Forecasting the conditional volatility of oil spot and futures prices with structural breaks and long memory models

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Abstract
This paper investigates whether structural breaks and long memory are relevant features in modeling and forecasting the conditional volatility of oil spot and futures prices using three GARCH-type models, i.e., linear GARCH, GARCH with structural breaks and FIGARCH. By relying on a modified version of Inclan and Tiao (1994)'s iterated cumulative sum of squares (ICSS) algorithm, our results can be summarized as follows. First, we provide evidence of parameter instability in five out of twelve GARCH-based conditional volatility processes for energy prices. Second, long memory is effectively present in all the series considered and a FIGARCH model seems to better fit the data, but the degree of volatility persistence diminishes significantly after adjusting for structural breaks. Finally, the out-of-sample analysis shows that forecasting models accommodating for structural break characteristics of the data often outperform the commonly used short-memory linear volatility models. It is however worth noting that the long memory evidence found in the in-sample period is not strongly supported by the out-of-sample forecasting exercise.

Keywords: oil markets, volatility forecasting, long memory, structural breaks, GARCH, RiskMetrics
JEL classifications: C22, C53, F47, G17, Q47, Q43

1. Introduction

There is now extensive evidence to suggest that oil price fluctuations influence economic activity and financial sector (e.g., Jones and Kaul, 1996; Hamilton, 1983; Basher and Sadorsky, 2006; Driesprong *et al.*, 2008). At the aggregate level, it is generally accepted that the rise in oil prices leads to reduce economic growth, non-oil industry performance and stock market activities in almost net oil-importing countries, while some positive effects are found for oil companies and net oil-exporting countries. Moreover, some recent studies have consistently documented that oil price changes affect economic activity and stock market returns in a nonlinear fashion (Ciner, 2001; Maghyereh and Al-Kandari, 2007; Zhang, 2008; Lardic and Mignon, 2008; Cologni and Manera, 2009). From a sectorial perspective, the sensitivity to oil price movements differs across different industries depending on the nature of the sector activity and the capacity of the industry to absorb and transmit the oil risk to its consumers and other economic sectors (Hammoudeh and Li, 2004; Boyer and Filion, 2007; Nandha and Faff, 2008).

Understanding oil price volatility is thus of great interest for both investors and policymakers. One of the main motivations is that the world oil markets have experienced over the last decades large price variations, and relatively higher price volatility. It is opportune to recall that after reaching a substantial decline to $19.33 per barrel in December 2001 induced by the world economic downturns as a result of the September 11, 2001 terrorist attack, the West Texas Intermediate (WTI) spot price at Cushing exhibited an upward trend reaching an unprecedented average level of $133.93 in June 2008. Obviously if oil price volatility persists, both producers and consumers may expose to substantial risk via the uncontrolled increases in inventory, transportation and production costs (Pindyck, 2004). Aggregate output dynamics and corporate earnings can be also severely affected, and policymakers should consider the volatility impacts of oil price shocks when conducting economic policies. Moreover, to the extent that oil price volatility provides information about risk levels and how financial asset returns should behave in response to oil shocks, accurately modeling and forecasting oil price volatility are crucial for financial decisions involving oil investments and portfolio risk management particularly with regard to the valuation issues of oil-related products and energy derivative instruments. That is, an investor with efficient oil-volatility forecast can exploit this information to better manage its portfolio (Kroner et al., 1995). Finally, some studies suggest crude-oil price volatility is substantially higher than that of other energy products since the mid-1980s (Plourde and Watkins, 1998; Regnier, 2007). This motivates future research on the behavior of crude-oil spot and futures price volatility because of its macroeconomic and microeconomic effects.

In the energy literature, several works have focused on the modeling and forecasting issues of both crude-oil spot and futures price volatility (e.g., Sadorsky, 2006; Narayan and Narayan, 2007; Kang et al., 2009; Agnolucci, 2009). Of the commonly used volatility models in financial economics, GARCH-type approach has received a particular interest from almost all previous papers. For instance, Narayan and Narayan (2007) use an ARCH/GARCH framework to examine the conditional volatility of crude oil price using daily data for the period 1991-2006 and find that price shocks have asymmetric and permanent effects on volatility. Kang et al. (2009) address the forecasting power of different competitive GARCH-volatility models including the standard GARCH, Fractionally Integrated GARCH (FIGARCH), Component-GARCH (CGARCH), and Integrated GARCH (IGARCH) for three crude-oil price benchmarks - WTI (USA), Brent (North Sea) and Dubai (Middle East). They show that the FIGARCH and CGARCH perform better than GARCH and IGARCH in modeling and forecasting oil-volatility persistence. Based on different GARCH specifications allowing for both normal and Student-t distributions of WTI and Brent daily oil returns, Cheong (2009) finds some evidence of asymmetric effects, heavy-tail innovation impacts and leverage effects[1]. As far as we know, two studies are concerned by the modeling and forecasting of the volatility in crude-oil futures using GARCH-family models (Sadorsky, 2006; Agnolucci, 2009). Their main findings indicate that GARCH models outperform a random walk process and forecasts based on implied volatility. Differently, Fong and See (2002) employ a Markov regime-switching approach allowing for GARCH-dynamics, and sudden changes in both mean and variance in order to model the conditional volatility of daily returns on crude-oil futures prices. They document that the regime-switching model performs better non-switching models, regardless of evaluation criteria in out-of-sample forecast analysis.

Albeit they have substantially contributed to the understanding of the behavior of crude-oil price volatility, it should be noted that previous works often assume a stable structure of parameters in the oil-return volatility process. This assumption means that the unconditional variance of crude-oil returns is constant, and leads to ignore the fact that crude-oil markets can expose to periods of large price changes commonly observed since the liberalization of these markets in the mid-1980s. Examples of such periods may include the episodes of world geo-political tensions, Gulf wars, Asian crisis, worries over Iranian nuclear plans, and US and global recessions. Obviously these shocks can cause breaks in the unconditional variance of oil price changes and thus the presence of structural breaks in the parameters of the GARCH dynamics used to model and forecast crude-oil volatility, which ultimately biases both empirical results and their implications. According to Mikosch and Stărică (2004), and Hillebrand (2004), neglecting structural breaks in the GARCH parameters induces upward biases in estimates of the persistence of GARCH-type conditional volatility. Thus, in case of

[1] Cheong (2009) employs some variants of GARCH-type models including in particular the GARCH model developed by Bollerslev (1986), the asymmetric power GARCH (APGARCH) model proposed by Ding et al. (1993), the fractionally integrated GARCH (FIGARCH) proposed by Baillie et al. (1996), the FIEGARCH (Bollerslev and Mikkelsen, 1996), and the FIAPARCH (Tse, 1998). The use of all these models aims at capturing the stylized facts of crude-oil conditional volatility, i.e., asymmetry, persistence, leverage and leptokurtic behavior.

commodities markets, previous works may overstate the degree of crude-oil volatility persistence without accounting for the possibility of structural breaks.

For the above reasons, in this paper we extend the existing literature by investigating the relevance of structural breaks and long memory in modeling and forecasting the conditional volatility of oil spot and futures prices. At the empirical stage, we build our test for structural breaks in the conditional volatility of daily oil spot and futures returns on the application of a modified version of Inclan and Tiao (1994)'s iterated cumulative sum of squares (ICSS) algorithm that allows for dependent processes. By inspecting the parameters of GARCH processes which are estimated over different subsamples separated by structural break dates, we provide clear evidence of parameter instability. In line with previous works (Kang et al., 2009, and references therein), we find that long memory is significantly present in the data and a FIGARCH model seems to better describe the behavior of time-varying oil-return volatility in several cases. More importantly, in the out-of-sample evaluation we show that forecasting models accommodating for the structural break characteristics of the data outperform the GARCH(1,1) and RiskMetrics in most of cases. In contrast, the long memory model outperforms the GARCH and RiskMetrics models only in few cases. At this stage we are questioning the evidence of long memory shown by the long memory tests and suspecting a spurious long memory.

As far as it is concerned by the behavior of oil volatility, our paper can be viewed as widely related to the contribution of Fong and See (2002) in the sense that we also consider the potential of instability in energy prices, but we are more general by firstly dating the structural breaks in the series studied, and secondly allowing our GARCH dynamics to accommodate for any detected breaks and long memory patterns. Further, the performance of our empirical GARCH with structural breaks and long memory is also compared to that of three commonly used forecasting models in the out-of-sample tests, which is not the case in Fong and See (2002).

The remainder of the paper is organized as follows. Section 2 describes the empirical framework that permits to examine the relevance of both structural breaks and long memory characteristics in the oil price data. Section 3 presents the data used and reports the results obtained from the empirical analysis. Section 4 concludes and discusses the main implications of the results.

2. Empirical method

We first compute the daily continuously compounded returns of all spot and futures price series by taking the difference between the logarithms of two successive prices as follows:

$$\varepsilon_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

where P_t is the spot or futures price of oil at time *t*.

Second, as we are interested in modeling and forecasting the unconditional variance of the returns series, we follow previous works and treat the unconditional and conditional mean of ε_t as zero (Rapach and Strauss, 2008 and references therein). We consider different competing models. If there is no break in the unconditional variance, a stable GARCH process can be used to characterize the conditional volatility of oil prices. However, the instability of the unconditional variance implies the introduction of structural breaks in the GARCH process. In line with most previous works of the existing literature on GARCH models, information criteria select the standard GARCH(1,1) model and we consider the latter as the benchmark model for comparison purpose.

