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The effects of crude oil shocks on stock market shifts behaviour: A regime switching approach

Chaker Aloui *, Rania Jammazi

International Finance Group-Tunisia, Faculty of Management and Economic Sciences of Tunis, Boulevard du 7 novembre, El Manar University, B.P. 248, C.P. 2092, Tunis Cedex, Tunisia

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ABSTRACT

In this paper we develop a two regime Markov-switching EGARCH model introduced by Henry [Henry, O., 2009. Regime switching in the relationship between equity returns and short-term interest rates. Journal of Banking and Finance 33, 405–414.] to examine the relationship between crude oil shocks and stock markets. An application to stock markets of UK, France and Japan over the sample period January 1989 to December 2007 illustrates plausible results. We detect two episodes of series behaviour one relative to low mean/high variance regime and the other to high mean/low variance regime. Furthermore, there is evidence that common recessions coincide with the low mean/high variance regime. In addition, we allow both real stock returns and probability of transitions from one regime to another to depend on the net oil price increase variable. The findings show that rises in oil price has a significant role in determining both the volatility of stock returns and the probability of transition across regimes.

1. Introduction

Now it is well documented that volatility shocks in crude oil (CO) markets have significant effects on a variety of economic activities. There is substantial empirical evidence to show a negative relationship between changes in CO prices and aggregate measures of output[1] and employment. Hamilton (1983) attested that increase in CO price precedes every recession cycle in the US. This point of view is supported by Mork (1989). According to this author, the effect of CO price volatility shocks on the output growth are asymmetric and there is a significant negative linkage between CO price increases and world economic growth. Similar results were provided by Hooker (1999). Also, Mork's conclusions are supported by the International Monetary Fund (2006) and the International Energy Agency (IEA, 2004) studies. Based on the OECD model, the IEA estimates that a 25 dollars to 35 dollars increase in the barrel price causes a two-year drop in the GDP of 0.3 percentage points in the US, 0.4 points in Japan and 0.5 points in the euro zone. If CO is a decisive determinant of economic growth, we would expect that increases in CO market prices will be significantly linked to the firms' expected earnings and consequently their stock price levels. Thus, the relationship between CO price volatility and stock markets seems to be quite evident. In their paper, Jones and Kaul (1996) documented that stock price movements can be accounted for by the impact of CO volatility shocks on real cash-flow. Similar results are provided by Park and Ratti (2008). According to these authors, oil price shocks account for a statistically significant 6% of the volatility in real stock returns for many European countries (Park and Ratti, 2008, p. 2587). These conclusions are supported by many other relevant papers such as Faff and Brailsford (1999), Sadorsky (1999, 2001, 2006), Papappetrou (2001), Ciner (2001), Jones et al. (2004), Faff and Nandha (2008), Ewing and Thompson (2007), Cong et al. (2008), Aloui et al. (2008). The main conclusion is that energy prices in general and oil prices in particular are likely to have a potential effect on the costs of factor inputs for many listed firms and therefore on their stock price behaviour.

In the last years, many empirical studies were focused on the shifts behaviour or structural breaks in stock market volatility. In fact, stock prices have experienced some periods in which their behaviour seem to change dramatically. The CO price increases in 1973–1974, the stock market crash in 1987, the Iraqi invasion of Kuwait at the end of 1990[2], the 1997 currency crisis in East Asian countries, the September, 11 terrorist attacks, the recent CO increases in 2007–2008 and the last

* Corresponding author. Tel.: +216 71 87 02 77x237.
E-mail addresses: chaker.aloui@fsegt.rnu.tn (C. Aloui), jamrania2@yahoo.fr (R. Jammazi).

[1] Concerning the dynamic linkage between oil volatility shocks and the macroeconomy, Hamilton (2008), Huntingon (2005), and Barsky and Kilian (2004) have provided reviews of the literature.

[2] The price of CO briefly spiked to more than 35 dollars per barrel in response to this war, returning to below 20 dollars several months after (Hung et al., 2008, p.1174).

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two financial crises on 2007 and 2008 can be given as examples. All these events cause changes in the dynamic process of financial time series and motivate the use of regime switching models. Hamilton (1989) proposes a Markov switching model to date and forecast real GNP growth by introducing discrete shifts in the mean between high-growth and low-growth regimes as an overcome to the drawback of linear approaches (the ARMA and the ARIMA models of Nelson and Plosser (1982), the unobservable components model of Watson (1986)…etc which fail in explaining business cycle features about duration of recession and expansion (asymmetry)). Kim and Nelson (1999) suggest a Markov regime switching model in the transitory of real GDP to capture business cycle asymmetry.

The Markov-switching autoregressive models (MS-AR) were largely used in stock markets. The main idea is to *capture the regime shifts behaviour*. Turner et al. (1989) and Chu et al. (1996) are the first to employ the MS-AR process. The study of Turner et al. (1989) was extended by Schaller and Norden (1997). These authors have provided strong evidence of regime switching behaviour in the stock market returns. In line with Schaller and Norden (1997), Hishiyima (1998) have tested the eventual presence of switching regimes in the aggregate stock market returns for five developed economies. He has identified a regime shifts behaviour in all the stock markets volatilities. The study of Maheu and McCurdy (2000) was focused on the US context. They have documented the switching between two regimes (high return-stable state and low return-volatile state). Concerned with the same context, Guidolin and Timmermann (2006) have suggested a *multivariate MS-AR model* to investigate the volatility spillovers and regime shifts in the dynamic linkage between US equity and bond markets. In a more recent paper, Ismail and Isa (2008) have proposed a two regime MS-AR model to capture regime shifts behaviour in both mean and variance in the Malaysian equity market. They concluded that the MS-AR model is able to capture the timing of regime shifts occurred during the period (1974–2003) and generated by the 1974 oil shock, 1987 stock market crash and Asian financial crisis in 1997 (Ismail and Isa, 2008, p. 44). Other authors have proposed the use of more advanced econometric techniques including the *MS-GARCH-type models*. They were concerned with two main research areas: 1) identifying regime shifts in stock markets and 2) assessing the impact of CO volatility shocks on the economic activity and the business cycles.

Regarding, this last research area, a growing number of empirical works have applied the MS model in order to capture nonlinearities and asymmetries which are present in the macroeconomic time series. In particular[3], Raymond and Rich (1997), Clements and Krolzig (2002) and Holmes and Wang (2003) have employed the MS approach to judge the impact of CO volatility shocks on US and UK business cycles. Manera and Cologni (2006) have analyzed the asymmetric affects of oil shocks on output growth for the G-7 countries. Using a MS-AR model, they have pointed out the role of oil shocks in explaining recessionary episodes. The same approach has been employed by Wang and Theobald (2008) to research regime switching behaviour in the return-generating processes of six Asian emerging stock markets (1970–2004) and the impact of financial liberalization on the return volatility. Their results provide a strong evidence of more than one regime in each stock market. Moreover, the conditional probabilities of each regime reveal mixed evidence concerning the impact of financial liberalization. In line with the paper of Wang and Theobald (2008), Diamantis (2008) have implemented the MS-ARCH-L model of Hamilton and Susmel (1994) to study for the structural breaks in volatility of four emerging Latin American emerging markets. They found evidence that there were volatility switching regimes in these countries during 1990s and early 2000s.

In connection with stock markets behaviour research, Hamilton and Susmel (1994) and Cai (1994) developed the *MS-ARCH* (SWARCH) model which has been implemented to divers financial time series including equity, foreign exchange rates and interest rates. Gray (1995) researched switching regimes in interest rates and foreign exchange time series and developed a MS-GARCH model. Dueker (1997) have chosen the US equity market and employed a similar model. In a more recent paper, Bauwens et al. (2006) suggested a Bayesian approach in order to estimate a symmetric MS-GARCH(1,1) model. Bae et al. (2007) have estimated the regime *switching threshold GARCH model*. In his study, Henry (2009) has employed a two regime *MS-EGARCH model* in order to investigate the relationship between short-term interest rates and the UK equity market. In the first regime (high return-low variance), he revealed that the conditional variance of equity returns responds persistently but symmetrically to equity return innovations. While in the other regime (low mean–high variance), he provided evidence that equity volatility responds asymmetrically and without persistence to shocks to equity returns. Moreover, Henry (2009) asserted that events in the money markets have an impact on the probability of transition across regimes. Concerning effects of oil shocks on the stock markets dynamics, we should note that the empirical literature on the MS-GARCH and/or MS-AR models applied to stock markets is extremely limited except for the work by Hammoudeh and Choi (2007). Using the unobserved-component model with Markov-switching heteroskedasticity (UC-MS) model, Hammoudeh and Choi (2007) researched the permanent and transitory returns in oil-sensitive of the Gulf Cooperation Council (GCC) stock markets. They revealed that spot oil market plays an important role in explaining the behaviour of GCC stock returns during changes in the fundamentals and the fads (Hammoudeh and Choi, 2007, p. 243). According to these authors, all the GCC stock returns have the same movement direction, whether in terms of total return, fundamentals or fads under both volatility regimes.

