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Oil price shocks, equity markets, and contagion effect in OECD countries

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Abstract

This paper revisits the dynamic linkages between the Brent oil market and OECD stock markets. Econometrically, we use a multivariate corrected dynamic conditional correlation fractionally integrated asymmetric power ARCH (c-DCC-FIAPARCH) process, controlling main financial time-series features such as asymmetry, volatility, and long memory. Based on daily data for 17 OECD stock markets from March 16, 1998 to February 23, 2018, we show three main findings. First, the impact of oil price shocks on the relationship between oil and stock markets is more pronounced during periods of global turmoil and asymmetric in all countries. Second, we do not observe a proper 'contagion effect' across all countries. Finally, this paper identifies five groups of countries based on the shape of the dynamic conditional correlation, which indicates that the relationship between oil and stock markets is segmented geographically. The findings have several policy implications.

JEL Classification: C10, E44, G15

Keywords: Financialization, Conditional correlations, Segmented geographically, c-DCC-FIAPARCH model

1. Introduction

Since 2002, the commodity market has experienced 'financialization', as financial investors represent more than 80% of the total investors (Gao and Süss, 2015). The most strategic and most volatile commodity is crude oil, leading to increased attention being paid to its prices with respect to those of other commodities. Interestingly, the attention to the dynamics of oil prices has been growing since the end of the 1990s, when different financial crises and events occurred, leading to boom or bust in international trade and, consequently, proving the high volatility of oil prices.

The theory of equity valuation might explain the impact of oil price fluctuations on stock prices. According to this theory, stock prices are obtained by discounting all expected future cash flows at the investors' required rate of return. For instance, a negative oil shock may reduce the corporate cash flow and rate of return. In addition,

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stock prices could be affected by oil price fluctuations through the channels of corporate earnings, low stock prices, and economic conditions. Based on these channels, crude oil presents some specificities compared to other commodities, especially those used in production processes.

Numerous studies have analysed the specificities of the relationship between oil and financial markets, finding a negative relationship between oil price and stock market returns. For instance, Arouri *et al.* (2011) use a multivariate GARCH to investigate volatility spillovers between oil and different stock market sectors in the US and Europe, using a weekly dataset from January 1998 to December 2009. They find that oil prices fluctuations affect both the European and the US stock markets. More recently, Chang *et al.* (2013) also use a multivariate GARCH model to study the volatility spillovers effect between oil prices fluctuations and the US and UK stock markets. Their results show no significant evidence of volatility spillovers between oil prices and stock markets. Further, Creti *et al.* (2013) analyse the time-varying correlations between oil prices, commodities, and stock market indexes, concluding that commodity price correlations increase after 2003, limiting hedging substitutability in portfolios, and become more significant after the financial crisis period in 2008. Using a Wavelet approach, Roboredo and Rivera-Castro (2014) study the daily connection between oil prices and the US and European financial markets. Their main finding supports that the oil price changes did not have a substantial effect on the stock market returns in the pre-crisis period. Sadorsky (2014) uses VARMA-AGARCH and DCCA-GARCH specifications to model the volatilities and conditional correlation dynamics between emerging stock markets, and copper, oil, and wheat prices. The results show the correlations between assets increased considerably after the financial crises and the hedge ratios vary extensively over the sample period, showing that hedged positions should be efficient frequently. More recently, Zhang (2017) investigates the oil-stock relationship from a global perspective. Based on the Diebold and Yilmaz (2009, 2012, 2014) measure of the oil-stock connection for six markets, they show that overall, oil price shocks have a limited effect on the world financial system. Huang *et al.* (2018) investigate the co-movement between oil stocks based on a frequency approach, from a multivariate perspective. Through different oil prices (Brent, Dubai, Minas, and OPEC, Shanghai Composite index), the authors show the relationship between oil stocks is tremendously different in the short run. Interestingly, the results support that investment in oil prices on the Brent, OPEC, and Chinese stock markets might be sources of risk reduction.

Some other studies analyse this issue by distinguishing between oil importing and exporting countries. For example, Filis *et al.* (2011) study co-movements and time varying correlations between oil and stock markets for both oil importing and exporting countries using a multivariate GARCH model. They conclude that conditional variances between stock and oil prices do not vary significantly between oil exporting and importing countries. Creti *et al.* (2014) use the frequency approach to study the time-varying correlations between oil prices and stock markets also by distinguishing between oil exporting and importing countries. Their results show the interdependence between oil prices and stock markets is more pronounced for oil exporters. Guesmi and Fattoum (2014), based on multivariate asymmetric GARCH models, show an important impact of oil prices on both oil importing and exporting countries.