We then proceed to estimate different specifications of the GARCH(1,1) model, namely the GARCH with structural breaks (SB-GARCH), the Fractionally Integrated GARCH

(FIGARCH), the 0.50 rolling window GARCH, the 0.25 rolling window GARCH, and the RiskMetrics, and to compare their predictive performance relative to the benchmark model. In what follows, we briefly present the models we use as well as tests of structural breaks and long memory.

2.1 Modeling oil price volatility

The standard GARCH(1,1) model developed by Bollerslev (1986) for conditional volatility is given by:

$$\begin{aligned} \varepsilon_t &= \sqrt{h_t}\, z_t, \quad z_t \mid I_{\text{t-1}} \to N(0,1) \\ h_t &= \varpi + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \end{aligned} \tag{2}$$

In Equation (2), z_t represents the white noise process which follows a normal distribution with a mean of zero and variance of one. I_{t-1} stands for the information set at time (t-1); ϖ refers to the deterministic term of the conditional volatility equation and is assumed to be positive. α and β are referred to as the ARCH and GARCH parameters which must satisfy the following constraints to preserve the stationarity condition: $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta \prec 1$. Note that $\alpha + \beta = 1$ implies that an integrated GARCH (IGARCH) specification is more appropriate for modeling the conditional volatility of the return series considered.

The FIGARCH(1,*d*,1) model, which nests a GARCH(1,1) model with no persistence in the volatility process (*d* = 0) and an IGARCH model with complete persistence (*d* = 1), takes the following form:

$$h_t = \varpi + \left[1 - (1-\beta L)^{-1}(1-\alpha L)(1-L)^d\right]\varepsilon_t^2 \tag{3}$$

where L is a lag polynomial so that $L\varepsilon_t = \varepsilon_{t-1}$ and d is the long memory parameter measuring directly the long-term persistence of a shock on conditional variance. The main advantage of the FIGARCH model is that it allows a finite persistence of volatility shocks, i.e., long memory behavior of oil return series and a slow rate of decay after a shock affecting the volatility.

The SB-GARCH(1,1) model is written as follows:

$$\begin{aligned} &\varepsilon_t = \sqrt{h_t}\, z_t ,\ \ z_t \left| I_{t\text{-}1} \right. \rightarrow N(0,1) \\ &h_t = \varpi_s + \alpha\varepsilon_{t-1}^2 + \beta\, h_{t-1} \end{aligned} \tag{4}$$

where w_s, $s = 0,1,\ldots k$, refer to deterministic coefficients of (k+1) segments in the conditional volatility process with k being the optimal number of structural breaks indentified by the ICSS algorithm. Thus, the unconditional variance, $w_s/(1-\alpha-\beta)$, can change from one regime to another.

The RiskMetrics model based on an expanding window is a restricted version of the simple GARCH(1,1) model with $\varpi = 0$, $\beta = 0.94$ and $\alpha + \beta = 1$. It has advantage of accommodating for potential structural breaks present in the data, but neglected in the model specification.

Finally, the 0.50 and the 0.25 rolling window GARCH models are one other than the standard GARCH(1,1) model estimated using a rolling window with sizes equal to one half and one quarter of the length of the estimation period respectively.

2.2 Structural break test

Examining whether energy prices and volatilities are subject to structural breaks over time is of great interest as individual and firms naturally wish to better manage the risks associated with frequent changes in energy markets (see, e.g., Lee and Lee, 2009; Lee et al., 2010). It is commonly accepted that variations in the price of oil and other energy assets reflects, in addition to changes in socio-political and economic instability as well as sudden changes in both world's energy demand and offer, several typical events such as market regulation, oil crises, technological changes in the renewable energy sector, and modifications in the storage and logistic infrastructure of international oil markets (see, e.g., Horsnell and Mabro, 1993; Charles and Darné, 2009). The observed substantial fluctuations in the oil spot and futures prices over the last decade, with most of the extreme movements occurred between 2006 and 2008 seem to suggest that oil price, returns, and volatility as measured by squared returns are usually subject to multiple breaks (see, Figures 1 to 3). Thus, ignoring the potential of structural instability in the oil-return volatility generating process would result in unreliable estimates of oil volatility, and in turn lead to inaccurate actions in energy risk management since oil price serves as underlying benchmark for pricing of many oil-related products and derivatives. More importantly, recent research shows that the presence of structural breaks or regime switches can generate "spurious long memory process" in the observed data series (see, e.g., Granger and Hyung, 2004; Choi and Zivot, 2007; Choi et al., 2010). That is, the evidence of high oil-price volatility persistence reported in previous studies (see, e.g., Elder and Serletis, 2008) may be overstated without appropriately taking structural change behavior into account. For instance, Choi and Hammoudeh (2009) find evidence that the long memory parameter for all the return series on oil and refined products is lower after adjusting for the presence of structural breaks.

As in this paper we are interested in testing the null hypothesis of a constant unconditional variance of the oil return series, modeled by the simple stable GARCH(1,1) model, against the alternative of structural breaks in the unconditional variance implying structural breaks in the GARCH process, the adjusted cumulative sum of squares statistics of Inclan and Tiao (1994) can be used and it is given by:

$$ICSS_a = \sup_k \left| T^{-0.5} F_k \right|$$

where $F_k = \hat{\gamma}^{-0.5}\left[C_k - (k/T)C_T\right]$, and $C_k = \sum_{t=1}^{k} \varepsilon_t$ for k = 1,…,T (total number of observations. $\hat{\gamma} = \hat{\delta}_0 + 2\sum_{i=1}^{m}\left[1 - i(m+1)^{-1}\right]\hat{\delta}_i$, $\hat{\delta}_i = T^{-1}\sum_{t=1}^{k}\left(\varepsilon_t^2 - \hat{\sigma}^2\right)\left(\varepsilon_{t-1}^2 - \hat{\sigma}^2\right)$, and $\hat{\sigma}^2 = T^{-1}C_T$. m is a lag truncation parameter selected using the procedure in Newey and West (1994). The estimate of the break date is the value of k that maximizes $\left|T^{-0.5}F_k\right|$. Under normality assumption of r_t, the asymptotic distribution of the $ICSS_a$ statistics is given by $\sup_c\left|W^*(c)\right|$, where $W^*(c) = W(c) - cW(1)$ is a Brownian bridge and $W(c)$ is the standard Brownian motion.

2.3 Tests of long memory

Long memory is an important empirical feature of any financial variables because its presence reveals the existence of nonlinear forms of dependence between the first and the second moments, and thus the potential of time-series predictability. As pointed out by Elder and Serletis (2008), the evidence of predictability in oil markets would imply the invalidity of weak-form informational efficiency and offer market operators the possibility to exploit any deviations of oil prices from their fundamental value in order to consistently earn abnormal profits.

In this paper we also test for the long memory property of the oil-return data. This is an essential task permitting the determination of the value for the long memory parameter d in the FIGARCH model. Concretely, the potential long memory component in the oil returns is examined by using the Geweke and Porter-Hudak (1983)'s GPH, the Robinson and Hendry

(1999)'s Gaussian Semiparametric (GSP), and the Sowell (1992)'s Exact Maximum Likelihood (EML) test statistics[2].

i) GPH estimator

The GPH estimate of the long memory parameter, *d*, is based on the following periodogram:

$$\ln\lfloor I(w_j)\rfloor = \beta_0 + \beta_1 \ln\lfloor 4\sin(w_j/2)\rfloor + e_j$$

where $w_j = 2\pi j/T$, $j = 1,2,...n$. e_j is the residual term. w_j represents the $n = \sqrt{T}$ Fourier frequencies and $I(w_j)$ denotes the sample periodogram defined as follows:

$$I(w_j) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} \varepsilon_t\, e^{-w_j t}\right|^2$$

The estimate of *d*, say $\hat{d}_{GPH}$, is $-\hat{\beta}_1$.

ii) GSP Estimator

Robinson and Hendry (1999) investigate the long memory in a covariance stationary series by using a semiparametric approach as:

$$f(w) = Gw^{1-2H} \quad as\ w \to 0^+$$

where $\frac{1}{2} < H < 1$ and $0 < G < \infty$, $f(w)$ being the spectral density of ε_t. As in the GPH estimation procedure, we define the periodogram with respect to the observations ε_t, $t = 1,...,T$ such as:

$$I(\lambda) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} \varepsilon_t e^{it\lambda}\right|^2$$

Accordingly, the estimate of the long memory parameter *H* is given by:

$$H = \underset{\Delta_1 \le h \le \Delta_2}{\arg\min}\, R(h)$$

[2] Interested readers are invited to see the corresponding papers for more details on the asymptotic properties and sensitivities of the test statistics.

where $0 < \Delta_1 < \Delta_2 < 1$, $R(h) = \log\left\{\frac{1}{m}\sum_{j=1}^{m}\frac{I(\lambda_j)}{\lambda_j^{1-2h}}\right\} - (2h-1)\frac{1}{m}\sum_{j=1}^{m}\log\lambda_j$, $m \in (0,[n/2])$, and $\lambda_j = 2\pi j/T$.