In summary, it can be stated that the regime shifts are identified in stock market behaviour. This motivates us to investigate whether these shifts exist in some developed stock markets and to check if they are associated with price shocks on CO markets. This research contributes to the literature by providing some response elements to this question: how can we assess the impact of CO market volatility shocks on major stock market return from an empirical position? More precisely, we seek evidence of period of high volatility in equity market returns and then to examine whether these periods are associated with events in the CO markets in a statistically significant approach.

In this study, we investigate the effects of CO volatility shocks on the regime shifts behaviour of three developed markets: France, U.K. and Japan over the sample period (1989:01–2007:12). Our methodology is based on a two regime MS-EGARCH model introduced by Henry (2009). This model allows the variance of stock returns to switch across different regimes and the regime, at any given date, is presumed to be the outcome of a Markov chain whose realizations are unobservable. Also, it is based on the assumption that stock return may move across different volatility regimes which characterized by the different perceptions and reactions of market participants to volatility shocks on CO markets. Furthermore, unlike existing MS-GARCH models, the model proposed in this study has sufficient flexibility to capture regime dependence in the impact, persistence and asymmetric response to a shock since the conditional variance depends on past shocks and the present and past states of the economy. Our study is distinguishable from previous empirical works in at least two points. First, a novelty of this paper is that we explicitly assess the dynamic impact of exogenous oil markets shocks on the behaviour of stock market returns by using a two regime MS-EGARCH model. To the best of our knowledge, it is the first study to employ this empirical approach. Secondly, the other innovative feature of our study is that we employ an EGARCH specification. This allows us to take jointly into account two major

[3] In our empirical review, our attention is focused on some recent studies. For earlier research, see Hamilton (1989), Turner et al. (1989) and Glosten et al. (1993).

characteristics of innovations to volatility: (1) time variation and asymmetry in the conditional variance within each regime and (2) dependence in the impact persistence and asymmetric response to shocks relative to stock market volatility. Furthermore, unlike most of the existing literature, we employ the net oil increase (NOPI) to approximate the volatility shocks in CO markets. This measure has been initially suggested by Hamilton (1996). The NOPI is assimilated to an event in the CO market and then it would be possible to investigate it influences not only the mean and/or the variance of the real stock return.

The remainder of this paper is organized as follows: section 2 presents the data and describes the Markov-switching EGARCH framework to be used in the analysis. The empirical results are displayed in section 3. Obviously, our attention is focused on the impact of CO market shocks on the business cycle in equity markets. In subsection 3.1., we check if regime shifts can be detected in the stock market volatility. Subsection 3.2., presents and discusses the relationship between CO market shocks and equity return dynamics in the context of the MS-EGARCH with fixed transition probabilities. The subsection 3.3 outlines the results associated with the MS-EGARCH

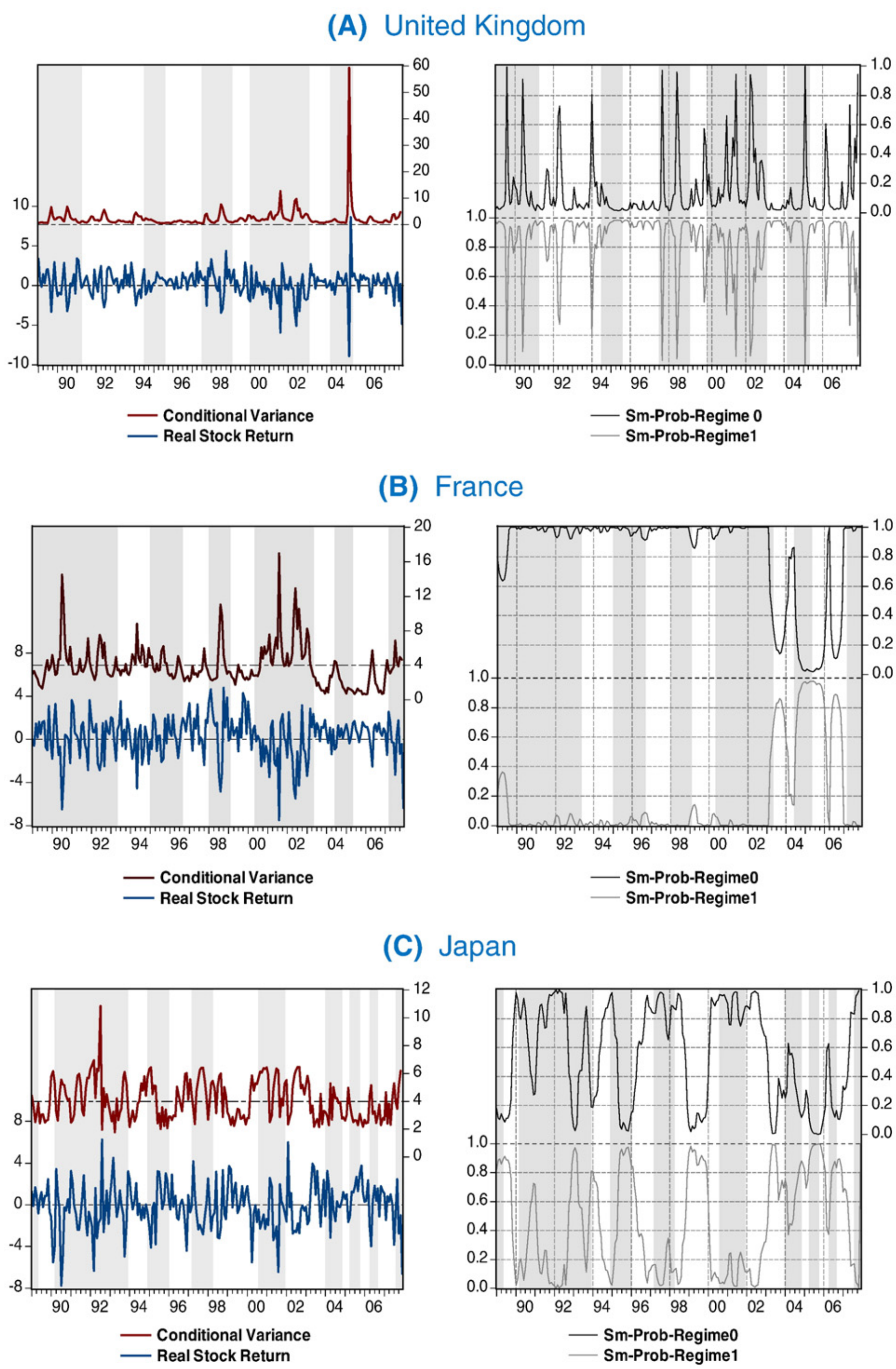

Fig. 1. The right vertical panel: monthly real returns and the conditional variance obtained from the MS-EGARCH model. The left vertical panel: smoothed probabilities of regime 0 and of regime 1 that the real stock return process is in regime 0 (the low mean–high volatility regime) at time (t) and in regime 1 (the high mean–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.

Table 1
Summary statistics of real stock returns and NOPI time series (monthly frequency, January 1989–December 2007).