Our study extends these previous studies by proposing a more flexible framework to measure the volatility spillover effect between oil and stock markets. Specifically, we employ the multivariate c-DCC-FIAPARCH specification to consider main financial volatility features. Our specification allows more flexibility for the conditional variance process, as it reacts asymmetrically to positive and negative shocks. Moreover, our approach captures the long-range volatility dependence. The convenience of our empirical framework is investigated through considering the dynamic interactions between the Brent oil market and 17 OECD stock markets over the period March 16, 1998–February 23, 2018, which is characterized by several peaks and troughs of oil prices, as well as several periods of financial turmoil.

Our analysis reveals two main findings about the interactions between oil prices and the major OECD stock markets. The impact of oil shocks on stock markets is more pronounced during periods of global turmoil. Our analysis contributes to the literature by identifying two types of correlation coefficient signs between stock and oil markets. First, we consider the US terrorist attack (2001) as the main source of the negative correlation between oil and stock markets. The positive trend is identified during other periods coinciding with aggregate demand-side oil price shocks, such as the Asian crisis (1997–1998), Chinese economic growth (2002), and the global financial crisis (2007–

2008). Our empirical method allows us to show the repercussions of these phenomena are not symmetric for the entire sample. Diversification opportunities were thus generally decreasing in all the studied countries. Moreover, based on the shape of the dynamic conditional correlation, we characterize five groups of countries for which the dynamic correlations between oil and stock markets are similar.[1] Therefore, although there exists a form of spillover effect among all markets, the diffusion of shocks and volatility does not reveal contagion, as the evolution of the dynamic correlations between oil and stock markets remain segmented geographically. Consequently, we do not observe a proper 'contagion effect', as least as the phenomenon defined by Forbes and Rigobon (2002), that is, the co-movement increase between markets after crises.

The rest of the paper is organized as follows. Section 2 introduces the empirical method used to assess the links between oil and stock markets. Section 3 describes the data and discusses the empirical results. Section 4 provides concluding remarks.

2. Methodology

Let x_t be an (18×18) vector composed from 17 OECD countries' stock markets prices and the oil price containing the return series in a conditional mean equation as follows:

$$x_t = \mu_t + \varepsilon_t \,, \tag{1}$$

where $\mu_t = E[x_t \| \Pi_{t-1}]$ is the conditional expectation of x_t based on previous information Π_{t-1}. ε_t is the error vector, assumed to be conditional multivariate normally distributed. ε_t has a zero mean and variance-covariance matrix $H_t \equiv \{h_{ij}\}$.

The model can be estimated through maximum likelihood methods if H_t is positive definite for all $\boldsymbol{\varepsilon}_t$ values in the sample. Furthermore, we assume μ_t is linearly specified, as follows:

[1] The five groups are as follows: United Kingdom, Australia, and Japan; New Zealand, Spain, and USA; Denmark, Norway, Sweden, and Switzerland; Ireland, Italy, and the Netherlands; and Canada, Finland, France, and Germany.

$$\mu_{i,t} = \Phi_0 + \Phi_1 x_{i,t-1},\ \forall \mathrm{i}\,, \tag{2}$$

where Φ_0 is a constant and Φ_1 measures the ARCH effect in the data series.

In this paper, we suggest using the DCC-GARCH process, as defined by Engle (2002), to model the dynamic conditional correlation between stock and oil markets. This model follows the generalized fractional cointegration process and the conditional variance-covariance matrix, which can be written as:

$$H_t = D_t R_t D_t'\,, \tag{3}$$

where H_t is the (18×18) symmetric matrix of dynamic conditional correlations and D_t a diagonal matrix of time-varying standard deviation from univariate GARCH models. These matrices can be written as:

$$\begin{aligned} D_t &= diag\left(\sqrt{h_{1,t}},\ldots,\sqrt{h_{k,t}}\right), \\ R_t &= diag\left(q_{11,t}^{-1/2},\ldots,q_{kk,t}^{-1/2}\right) Q_t\ diag\left(q_{11,t}^{-1/2},\ldots,q_{kk,t}^{-1/2}\right), \\ Q_t &= \left(1-\theta_1-\theta_2\right)\bar{Q} + \theta_1 \eta_{t-1}\eta_{t-1}' + \theta_2 Q_{t-1}\,, \\ \eta_t^* &= diag\left\{Q_t\right\}^{1/2} \eta_t\,, \end{aligned} \tag{4}$$

