed probabilities to reference recession phases in order to assess the ability of the model to produce business cycle features in a dynamic analysis. The dating of the first regime produced by all the models is

[19] It is defined as the absolute difference between Cst_2 and Cst_1.

[20] It is interesting to note that the date 1999 for a structural break coincides roughly with financial crisis and hard times in Asia.

[21] The optimal number of lags on oil price changes is equal to one for each MS-VAR specification.

[22] It is favorable to consider crude oil returns as exogenous because in practice this hypothesis simplifies the estimation procedure of the MS-VAR model (estimating the impact of endogenous independent variable would be complex and therefore, it is quite difficult to achieve convergence since we have a large number of additional parameters to estimate).

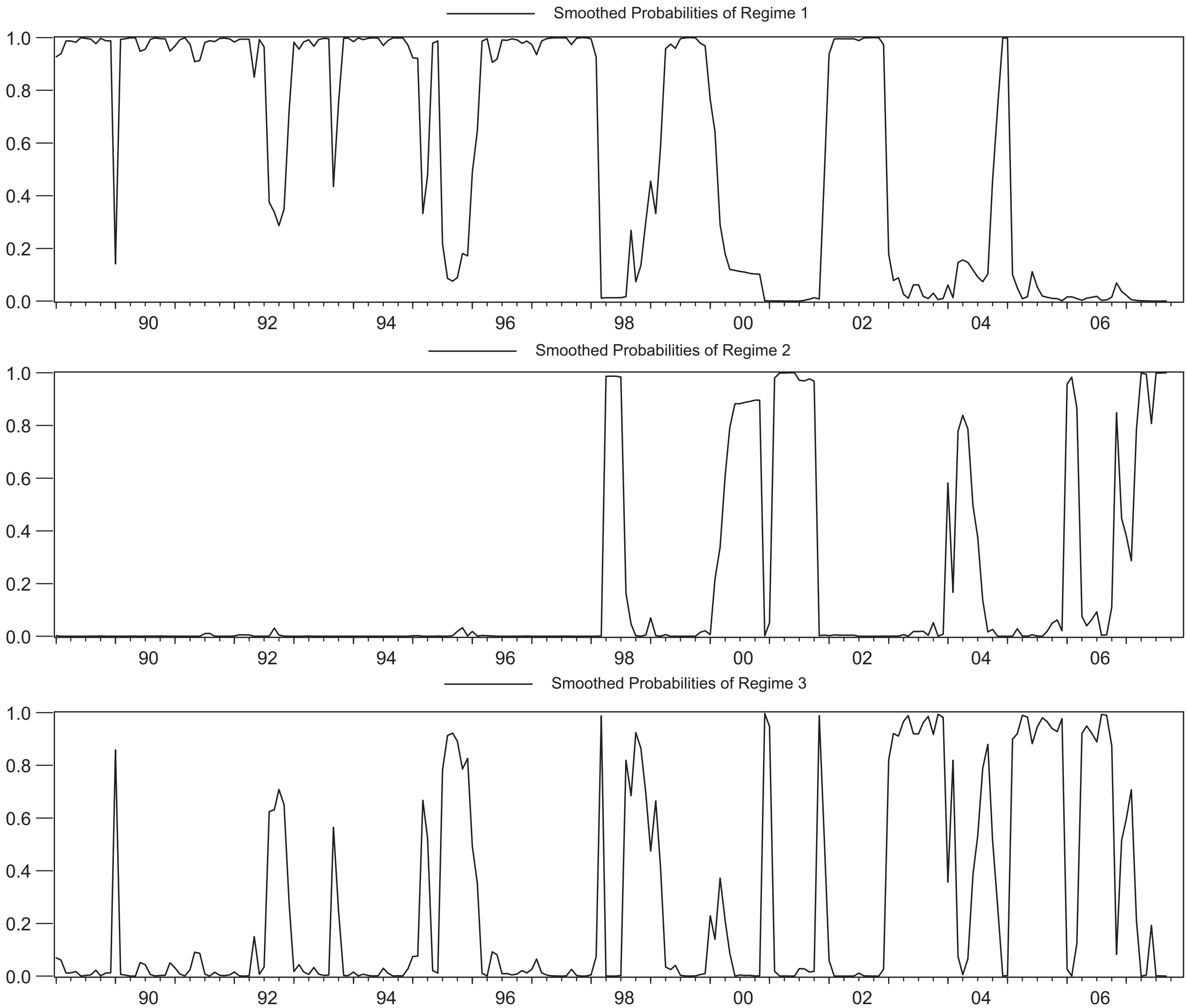

Fig. 7. The estimated smoothed probabilities of regimes 1, 2 and 3.

indicated in Table 8.[23] As regard to the dating results of the recession regime, model 2 provides almost the same results as model 1. The models are able to delineate 1990–1991 oil crisis due to the first Gulf war, 1994 Mexican peso crisis, 1997–1998 East Asian currency crisis, 2000–2001 US energy crisis due to manipulation by electricity producers Enron and Reliant Energy, 2003–2005 US-Iraq war commenced in 2003 as well as the 2007 US subprime crisis estimated in the whole sample analysis. This can also be visually justified using the monthly patterns of the return and the volatility for the three countries shown on the upper horizontal panel of Figs. 8–11 where declines in real stock returns are closely correlated with the high volatility state especially in the official recession periods (the shaded area in the diagrams). The stock market contractions differ in length and severity. The duration of the 16 contractions are ranged from 4 to 125 months (see Table 8). The longest stock market recession is associated with the 2000–03 crisis. Moreover, in these models, the estimates for each country indicate that the market was moderately volatile few months before the beginning of each crisis. Interestingly, Table 6 shows also the estimated interaction parameters between shifts in the original/generated CO components and the degree of turbulence or stability in the stock market (the three stock market phases). We begin by exposing the results for extended 2 and 4 models, respectively. The findings for UK, show that while the coefficients on the oil_{t-m} are all negative, only oil_{t-3} are significant at 1% significant level. This suggests that the crude oil shocks have a delayed negative impact on the low stock market volatility regime in UK. Looking at the coefficients, the significant negative impact on the low variance stock market regime has approximately the size of -0.07 and -0.08, respectively for WTI and Brent while the effects during high and medium stock market volatility regimes are insignificant. It can be observed that in the case of France, the negative effect of an increase in the crude oil volatility shocks in the moderate regime is around 0.3 whereas the negative effect during low volatility regime is much less pronounced (0.06). On the other hand, shocks during recessions have a positive sign but insignificant. The results apparently indicate for these two countries that CO shocks

[23] To conserve space, we report only the dating periods for models 2 and 4 and the results of models 1 and 3 are available upon request.