	Mean	Max.	Min.	S.D.	Skewness	Kurtosis	J–B.	Probability	Obs.
FTSE100	0.203	8.61	−8.9	1.73	−0.62	8.64	317.4	0.000	228
CAC40	0.206	4.78	−7.4	1.97	−0.78	4.46	43.62	0.000	228
Nikkei225	−0.15	6.24	−7.7	2.22	−0.30	3.75	9.026	0.000	228
WTI	1.86	17.41	0.00	3.40	2.18	7.52	375.1	0.000	228
Brent	1.75	17.01	0.00	3.47	2.33	8.07	452.3	0.000	228

Notes: FTSE100, CAC40 and Nikkei225 are the real stock returns (stock return–inflation rate). S.D. is the standard deviation. J–B is the Béra and Jarque (1980) normality test statistic. Time series have monthly frequency and cover the sample period (January 1989–December 2007). Probability denotes the marginal significance levels.

framework with time-varying transition probabilities. The summary and some concluding remarks are displayed in section 4.

2. Data and methodology

2.1. Data, variables specification and preliminary analysis

In this study we employ real stock returns respectively of three major industrial countries, namely: Japan (Nikkei225), UK (FTSE100) and France (CAC40), and the closing prices of two major CO products, defined as the US price of West Texas Intermediate Cushing (WTI) and the Europe Brent which are quoted in Dollars per barrel. The sample period covers, in monthly frequency, January 1989 to December 2007 for a total of 228 observations. CO price time series were extracted from the US Department of Energy (Energy Information Administration). While stock index series[4] are taken from the International Financial Statistics databases (IFS). The stock market asset returns are computed as follows:

$$r_t = 100 \times \ln(P_t / P_{t-1}) \tag{1}$$

Where $P(t)$ is the stock price on month (t). 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. We use monthly return series because we suppose that regime shifts can be detected more clearly across time if we use data on low frequency. On the one hand, quarterly data does not offer enough observations and would make analysis during crisis periods worthless as crises tend to be relatively short-lived. On the other hand, daily data would be too noisy to analyze and could lead to unclear estimation results (Ramchand and Susmel, 1998). This feature can be verified by plotting the monthly return series for the three stock markets (Fig. 1). As seen in Fig. 1. Right vertical panel, large negative returns can be detected over the sample period. This aspect show that regime shifts happen during this period. The choice of the oil price variable is an important issue.[5] Following Hamilton (1996), we choose the “net oil price increase” variable (NOPI) that relates the current price of oil to its value over the previous year rather than the previous month. More precisely, the variable is defined to be equal to the difference between the current monthly closing price of oil and the previous year's maximum if positive and zero otherwise. The NOPI is expressed as follows:

$$\mathrm{NOPI}\begin{cases} = \mathrm{oil}_t - \max(\mathrm{oil}_{t-1}, \ldots, \mathrm{oil}_{t-12}, \ \text{if } \mathrm{oil}_{t-1}, \ldots, \mathrm{oil}_{t-12}) \\ = 0, \text{ otherwise} \end{cases} \tag{2}$$

In other words, oil price changes are assumed to have an effect on the economy only when oil is trading at a higher price than at any other time in the previous year. In order to identify the effects of oil price shocks on the real stock returns, we first need to find an appropriate indicator of oil price shocks to incorporate into the MS-EGARCH model. We use as indicator of oil price movement, the NOPI's proposed by Hamilton. This choice is motivated by the well-known finding that this variable has a stable relationship with macroeconomic variables. It assumes that if the current oil prices in a given period are above their peak value over the previous year, then it is expected to have an impact. However, if oil prices are not above their previous peak, then this variable is equal to zero and it has no impact. This measure is also supported by Cobo-Reyes and Pérez Quirós (2005) who analyze the relationship between oil price shocks and the stock returns using the model of Hamilton (1989)[6]. Hamilton (1996) has introduced the concept of NOPI in a VAR model in order to detect a significant relationship between oil prices and real output in the US. Using a MS-AR model to investigate the asymmetric effect of oil shocks on output growth for the G-7 countries, Manera and Cologni (2006) showed that the NOPI and oil volatility are the oil shocks definitions which contribute to a better description of the oil shocks effects on economic growth. In their paper, Park and Ratti (2008) have employed the NOPI measure to investigate the impact of oil shocks on real stock returns in the US and 13 European countries over the period (1986:01–2005:12). They found that oil price shocks had a negative impact on equity markets. Also, Cong et al. (2008) have chosen the NOPI variable as a nonlinear transformation of the CO time series in order to research the impact of CO market volatility shocks on Chinese stock market behaviour. They found that some important oil price shocks depress Chinese oil company stock prices (Cong et al., 2008, p. 3544).

In Fig. 1 (right vertical panel), we manage to detect the presence of volatility clustering phenomenon where large (small) price changes tend to be followed by large (small) price changes over consecutive month. Such volatility clustering is a common motivation for the use of GARCH models as conditional characterization of real stock returns. Table 1 reports some monthly descriptive statistics for the FTSE100, CAC40 and Nikkei225 real stock returns and the NOPI for the WTI and Europe Brent commodities.

From this table, it is clear that the mean of the time series are relatively small compared to the standard deviations (especially for the real stock returns). The Nikkei225 real stock returns exhibit the highest standard deviation with a negative return average. We note that the NOPI of the WTI and Europe Brent have by far the highest volatility of all the times series. In terms of distributions, all the real

[4] In our study, oil prices are measured in US dollars, however stock prices are in national units. We do not use the dollar/local currency spot exchange rate to convert local real stock prices to US dollars. Obviously, we expect to come up with different results if we have used a common currency. It would, however, be a topic for future research.

[5] Raymond and Rich (1997) prefer the net oil price compared to previous 1 year of Hamilton (1996) as a substitute to Mork's oil price. Hamilton (2003) propose the net oil price compared to previous 3 years as an alternative to the net oil price compared to previous 1 year of Hamilton (1996). Hamilton (2003) also accept oil price of Lee et al. (1995) (LNR oil price) as the illustrative oil price. Clements and Krolzig (2002) select LNR oil price by using the best fit in an Autoregressive-Distributed Lag (ADL) model.

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

stock returns are governed by slightly skewed distributions (i.e. negative skewness), while the NOPI of the WTI and Europe Brent CO have a tendency toward positive skewness. The kurtosis values are high with the maximum of 8.64 for the FTSE100 and a minimum of 3.75 for the Nikkei225 real stock returns. According to the Béra and Jarque (1980) test, it is evident to note that the hypothesis of normal distribution is rejected at the 1% significance level for all the series. It is anticipated that the NOPI variable will captures the domestic economic and financial conditions in each economy and the stock market. The lag structure for this variable is important in relation to the information set available at any point in time. In our analysis, the NOPI variable is restricted to enter the model with a one month lag.

A stylized fact of individual financial time series is that they are non stationary in their levels but they are stationary in their first differences (i.e. they are $I(1)$). For our data, we have applied two usual unit root tests: the Augmented Dickey and Fuller (1979) (ADF) and the Phillips and Perron (1988) (PP) tests in order to insure that all the time series are $I(1)$. The obtained results reveal that the stock market indexes and CO spot prices are non stationary at the 1% significance level. Furthermore, real stock returns and the NOPI time series are stationary[7] at the same significance level. Overall, all the series have a single unit root or are integrated of degree one. This result is consistent with previous empirical studies including, among others, Manera and Cologni (2006), Park and Ratti (2008), Cong et al. (2008).

2.2. The Markov-switching exponential GARCH (MS-EGARCH) framework

First, consider a simple EGARCH (1,1) process introduced by Nelson (1991) for y_t,

$$y_t = f(x_t;\vartheta) + \varepsilon_t \qquad \varepsilon_t / I_{t-1} \rightarrow D(0, h_t) \tag{3}$$

$$\ln(h_t) = \omega_0 + \varphi\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta\ln(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \tag{4}$$

$f(x_t;\vartheta)$ refers to the conditional mean, x_t is a vector of M explanatory variables, that may include lagged y_t's, ϑ is a $(M\times1)$ vector of parameters, I_{t-1} is the information set that contains all information available at time $(t-1)$, and ε_t is the error term. The conditional variance follows an EGARCH(1,1) process, as given in Eq. (4). As a conditional distribution, D, the Student-t proposed by Bollerslev (1987) is generally used. h_t, the estimated conditional variance, is strictly positive and it does not require the need of non-negativity constraints used in the estimation of GARCH models. Eq. (4) demonstrates an asymmetric effect of negative news on the variance, or the leverage effect. According to, Black (1976) and Nelson (1991) the stock return volatility is generally affected by the asymmetric stock price increases and decreases. In this equation, the asymmetry effect in volatility is captured by the coefficient γ. At present, it is interesting to account for the drawback of the GARCH models, announced by Lamoureaux and Lastrappes (1990). According to these authors, the high degree of persistence showed by the standards GARCH processes may be spurious in the presence of structural breaks in the conditional variance. Using a more realistic approach, regime switching model, Hamilton and Susmel (1994)[8] corroborate this assumption. Within this change of regime framework, Hamilton and Susmel (1994)[9] have modified the conditional variance equation to make the conditional variance depend on the state of the economy.