where $Q_t = \left(q_{ijt}\right)$ is a symmetric positive matrix, which is assumed to vary according to a GARCH-type process, with $\bar{Q}$ being an (18×18) unconditional variance matrix of standardized residuals $\eta_{i,t}$. θ_1 and θ_2 capture the effects of shocks to dynamic correlations. The correlation coefficient is defined as follows:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\,q_{jj,t}}}\,. \tag{5}$$

To develop the lack of regularity and potential bias for the estimated parameters of the DCC-GARCH model of Engle (2002), Aielli (2008) suggests a corrected dynamic conditional correlation (c-DCC) process. The conditional standard deviation of the FIAPARCH process is expressed as:

$$h_{i,t}^{\delta_i/2} = \omega_i + \left\{ 1 - \left(1 - \psi_i\left(L\right)\right)^{-1} \phi_i\left(L\right)\left(1-L\right)^{d_{v_i}} \right\} \left(\left|\varepsilon_{i,t}\right| - \gamma_i \varepsilon_{i,t}\right)^{\delta_i} , \tag{6}$$

with $-1 < \gamma_i < 1$ and $\delta_i > 0$,

where

- $h_{i,t}$ refers to the conditional variance of $x_{i,t}$; ω_i is the mean of the process;
- d_{v_i} represents the fractional degree of integration of $h_{i,t}$;
- $\psi_i\left(L\right)$ and $\phi_i\left(L\right)$ are the lag polynomials of the respective orders P and K;
- power term δ_i plays the role of a Box-Cox transformation of the conditional standard deviation $h_{i,t}^{1/2}$; and
- γ_i denotes the asymmetry coefficient accounting for the leverage effect.
- When $\gamma_i > 0$, negative shocks have more impact on conditional volatility than positive shocks. When $\gamma_i < 0$, the magnitude of shocks is being captured by the term $\left(\left|\varepsilon_{i,t}\right| - \gamma\varepsilon_{i,t}\right)$

The multivariate framework thus incorporates the features of asymmetries and persistence, which are typically observed for stock markets and oil prices. This framework nests other GARCH processes that exist in the literature and is relatively parsimonious compared to other multivariate models in extant studies.

3. Empirical Analysis

3.1. Data description

The dataset includes daily Stock Market Indices for 17 OECD countries and the Brent crude oil index in from 16/03/1998 to 23/02/2018.

The stock markets under investigation are: the United States (NASDAQ 100), Canada (TSX), Finland (Helsinki General), France (CAC 40), Germany (DAX 30), Ireland (ISEQ), Italy (Milan MIB), the Netherlands (AEX), Spain (Madrid General Index, MGI), Denmark (KFX Copenhagen), Norway (Oslo Stock Exchange, OSE), Sweden (Stockholm Index), Switzerland (Zurich Swiss Market Index, ZSMI), the United Kingdom (FTSE 100), Australia (All Ordinaries Index, AOI), Japan (Nikkei 225), and New-Zealand (New Zealand Stock Exchange 50, NZSE 50).

Our dataset is obtained from DataStream and Morgan Stanley Capital International. The indices were taken with reinvestment of dividends from the database.

Table 1 reports the main statistics of the return series for stock market indices for the 17 OECD countries considered.