Table 6
Maximum likelihood estimates of the MS(3)-VAR(1).

	Model 1			Model 2			Model 3			Model 4		
	UK	France	Japan	UK	France	Japan	UK	France	Japan	UK	France	Japan
Cst 1	−0.17 (−0.4)	−0.45 (0.0)	−3.27* (−1.5)	−0.13 (−0.4)	−0.42 (−0.8)	−3.37* (−1.8)	−0.75* (1.5)	−1.25* (−1.8)	−1.48*** (−2.2)	−0.17 (−0.6)	−0.67 (−0.5)	−3.70*** (−2.1)
Cst 2	−0.16 (−0.6)	0.19 (0.2)	−0.96** (−1.9)	−0.11 (−0.4)	0.35 (0.3)	−0.94*** (−2.2)	0.33 (1.2)	0.41 (0.6)	−1.26*** (−2.9)	−0.26 (−0.3)	−0.01 (−0.0)	−1.07 (−1.2)
Cst 3	0.82*** (5.2)	1.04*** (6.6)	1.30*** (3.1)	0.82*** (4.4)	1.04*** (4.6)	1.36*** (2.5)	0.87*** (5.0)	1.12*** (7.0)	1.63*** (5.2)	0.82*** (3.4)	1.09*** (6.2)	1.19*** (2.1)
AR_{t-1} 1	0.04 (0.4)	0.20*** (2.5)	0.67*** (3.8)	0.03 (0.4)	0.20*** (2.6)	0.66*** (4.3)	0.37*** (2.9)	0.48*** (4.5)	0.34* (1.9)	0.03 (0.2)	0.18* (1.5)	0.67*** (3.8)
AR_{t-1} 2	0.37*** (4.0)	0.55*** (2.5)	0.19*** (2.2)	0.37*** (2.5)	0.62*** (3.4)	0.18*** (2.3)	−0.02 (−0.3)	0.17* (1.5)	0.31*** (3.6)	0.42* (1.7)	0.65*** (8.0)	0.19 (1.1)
AR_{t-1} 3	−0.06 (−0.5)	−0.07 (−1.0)	0.05 (0.4)	−0.04 (−0.5)	−0.07 (−0.9)	0.04 (0.4)	−0.11 (−0.6)	−0.10* (−1.3)	0.09 (0.8)	−0.05 (−0.4)	−0.06 (−0.7)	1.19* (1.3)
Oil_{t-1} 1	−0.04 (−0.5)	0.06 (0.1)	0.07 (0.7)	−0.03 (−0.4)	0.02 (0.2)	0.12* (1.3)	−0.05 (−0.8)	−0.01 (−0.2)	0.15*** (3.3)	−0.03 (−0.3)	0.01 (0.1)	0.11 (1.2)
Oil_{t-1} 2	−0.12* (−1.7)	−0.30*** (−2.1)	−0.04 (−0.4)	−0.16 (−1.1)	−0.28* (−1.5)	−0.03 (−0.4)	−0.02 (−1.2)	−0.03 (−0.4)	−1.26*** (−2.9)	−0.10 (−1.2)	−0.26*** (−5.5)	−0.04 (−0.2)
Oil_{t-1} 3	−0.06*** (−2.5)	−0.06*** (−2.2)	−0.12* (−1.4)	−0.07*** (−2.5)	−0.06* (-1.5)	−0.16* (−1.1)	−0.10* (−1.9)	−0.07* (−1.6)	−0.16* (−1.9)	−0.08*** (−2.1)	−0.06* (−1.6)	−0.09 (−0.8)
SE 1	1.51*** (7.7)	1.86*** (8.3)	1.62*** (7.8)	1.52*** (6,8)	1.86*** (7,4)	1.61*** (7,1)	1.40*** (5.6)	1.62*** (5.5)	1.49*** (5.8)	1.53*** (7.1)	1.05*** (4.3)	1.63*** (6.1)
SE 2	0.74*** (4.0)	1.23*** (4.2)	1.34*** (5.0)	0.71*** (4,9)	1.24*** (4,4)	1.30*** (3,4)	0.79*** (6.0)	1.43*** (3.9)	1.29*** (4.2)	0.75*** (3.4)	1.82*** (6.7)	1.37*** (6.0)
SE 3	0.60*** (4.1)	0.70*** (4.3)	1.32*** (3.3)	0.60*** (4,6)	0.70*** (4,4)	1.29*** (3,1)	0.65*** (6.2)	0.65*** (6.7)	1.00*** (2.4)	0.54*** (2.0)	0.75*** (2.6)	1.29*** (2.9)
$Q(12)$	7.406	7.036	8.918	7.070	6.513	8.481	6.370	5.821	7.051	8.090	6.978	9.535
$Q^2(12)$	46.29	9.934	16.87	46.07	10.33	16.73	17.36	8.529	13.57	14.56	9.237	19.07
Ln L	−756.73			−755.66			−762.12			−754.21		
LR	29.108			31.248			18.328			34.148		

Notes: One lag dependent variables are included in all the models. Student-*t* statistics of parameters are reported in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1%. The Likelihood Ratio (LR) test is computed as follows: $2\times|\ln L \text{ of } H_1 - \ln L \text{ of } H_0|$, where H_0 is the MS(3)–VAR(1) model with undecomposed oil prices and H_1 is the MS(3)–VAR(1) model with decomposed oil variable, both with constant transition probabilities.

Table 7
Estimated transition probabilities of the MS(3)–VAR(1) models.