Following, Henry (2009), the basic MS-EGARCH(1,1) model[10] can be written as follows:

$$y_t = \mu_{it} + \varepsilon_t \qquad \varepsilon_t / I_{t-1} \rightarrow D\left(0, h_{i,t}\right) \tag{5}$$

$$\ln(h_{it}) = \omega_i + \varphi_i\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{it-1}}}\right| - \sqrt{2/\pi}\right] + \beta_i\ln\left(h_{i,t-1}\right) + \delta_i\frac{\varepsilon_{t-1}}{\sqrt{h_{i,t-1}}} \tag{6}$$

We assume the existence of two states, i, indexed by a latent variable, s_t, which takes two values, 0 (recession period) and 1 (expansion period), depending on the state of the economy. The transition between the states is governed by a first order Markov process[11] as follows (Hamilton, 1989):

$$\begin{aligned} P(s_t = 0 / s_{t-1} = 0) &= p_{00} \\ P(s_t = 0 / s_{t-1} = 1) &= 1 - p_{11} \\ P(s_t = 1 / s_{t-1} = 0) &= 1 - p_{00} \\ P(s_t = 1 / s_{t-1} = 1) &= p_{11} \end{aligned} \tag{7}$$

With p is the probability that the economy switches at time t from state 1 (or 0) to state 0 (or 1). It is convenient to summarize these transition probabilities in a (2×2) matrix P[12]. When the transition probabilities are assumed to be constant, the logistic functional form is as:

$$p_{00} = \frac{e(\theta_0)}{1 + e(\theta_0)} \quad \text{and} \quad p_{11} = \frac{e(\partial_0)}{1 + e(\partial_0)} \tag{8}$$

According to Hamilton (1989) and Gray (1995), the MS-EGARCH can be estimated using maximum Likelihood techniques. As mentioned above, to the best of our knowledge, it is the first time a MS-EGARCH(1,1) process is estimated in order to research the impact of CO price shocks on the stock markets shifts behaviour. Furthermore, unlike existing MS-GARCH models, the model chosen in this research has sufficient flexibility to capture regime dependence in the impact, persistence and asymmetric response to a shock (Henry, 2009, p. 7) since the conditional variance depends on past shocks and the present and past states of the economy. The weakness of this model is that it implies that the expected durations[13] of expansions or recessions can differ, but they are forced to be constant over time. Naturally, the expected duration of an expansion or recession is generally though to fluctuate with the principal strength of the economy. As noted by Filardo and Gorgon (1998), with fixed transition probabilities, the expected durations do not vary over the cycle. This means that exogenous shocks, macroeconomic policies and an economy's own internal propagation mechanisms do not influence the probability of how long an expansion or contraction will persist. To resolve this problem it is recommended to incorporate time-varying transition probabilities into the model, by using a specification for the transition probabilities that reflects information about where the economy is advancing. The variations in the transition probabilities will produce variations in the expected durations (Filardo and Gorgon, 1998). By allowing the transition matrix (P) to depend on

[7] Unit root test results are not shown here and they are available upon request.

[8] They applied the switching ARCH model to weekly US stock index returns and they have provided strong evidence of regime shifts in the scale of ARCH process. Additionally, they asserted that accounting for regime shifts led to noticeable reduction in the degree of residual volatility persistence.

[9] We can mention other implements of these specifications as Cai (1994), Brunner (1991) and Hall and Sola (1996).

[10] Opposite to the SWARCH and MS-GARCH models, a MS-EGARCH guarantees that the conditional variance h_t is positive by construction, without the use of non-negativity constraints.

[11] Which means that the current regime (s_t) depends only on the regime in the preceding period (s_{t-1}).

[12] The fixed transition probability matrix (P), are noted as follow: $\begin{bmatrix} p_{00} & 1-p_{11} \\ 1-p_{00} & p_{11} \end{bmatrix}$.

[13] With fixed transition probabilities, the expected duration of the regime (j) is given by: $E(D) = \frac{1}{1-p_{jj}}$, $j = 1, 2$.

Table 2
The likelihood ratio test results.

Stock market	MS-EGARCH ($\ln L_{\text{MS-EGARCH}}$)	EGARCH ($\ln L_{\text{EGARCH}}$)	LR test statistic[a]
U.K.	−403.842	−409.468	11.252
France	−455.8	−460.691	9.782
Japan	−492.394	−499.233	13.682

[a] The LR test statistic approximately follows a χ^2 distribution. The degree of freedom is equal to the number of parameters appearing under the alternative hypothesis. In our case, there are two additional parameters to the EGARCH(1,1) model.

some variable x_{t-1}, the time-varying transition matrix $P(t)$ will be formulated as follows:

$$P(t) = p_{ij}^{t}(x_{t-1}) = P(s_t = j / s_{t-1} = i, x_{t-1}) = \begin{bmatrix} p_{00}^{t}(x_{t-1}) & 1 - p_{11}^{t}(x_{t-1}) \\ 1 - p_{00}^{t}(x_{t-1}) & p_{11}^{t}(x_{t-1}) \end{bmatrix} \quad (9)$$

In this equation, x_{t-1} is the information variable(s) upon which the evolution of the unobserved regime will depend. In our analysis, we consider as information variable the CO price shock measured by the NOPI. In this way, it is possible to research whether events in the CO market influence not only the mean and/or the variance of the real stock return (y_t) but also the probabilities of a change in regime. The extended MS-EGARCH(1,1) model will be written as follows:

$$y_t = \mu_{it} + \eta_i \text{NOPI}_{t-1} + \varepsilon_t, \qquad \varepsilon_t / I_{t-1} \rightarrow D\left(0,\ h_{i,t}\right) \quad (10)$$

$$\ln(h_{it}) = \omega_i + \varphi_i \left[\left| \frac{\varepsilon_{t-1}}{\sqrt{h_{i,t-1}}} \right| - \sqrt{2/\pi} \right] + \beta_i \ln\left(h_{i,t-1}\right) + \delta_i \frac{\varepsilon_{t-1}}{\sqrt{h_{i,t-1}}} + \lambda_i \text{NOPI}_{t-1} \quad (11)$$

Consider the parameterization of the state transition probabilities:

$$p_{00}^{t} = \Pr(s_t = 0) = \frac{e(\theta_0 + \theta_1 \text{NOPI}_{t-1})}{1 + e(\theta_0 + \theta_1 \text{NOPI}_{t-1})} \quad (12a)$$

and

$$p_{11}^{t} = \Pr(s_t = 1) = \frac{e(\partial_0 + \partial_1 \text{NOPI}_{t-1})}{1 + e(\partial_0 + \partial_1 \text{NOPI}_{t-1})} \quad (12b)$$

Filardo (1994) noted that this form of functions constraints the transition probabilities into the interval [0,1]. It follows that;

$$\frac{\partial p_{00}^{t}}{\partial x_{t-1}} = \theta_1 p_{00}^{t}\left(1 - p_{00}^{t}\right) \quad (13a)$$

and

$$\frac{\partial p_{11}^{t}}{\partial x_{t-1}} = \theta_1 p_{11}^{t}\left(1 - p_{11}^{t}\right) \quad (13b)$$

The transition probabilities are non-negative and bounded between zero and unity in magnitude, implying that the signs of $\frac{\partial p_{00}^{t}}{\partial \text{NOPI}_{t-1}}$ and $\frac{\partial p_{11}^{t}}{\partial \text{NOPI}_{t-1}}$ are governed by the signs of θ_1 and ∂_1. For $\theta_1 > 0$ a high level in NOPI_{t-1} implies that the equity returns are more likely to stay in regime 0. Conversely, $\theta_1 < 0$ implies that a switch to the high volatility state is more likely following a high level in NOPI_{t-1}.