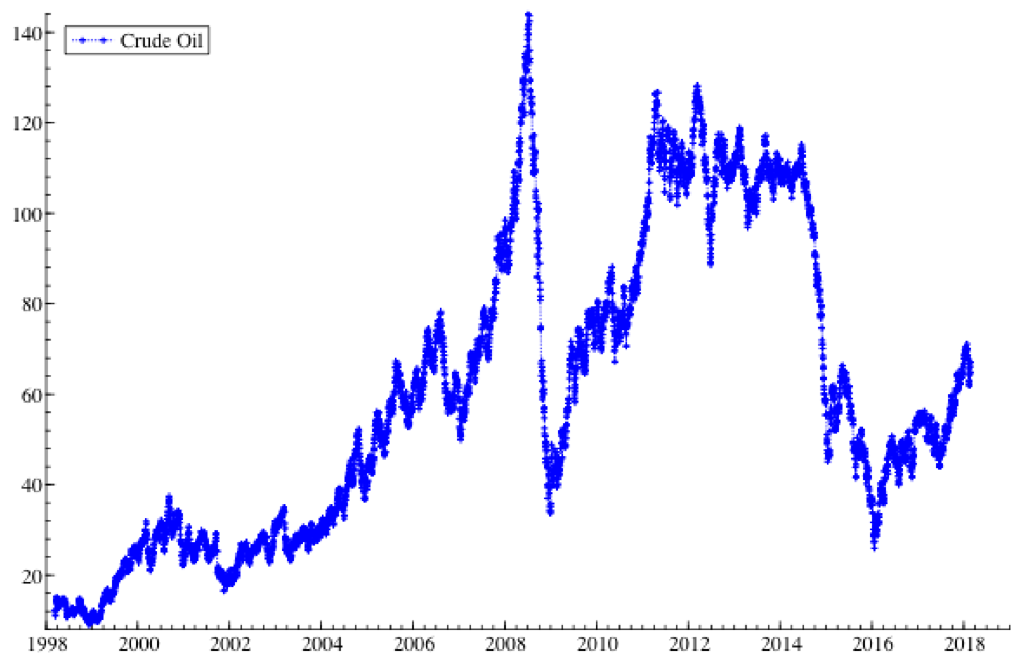
Table 1. Descriptive statistics of return series

Variable	Min	Mean	Max	S.D	Sk	Kr	J-B	ARCH-LM test (5)	ARCH LM test (10)	LB-Q (5)	LB-Q (10)
France	-0.0947	7.83e-05	0.10595	0.0144	-0.0512	4.8149	5030.1 (0.0000)	179.86***	101.99***	13.5795***	15.3877***
UK	-0.0926	4.35e-05	0.093843	0.0117	-0.1461	5.9358	7659.8 (0.0000)	276.82***	150.23***	17.6077***	21.8327***
Canada	-0.0978	0.0001	0.093703	0.0108	-0.6579	9.5059	19973 (0.0000)	230.26***	180.62***	6.53227	9.41205
Finland	-0.1740	0.0001	0.14563	0.0178	-0.3499	7.5704	12536 (0.0000)	55.432***	37.481***	5.80869***	9.78475***
Ireland	-0.1396	5.28e-05	0.097331	0.0135	-0.6255	8.2732	15184 (0.0000)	211.76***	134.50***	7.43274	12.3612
Italy	-0.1333	-5.91e-05	0.10877	0.0154	-0.1971	4.7498	4926.5 (0.0000)	136.71***	81.102***	15.5363***	19.9067**
Netherlands	-0.0959	1.10e-05	0.10028	0.0142	-0.1281	6.1355	8178.3 (0.0000)	300.08***	169.58***	11.7589**	15.8494
Spain	-0.1331	3.68e-05	0.13737	0.0142	-0.1460	6.5257	9254.2 (0.0000)	104.67***	61.694***	11.5952**	12.6752
Denmark	-0.1164	0.0002	0.085195	0.0125	-0.2483	5.6202	6903.8 (0.0000)	226.46***	126.98***	11.7749**	13.2411
Norway	-0.0970	0.0003	0.091864	0.0134	-0.5859	6.2495	8768.3 (0.0000)	342.52***	193.37***	3.00069	5.51380
Sweden	-0.0880	0.0001	0.11023	0.0148	0.0566	4.1055	3658.2 (0.0000)	131.37***	79.240***	10.1556*	12.1440
Switzerland	-0.0907	3.93e-05	0.10788	0.0118	-0.175	6.5906	9446.7 (0.0000)	275.01***	143.96***	17.4905***	21.0340**
Australia	-0.0855	0.0001	0.053601	0.0093	-0.5398	5.9532	7938.9 (0.0000)	230.00***	136.96***	1.46651	2.98140
Germany	-0.0887	0.0001	0.10797	0.0149	-0.0904	4.3053	4027.0 (0.0000)	181.85***	109.97***	6.45572	7.44686
New Zealand	-0.0870	0.0001	0.092612	0.0113	-0.4556	5.5820	6937.6 (0.0000)	247.26***	137.86***	11.1575**	20.8884**
USA	-0.1111	0.0003	0.17203	0.0179	0.1163	6.4249	8964.2 (0.0000)	163.90***	116.43***	10.7041*	12.6921
Japan	-0.1211	4.77e-05	0.13235	0.0147	-0.3597	6.4340	9090.0 (0.0000)	286.38***	162.20***	3.92660	5.34264
Oil	-0.1989	0.0003	0.16256	0.0225	-0.0924	4.6377	4672.0 (0.0000)	60.502***	33.837***	1.93141	6.84820