	P_{i1}	P_{i2}	P_{i3}	Duration	
Model 1	Regime1	0.7914	0.0428	0.2429	4.79
	Regime2	0.1060	0.5161	0.0489	2.06
	Regime3	0.1024	0.4410	0.7080	3.42
Model 2	Regime1	0.7949	0.0461	0.2406	4.87
	Regime2	0.1098	0.5312	0.0452	2.13
	Regime3	0.0951	0.4226	0.7141	1.32
Model 3	Regime1	0.3826	0.6450	0.3725	1.62
	Regime2	0.3793	0.1726	0.0243	1.21
	Regime3	0.2380	0.1823	0.6030	2.52
Model 4	Regime1	0.7574	0.0034	0.2445	4.12
	Regime2	0.0884	0.4676	0.0847	1.87
	Regime3	0.1541	0.5289	0.6706	3.03

do not have influences during recession period. Moreover, significant effects on moderate (for France) and expansion (for UK and France) stock market volatility phases occur negative[24] and shorter lived (since the average durations of the moderate and expansion regimes are lower). Put it differently, the CO shocks impact negatively on the stock market volatility during the moderate regime and then the negative effect switches to the expansion regime to show a minor influence of CO shocks during expansionary stock market phase.[25] However, this effect seems fully absorbed during recession stock market phase.[26] With regard to Japan, the obtained results suggest that oil price shock (only for WTI) has significant effect on the stock market volatilities. This is true both if the stock market was in a recession and if it was in an expansion at the time CO volatilities were raised. The effects change sign between the expansion to recession regimes where they go from negative −0.16 to positive 0.12. The implication of our findings is that improvement in energy efficiency in France and UK has an important role in reducing oil shocks on the high volatility stock market regime. However, diverse factors other than oil shocks may have a role in explaining stock market downturns.[27] For Japan, we may point out that WTI effect on the stock market is more harmful since it cannot be stopped immediately and continue to propagate across the two extreme regimes. The results demonstrate also that the effect of a change in crude oil shock on the medium stock market volatility regime is clearly negative but insignificant. As Kilian and Park (2007) reported only oil price increase driven by precautionary demand for crude oil reflects fears about the availability of future oil supplies.[28] Consequently, the positive linkage to the recessionary stock market phase highlights the decreased hedging policy efficiency in Japan to neutralize world oil prices effect on the volatility of stock market. Therefore, Japan with their great oil

[24] This result is consistent with the one provided by Park and Ratti (2008) who found that oil price shocks have a statistically significant negative impact on real stock returns in the U.S. and 12 European oil importing countries including France, UK and Japan.

[25] The probabilities $\text{Prob}(s_t = 2/s_{t\text{-}1} = 3) < \text{Prob}(s_t = 3/s_{t\text{-}1} = 2)$ for models 2 and 4, respectively reflect the high chance that the moderate regime is followed by the expansion regime.

[26] the probabilities $\text{Prob}(s_t = 3/s_{t\text{-}1} = 1) < \text{Prob}(s_t = 1/s_{t\text{-}1} = 3)$ for models 2 and 4 respectively point out that the expansionary stock market phase shows a relative high probability to be followed by a recessionary stock market phase.

[27] Apergis and Miller (2009) concluded that the small magnitude of structural shocks effect on the stock market returns could be an indication that other variables such as exchange rates, interest rates…etc may determine the movement in stock market returns.

[28] The increase of oil prices is argued to have been determined by a rapid increase in demand for oil by high growth countries (China, India and Brazil) to meet industrialization and urbanization (Cologni and Manera, 2009).