It is important to note that under several assumptions presented in Robinson and Hendry (1999), the semiparametric estimator of the long memory parameter is consistent and asymptotically normal.

iii) EML estimator

Sowell (1992) proposes to estimate the long memory parameter d in the ARFIMA(p,d,q) model using the exact maximum likelihood method according to which the log-likelihood function is given by:

$$\log L_T(\bar{\varepsilon},\theta) = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\ln|\Sigma(\theta)| - \frac{1}{2}\bar{\varepsilon}^t\Sigma^{-1}\bar{\varepsilon}$$

where $\bar{\varepsilon}$ is the vector of ε_t, Σ its covariance-variance matrix, and the EML estimator of the unknown parameter vector θ is such as:

$$\hat{\theta} = \arg\max_{\theta} L_T(\bar{\varepsilon},\theta).$$

2.4 Predictive model selection

In the out-of-sample analysis, volatility forecasts are generated for 1-day, 20-day and 60-day ahead horizons, which correspond to 1-day, 1-month and 3-month ahead predictions when daily data are examined. The estimation of the above GARCH volatility models is carried out using quasi-maximum likelihood. More precisely, each sample of T observations is split in two parts. The first one is reserved to estimate the model parameters to be used to generate the forecasts. The second part is left for the out-of-sample comparisons. When using the rolling forecasts the parameters are updated before each new prediction. These predictions are then used to select the best model based on out-of-sample forecast error comparison. We assess the predictive accuracy of the forecasts given by the competing models relative to those of the simple GARCH(1,1) model on the basis of two loss functions[3].

Following Stărică et al. (2005), we consider the aggregate mean square forecast error (MSFE) criterion as follows:

$$MSFE = \left[P-(s-1)\right]^{-1}\sum_{t=R+s}^{T}\left(\tilde{\varepsilon}_t^2 - \tilde{\hat{h}}_{t/t-s,i}\right)^2$$

where $\tilde{\varepsilon}_t^2 = \sum_{j=1}^{s}\varepsilon_{t-j+1}^2$ and $\tilde{\hat{h}}_{t/t-s,i} = \sum_{t=R+s}^{T}\hat{h}_{t-(j-1)/t-s,i}$. $\hat{h}_{t,i}$ is the volatility prediction generated by model *i* at time *t*. *s* and *P* are the forecast horizon and the number of out-of-sample forecasts, respectively.

The second metrics we use to evaluate forecasting models is the VaR (Value at Risk) mean loss function (Gonzalo-Riviera et al., 2004). It is given by:

$$MVaR = \left[P-(s-1)\right]^{-1}\sum\left(0.05 - d_{t,i}^{0.05}\right)\left(\tilde{\varepsilon}_t - VaR_{t,i}^{0.05}\right)$$

where $d_{t,i}^{0.05} = 1\left(\tilde{\varepsilon}_t < VaR_{t,i}^{0.05}\right)$ and $1(.)$ is an indicator function equaling 1 when its argument is satisfied. $VaR_{t,i}^{0.05}$ is empirically determined by simulating the cumulative returns $\tilde{r}_t$ using the corresponding GARCH(1,1) process 5000 times and picking up the 250$^{\text{th}}$ element of the simulated ordered empirical distribution of the cumulative returns. The use of the above loss functions is motivated by the fact that aggregating helps to reduce idiosyncratic noise in squared returns (Rapach and Strauss, 2008). In particular, the second loss function does not require the computation of latent volatility h_t, and VaR is one of the most often used risk management tools in finance.

[3] Forecasts based on the SB-GARCH model are generated only if at least one structural break is detected in the GARCH parameters once the adjusted ICSS test is applied.

3. Data and results

3.1 Data

The data we use in this paper consist of time series of daily spot and futures prices for maturities of one, two, and three months of WTI crude, gasoline, and heating oil, which are obtained from Datastream database. All prices are expressed in US dollars and collected over the period from January 2, 1986 to October 20, 2009. The in-sample period ranges from January 2, 1986 to December 31, 2008, while the period from January 1, 2009 to October 20, 2009.

Table 1 presents the descriptive statistics for the return series of spot and futures oil prices as well as their stochastic properties. The results indicate that the daily average return of all the series, ranging from 0.015% (1-month and 3-month gasoline futures contracts) to 0.042% (2-month gasoline futures contracts), is positive and almost quite similar. The unconditional volatility of the return series on the daily basis is substantial as indicated by their standard deviations with values ranging from 1.965% (3-month gasoline) to 2.719% (spot gasoline). All the series are negatively skewed, and display significant excess kurtosis, except for 2-month heating oil and gasoline. These findings suggest that our oil return series have fatter tails and longer left tail (extreme negative returns) than a normal distribution, which confirms the results of the Jacque-Bera test for normality, not reported here to conserve spaces.

We plot in Figures from 1 to 3 the synchronous time-paths followed by the different oil price series, oil returns and oil volatility as measured by squared returns in order to apprehend their joint dynamics. As it can be observed, we visualize some signs of volatility clustering (i.e., alternatives between periods of high return instability and periods of stability) and persistence (i.e., return volatility tends to remain in the same regime for a long time span). Further, the presence of several sudden changes in the time series may indicate the occurrence of structural breaks.

Figure 1
Dynamics of crude oil, gasoline and heating oil spot and futures prices

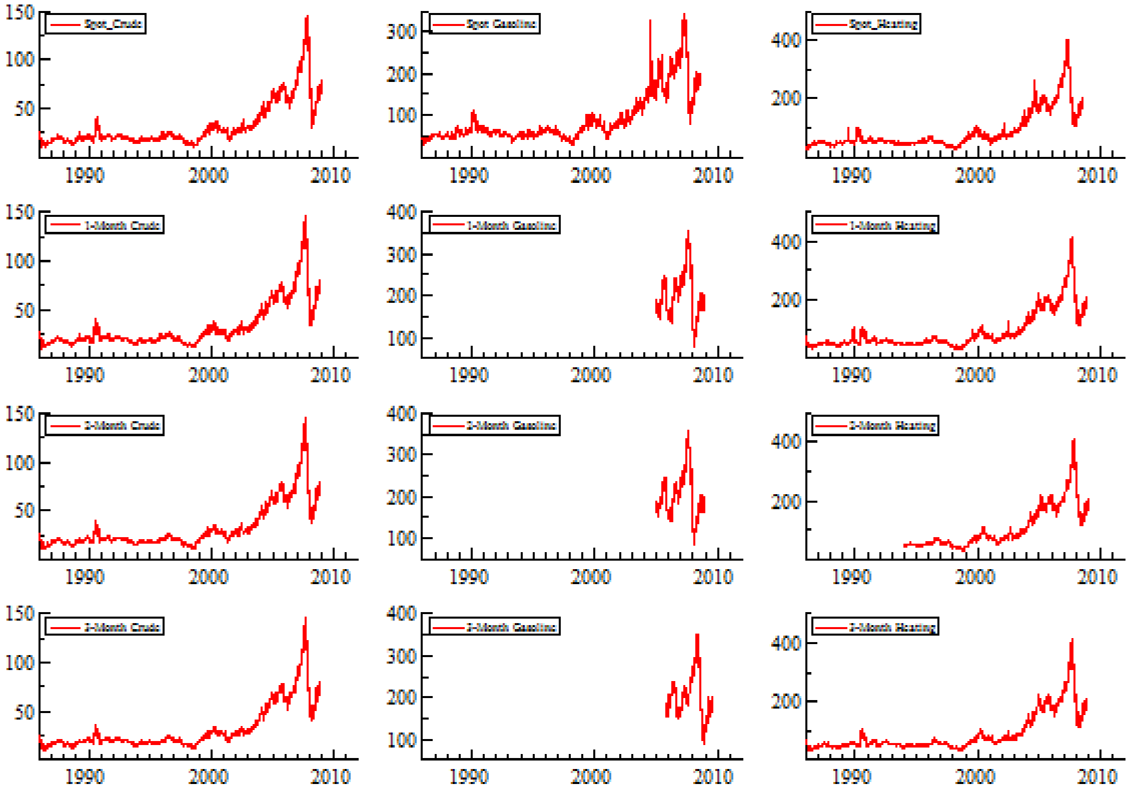


Figure 2
Dynamics of crude oil, gasoline and heating oil spot and futures returns