*Note: * and ** imply the rejection of the null hypothesis for normality using the Jarque-Bera statistic, for no ARCH effects using the ARCH LM test, and for no autocorrelation using the Ljung-Box Q-statistic test at 1% and 5%, respectively. S.D, SK, Kr, and J-B denote the standard deviation, the skewness, the kurtosis, and the Jarque-Bera test, respectively. (.) denotes the p-values of the Jarque-Bera test.*

The skewness coefficients are negative for all stock markets returns, except for Sweden and the USA, showing asymmetric behaviour for returns distribution. The kurtosis coefficients are greater than 3, supporting a fat-tail behaviour for all stock market returns distributions. The Jarque-Bera test confirms the results of skewness and kurtosis for the rejection of the normal distributions for all studied returns. The Engle ARCH shows the presence of ARCH effects in the return series. The distributions of the stock market returns are non-Gaussian, characterized by fat tails and clustering volatility, which justifies the choice of the GARCH processes to model their conditional volatility. The Brent oil price fluctuations (Figure 1) show many peaks (2001, 2008, 2011, and 2014). All these fluctuations are mostly related to aggregate demand-side oil price shocks (Asian economic crisis, housing market crises, rising demand of oil from China, and global financial crisis).

Figure 1. Dynamic of Brent crude oil prices, in dollars, from 1998 to 2018



3.2. Long-memory test statistic

From a theoretical viewpoint, the efficiency market hypothesis (EMH) challenged the debate around the long-memory behaviour in the dynamic of stock markets for stock prices or indexes. The EMH is supported when the process of generating data for financial market returns follows a random walk. In other words, the stock market returns characterized by long memory dynamics are evidence against the EMH.

From an econometric viewpoint, the literature of long memory in financial series has evolved considerably. Mandelbrot (1971) supports that stock returns exhibit a long-memory behaviour through using the rescaled-Range (R/S) test developed by Hurst (1951). This test has been challenged based on its incapacity to distinguish between short and long memory, leading to the modified version of the R/S test, developed by Lo (1991). This measure has been challenged by Willinger *et al.* (1999) as a weakness to identify short memory for synthetic time series with a low level of long memory. Therefore, several tests have been developed in the literature, among them Perron and Qu's (2010) test aiming to distinguish between true and spurious long memory, which might be explained based on structural breaks.

We use here four measures of long memory. We employ the Hurst-Mandelbrot's Classical R/S Statistic test, modified (R/S) test, spectral regression method suggested by Geweke and Porter-Hudak (1983) (GPH test), and Gaussian semi-parametric (GSP) test suggested by Robinson (1995).

Table 2 presents the results of long memory tests for the market returns of 17 OECD countries and for the Brent crude oil prices.[2]

[2] Data stationarity is verified based on the four-unit root tests: Dickey and Fuller (1979) (ADF), Phillips-Peron (1988) (PP), and Kwiatkowski *et al.* (1992) (KPSS) tests. The logarithmic return and squared return series of all 18 variables support stationarity. To save space, stationary results are available upon request.