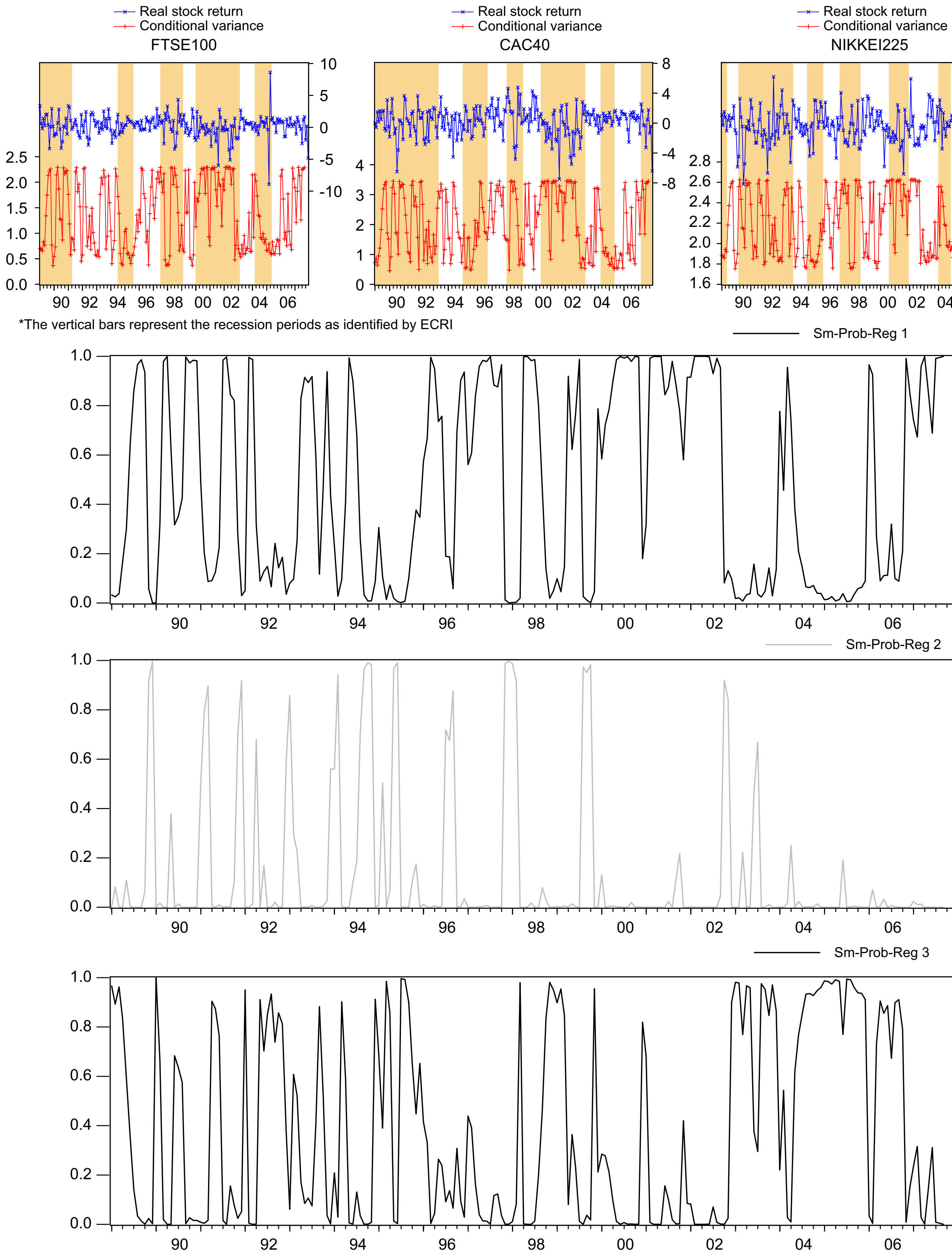

Fig. 8. Model 1 (original return series of WTI).*

dependency may have more fragile economic recovery and it is incapable to react to the oil shock as rapid as the other two economies. As Figs. 12–15 shown, there is often a close relationship between the generated oil price changes and the real stock market volatility for UK, France and Japan. Several features of this relationship are noteworthy. Taking the case of UK, we can observe that an