3. Model selection and estimation results

3.1. Regime shifts diagnostics

We should note that the selection of the regime switching process is complicated because the identification of the number of regimes in MS models cannot be realized via the usual likelihood ratio, Lagrange multiplier, or Wald tests since their asymptotic distributions are non-standard. To overcome this problem, we have employed the likelihood ratio test (LR) suggested by Garcia and Perron (1996). Thus, we test the null hypothesis of no switching in stock market volatilities represented by an EGARCH(1,1) process (single regime) against an alternative specification MS-EGARCH[14] which involves switching in the stock market volatilities (two regimes). We should mention that we have jointly estimated the mean and the variance. Using the Akaike (1974), and Hannan and Quinn (1979) information criteria, the autoregressive order in the mean equation was determined to be zero and for the variance equation, we found that the EGARCH(1,1) model describes each of the real stock returns series well. The LR test statistic[15] is defined as $\text{LR} = 2|\ln L_{\text{MS-EGARCH}} - \ln L_{\text{EGARCH}}|$ and the critical value is based on the p-values of Davies (1987) as suggested by Garcia and Perron (1996). The outcomes are reported in Table 2.

As shown in Table 2, the log-likelihood ratio test of the MS model with constant transition probabilities and two regime shifts is higher than the EGARCH(1,1) model for all the stock markets. Thus, we are able to reject the null hypothesis of no switching at a significance level of 5%. Therefore, it is clear that there is a strong evidence of regime shifts in all the stock market volatilities. We conclude that the volatility of the real stock returns is better described by a two-state regime switching EGARCH model than a single regime EGARCH model. This result is in particular consistent with the findings of Henry (2009).

3.2. The MS-EGARCH model with fixed transition probabilities

In this subsection, we discuss the estimating results of the univariate two regime MS-EGARCH(1,1) model with fixed transition probabilities for the real stock returns of the U.K., France and Japan.

From these results, we can draw the following comments:

(1) All parameters in variance (h_{it}) and mean (μ_{it}) equations are regime dependent (they are allowed to switch across regimes). An appealing feature of regime switching models is that they allow the joint estimation of regime shifts, ARCH and asymmetry effects. Another interesting feature of regime switching models is that the regimes are not assumed to be observable by the econometrician, but it can be identified from the estimation process.

(2) Each of the two regimes identified for the real stock market returns has a clear economic interpretation. From this table, we can denote that there are three interesting results. First, we identify two types of regime: the first one regime captures the behaviour of the stock market in a recession state or in the "bear market" with low expected return and high variance. Whereas, the other regime (regime 1) captures the behaviour of the stock market in an expansion state or in the "bull market" with high expected return and low variance. It can be seen that the intercept in the conditional variance of regime 0, $\hat{\omega}_0$, is higher than the one of regime 1, $\hat{\omega}_1$, where the monthly values are 1.91% for Japan, 1.8% for U.K. and 1.15% for France.

[14] This choice is grounded at the work of Henry (2009) who performed a very similar analysis in his paper on British stock market (FTSE100).

[15] This LR test statistic approximately follows a c^2 distribution. The degree of freedom is equal to the number of parameters appearing under the alternative hypothesis. In our case, there are two additional parameters to the EGARCH(1,1) model.

Additionally, the monthly variance value for regime 1 is around 0.6% to 0.9%. The average return during the recession state is estimated to 0.24% per month for France and it is not statistically different from zero, whereas, in regime 1, the average depreciation jumps to 0.86% per month. Besides that the negative sign of the expected return, $\hat{\mu}_0$ indicate that the real stock return tend to fall about 1.66% monthly for U.K. and 0.97% monthly for Japan, when it follow the first regime. Furthermore, the positive signs of the expected return $\hat{\mu}_1$ indicates that the stock return tend to increase about 0.5% and 0.88% monthly respectively.

(3) In order to identify which regime is more persistent, we need to interpret the probability estimates. The estimates of transition probabilities p_{00} and p_{11} are both highly significant for all the real stock returns. We cannot e that, for FTSE100 and CAC40 series, the probabilities of staying in regime 0 are smaller (the values of p_{00} are about 0.885 and 0.884, respectively) than the probabilities of staying in regime 1 (the values of p_{11} are about 0.892 and 0.977 respectively). The expected duration of staying in regime 0 are about 8.7 and 8.6 months and the expected duration of staying in regime 1 are about 9.3 and 43.5 months respectively. Then, it can be shown that the second regime, which is associated with high expected return and lower variance, is more persistent. This regime can be referred to the state where the stock markets are in the expansion phase or in the "bull market." The expected duration of being in an expansion phase is longer than in a recession phase, which imply that only an extremely event can switch the real stock return or volatility series of the British and French stock markets from regime 1 to regime 0. On the other hand, for the Japan, the probability of staying in regime 0 is higher ($p_{00}=0.9$) than the probability of staying in regime 1 ($p_{11}=0.87$) and the expected duration of staying in regime 0 is 10 months whereas the expected duration of staying in regime 1 is 7.7 months. This result implies that regime 0 is more persistent. Put it differently, the recession state of the Japanese stock market is much longer than its expansion phase.

(4) Additionally, the GARCH parameters, β_0, which captures the persistence in the conditional volatility are significant for all the return series while their δ_0 are insignificantly different from zero. Moreover, as $\delta_1<0$ are significantly different from zero, the French market will react more sharply to positive innovations to returns than negative innovations of equal size.

(5) Another advantage of using the MS model is that it provides the conditional regimes probabilities of being in regime 0, and regime 1 at time (t). In estimating regime switching models, two different conditional probabilities are of interest. The filter probability, which is commonly reported in the regime switching literature, is of interest in forecasting. The smoothed probability is of interest in determining if and when regimes switches occur[16]. This later is very valuable in helping to understand more about the economic interpretation that was made earlier using the estimated parameters.

(6) In order to check whether the two-state Markov-switching variance captures most of the dynamics in the real stock return time series, we applied the diagnostic test of Box–Pierce (B–P) (to order 12) to the standardized residuals. The test outcomes are presented in Table 3. As shown, the B–P test supports the whiteness of the residuals. Similarly, the null hypothesis for no serials correlations in the squared residuals (to order 12) is accepted indicating no remaining heteroscedasticity in the residuals. These results suggest that the two-state Markov-switching models provide a reasonable approximation of the heteroscedasticity in monthly real stock returns.

Hence, to further support the interpretation of two regimes, we plot in Fig. 1(left vertical panel) the smoothed probabilities generated from the model MS-EGARCH(1,1) with two regimes fitted to all the stock return time series of each country. The smoothed probability that the economy was at state 1 is the mirror image that at the state 0. The probability of recessions and expansions can be interpreted as a representation of stock return phases for each economy. In order to

Table 3
Estimation results of the two regime univariate MS-EGARCH(1,1) model with fixed transition probabilities.

$y_t=\mu_{it}+\varepsilon_t,\ \varepsilon_t/I_{t-1}\rightarrow D(0,\ h_{i,t})$

$\ln(h_{it}) = \omega_i + \varphi_i\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{it-1}}}\right| - \sqrt{2/\pi}\right] + \beta_i \ln(h_{i,t-1}) + \delta_i \frac{\varepsilon_{t-1}}{\sqrt{h_{i,t-1}}}$

	FTSE100	CAC40	Nikkei225
μ_0	−1.6602***	0.2416*	−0.9799***
	(−2.10)	(1.40)	(−3.58)
μ_1	0.5030***	0.8573***	0.8871***
	(2.34)	(5.12)	(2.51)
ω_0	1.8082***	1.1508***	1.9123***
	(3.23)	(2.81)	(5.14)
ω_1	0.63557***	0.7179	0.8653***
	(2.79)	(1.21)	(2.64)
φ_0	0.4691	0.7249***	0.1136
	(0.61)	(2.19)	(0.18)
φ_1	0.9238***	−0.9560***	−0.4190
	(6.83)	(−2.71)	(−0.93)
β_0	0.2811	0.5635***	0.3459
	(0.51)	(2.57)	(0.94)
β_1	0.7206***	−0.6376***	−0.6769***
	(8.27)	(−2.62)	(−3.74)
δ_0	−2.4331	−1.5927	0.8813
	(−0.41)	(−0.94)	(0.76)
δ_1	−1.2317	0.31228***	−0.3528
	(−1.02)	(6.027)	(−0.40)
θ_0	1.4657***	3.7526***	2.1576***
	(3.93)	(4.4030)	(2.60)
∂_0	2.1133***	2.0384**	1.9393*
	(2.12)	(1.90)	(1.89)
p_{00}	0.8856	0.8847	0.8963
p_{11}	0.8921	0.9770	0.8742
Log-likelihood	−403.84	−455.8	−492.39
Q(12)	10.3825**	17.5869**	18.1732**
$Q^2(12)$	10.5519**	4.8775**	12.0513**

Notes: Student-*t* statistics of parameters are reported in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1%. The null hypothesis in Box–Pierce test at lag 12, Q(12), is that the residuals are serially uncorrelated and $Q^2(12)$ test checks for no serial correlations in the squared residuals at lag 12. The *t*-student statistics are reported between parentheses.