Table 2. Long-memory test results

Variable	Data	Hurst-Mandelbrot's Classical R/S Statistic	Modified R/S Statistic	GPH test			GPS test		
				$M = T^{0.5}$	$M = T^{0.6}$	$M = T^{0.7}$	M = T/4	M = T/8	M = T/16
France	Return	1.1396	1.1499	0.0579 (0.0828) [0.4843]	0.0095 (0.0519) [0.8546]	0.0049 (0.0331) [0.8816]	-0.0707 (0.0138) [0.0000]	-0.0556 (0.0195) [0.0045]	0.0003 (0.0277) [0.9906]
	S. return	4.1376	3.7924	0.4354 (0.0828) [0.0000]	0.4660 (0.0532) [0.0000]	0.4212 (0.0348) [0.0000]	0.3641 (0.0138) [0.0000]	0.4046 (0.0195) [0.0000]	0.5063 (0.027) [0.0000]
UK	Return	0.9225	0.9344	0.0331 (0.0828) [0.6895]	-0.0583 (0.0519) [0.2619]	-0.0380 (0.0331) [0.2507]	-0.0879 (0.0138) [0.0000]	-0.0710 (0.0195) [0.0003]	-0.0631 (0.0277) [0.0228]
	S. return	4.7865	4.3028	0.3400 (0.0829) [0.0000]	0.4277 (0.0533) [0.0000]	0.4003 (0.0353) [0.0000]	0.4373 (0.0138) [0.0000]	0.4255 (0.0195) [0.0000]	0.48842 (0.0277) [0.0000]
Canada	Return	0.9864	0.9861	0.0471 (0.0828) [0.5689]	0.0940 (0.0519) [0.0704]	0.0374 (0.0331) [0.2580]	-0.0301 (0.0138) [0.0294]	-0.0316 (0.0195) [0.1068]	0.02740 (0.0277) [0.3230]
	S. return	5.7188	5.0301	0.3823 (0.0828) [0.0000]	0.5640 (0.0548) [0.0000]	0.4702 (0.0351) [0.0000]	0.3283 (0.0138) [0.0000]	0.5974 (0.0195) [0.0000]	0.5080 (0.027) [0.0000]
Finland	Return	1.4590	1.4519	0.0276 (0.0828) [0.7388]	0.0778 (0.0519) [0.1342]	0.0289 (0.0331) [0.3811]	-0.0211 (0.0138) [0.1265]	-0.0061 (0.0195) [0.7554]	0.0510 (0.027) [0.0656]
	S. return	7.8467	7.3961	0.6716 (0.0828) [0.0000]	0.4320 (0.0522) [0.0000]	0.2450 (0.0335) [0.0000]	0.2109 (0.0138) [0.0000]	0.2855 (0.0195) [0.0000]	0.3495 (0.027) [0.0000]

Variable	Data	Hurst-Mandelbrot's Classical R/S Statistic	Modified R/S Statistic	GPH test			GPS test		
				$M = T^{0.5}$	$M = T^{0.6}$	$M = T^{0.7}$	M = T/4	M = T/8	M = T/16
Ireland	Return	1.6768	1.6768	0.2016 (0.0828) [0.0149]	0.1056 (0.0519) [0.0421]	0.0220 (0.0331) [0.5055]	-0.0251 (0.0138) [0.0695]	0.0106 (0.0195) [0.5859]	0.0752 (0.027) [0.0067]
	S. return	6.9014	6.1485	0.5047 (0.0828) [0.0000]	0.4614 (0.0523) [0.0000]	0.4271 (0.0335) [0.0000]	0.3315 (0.0138) [0.0000]	0.4740 (0.0195) [0.0000]	0.4114 (0.027) [0.0000]
Italy	Return	1.1153	1.1265	0.1501 (0.0828) [0.0700]	-0.0055 (0.0519) [0.9142]	0.0333 (0.0331) [0.3143]	-0.0298 (0.0138) [0.0311]	-0.0141 (0.0195) [0.4718]	-0.0019 (0.0277) [0.9435]
	S. return	4.9968	4.5910	0.3736 (0.0833) [0.0000]	0.4001 (0.0526) [0.0000]	0.4089 (0.0342) [0.0000]	0.3304 (0.0138) [0.0000]	0.3666 (0.0195) [0.0000]	0.4651 (0.0277) [0.0000]
Netherlands	Return	1.2485	1.2456	0.0955 (0.0828) [0.2490]	0.0509 (0.0519) [0.3269]	0.0483 (0.0331) [0.1444]	-0.0467 (0.0138) [0.0007]	-0.01142 (0.0195) [0.5598]	0.00251 (0.0277) [0.9277]
	S. return	4.7536	4.2897	0.3915 (0.0828) [0.0000]	0.4539 (0.0525) [0.0000]	0.5062 (0.0345) [0.0000]	0.4041 (0.0138) [0.0000]	0.4776 (0.019) [0.0000]	0.58719 (0.0277) [0.0000]
Spain	Return	1.0695	1.0592	-0.0345 (0.0828) [0.6765]	-0.0122 (0.0519) [0.8132]	-0.0098 (0.0331) [0.7661]	-0.0578 (0.0138) [0.0000]	-0.0439 (0.0195) [0.0250]	0.0095 (0.0277) [0.7302]
	S. return	4.8919	4.5557	0.3904 (0.0847) [0.0000]	0.3594 (0.0541) [0.0000]	0.3646 (0.0349) [0.0000]	0.3041 (0.0138) [0.0000]	0.3635 (0.0195) [0.0000]	0.3992 (0.0277) [0.0000]