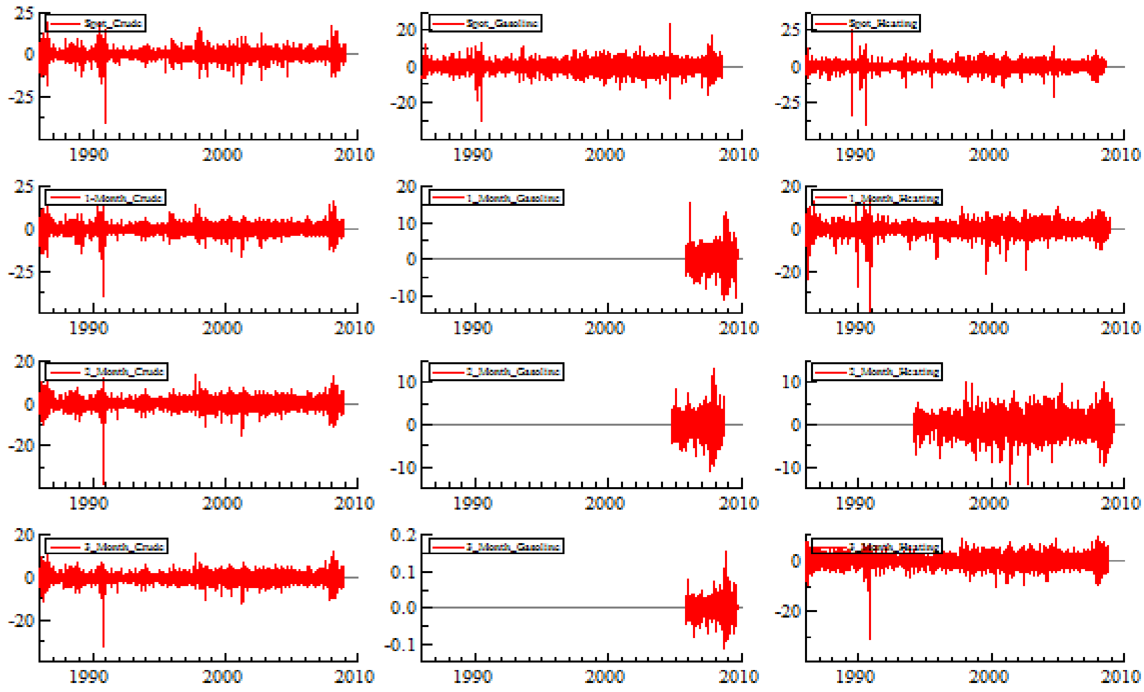
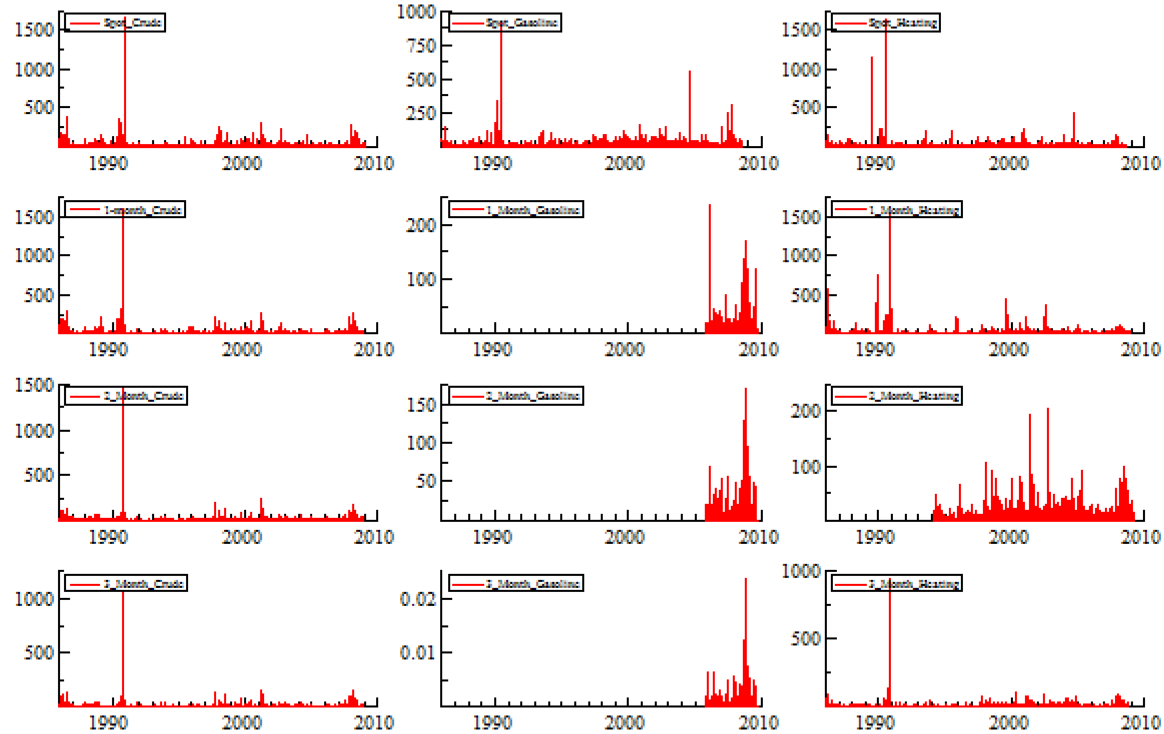


Figure 3
Dynamics of crude oil, gasoline and heating oil spot and futures squared returns



We also perform the Ljung-Box and Engle (1982) LM ARCH tests to further analyze the distributional characteristics of oil return series and report the results in Table 1. These tests provide clear indication of autocorrelation and ARCH effects in the series considered. In contrast, the West and Cho (1995) modified Ljung-Box test which is robust to conditional heteroscedasticity shows that there is significant autocorrelation at conventional levels, except for heating oil spot returns, 2-month crude-oil returns, 2-month gasoline and heating oil returns. Overall, the stylized facts of oil returns reported in Table 1 justify our choice of using GARCH processes to model their conditional volatility.

Table 1
Descriptive statistics of sample data

	Spot Crude	Spot Gasoline	Spot Heating	1m Crude	1m Gasoline	1m Heating	2m Crude	2m Gasoline	2m Heating	3m Crude	3m Gasoline	3m Heating
Mean (%)	0.019	0.024	0.028	0.018	0.015	0.016	0.019	0.042	0.360	0.020	0.015	0.019
	(0.034)	(0.035)	(0.034)	(0.033)	(0.034)	(0.032)	(0.029)	(0.038)	(0.035)	(0.027)	(0.027)	(0.026)
Std. Dev. (%)	2.651	2.719	2.643	2.586	2.527	2.541	2.250	2.194	2.198	2.090	1.965	2.058
	(0.069)	(0.051)	(0.077)	(0.067)	(0.060)	(0.072)	(0.063)	(0.045)	(0.036)	(0.052)	(0.044)	(0.046)
Skewness	-0.787	-0.172	-0.988	-0.823	-0.647	-1.424	-0.948	-0.052	-0.193	-0.800	-0.472	-0.742
	(0.571)	(0.278)	(0.657)	(0.582)	(0.393)	(0.570)	(0.764)	(0.191)	(0.114)	(0.600)	(0.435)	(0.521)
Kurtosis	14.500	6.441	18.100	14.321	9.963	17.432	17.162	3.543	2.224	12.987	8.679	10.324
	(7.870)	(2.370)	(8.457)	(8.273)	(3.900)	(7.981)	(12.289)	(0.900)	(0.505)	(8.888)	(5.197)	(7.486)
Minimum (%)	-40.640	-30.139	-40.463	-40.047	-30.986	-39.094	-38.407	-15.151	-14.348	-32.820	-26.094	-30.864
Maximum (%)	19.151	23.529	25.392	16.409	19.486	13.994	13.788	14.861	10.297	12.115	14.246	9.387
Modified	32.312	47.090	20.451	32.794	30.060	33.848	25.372	18.996	22.221	28.650	31.587	29.654
Ljung-Box	[0.040]	[0.000]	[0.430]	[0.035]	[0.068]	[0.027]	[0.187]	[0.522]	[0.328]	[0.094]	[0.047]	[0.075]
Ljung-Box	680.224	1062.00	505.089	366.465	235.812	393.536	447.031	77.412	513.755	562.712	192.156	434.421
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
LM ARCH	106.430	369.112	215.955	159.163	43.714	45.529	66.477	10.060	41.057	90.846	41.896	40.162
(q=2)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.006]	[0.000]	[0.000]	[0.000]	[0.000]
LM ARCH	299.235	579.520	324.890	366.465	125.961	162.433	233.647	36.214	171.141	213.648	107.903	120.192
(q=10)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: This table reports the basic statistics of sample data and their stochastic properties over the period from January 2, 1986 to October 20, 2009. Data contain the spot and futures prices of the West Texas Intermediate crude oil benchmark, Gasoline and Heating oil. For futures prices, we gather data on one-month, two-month and three-month NYMEX futures contracts. Daily returns are computed as the difference between the logarithms of two successive prices. Numbers in parenthesis are the standard deviations. Modified Ljung-Box and Ljung-Box refer to the empirical statistics of modified and Ljung-Box tests for serial correlation with k lags, while LM ARCH refers to the empirical statistics of the Lagrange Multiplier test for conditional heteroscedasticity applied to residuals. The associated probabilities are reported in brackets.

3.2 In-sample analysis

We first investigate whether structural breaks are present in the temporal dynamics of the twelve oil squared return series over the period considered by applying the modified ICSS algorithm[4]. The test results regarding the number and the exact dates of breaks, reported in Table 2, indicate that five out of the twelve series exhibit structural breaks in their unconditional variance dynamics. Indeed, the ICSS algorithm selects one break for gasoline spot price, 1-month heating oil futures price, and 2-month gasoline futures price; three breaks for 1-month gasoline futures price; and four breaks for 2-month heating oil futures price. We thus observe that structural breaks often occur in the volatility process of gasoline and heating oil price data, whereas crude oil prices are not exposed to such abrupt behavior. These indentified breaks are a priori associated with some significant economic events in the world oil markets as shown in Table 2.