Table 4
Growth rate cycle peak and trough dates (1989–2007).

	Peak or through	United Kingdom	France	Japan
1988–1989	P			01/1989
	T			05/1989
1989–1993	P	01/1989	01/1989	03/1990
	T	04/1991	05/1993	12/1993
1993–1996	P	07/1994	01/1995	12/1994
	T	08/1995	09/1996	01/1996
1996–1999	P	07/1997	01/1998	03/1997
	T	02/1999	02/1999	04/1998
1999–2003	P	01/2000	05/2000	08/2000
	T	02/2003	05/2003	12/2001
2003–2004	P	03/2004	06/2004	01/2004
	T			11/2004
2004–2005	P	05/2005	05/2005	04/2005
	T			10/2005
2005–2006	P			04/2006
	T			09/2006
2006–2007	P		03/2007	08/2007
	T			

Source: "Economic Cycle Research Institute" (ECRI).

[16] The filtered probability is based on information available at (t) ($\Pr[S_t=1/\Phi_{t-1}]$) and the smoothed probability is based on the entire sample ($\Pr[S_t=1/\Phi_t]$).

analyze the volatility phases of the stock market, we define turning points based on whether the probabilities of recessions and expansions are smaller or greater than 50%. For example, the beginning of a recession occurs when the probability of a recession moves from below 50% to above 50%. This rule provides a good definition of turning points because the estimated probabilities clearly distinguish times when an expansion is more likely from those when a recession is more likely[17]. The findings indicate that the MS-EGARCH model performs well in getting the direction of change in a series either the series is in regime 0 or 1. Fig. 1 (right vertical panel) shows also that the variance is switching between two regimes, with one corresponding to a low return-high volatility state (or recession phase) and the other to a high return-low volatility state (or expansion phase). Additionally, these models perform well in predicting the regime state with recessions shown by shading in these diagrams. We can clearly describe and analyze these probabilities by trying to link individual hikes in volatility to international/or national news developments possibly influencing national stock markets by increasing their volatilities. To do so, we adopt the turning point chronology of the "Economic Cycle Research Institute" (ECRI) for the growth rate in each of the three developed countries over the period of 1989–2007. Peak and trough dates for the growth cycles are summarized in Table 4[18].

According to the recession's periods, United Kingdom and France experienced five or six recessions during the sample period. However, Japan experienced three additional recessions; in the beginning of 1989, 2005 and in 2006. The recession periods are closer for UK than for France and Japan. The most similar recessions across the countries are those that took place at the beginning of 1990 (oil crisis), 1994 (Mexican Peso crisis), 1997 (The currency crisis in East Asian countries) and 2001 (economic recession in US) which hit all the economies at about the same time. The 1990s recession was a long one for France and Japan lasting 53 and 46 months respectively, followed by the one in 2001. Conversely, the later one was longer for UK and it lasted about 38 months. These countries displayed another recession in 2004/2005. The 2007s recession hit Japan and France at about the same time but did not hit UK. Fig. 1 (left vertical panel) compares the smoothed probabilities of recessions obtained from our model with the ECRI dating of recessions for each country. The duration of each regime obtained by the model for the return series are reported in Table 5. By visual inspection of Fig. 1and Table 4, we note that most of the examined countries show a relative strong coincidence between periods of high volatility-low return regimes of the time series and international crises. The closest estimated smoothed probabilities of recessions are for United Kingdom. This country serves as a control country, because it is not very affected by the crises happen in the world and it shows different behaviour than the Japan and France countries in terms of volatility states. Having a look at the right vertical panel of Fig. 1, UK seems to be affected only by 2004/2005 crisis, where the English stock market showed big increases in volatilities. During all other crises periods mentioned, UK shows low increases in volatility but they are characterized by strong falls in real stock returns. Then, during these periods, UK looks relatively affected. This is could be justified by the plots of the smoothed probabilities where several periods of low return-high volatility state are clearly detected (the plot of the smoothed probabilities for regime 0 shows

Table 5
Duration of regime 0 and 1 (values of the smoothed probability that are near to unity).

Country	Regime 0 (recession)	Regime 1 (expansion)
United Kingdom	1989M08	1989M09–1990M05
	1990M06	1990M07–1992M03
	1992M04–1992M05	1992M06–1993M12
	1994M01	1994M02–1997M08
	1997M09	1997M10–1998M05
	1998M06–1998M07	1998M08–1999M10
	2001M07	2001M08–2002M03
	2002M04–2002M05	2002M06–2005M01
	2005M02	2005M03–2006M02
	2007M11–2007M12	
France	1989M01–2003M03	2003M04–2004M01
	2004M02–2004M06	2004M07–2006M02
	2006M03–2006M04	2006M05–2006M12
	2007M01–2007M12	
Japan	1989M11–1990M09	1990M10–1991M01
	1991M02–1992M09	1992M10–1993M06
	1993M07–1993M10	1993M11–1994M04
	1994M05–1995M04	1995M05–1996M04
	1996M05–1998M11	1998M12–2000M01
	2000M02–2003M02	2003M03–2004M02
	2007M05–2007M12	

some signs of synchronization of their peaks with international crises) but they seem to be frequent and shorter lived (it lasts about 1 month) if compared with those identified by ECRI which appear to be much fewer and longer lasting. Moreover, the model manages to identify another period of recession that took place in 2002. This crisis seems to have a severe effect on the volatility of this country (the period of recovery lasted at least 3 years). The occurring of this recession period can probably be attributed to the Argentinean crisis in 2002. France shows another different picture than UK and Japan. Subsequently, along the period preceding 2003, France experienced a single long recession while UK and Japan had four recessions during this period. Its stock market return shows strong increases in the smoothed probability between mid 1989 and at the beginning of 2003. Another increase in the evolution of the probability can be observed around 2000, around 2004 (these two recessions started 2 or 3 years later than the ECRI dating recession periods) and around 2007. In the case of Japan, it showed many periods with low return-high volatility state. It seems to have a stock market with strong volatilities throughout nearly all recessions periods detected by ECRI, which also shows that the smoothed probability of being in the low return-high volatility state is near unity during major international crises. On the other hand, two shorter peaks in its smoothed probabilities occurred close to each other for the period between 2004 and 2006. During these crises periods, Japan looks relatively unaffected and did not show significant increases in the volatility. Additionally, the small hikes in the volatility of its stock market do not seem to indicate crises, because they are not characterized by strong falls in monthly real stock returns. In summary, a very interesting feature of the graphical analysis of Fig. 1seems to be that most countries examined show a relative coincidence between periods of low return-high volatility regimes and international crises.

3.3. The impact of CO market shocks and volatility behaviours across regimes

In this subsection, we augmented the MS-EGARCH by incorporating the NOPI variable of the WTI and the Brent only in the variance equation[19] for each real stock return. Our main intention is to see whether oil price increases are statistically linked to real equity returns and whether they can explain behaviour shifts in stock

[17] Hamilton (1989) define in his paper of business cycles, a recession (or expansion) could be present at time t if the conditional probability of being in regime 0 (or 1) is over 70% (under 30%) at that time. So if $P_i(s_t=0)>0.7$; country i will be considered to be in state 0. If $P_i(s_t=1)<0.3$; country i will be considered to be in state 1. For values of $0.3<P_i<0.7$; country i is neither in the "low" nor in the "high" volatility state. This definition tends to extend the study by using more than 2 states of volatility (example low, medium and high volatility regime). We make a simpler analysis by reducing it with to just two regimes.