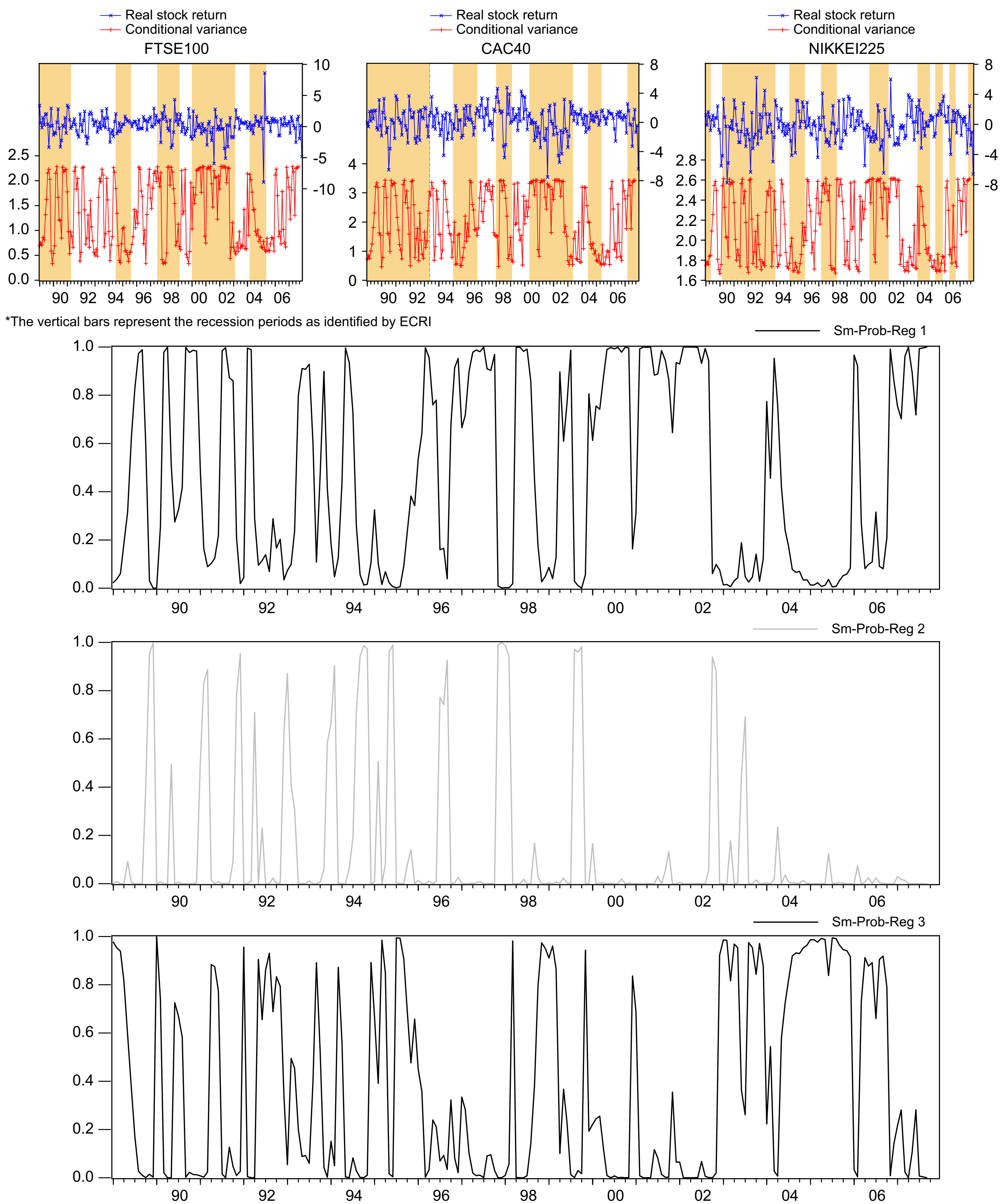

Fig. 9. Model 2 (generated return series of WTI).*

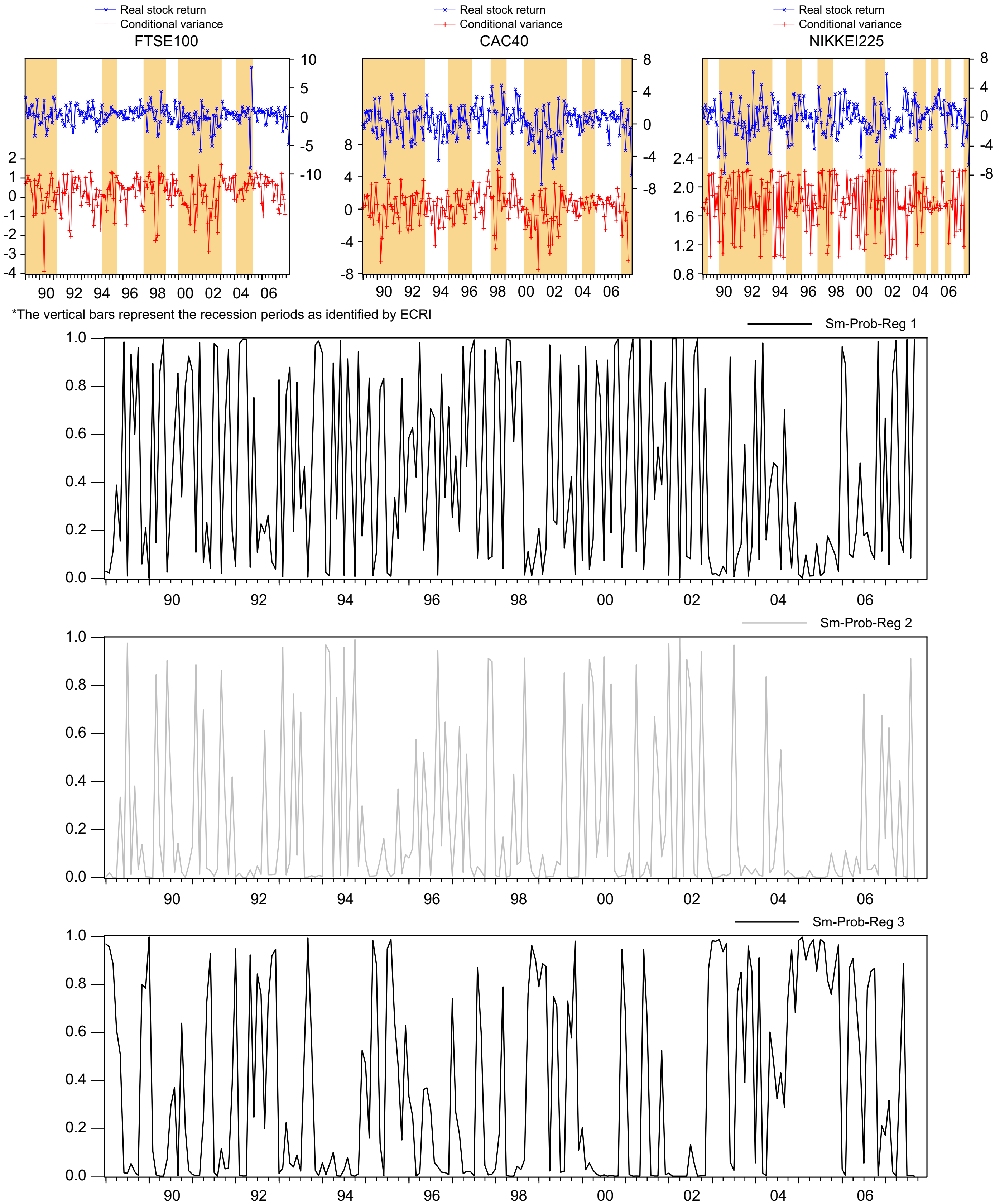

Fig. 10. Model 3 (original return series of Brent).*

increase in CO volatility is matched negatively to the medium/low stock market volatility. However, changes in the crude oil seem not associated to the high stock market volatility (such as the well-defined 1990 CO prices increase). Furthermore, if we compare the plots (of Figs. 9 and 11) of the smoothed probabilities of being in the moderate and low volatility regimes respectively with those provided