We then proceed to estimate the conditional volatility of the twelve oil squared return series considered using a standard GARCH(1,1) model both over the full sample period and subsample periods defined by the previously identified structural break dates. The obtained results for GARCH parameters are fully reported in Table 3. A careful inspection of the Panel A indicates that GARCH(1,1) model successfully captures the time-varying patterns of conditional volatility well-documented in the finance literature, since the estimates are all significant at the conventional levels. It is shown in particular that conditional volatility of all the oil returns are quite persistent over time in view of the sum $(\alpha + \beta)$ which ranges from 0.981 for heating oil spot returns to 0.996 for crude oil spot returns and 2-month gasoline returns. This finding implies that periods of high volatility tend to be followed by those of high volatility, and periods of low volatility by those of low volatility. It is also indicative of the presence of a long memory component in the volatility dynamics.

[4] Very similar results were obtained using absolute returns.

Table 2
Structural break tests

Oil return series	Number of breaks	Breakpoint dates	Main corresponding events
Spot Crude	0		
Spot Gasoline	1	04/03/1997	Asian economic and financial crisis
Spot Heating	0		
1m Crude	0		
1m Gasoline	3	08/04/1986 08/11/1993 08/13/1997	First Gulf war between Iran and Iraq OPEC overproduction and weak demand Asian economic and financial crisis
1m Heating	1	07/28/1986	First Gulf war between Iran and Iraq
2m Crude	0		
2m Gasoline	1	11/27/1997	Asian economic and financial crisis
2m Heating	4	11/21/1994 12/12/1995 02/19/2008 08/18/2008	Oil workers' strike in Nigeria Latin American crisis Subprime and international financial crisis Subprime and international financial crisis
3m Crude	0		
3m Gasoline	0		
3m Heating	0		

Notes: this table reports the results of the structural break tests based on the application of the modified ICSS algorithm to the twelve returns series on oil spot and futures prices for the period from January 2, 1986 to December 31, 2008.

By comparing the estimation results in Panel B to those in Panel A, one should note at least the two following stylized facts for the series exposed to structural breaks. First, both the size and significance of the estimated parameters are not stable over time and display significant differences across subsamples. These differences can be merely learnt from the changes in the unconditional variance measure $\omega_S/(1-\alpha-\beta)$ and signify that conditional volatility of interested series is effectively characterized by different dynamic processes depending on subsample periods. In particular, there is evidence to suggest that several subsamples are characterized by conditional homoscedasticity in variance because the estimates of both α and β are equal to zero: first subsample of 1-month gasoline, as well as the first, second, fourth and fifth subsamples of the second subsample of 2-month heating oil.

Table 3
Estimation results of GARCH(1,1) models

	Spot Crude	Spot Gasoline	Spot Heating	1m Crude	1m Gasoline	1m Heating	2m Crude	2m Gasoline	2m Heating	3m Crude	3m Gasoline	3m Heating
Panel A. GARCH(1,1) estimation results over the full sample												
ω	0.064***	0.117***	0.149***	0.060***	0.098***	0.085***	0.047***	0.015**	0.031***	0.030***	0.039***	0.036***
	(0.014)	(0.024)	(0.025)	(0.012)	(0.021)	(0.014)	(0.010)	(0.007)	(0.011)	(0.006)	(0.010)	(0.007)
α	0.098***	0.090***	0.112***	0.085***	0.081***	0.090***	0.079***	0.016***	0.036***	0.069***	0.054***	0.053***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.006)	(0.007)	(0.004)	(0.005)	(0.006)	(0.007)	(0.005)
β	0.898***	0.896***	0.869***	0.908***	0.908***	0.900***	0.913***	0.980***	0.957***	0.925***	0.937***	0.938***
	(0.009)	(0.009)	(0.010)	(0.008)	(0.010)	(0.007)	(0.008)	(0.004)	(0.006)	(0.006)	(0.008)	(0.006)
$\alpha + \beta$	0.996	0.986	0.981	0.993	0.989	0.990	0.992	0.996	0.993	0.994	0.991	0.991
$\omega/(1-\alpha-\beta)$	20.794	9.163***	8.235***	10.145***	9.197***	8.864***	6.602***	5.158***	5.251***	6.228***	4.669***	4.577***
	(20.415)	(1.784)	(1.448)	(4.004)	(2.189)	(2.330)	(1.959)	(0.939)	(0.976)	(2.334)	(0.855)	(0.784)
Panel B. GARCH(1,1) estimation results over the subsamples defined by structural breakpoint dates reported in Table 2												
Subsample 1												
ω		0.162***			16.951***	1.267		0.075**	2.671***			
		(0.036)			(2.033)	(1.044)		(0.038)	(0.353)			
α		0.109***			0.000	0.066		0.027**	0.000			
		(0.012)			(0.000)	(0.043)		(0.011)	(0.000)			
β		0.861***			0.000	0.892***		0.944***	0.000			
		(0.015)			(0.000)	(0.051)		(0.019)	(0.000)			
$\alpha + \beta$		0.970			0.000	0.968		0.971	0.000			
$\omega/(1-\alpha-\beta)$		5.601***			16.951***	30.944***		2.717***	2.671***			
		(0.854)			(2.033)	(13.690)		(0.256)	(0.353)			
Subsample 2												
ω		0.609***			0.114***	0.090***		0.194	1.366***			
		(0.161)			(0.034)	(0.016)		(0.183)	(0.139)			
α		0.076***			0.115***	0.088***		0.015*	0.000			
		(0.012)			(0.020)	(0.007)		(0.009)	(0.000)			
β		0.856***			0.867***	0.900***		0.950***	0.000			
		(0.025)			(0.022)	(0.007)		(0.039)	(0.000)			
$\alpha + \beta$		0.932			0.982	0.988		0.965	0.000			
$\omega/(1-\alpha-\beta)$		9.154***			7.010***	7.700***		5.747***	1.366***			
		(0.542)			(2.651)	(1.653)		(0.254)	(0.139)			
Subsample 3												

ω	0.721*	0.104**
	(0.345)	(0.042)
α	0.081***	0.037***
	(0.031)	(0.008)
β	0.733***	0.940***
	(0.107)	(0.015)
$\alpha + \beta$	0.814	0.977
$\omega/(1-\alpha-\beta)$	3.879***	4.823***
	(0.255)	(0.350)
Subsample 4		
ω	1.153***	16.417***
	(0.507)	(1.834)
α	0.060***	0.000
	(0.021)	(0.000)
β	0.791***	0.000
	(0.080)	(0.000)
$\alpha + \beta$	0.851	0.000
$\omega/(1-\alpha-\beta)$	7.795***	16.417***
	(0.344)	(1.834)
Subsample 5		
ω		5.751***
		(0.752)
α		0.000
		(0.000)
β		0.000
		(0.000)
$\alpha + \beta$		0.000
$\omega/(1-\alpha-\beta)$		5.751***
		(0.752)

Notes: this table reports the estimation results of GARCH(1,1) models for all the squared return series we study over the full sample as well as those of GARCH(1,1) models over different subsamples defined by the structural breakpoints. Standard deviations are in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

Second, it is observed that none of the sum $(\alpha + \beta)$ has the value above the lowest degree of persistence we find in Panel A (i.e., 0.981 for heating oil spot returns), which clearly evidences that GARCH estimates without controlling for structural change issues overstate the persistence degree in the conditional volatility. However, the volatility persistence still remains high across subsamples, apart some regimes where $(\alpha + \beta) = 0$. According to these signs of long memory, shocks to conditional volatility tend to disappear at a hyperbolic rate which is slower than the exponential rate of decay of shocks in the GARCH model setting (Baillie, 1996).

Before moving to the out-of-sample forecast evaluation, it is convenient to further examine the long memory property in the volatility of oil return series. In the literature, some studies have analyzed the persistence of long memory in crude oil and refined products markets (Tabak and Cajueiro, 2007; Choi and Hammoudeh, 2009; Kang et al., 2009) using econometric techniques such as modified R/S statistics, and GARCH-type models suitable for capturing long memory. Following these studies, we also perform several long memory tests.

Table 4
Diagnostic tests for long memory

	Spot Crude	Spot Gasoline	Spot Heating	1m Crude	1m Gasoline	1m Heating	2m Crude	2m Gasoline	2m Heating	3m Crude	3m Gasoline	3m Heating
GPH	0.112	0.174	0.145	0.131	0.127	0.112	0.089	0.057	0.082	0.082	0.088	0.070
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
GSP	0.134	0.184	(0.142)	0.143	0.126	0.106	0.117	0.097	(0.100)	0.129	0.125	0.112
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EML	0.122	0.194	0.155	0.140	0.093	0.092	0.107	0.064	0.102	0.115	0.093	0.090
	(0.000)	(0.000)	(0.000)	(0.000)	(0 .000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: this table reports the results from three long memory tests applied to squared return series: GPH, GSP and EML. The p-values are given in parenthesis.

Table 4 provides the results of three long memory tests applied to squared oil return series (GPH, GSP, and EML). Obviously, these tests show that all the oil spot and futures squared returns exhibit strong evidence of long memory patterns as the null hypothesis of no persistence is always rejected at the 1% level. This implies that oil price volatility would tend to be range-dependent, persist and decay slowly. As suggested by Baillie (1996), a FIGARCH model seems to be better equipped to reproduce the volatility persistence of the oil return series under consideration. We then fit a FIGARCH(1,*d*,1) to the twelve oil returns series and report the results in Table 5. All the estimates of the long memory parameters, *d*, are statistically significant at the 1% level, and they are also very different from unity, which thus confirm effectively the findings of the long memory tests on squared returns. It is also worth noting that the conditional volatility of crude oil spot and futures returns have generally stronger long memory than gasoline and heating oil. Without loss of generality, these results have important implications for derivatives trading relying on the persistence of oil price tendencies (increasing or decreasing).