[18] Denise et al. (2003) note that "cycles in the growth rate typically exhibit more frequent regime changes than classical cycles, since a period of lower growth may be sufficient to define a growth recession without leading to the output decline required for a recession in terms of classical cycle", (Denise et al., 2003, p.4).

[19] We have also incorporated the variables NOPI in the mean and in the variance equations, but these estimations did not deliver any reasonable results.

Table 6
Augmented two regime univariate MS-EGARCH(1,1) model with fixed transition probabilities.

	FTSE100		CAC40		Nikkei225	
	WTI	Brent	WTI	Brent	WTI	Brent
μ_0	−0.36**	−0.14**	−0.88**	0.16*	−1.55***	−0.14**
	(−1.8)	(−2.1)	(−1.7)	(1.5)	(−3.5)	(−1.9)
μ_1	0.31**	0.58***	0.77***	0.73***	0.65***	1.24***
	(1.7)	(5.7)	(3.6)	(4.3)	(3.4)	(14.9)
ω_0	1.58***	1.39*	1.83***	2.96***	1.35***	4.02***
	(3.6)	(1.6)	(4.9)	(4.4)	(5.2)	(5.0)
ω_1	1.22***	0.39***	0.40***	1.03***	0.82***	1.57***
	(4.2)	(3.1)	(3.4)	(3.5)	(2.8)	(10.1)
φ_0	1.05***	0.49*	0.04	0.76**	−0.6*	−0.02
	(6.6)	(1.6)	(0.1)	(2.7)	(−1.3)	(−0.12)
φ_1	0.14	0.13	0.05	−1.01***	−0.01	−0.32
	(0.2)	(0.5)	(0.1)	(−3.3)	(−0.05)	(−1.2)
β_0	0.83***	0.61***	0.24*	0.58***	−0.72***	−0.53**
	(15.)	(3.8)	(1.3)	(3.1)	(−3.5)	(−2.2)
β_1	0.13	0.03	−0.4***	−0.66***	−0.48***	−0.13
	(0.2)	(0.1)	(−3.1)	(−2.6)	(−2.7)	(−0.8)
δ_0	−1.2	2.45	1.1	−1.46	0.18	−0.96
	(−0.7)	(0.3)	(0.5)	(−1.2)	(0.1)	(−1.1)
δ_1	−1.22	−5.17	−0.3	0.29***	−0.38	−0.88*
	(−0.2)	(−0.4)	(−1.1)	(2.6)	(−0.9)	(−1.3)
λ_0	0.13	0.02**	0.47***	0.45***	0.29**	0.54***
	(1.1)	(1.8)	(6.2)	(6.5)	(2.5)	(5.6)
λ_1	−0.15**	−0.13**	−0.1***	−0.18**	−0.13**	−0.13***
	(−2.7)	(−2.5)	(−2.9)	(−2.4)	(−2.1)	(−3.4)
θ_0	−2.30***	4.06***	1.99***	4.15***	1.96**	2.23**
	(3.08)	(6.4)	(3.0)	(4.0)	(2.1)	(2.0)
∂_0	2.57***	3.26***	2.7***	2.67***	1.93***	4.10***
	(3.0)	(4.3)	(4.1)	(2.6)	(3.0)	(4.5)
p_{00}	0.9092	0.9831	0.8807	0.9356	0.7243	0.7751
P_{11}	0.92938	0.9633	0.9406	0.9246	0.8743	0.9837
Log-likelihood	−399.559	−402.64	−451.06	−451.41	−487.68	−493.34
Q(12)	9.10***	13.52***	20.80***	18.61***	16.17***	17.25***
$Q^2(12)$	10.64***	12.65***	14.52***	16.72***	11.14***	13.55***
LR	8.566**	2.386*	9.478***	8.764**	9.416***	1.892

Notes: 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: $2\times|\text{likelihood of } H_1 - \text{likelihood of } H_0|$, where H_0 is the MS-EGARCH model without NOPI and H_1 is the MS-EGARCH model with the NOPI variable, both with constant transition probabilities.

markets. In the first step, we extend the MS-EGARCH model with fixed transition probabilities. In the second step, we relax the assumptions of fixed transition probabilities and we search whether an increase in the CO price influences not only the variance of the real stock returns but also the probabilities of a change in regime.

3.3.1. MS-EGARCH with fixed transition probabilities

Methodologically, in order to find out whether oil price increases are significantly correlated to real stock returns, we compare the log-likelihood values of the two models with and without the NOPI variable. Table 6 displays the estimation results for the MS-EGARCH(1,1) model with fixed transition probabilities, and at the bottom of each column, the LR tests are reported. These tests reveal[20] that, in two cases (France and U.K.), the MS-EGARCH model incorporating the NOPI variable has a larger log-likelihood (except for Japan)[21] compared to the simple MS-EGARCH model with constant transition probabilities (see Table 3). In general, based on this test, we reject the latter model at 10% and 5% significance levels. These findings provide evidence that oil price increases are statistically correlated to real equity returns. Our result is consistent with some previous empirical studies concerned with real stock returns, including among others Maghyereh (2004), Park and Ratti (2008). In addition, after accounting for CO price volatility, the overall behaviour across regimes is similar to that reported in Table 3 (MS-EGARCH without the NOPI variable). The estimates for regimes 0 are consistent with a "low mean–high variance" regime. Conversely, regime 1 is characterized by a "high mean and a low variance." Again, there is no symmetric response in volatility to news, ε_{t-1}.

As shown in Table 6, the estimated coefficients relative to the NOPI of WTI and/or Brent are statistically significantly different from zero. Correspondingly, the NOPI of the WTI and/or the Brent impacts on the conditional variance of real equity returns are statistically significant. This effect is positive in regime 0 and negative in regime 1. Moreover, it is interesting to note that $|\lambda_0|>|\lambda_1|$ for France and Japan. This implies that, in a "recession state," the positive effect of oil price on stock returns is between 3 and 5 times much stronger than its negative effect in an "expansion state." This result is consistent with the conclusions of Sadorsky (1999) for the US that the response of stock market to oil price shocks is asymmetric. According to this author, positive oil price shocks explain more forecast error of variance in real stock returns than negative shocks during the full sample period. However, for the UK, the positive effect of the oil price in a "recession state" is less than its negative effect in an "expansion state." Moreover, the influence of the Brent CO price is more 5 times higher than the effect of the WTI CO price on stock returns. Finally, to see whether the selected model is well specified, we applied the B–P test (to order 12) to the standardized and squared residuals (to order 12). The outcomes are displayed in the bottom of the Table 6. They show that the MS-EGARCH(1,1) model provides a reasonable approximation of the heteroscedasticity in the all the real stock return time series.

3.3.2. MS-EGARCH model with explained transition probabilities

As mentioned above, this model extends the previous specification by letting the probability to depend upon the NOPI variables (Eqs. (12a) and (12b)). In other words, any fluctuations in oil_{t-1} will lead the probabilities of a switch in regime to vary over time. By relaxing the assumptions of fixed transition probabilities, it is possible to research whether an increase in the CO price influences not only the variance of y_t but also the probabilities of a change in regime. As before, significance of λ_i indicates that the conditional variance of y_t reacts in a possibly state to oil_{t-1}. We use (oil_{t-1}) as the information set in the transition probabilities specification since this reflects oil increases prior to the shock that generate the variance of the equity at t. To ensure a more direct comparison between the fixed transition probability and time-varying transition probability models, we use again the LR test. As reported in Table 7, the log-likelihood of the MS-EGARCH(1,1) model with dependent probabilities is larger compared to the simple MS-EGARCH(1,1) model with constant transition probabilities (see Table 6). Based on the LR test, we reject the null hypothesis of constant transition probabilities in favor of the MS-EGARCH with time-varying probabilities specification at the 5% significance level. This implies that there is evidence of a statistically significant and regime dependent response of real stock market return volatilities to the CO shocks. Additionally, the assumption of time-varying probabilities, in the previous model, fits the data better than a fixed transition probabilities model. Table 7 provides the estimating results of the MS-EGARCH(1,1) with time-varying transition probabilities model. Again, the obtained results are consistent with the presence of two regimes in y_t, a "high mean–low variance" regime (i.e. regime 1), and a "low mean–high variance regime" (i.e. regime 0). We notice that in the transition probability equation (i.e. Eqs. (12a) and (12b)), all the coefficients ∂_1 are statistically significant at 5% level. Since ∂_1 is negative, this shows that a low $NOPI_{t-1}$ increases the probability of staying in (i.e. the persistence of) a "high mean–low variance" regime (i.e. regime 1). While, in the other regime, as $NOPI_{t-1}$ becomes increasingly high, the probability of staying in the "low return-high variance" regime (i.e. regime 0) increases as $\theta_1>0$. Finally, within each regime, the residual ARCH effects are small and insignificant,

[20] Under the null hypothesis, the LR test is distributed asymptotically as $c^2(2)$.