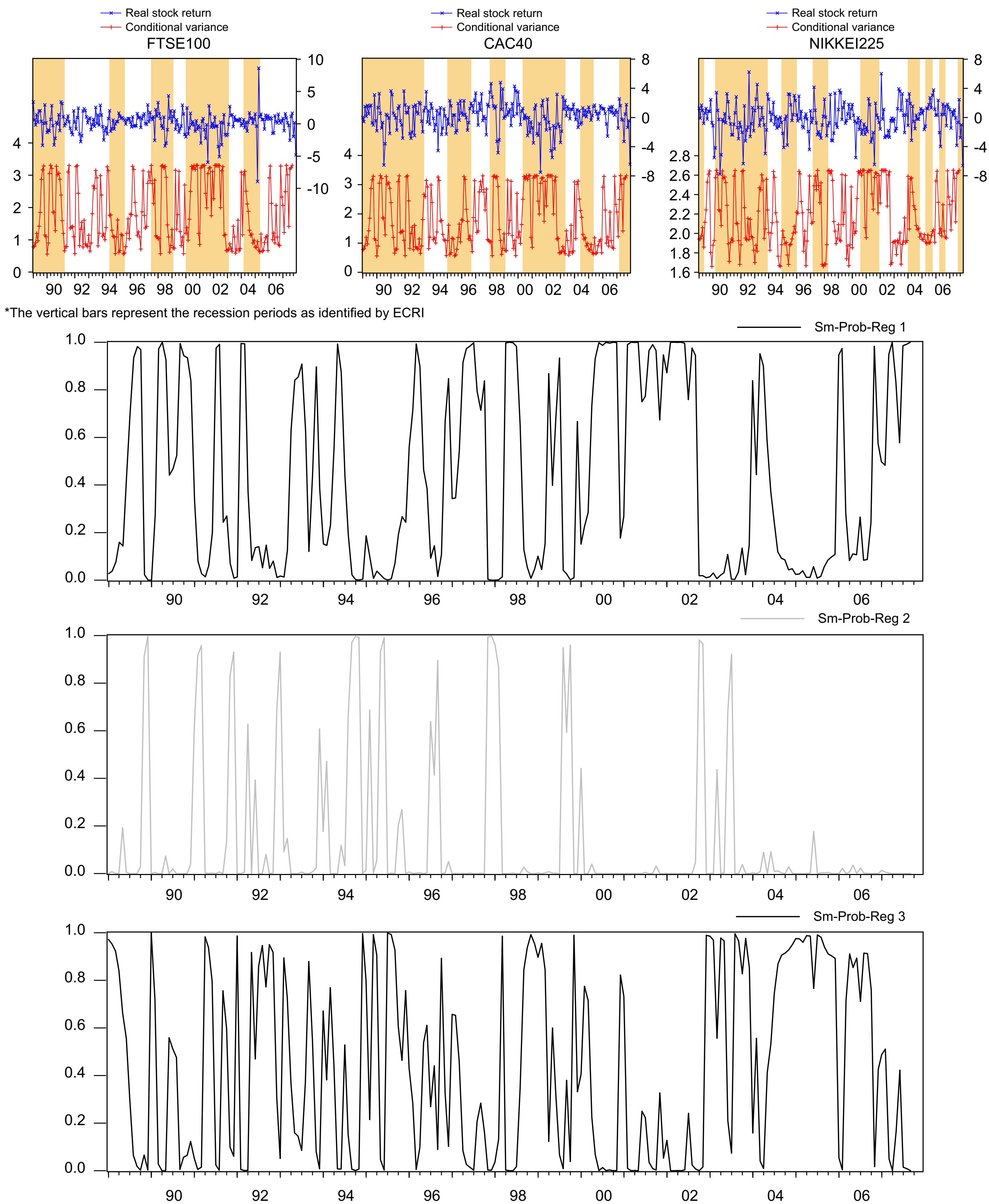

Fig. 11. Model 4 (generated return series of Brent).*

by the benchmark model (Fig. 7), we perceive that after accounting for the CO shocks, the second regime especially for the pre-1999 period (as well as the third regime over the sample period) not detected by the benchmark model become materialized and seem to be frequent and short-lived. This would suggest that the negative relationship occurred in the moderate and/or the expansion regime

Table 8
Reference and estimated recession dates extracted from models 2 and 4.

Reference			Model 2	Model 4
UK	France	Japan		
89M01–91M04	89M01–93M05	89M01–89M05	89M06–89M10 [0.802]	89M09–90M01 [0.804]
		90M03–93M12	90M06–90M08 [0.827]	90M06–90M08 [0.965]
			90M12–91M03 [0.986]	90M11–91M03 [0.832]
			91M10–92M01 [0.928]	91M10–91M11 [0.983]
			92M05–92M06 [0.992]	92M05–92M06 [0.994]
			93M07–93M11 [0.829]	93M07–93M11 [0.772]
94M07–95M08	95M01–96M09	94M12–96M01	94M08–94M10 [0.885]	94M07–94M09 [0.810]
			96M04–96M09 [0.778]	96M04–96M07 [0.791]
97M07–99M02	98M01–99M02	97M03–98M04	97M01–98M01 [0.888]	97M06–98M01 [0.844]
			98M07–98M11 [0.965]	98M07–98M11 [0.925]
			99M07–99M10 [0.814]	99M09–99M10 [0.805]
00M01–03M02	00M05–03M05	00M08–01M12	00M03–01M02 [0.895]	00M07–01M02 [0.955]
			01M05–02M12 [0.946]	01M05–02M12 [0.929]
04M03–05M05	04M06–05M05	04M01–04M11	04M06–04M07 [0.855]	04M06–04M08 [0.813]
		05M04–05M10		
		06M04–06M09	06M04–06M05 [0.943]	06M04–06M05 [0.959]
	07M03	07M08	07M02–07M12 [0.897]	07M06–07M12 [0.904]

Notes: Figures in brackets indicate the average regime probabilities for the specific periods. Reference: Peak and Trough dates of the growth rate cycles (1989–2007) for UK, France and Japan, source: Economic Cycle Research Institute (ECRI).

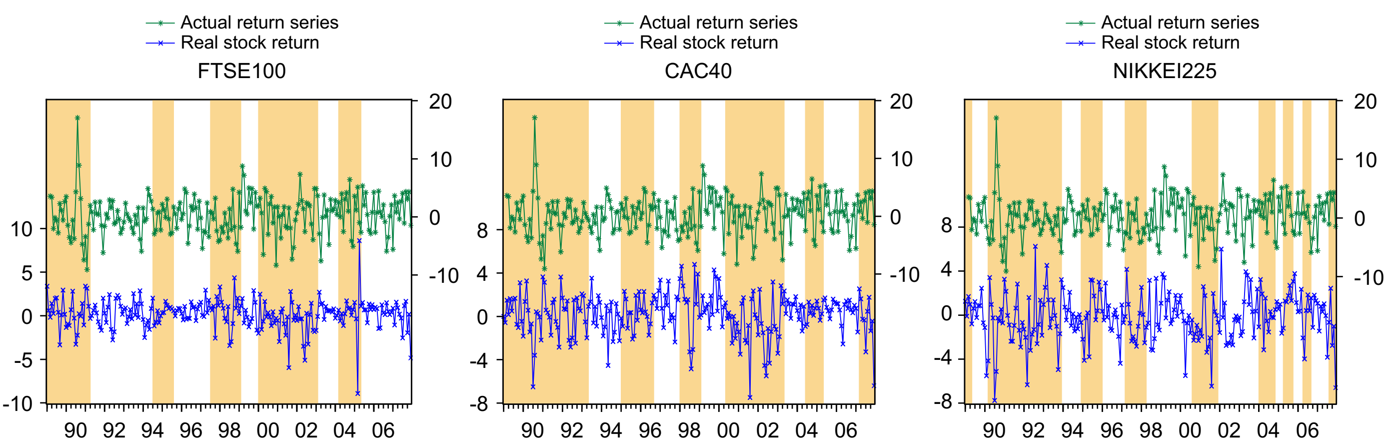

Fig. 12. Real stock returns-original return series of WTI*.