Table 5

Estimates of FIGARCH(1,*d*,1) model for daily oil spot and futures return volatility

	Spot Crude	Spot Gasoline	Spot Heating	1m Crude	1m Gasoline	1m Heating	2m Crude	2m Gasoline	2m Heating	3m Crude	3m Gasoline	3m Heating
ω	0.198***	0.256***	0.216***	0.140***	0.307***	28.210***	0.123***	0.461***	0.309***	0.126***	0.135***	0.128***
	(0.038)	(0.060)	(0.044)	(0.025)	(0.068)	(7.373)	(0.024)	(0.104)	(0.092)	(0.027)	(0.031)	(0.033)
ϕ	0.133***	0.182***	0.120***	0.149***	0.213***	-0.447***	0.099***	0.377***	0.200***	0.096***	0.222***	0.234***
	(0.037)	(0.037)	(0.035)	(0.037)	(0.053)	(0.066)	(0.031)	(0.018)	(0.053)	(0.042)	(0.040)	(0.037)
β	0.617***	0.552***	0.649***	0.723***	0.536***	-	0.663***	0.572***	0.511***	0.594***	0.631***	0.622***
	(0.056)	(0.061)	(0.075)	(0.046)	(0.067)		(0.051)	(0.025)	(0.072)	(0.061)	(0.054)	(0.059)
d	0.620***	0.463***	0.649***	0.700***	0.449***	0.609***	0.632***	0.245***	0.329***	0.578***	0.470***	0.448***
	(0.053)	(0.054)	(0.087)	(0.074)	(0.050)	(0.044)	(0.060)	(0.036)	(0.042)	(0.054)	(0.055)	(0.053)

Notes: this table reports the results of the QML (quasi-maximum likelihood) estimation of FIGARCH model for daily oil return series. ω, $(\phi+\beta)$, and *d* refer to the long-term unconditional variance, the measure of volatility persistence and the long memory parameter. Robust standard errors are given in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

Summarizing all, our in-sample analysis shows that structural breaks are indeed present in the dynamics of several oil price volatility series. The variation in the standard GARCH(1,1) estimates across different subsamples separated by the breakpoint dates identified by the ICSS further suggests that structural breaks are a relevant empirical feature of the volatility of several oil-return series and accounting for them in *ex-post* volatility estimation permits to avoid spurious persistence level. Finally, long memory also appears to be an important property characterizing the volatility process of oil returns as indicated by the results of the FIGARCH estimates.

3.3 Out-of-sample analysis and forecasting performance

This subsection examines the forecasting performance of five competing models for oil spot and futures return volatility: RiskMetrtics, GARCH 0.5 rolling window, GARCH 0.25 rolling window, FIGARCH and SB-GARCH. The predictive performance of these competing models is compared to the most used volatility model: the GARCH(1,1) expanding window model which is a standard GARCH(1,1) model estimated on an expanding window as compared to the in-sample period. To evaluate and compare the out-of-sample forecasting performance across models, we consider our two loss functions: the mean square forecast error (*MSFE*) and the mean Value-at-Risk (*MVaR*). A model with lowest loss function is said to provide best volatility forecasts.

The out-of-sample period, which is used for forecasting purpose, covers the period from January 1, 2009 to October 20, 2009 with a total of 202 daily observations. To generate volatility forecasts, we use recursive forecasting technique that consists of fixing the initial date and adding each new observation one at a time to the out-of-sample period. The results for horizons of 1-, 20-, and 60-day ahead forecasting over the expanding window of data are reported in Tables 6, 7 and 8.

When looking at the results of the 1-day ahead forecast horizon in Table 6, we observe that the GARCH(1,1) expanding window model has the smallest mean loss only for gasoline 2-month futures returns, and for spot crude oil returns and heating oil 2-month futures returns, according to the MSFE and MVaR loss functions, respectively. Thus in most cases it provides less accurate forecasts than RiskMetrics and other volatility models. The RiskMetrics model has the lowest mean loss in five out of twelve cases (spot crude oil, spot gasoline, and 1-month, 2-month and 3-month crude oil) according to the MSFE criterion, but only two out of twelve cases according to the *MVaR* criterion. As for the other competing models, they generally lead to improve the predictive ability relative to the benchmark model for gasoline and heating oil return series. The evidence of superior forecasting performance of competing models is clearly significant with respect to the *MVaR* criterion.

Table 6
Out-of-sample predictive accuracy of competing models: 1-day horizon

	Spot Crude	Spot Gasoline	Spot Heating	1m Crude	1m Gasoline	1m Heating	2m Crude	2m Gasoline	2m Heating	3m Crude	3m Gasoline	3m Heating
MSFE criterion												
GARCH(1,1) Ex. window	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**	1.000	1.000	1.000	1.000
RiskMetrics	**0.985**	**0.992**	1.009	**0.997**	0.982	0.993	**0.992**	1.026	1.019	**0.999**	1.009	1.005
FIGARCH	1.008	1.028	1.031	1.019	1.007	1.005	1.006	1.006	1.001	1.006	0.997	1.009
GARCH(1,1) 0.5 RW	0.998	**0.992**	**0.973**	1.015	0.991	0.973	1.018	1.009	**0.999**	1.021	0.986	1.002
GARCH(1,1) 0.25 RW	1.014	1.007	0.986	1.006	**0.978**	**0.955**	0.996	1.012	1.011	1.000	**0.979**	**0.998**
SB-GARCH(1,1)	No break	**0.992**	No break	No break	0.998	0.956	No break	1.001	1.068	No break	No break	No break
5% MVaR criterion												
GARCH(1,1) Ex. window	**1.000**	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**	1.000	1.000	1.000
RiskMetrics	1.007	0.992	**0.943**	**0.994**	0.964	1.008	0.968	1.010	1.022	0.996	1.009	0.989
FIGARCH	1.024	0.997	0.998	1.010	0.996	1.026	**0.971**	0.983	1.035	**0.985**	0.984	1.004
GARCH(1,1) 0.5 RW	1.019	0.994	0.963	1.014	0.985	0.986	1.024	**0.965**	1.012	1.026	0.988	0.977
GARCH(1,1) 0.25 RW	1.048	0.989	0.948	1.005	**0.955**	**0.902**	0.977	0.966	1.013	0.996	**0.973**	**0.972**
SB-GARCH(1,1)	No break	**0.983**	No break	No break	1.001	0.947	No break	0.987	1.023	No break	No break	No break

Notes: this table reports the results of 1-day forecasting horizon for competing volatility models: GARCH(1,1) expanding window, RiskMetrics, FIGARCH(1,*d*,1), GARCH(1,1) 0.50 rolling window, GARCH(1,1) 0.25 rolling window, and GARCH(1,1) with breaks. We compute the ratio of the mean loss to the mean loss of the GARCH(1,1) expanding window model is given. The GARCH(1,1) with breaks is estimated for the return series for which we detect structural changes by using the ICSS algorithm. A bold entry denotes the model with the lowest mean loss among the competing models.

One should however note that the models accommodating explicitly for long memory and structural breaks, FIGARCH(1,*d*,1) and GARCH(1,1) with breaks, outperform other models in only few cases over the out-of-sample forecasting period, namely 1-month gasoline (MSFE) and 1-month gasoline and 2-month crude and 3-month crude (MVaR). Indeed, the *MSFE* does not select the FIGARCH model, while it is chosen only twice for the 2-month and 3-month crude oil futures returns by the *MVaR*. The GARCH(1,1) with breaks shows superior predictive ability relative to the remaining models only for gasoline spot returns. Nevertheless, on the one hand, when structural breaks are found, SB-GARCH outperforms the standard GARCH(1,1) in most cases, on the other hand, the FIGARCH model gives better forecasts than the benchmark in seven cases according the MVaR criterion. Finally, the competing models that allow for instabilities and accommodate for changes in the estimates lead to significant reduction of the loss function compared to the benchmark.