[21] For Japan, the log-likelihood of the model including the NOPI of the Brent decline from −492.3 to −493.3. Then, we can denote that this model doesn't describe the data well.

Table 7
Augmented MS-EGARCH(1,1) model with time-varying probabilities.

$$y_t = \mu_{it} + \varepsilon_t, \qquad \varepsilon_t / I_{t-1} \rightarrow D(0,\ h_{i,t}) \ln(h_{it}) = \omega_i + \varphi_i \left[\left| \frac{\varepsilon_{t-1}}{\sqrt{h_{it-1}}} \right| - \sqrt{2/\pi} \right] + \beta_i \ln(h_{i,t-1}) + \delta_i \frac{\varepsilon_{t-1}}{\sqrt{h_{i,t-1}}} + \lambda_i \mathrm{NOPI}_{t-1}$$

$$p_{00}^t = \Pr(s_t = 0) = \frac{e(\theta_0 + \theta_1 \mathrm{NOPI}_{t-1})}{1 + e(\theta_0 + \theta_1 \mathrm{NOPI}_{t-1})} \text{ and } p_{11}^t = \Pr(s_t = 1) = \frac{e(\partial_0 + \partial_1 \mathrm{NOPI}_{t-1})}{1 + e(\partial_0 + \partial_1 \mathrm{NOPI}_{t-1})}$$

	FTSE100		CAC40		NIKKEI225	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
μ_0	0.25	−0.34	0.03***	0.18	−0.47	−1.33***
	(0.1)	(−1.0)	(0.1)	(0.6)	(−1.1)	(−3.4)
μ_1	0.40***	0.31**	0.75***	0.66***	0.54***	0.31*
	(4.0)	(1.9)	(4.9)	(2.4)	(2.0)	(1.4)
ω_0	1.86**	1.12***	1.83***	1.23***	1.82***	2.08***
	(1.9)	(6.4)	(4.7)	(2.8)	(2.6)	(6.3)
ω_1	0.42***	1.04***	0.04***	0.59***	1.72***	1.48***
	(3.5)	(2.7)	(19.8)	(2.4)	(6.5)	(7.2)
φ_0	1.18***	0.96***	0.15***	0.68*	−0.15	−0.64*
	(4.2)	(4.2)	(0.2)	(1.4)	(−0.4)	(−1.5)
φ_1	1.32***	0.23	1.09	−0.43	0.21	−0.18
	(3.5)	(0.2)	(1.5)	(−0.9)	(0.5)	(−0.4)
β_0	0.80***	0.81***	0.29	0.52**	−0.35*	0.32
	(2.0)	(12.9)	(0.5)	(1.9)	(−1.6)	(1.1)
β_1	0.75***	0.18	0.52	−0.72***	−0.41***	−0.09***
	(3.9)	(0.2)	(0.6)	(−3.7)	(−2.5)	(−2.0)
δ_0	0.05***	−2.22	1.84***	−1.77	1.50	−1.01***
	(2.2)	(−0.6)	(4.8)	(−0.5)	(0.6)	(−31.)
δ_1	−0.27*	−11.1	0.04**	−0.31	−0.52*	−0.82
	(−1.7)	(−0.2)	(1.9)	(−0.85)	(−1.5)	(−0.9)
λ_0	0.01	0.03***	0.12***	0.10*	0.18***	0.30***
	(1.2)	(2.0)	(3.1)	(1.6)	(2.1)	(5.3)
λ_1	−1.11	−0.08***	−0.08***	−0.28***	−0.14***	−0.09***
	(−2.5)	(−2.4)	(−1.9)	(−2.1)	(−2.4)	(−2.0)
θ_0	0.87***	0.41***	0.65***	0.01***	0.51***	0.19***
	(13)	(6.1)	(4.3)	(23.5)	(6.09)	(2.8)
θ_1	0.30***	1.26***	0.31***	1.17***	0.48***	0.95***
	(4.0)	(4.3)	(5.5)	(20.5)	(13.8)	(11.2)
∂_0	0.06***	0.78***	0.99***	0.97***	0.96***	0.99***
	(5.6)	(11.9)	(8247.6)	(258.)	(259.8)	(984.)
∂_1	−0.05***	−0.35***	−1.17***	−0.78***	−0.70***	−0.85***
	(2.0)	(−13.7)	(−4.1)	(−13.0)	(−16.7)	(−8.6)
Log-likelihood	−308.087	−354.487	−421.796	−402.491	−404.17	−467.158
Q(12)	5.6743	10.095	15.3861	18.338	11.978	9.395
$Q^2(12)$	7.808	6.7574	9.1503	3.8846	18.252	3.6186
LR	182,944	96.32	58.53	97.85	167.03	52.36

Notes: we estimate two versions of regime switching EGARCH(1,1) models, all with time-varying transition probabilities and Student-*t* density. The models are: model 1 allows the transition probabilities to vary with the lagged net oil price increase of the WTI. Model 2 allows the transition probabilities to vary with the lagged net oil price increase of the Brent. The likelihood ratio test (LR) is computed as follow: $2 \times |\text{log-likelihood of } H_1 - \text{log-likelihood of } H_0|$, where H_0 is the MS-EGARCH(1,1) model with constant transitions and H_1 is the MS-EGARCH(1,1) model with time-varying transitions. The sample period is from January 1989 to December 2007, a total of 228 observations. *, **, *** denote statistical significance at 10, 5 and 1%, respectively.

indicating that the volatility process is better described by a regime switching model than a standard EGARCH model.

4. Summary and concluding remarks

In this paper we have studied the role of CO market volatility shocks in explaining the equity markets behaviour using monthly data covering the period (December, 1987–January 2007). Our study is concerned with two major CO assets (WTI and Europe Brent) and three developed stock markets (France, U.K. and Japan). The empirical approach was based on a two regime MS-EGARCH(1,1) model. This approach is justified by the fact that we are able to take into account two major types of innovation to volatility. First, it allows switching between two regimes (low mean and high volatility). Second, we can consider for the time variation and asymmetry in the conditional variance within each regime. Furthermore, our model allows for regime dependence in the impact, persistence and asymmetric response to shocks to stock market volatility. To the best of our knowledge, it's the first study to employ this approach in order to assess the impact of CO market volatility shocks on equity markets dynamics. Through the analysis of results and discussion, we can draw the following conclusions:

Our MS-EGARCH specification with switching in the mean and in the variance offer a better statistical fit to the data. Our results suggest that real stock returns display significant evidence of regime switching, with strong evidence of two regimes in the data. The first regime is consistent with low mean–high variance regime. This regime tends to dominant only for Japan. Whereas the second regime which is consistent with high mean–low variance appears to be dominant for UK and France.

Furthermore, under this model, we find that ARCH and the leverage effects are significantly reduced when switching is allowed. Our estimates attribute most of persistence in real stock return volatility to the persistence of low and high regime. We analyze the dating of volatility states provided by the MS-EGARCH model. The low return-high volatility regime is to some degree associated with economic recession. The effects of the international crises were short-lived for United Kingdom: 1 month after the crash the market had returned to the high return-low volatility state.

Extending the MS-EGARCH model to allow for the relationship between oil price shocks and real stock returns. We find evidence that the net oil price increase variable play a significant role in determining both the volatility of real returns and the probability of the transition across regimes.

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