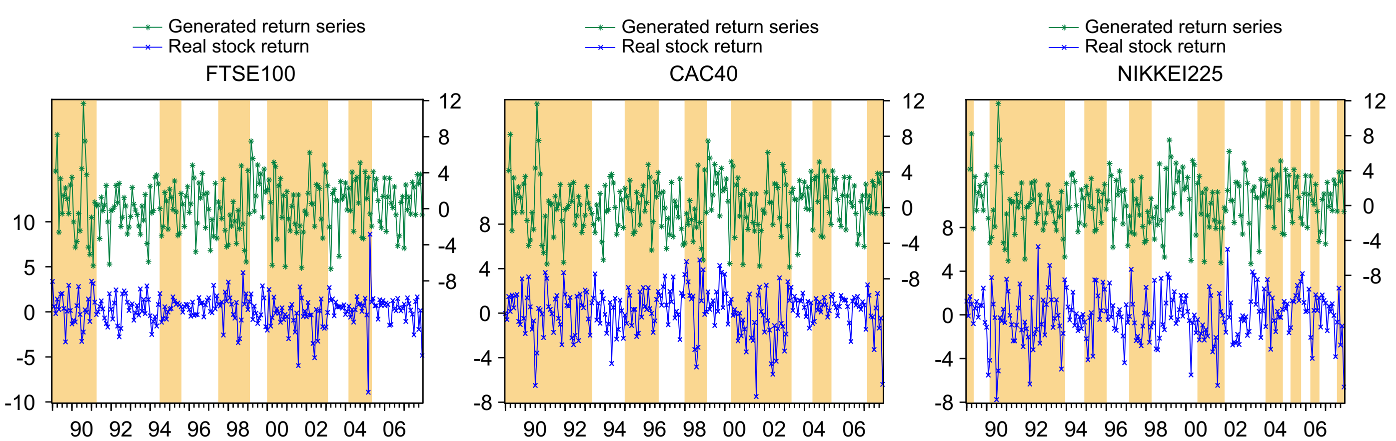

Fig. 13. Real stock returns-generated return series of the WTI*.

appears to fall apart after the IT-bubble where the stock market is more volatile. This finding is in line with that reported by Miller and Ratti (2009) who found that the stability of the long-run relationship between crude oil shocks and stock market prices over the pre-1999 period appears to disintegrate and even change sign in some cases. They argue that a feasible explanation for stock market prices lies in speculative bubbles, as perhaps investors still believe the increase in the oil price since 1998—like those in 1979 and 1990—is only temporary. It follows that investors' adjustments for the post-1999 period are responsive to a broader set of oil market information, i.e. any crude oil shock that disturbs index return parity conditions will lead them to adjust their portfolio allocation. In contrast during the

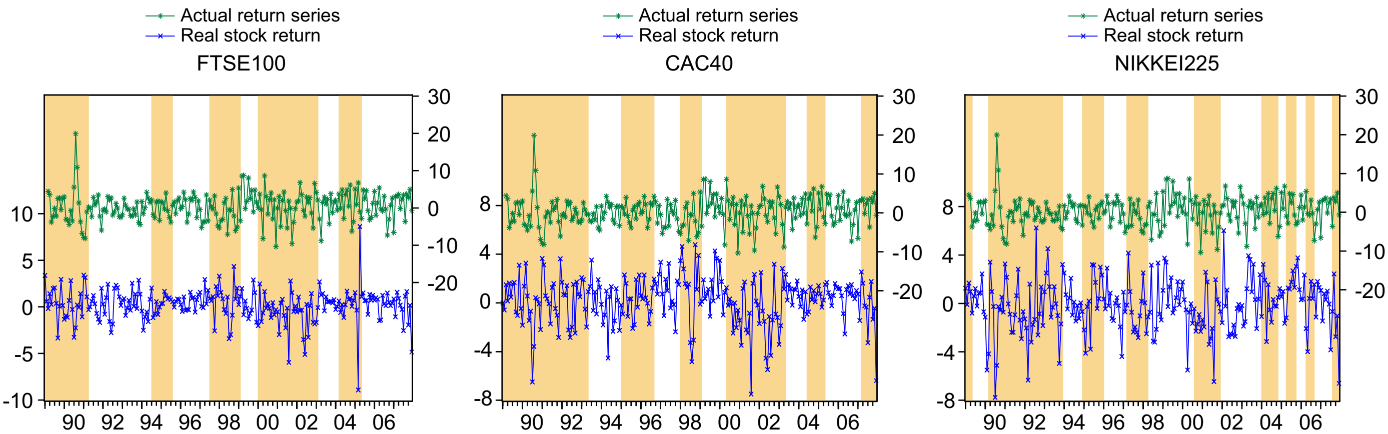

Fig. 14. Real stock returns-original return series of the Brent*.

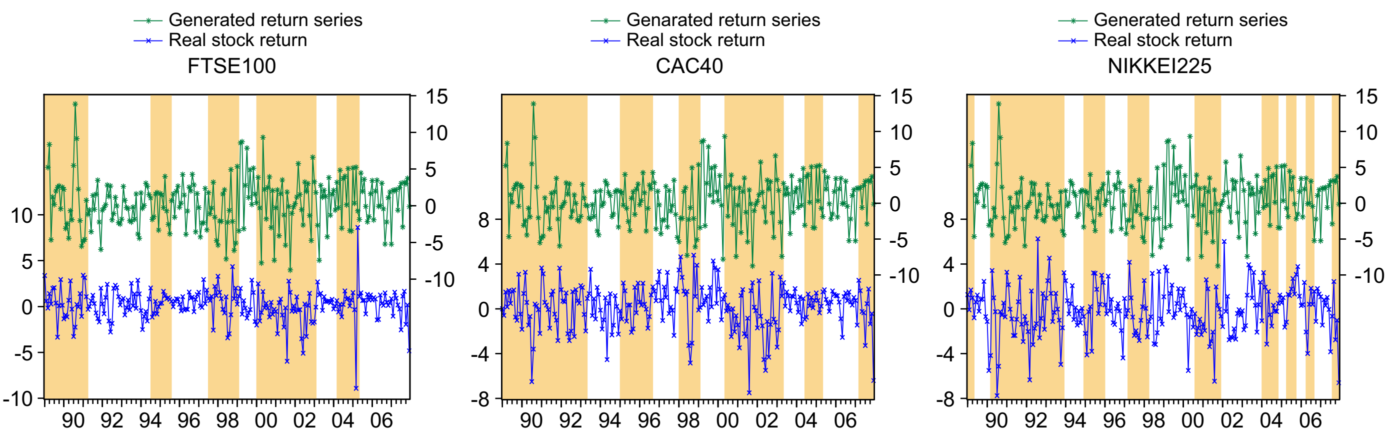

Fig. 15. Real stock returns-generated return series of the Brent.*

pre-1999 period investors are more certain about market prospects and, thus are not likely to shuffle portfolios. These empirical results come to the conclusion that crude oil shocks play a significant role in explaining the sharp Japanese stock market downturns but did not affect the recessionary stock market volatility in France and UK. Lastly, while many of the patterns that emerge in model 1 and 3 are similar to those we have seen in models 2 and 4, the estimated parameters (oil) in the first ones show differences in magnitude, sign and significance (especially for model 3). Therefore we can conclude by arguing that models 2 and 4 are useful in that they provide quantitative guidelines about the relationships exhibited by the data series matched along the sample size.