Table 7
Out-of-sample predictive accuracy of competing models: 20-day horizon

	Spot Crude	Spot Gasoline	Spot Heating	1m Crude	1m Gasoline	1m Heating	2m Crude	2m Gasoline	2m Heating	3m Crude	3m Gasoline	3m Heating
MSFE criterion												
GARCH(1,1) Ex. window	1.000	1.000	1.000	**1.000**	1.000	1.000	**1.000**	1.000	1.000	**1.000**	1.000	**1.000**
RiskMetrics	**0.915**	1.350	1.842	1.056	**0.976**	0.970	1.183	1.885	1.266	1.180	1.164	1.136
FIGARCH	0.977	2.176	2.125	1.102	1.276	0.936	1.359	0.979	0.998	1.275	0.992	1.113
GARCH(1,1) 0.5 RW	1.147	**0.903**	**0.782**	1.196	1.050	0.591	1.524	1.051	**0.935**	1.354	0.775	1.191
GARCH(1,1) 0.25 RW	1.548	1.026	1.167	1.103	1.025	**0.342**	1.194	1.080	1.231	1.083	**0.754**	1.129
SB-GARCH(1,1)	No break	0.904	No break	No break	0.980	0.357	No break	**0.870**	2.302	No break	No break	No break
5% MVaR criterion												
GARCH(1,1) Ex. window	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
RiskMetrics	1.027	1.008	1.020	1.026	1.021	1.176	1.053	1.298	1.017	1.030	1.052	1.018
FIGARCH	1.049	0.967	1.048	1.039	1.046	0.845	1.043	0.963	**0.963**	1.033	0.956	1.027
GARCH(1,1) 0.5 RW	1.150	0.946	**0.983**	**0.964**	**0.996**	0.926	**0.907**	0.655	0.972	**0.873**	0.957	**0.997**
GARCH(1,1) 0.25 RW	1.625	0.944	1.006	1.021	1.052	**0.571**	0.999	**0.647**	1.032	0.985	**0.864**	1.036
SB-GARCH(1,1)	No break	**0.940**	No break	No break	1.004	0.782	No break	0.806	1.030	No break	No break	No break

Notes: this table reports the results of 20-day forecasting horizon for competing volatility models: GARCH(1,1) expanding window, RiskMetrics, FIGARCH(1,*d*,1), GARCH(1,1) 0.50 rolling window, GARCH(1,1) 0.25 rolling window, and GARCH(1,1) with breaks. We compute the ratio of the mean loss to the mean loss of the GARCH(1,1) expanding window model is given. The GARCH(1,1) with breaks is estimated for the return series for which we detect structural changes by using the ICSS algorithm. A bold entry denotes the model with the lowest mean loss among the competing models.

For the 20-day ahead forecast horizon in Table 7, it is shown that the benchmark model has the highest mean loss in all cases according to MVaR and in eight cases according to *MSFE* criterion. The GARCH(1,1) 0.5 and 0.25 rolling window models outperform the GARCH(1,1) expanding window model and RiskMetrics model for five cases according to the *MSFE* loss function. The GARCH(1,1) with structural breaks gives better forecast than the GARCH(1,1) expanding window model for four cases while it is the best model for only one case. With respect to the *MVaR* loss function, the models accommodating for instabilities in the volatility process give better forecasts than the benchmark in eleven (seven) cases according the MVaR

(MSFE). The FIGARCH forecasts are better than those of other models in only one case (2-month heating) according to the MVaR criterion but it gives better forecasts than the benchmark GARCH(1,1) model in five cases according to both criteria. We also remark that the mean losses of the competing models selected by evaluation criteria are substantially reduced in comparison to those reported in Table 6.

Table 8
Out-of-sample predictive accuracy of competing models: 60-day horizon

	Spot Crude	Spot Gasoline	Spot Heating	1m Crude	1m Gasoline	1m Heating	2m Crude	2m Gasoline	2m Heating	3m Crude	3m Gasoline	3m Heating
MSFE criterion												
GARCH(1,1) Ex. window	1.000	**1.000**	1.000	1.000	1.000	1.000	**1.000**	1.000	1.000	**1.000**	1.000	**1.000**
RiskMetrics	1.021	2.286	3.203	1.481	1.352	0.301	2.214	0.972	1.948	1.806	1.638	1.790
FIGARCH	**0.988**	5.222	5.571	1.430	2.585	0.936	2.710	**0.907**	0.724	2.202	1.102	1.300
GARCH(1,1) 0.5 RW	1.254	1.126	**0.637**	**0.964**	1.100	**0.001**	1.608	7.829	**0.716**	1.083	**0.628**	1.485
GARCH(1,1) 0.25 RW	1.967	1.371	1.392	1.074	1.287	2.761	1.451	7.286	1.878	0.937	0.693	1.607
SB-GARCH(1,1)	No break	1.151	No break	No break	**0.909**	0.880	No break	2.468	3.146	No break	No break	No break
5% MVaR criterion												
GARCH(1,1) Ex. window	**1.000**	**1.000**	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
RiskMetrics	1.074	1.024	1.051	1.073	1.054	0.736	1.091	1.445	1.037	1.060	1.102	1.084
FIGARCH	1.150	1.147	1.108	1.042	1.095	0.516	1.083	0.916	**0.951**	1.062	0.879	1.045
GARCH(1,1) 0.5 RW	1.375	1.056	**0.996**	**0.852**	**0.928**	0.605	**0.852**	0.617	0.960	**0.822**	0.903	**0.983**
GARCH(1,1) 0.25 RW	1.847	1.054	1.013	0.976	1.013	0.094	1.012	**0.615**	1.039	0.984	**0.732**	1.064
SB-GARCH(1,1)	No break	1.051	No break	No break	1.173	**0.007**	No break	0.776	1.024	No break	No break	No break

Notes: this table reports the results of 60-day forecasting horizon for competing volatility models: GARCH(1,1) expanding window, RiskMetrics, FIGARCH(1,*d*,1), GARCH(1,1) 0.50 rolling window, GARCH(1,1) 0.25 rolling window, and GARCH(1,1) with breaks. We compute the ratio of the mean loss to the mean loss of the GARCH(1,1) expanding window model is given. The GARCH(1,1) with breaks is estimated for the return series for which we detect structural changes by using the ICSS algorithm. A bold entry denotes the model with the lowest mean loss among the competing models.

Results of the 60-day ahead forecasting horizon (Table 8) almost confirm those we reported in Table 7. First, there are only four (two) cases where the GARCH(1,1) expanding window model has the lowest mean loss with respect to the *MSFE* (*MVaR*) criterion, thus gives the superiority of out-of-sample volatility forecasts relative to the other models. Second, GARCH models incorporating instable structures continue to generate lower mean losses than the benchmark model in ten (seven) cases according to the *MSFE* (*MVaR*). Similarly, the results provide little evidence of superior predictive power of the FIGARCH(1,d,1) compared to other competing models. However it outperforms the benchmark in four cases according to the two criteria. It should be finally noted that RiskMetrics model is no longer relevant for out-of-sample volatility forecasts according to neither *MSFE* nor *MVaR* loss functions. The best performing model in case of 1-month heating oil futures returns (GARCH with structural breaks) attains a mean loss reduction of 99.993%.

Table 9
Out-of-sample predictive accuracy: loss function based on the *MSFE* and *MVaR*

		Spot Crude	Spot Gasoline	Spot Heating	1m Crude	1m Gasoline	1m Heating	2m Crude	2m Gasoline	2m Heating	3m Crude	3m Gasoline	3m Heating
MSFE loss function													
H=1	Mean	1.001	1.038	1.002	1.010	0.985	0.960	1.000	1.003	1.095	1.002	0.986	1.000
	T mean	0.994	1.001	0.989	1.002	0.989	0.966	0.999	1.005	1.013	1.000	0.987	0.999
H=20	Mean	1.052	1.953	1.394	1.079	0.966	0.500	1.093	0.966	1.274	1.005	0.804	1.066
	T mean	1.015	1.129	1.078	1.025	0.984	0.478	1.057	0.989	1.210	0.999	0.804	1.065
H=60	Mean	1.209	3.308	1.964	2.202	1.039	0.811	1.155	4.711	1.659	0.943	0.716	1.252
	T mean	1.077	1.832	1.243	1.142	1.025	0.694	1.047	4.655	1.392	0.790	0.714	1.242
5% MVaR loss function													
H=1	mean	1.042	0.981	0.964	1.016	0.968	0.945	0.992	0.978	1.003	1.005	0.986	0.977
	T mean	1.022	0.989	0.964	0.998	0.980	0.953	0.987	0.978	1.009	0.999	0.986	0.986
H=20	mean	1.158	0.975	1.016	1.025	1.030	0.716	1.007	0.730	1.031	1.029	0.916	1.031
	T Mean	1.122	0.963	1.005	0.998	1.018	0.744	0.985	0.733	1.011	0.971	0.923	1.014
H=60	Mean	1.302	1.110	1.049	1.000	1.009	0.367	1.016	0.718	1.028	0.999	0.850	1.041
	T mean	1.287	1.070	1.021	0.971	0.991	0.335	0.987	0.715	1.009	0.976	0.854	1.023

Notes: this table reports the ratio of the mean loss for the mean and the trimmed mean combination forecasts to the mean loss for the GARCH(1,1) model.

Table 9 reports the ratio of the mean loss for the mean and the trimmed mean combinations forecasts to those of the benchmark, i.e. the GARCH(1,1) model. The upper part shows that, based on the MSFE loss function, the mean and trimmed mean are lower than those of the GARCH(1,1) model for the 1-month gasoline, 1-month heating, and 3-month gasoline. Better forecasting ability of the competing models can be seen in the lower part of Table 9 in view of numerous ratios with values lower than unity. In addition, all the series are concerned with the improvement of their forecast accuracy since the associated ratios reveal a decreasing trend, even those remaining above unity.

Overall, the results of our out-of-sample analysis from Table 6 to Table 9 indicate that accommodating for instabilities and structural breaks often leads to improve the quality of volatility forecasts of oil spot and futures returns, regardless of the evaluation criteria having been used to select the best performing models. We find that GARCH(1,1) rolling window models and GARCH with breaks have the lowest loss function for the majority of the cases, whereas the benchmark model, GARCH(1,1) expanding window, tends to have inferior predictive power relative to competing models at the longer forecast horizons. As for FIGARCH model that explicitly allows for the persistence of long memory in oil return volatility, it is relevant at most in two cases (60-day horizon), which is not consistent with the strong evidence of long memory revealed by the GPH, GSP, and EML tests. These findings lead us to conclude that structural breaks are a relevant feature of oil return volatility, and that long memory evidence may be spurious. For future research, it is therefore important to discriminate between long memory and nonlinearity.

4. Conclusion

In this paper we examined competing GARCH-type models in order to model and forecast oil price volatility over the last turbulent decades. We particularly extended the previous works by investigating the relevance of structural breaks and long memory in modeling and forecasting the conditional volatility of oil spot and futures prices. Empirical findings from in-sample analysis suggests that structural breaks are indeed present in the dynamics of several oil price volatility series and that SB-GARCH models appear to be relevant to better describe the behavior of time-varying oil-return volatility. Long memory equally seems to characterize the volatility process of oil returns as indicated by the results of the FIGARCH estimates.

Results of the out-of-sample analysis indicate that taking into account the instabilities and structural breaks in the volatility dynamics of oil spot and futures returns often leads to improve the quality of volatility forecasts. Accommodating for long memory in oil return volatility also helps to improve forecasting results in some cases. In particular, we provide evidence that long-horizon forecasts of spot and futures oil price volatility generated by short memory stable volatility models, namely RiskMetrics and GARCH(1,1), are often inferior to forecasts obtained from GARCH(1,1) rolling windows, BS-GARCH and FIGARCH models allowing respectively for instabilities and long memory in the unconditional variance.

There are several avenues for future research. First, the evidence of long memory in the in-sample period is not strongly supported by the out-of-sample forecasting exercise. The persistence detected in the returns dynamic may be spurious and due to other forms of nonlinearities. Further investigation of this point would be informative. Second, in this paper we considered as a benchmark a standard linear GARCH(1,1) model. However, recent works on stock returns suggest that taking into account asymmetric effects helps to improve in-sample and out-of-sample model performances. Thus, it would be interesting in future empirical investigations to consider asymmetric volatility models such as exponential GARCH and GJR-GARCH models. Finally, further research could examine shock transmission and the links of causality between oil and oil-related products using multivariate volatility models.

References

Agnolucci, P., 2009. Volatility in crude oil futures: A comparison of the predictive ability of GARCH and implied volatility models. Energy Economics 31, 316-321.

Baillie, R., Bollerslev, T., Mikkelsen, H., 1996. Fractionally integrated generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 74, 3-30.

Basher, S.A., Sadorsky, P., 2006. Oil price risk and emerging stock markets. Global Finance Journal 17, 224-251.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307-327.

Bollerslev, T., Mikkelsen, H.O., 1996. Modeling and pricing long-memory in stock market volatility. Journal of Econometrics 73, 151-184.

Boyer, M.M., Filion, D., 2007. Common and fundamental factors in stock returns of Canadian oil and gas companies. Energy Economics 29, 428-453.

Charles, A., Darné, O., 2009. The efficiency of the crude oil markets: Evidence from variance ratio tests. Energy Policy 37, 4267-4272.

Cheong, C.W., 2009. Modeling and forecasting crude oil markets using ARCH-type models. Energy Policy 37, 2346-2355.

Choi, K., Hammoudeh, S., 2009. Long memory in oil and refined products markets. Energy Journal 30, 57-76.

Choi, K., Hammoudeh, S., 2009. Long memory in oil and refined products markets. Energy Journal 30, 57-76.

Choi, K., Yu, W-C., Zivot, E., 2010. Long memory versus structural breaks in modeling and forecasting realized volatility. Journal of International Money and Finance, *forthcoming*.

Choi, K., Zivot, E., 2007. Long memory and structural changes in the forward discount: An empirical investigation. Journal of International Money and Finance 26, 342-363.

Ciner, C., 2001. Energy shock and financial market nonlinear linkages. Studies in Nonlinear Dynamics and Econometrics 5, 203-212.

Cologni, A., Manera, M., 2008. Oil prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries. Energy Economics 30, 856-888.

Ding, Z., Granger, C.W.J., Engle, R.F., 1993. A long memory property of stock market returns and a new model. Journal of Empirical Finance 1, 83-106.

Driesprong, G., Jacobsen, B., Maat, B., 2008. Striking oil: another puzzle?. Journal of Financial Economics 89, 307-327.

Elder, J., Serletis, A., 2008. Long memory in energy futures prices. Review of Financial Economics 17, 146-155.

Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50, 987-1007.

Fong, W.M., See, K.H., 2002. A Markov switching model of the conditional volatility of crude oil futures prices. Energy Economics 24, 71-95.

Geweke, J.P., Porter-Hudack, S. 1983. The estimation and application of long memory time series models. Journal of Time Series Analysis 4, 221-238.

Granger, C.W.J., Hyung, N., 2004. Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. Journal of Empirical Finance 11, 399-421.

Hamilton, J.D., 1983. Oil and the macroeconomy since World War II. Journal of Political Economy 91, 228-248.

Hammoudeh, S., Li, H., 2004. Risk-return relationships in oil-sensitive stock markets. Finance Letters 2, 10-15.

Hillebrand, E., 2005. Neglecting parameter changes in GARCH models. Journal of Econometrics 129, 121-138.

Horsnell, P., Mabro, R., 1993. Oil markets and prices: the Brent market and the formation of world oil prices. Oxford University Press, Oxford.

Inclán, C., Tiao, G.C., 1994. Use of cumulative sums of squares for retrospective detection of changes in variance. Journal of the American Statistic Association 89, 913-923.

Jones, C.M., Kaul, G., 1996. Oil and the stock markets. Journal of Finance 51, 463-491.

Kang, S.H., Kang, S.M., Yoon, S.M., 2009. Forecasting volatility of crude oil markets. Energy Economics. Energy Economics 31, 119-125.

Kroner, K.F., Kneafsey, K.P., Claessens, S., 1995. Forecasting volatility in commodity markets. Journal of Forecasting 14, 77-95.

Lardic, S., Mignon, V., 2008. Oil prices and economic activity: an asymmetric cointegration approach. Energy Economics 30, 847-855.

Lee, C., Lee, J., 2009. Energy prices, multiple structural breaks, and efficient market hypothesis. Applied Energy 86, 466-479.

Lee, Y-H., Hu, H-N., Chiou, J-S., 2010. Jump dynamics with structural breaks for crude oil prices. Energy Economics 32, 343-350.

Maghyereh, A., Al-Kandari, A., 2007. Oil prices and stock markets in GCC countries: new evidence from nonlinear cointegration analysis. Managerial Finance 33, 449-460.

Mikosch, T., Stărică, C., 2004. Nonstationarities in financial time series, the long-range dependence, and the IGARCH effects. Review of Economics and Statistics 86, 378-390.

Nandha, M., Faff, R., 2008. Does oil move equity prices? A global view. Energy Economics 30, 986-997.

Narayan, P.K., Narayan, S., 2007. Modelling oil price volatility. Energy Policy 35, 6549-6553.

Newey, W.K., West, K.D., 1994. Automatic lag selection in covariance matrix estimation. Review of Economic Studies 61, 631-654.

Pindyck, R.S., 2004. Volatility and commodity price dynamics. Journal of Futures Markets 24, 1029-1047.

Plourde, A., Watkins, G.C., 1998. Crude oil prices between 1985 and 1994: how volatile in relation to other commodities?. Resource and Energy Economics 20, 245-262.

Poon, S.H., Granger, C.W.J., 2003. Forecasting volatility in financial markets: a review. Journal of Economic Literature 41, 478-539.

Rapach, D.E., Strauss, J.K., 2008. Structural breaks and GARCH models of exchange rate volatility. Journal of Applied Econometrics 23, 65-90.

Regnier, E., 2006. Oil and energy price volatility. Energy Economics 29, 405-427.

RiskMetrics Group (1996). RiskMetrics-Technical Document (New York: J.P. Morgan/Reuters).

Robinson, P.M, Hendry, D., 1999. Long and short memory conditional heteroscedasticity in estimating the memory parameter of levels. Econometric Theory 15, 299-336.

Sadorsky, P., 2006. Modeling and forecasting petroleum futures volatility. Energy Economics 28, 467-488.

Sowell, F., 1992. Maximum likelihood estimation of stationary univariate fractionally integrated time series models. Journal of Econometrics 53, 165-188.

Stărică, C., Herzel, S., Nord, T., 2005. Why does the GARCH(1,1) model fail to provide sensible longer-horizon volatility forecasts?. Working Paper, Chalmers University of Technology.

Tabak, B.M., Cajueiro, D.O., 2007. Are the crude oil markets becoming weakly efficient over time? A test for time-varying long-range dependence in prices and volatility. Energy Economics 29, 28-36.

Tse, Y., 1998. The conditional heteroscedasticity of the yen-dollar exchange rate. Journal of Applied Econometrics 193, 49-55.

West, K.D., Cho, D., 1995. The predictive ability of several models of exchange rate volatility. Journal of Econometrics 69, 367-391.

Zhang, D., 2008. Oil shock and economic growth in Japan: a nonlinear approach. Energy Economics 30, 2374-2390.