4. Energy conservation policy[29]

Oil prices are of overriding concern. As economic activity is heavily dependent on energy use, runway energy prices could become inflationary and cause an economic recession. The government uses various measures and policies to combat a recession and stabilize the economy. As reported by several authors (Cologni and Manera (2009) among others), oil prices appear to have vanished their ability to shock macroeconomics and seem to have had no harmful effect on global growth, in recent years. Aspects of policy have changed in ways that may explain the decline in the impact of oil prices. In this section, we present policies carried out by authorities that may have had a role in fundamentally reducing short-term economic implications of oil shocks. These aspects involve the importance of energy efficiency improvements. In 2008, total worldwide energy consumption was 474 exajoules. Global energy consumption is projected to grow by 50 percent between 2005 and 2030, driven by vigorous economic growth and growing populations in the world's developing countries (IEO, 2008).[30] G8 countries have long give high priority to energy intensity or efficiency for national development as the industrialized world considers the double pressures of increased energy demand from transition economies and volatile oil prices. Indeed, government leaders shift their focus on examining mechanisms that might disconnect their economies from energy price shocks in the international market (i.e. diversifying energy sources and reducing dependence on fossil fuels—of which many G8 nations are net importers). The energy ratio is the ratio of overall primary energy consumption to GDP at constant prices. Since experiencing the oil crises of the 1970s, G7 countries have taken measures to promote energy conservation for the respective sectors. All G8 countries have seen improvements in the energy ratio since 1970 with growth in GDP exceeding that of primary energy consumption. Japan, in percentage terms, has the world's most energy-efficient country (IEA, 2009). Despite this improvement, there still remains a large potential for further energy savings particularly for industry

[29] We thank authors for their thoughtful comments on our paper.

[30] The International Energy Outlook released by the Energy Information Administration (EIA, 2008).

sector. Energy intensities of G8 countries depending on whether GDP is measured as Purchasing Power Parity (PPP) or Market Exchange Rates (MER), has exhibited a downturn trend. The average annual decline in energy intensity, between 1990 and 2007, is about 2.34% for UK, 1.06% for France and 0.61% for Japan. The total industrial energy intensity has fallen by 66 percent since 1970 followed by the service sector (61 percent) and household sector (55 percent) (BERR, 2008). By contrast, energy intensity in the transport sector has remained moderately flat over the last 30 years. All countries have some degree of national energy efficiency policies. Economic, energy security and environmental challenges form a dominant part of the current energy efficiency policy concern. Among the energy efficiency action plan, we cite for example the encouragement for the scrap of old vehicles and the launch of a zero-interest loan program for residential energy efficiency improvements in France. In Japan, a replacement of older vehicles with new fuel energy efficient and investing R&D into innovative energy efficiency technologies are examples of measures. Since oil has become easier to substitute with other renewable resources, the impact of oil shocks has been dampened. This also helps support our finding relative to the lower oil shocks impact on stock market recessionary phases in the post-1999 period in contrast to the pre-1999 period.

5. Conclusion

Given that investors use portfolio diversifications as a strategy to minimize risk, the analysis of the linkages between oil prices and stock prices is of high importance for investors' optimal portfolio decision. This paper proposes a general method for analyzing changes in crude oil prices and identifying their relative contributions in the variability of the stock market returns for UK, France and Japan over the period January 1989–December 2007. Consequently, we first apply the "â Trous Haar Wavelet" (THW) framework on the CO prices that emphasized the determination of the de-noised series. When applying this technique, we are able to extract the driving dynamics of crude oil prices and to bring out past events that were not originally visible. We then test the effect of real stock returns on both the original and the generated series in the presence of structural breaks based on the trivariate MS-VAR Model. The results of this paper are consistent with much of the previous researches. In particular, we find that (1) the conceptual frameworks of the THW transform seem to have the capability for exploring and understanding various dynamic features of the crude oil prices; (2) The impulse response functions analysis suggests the existence of a long-run effect of oil prices on stock prices before 1999 but it disintegrates after this date. (3) Results from the smoothed probability of regime 2 provided by the benchmark regime switching model of the stock market variables suggest that stock market returns are more volatile during the post-1999 period which coincides with the IT-bubble. (4) The three regimes MS-VAR models, extended by the resultant wavelet filtered CO series, turn out to provide much useful results for the effect of a change in CO prices on the stock market volatility phases. We conclude that empirical results tend to confirm those of Kilian and Park (2007) as well as Miller and Ratti (2009). First, given the high chance that the expansion is followed by a recession, we found that the stock market variables respond negatively and temporarily to the crude oil changes during moderate (France) and expansion (UK and France) phases but not at level to plunge them into a recession phase. However, the effect of WTI changes occurred in the expansion regime has driven the Japanese stock market into a recession phase. This may illuminate the important role that policy makers play in order to counteract any inflationary impact of higher prices with monetary policy in UK and France contrary to Japan, who maybe unable to completely offset the increased variability of oil shocks contributing into the vulnerability of the stock market. A fresh question appears a matter of further research, that might extend the understanding of this relationship: given that the stock market is presumably in an expansion, does a rise in CO rates increase the probability of a recession? To answer this research question, one can extend our framework by assuming time-varying transition probabilities and allowing them to be function of changes in CO rates. Second, by examining the smoothed probabilities, it appears that the stability of the negative relationship between crude oil shocks and the stock market volatility is hard to maintain after the IT-bubble of 1999. This can lead investors to make suboptimal investments decisions. Finally, we should not forget the role of technological improvements, which may reduce the impact of oil shock, by reducing the dependences on oil.

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