Variable	**Data**	**Hurst-Mandelbrot's Classical R/S Statistic**	**Modified R/S Statistic**	**GPH test**			**GPS test**		
				M = $T^{0.5}$	**M = $T^{0.6}$**	**M = $T^{0.7}$**	**M = T/4**	**M = T/8**	**M = T/16**
Denmark	Return	1.2951	1.2671	0.1280 (0.0828) [0.1222]	0.0865 (0.0519) [0.0959]	0.0680 (0.0331) [0.0399]	-0.0148 (0.0138) [0.2857]	-0.0171 (0.0195) [0.3826]	0.03844 (0.0277) [0.1658]
	S. return	5.3906	4.8839	0.3972 (0.0828) [0.0000]	0.4264 (0.0535) [0.0000]	0.4021 (0.0355) [0.0000]	0.3423 (0.0138) [0.0000]	0.4497 (0.0195) [0.0000]	0.5336 (0.0277) [0.0000]
Norway	Return	1.4192	1.4115	0.1729 (0.0828) [0.0368]	0.0811 (0.0519) [0.1185]	0.0681 (0.0331) [0.0396]	0.0043 (0.0138) [0.7549]	0.0172 (0.0195) [0.3782]	0.0928 (0.027) [0.0008]
	S. return	6.5756	5.8293	0.3994 (0.0828) [0.0000]	0.5795 (0.0534) [0.0000]	0.5435 (0.0345) [0.0000]	0.4010 (0.0138) [0.0000]	0.5540 (0.0195) [0.0000]	0.6778 (0.027) [0.0000]
Sweden	Return	1.3010	1.3156	0.0575 (0.0828) [0.4876]	0.0733 (0.0519) [0.1582]	0.0410 (0.0331) [0.2155]	-0.0521 (0.0138) [0.0002]	-0.0461 (0.0195) [0.0185]	0.0459 (0.027) [0.0975]
	S. return	5.0665	4.6702	0.5130 (0.0832) [0.0000]	0.4757 (0.0533) [0.0000]	0.3746 (0.0340) [0.0000]	0.300 (0.0138) [0.0000]	0.3654 (0.0195) [0.0000]	0.4691 (0.027) [0.0000]
Switzerland	Return	1.0616	1.0444	-0.0138 (0.0828) [0.8677]	0.0020 (0.0519) [0.9690]	-0.0381 (0.0331) [0.2497]	-0.0577 (0.0138) [0.0000]	-0.0605 (0.0195) [0.0020]	-0.0221 (0.0277) [0.4238]
	S. return	4.0094	3.4542	0.3129 (0.0828) [0.0002]	0.3456 (0.0527) [0.0000]	0.3419 (0.0343) [0.0000]	0.3772 (0.0138) [0.0000]	0.3797 (0.0195) [0.0000]	0.4194 (0.027) [0.0000]

Variable	Data	Hurst-Mandelbrot's Classical R/S Statistic	Modified R/S Statistic	GPH test			GPS test		
				$M = T^{0.5}$	$M = T^{0.6}$	$M = T^{0.7}$	M = T/4	M = T/8	M = T/16
Australia	Return	1.2496	1.2539	0.1475 (0.0828) [0.0750]	0.0842 (0.0519) [0.1051]	0.0104 (0.0331) [0.7520]	-0.0260 (0.0138) [0.0603]	-0.0185 (0.0195) [0.3447]	-0.0018 (0.0277) [0.9464]
	S. return	7.1805	6.4493	0.3795 (0.0852) [0.0000]	0.38902 (0.0566) [0.0000]	0.3227 (0.036) [0.0000]	0.3438 (0.013) [0.0000]	0.4145 (0.0195) [0.0000]	0.4340 (0.027) [0.0000]
Germany	Return	1.3366	1.3404	0.0273 (0.0828) [0.7413]	0.0652 (0.0519) [0.2093]	0.0330 (0.0331) [0.3188]	-0.0256 (0.0138) [0.0642]	-0.0238 (0.0195) [0.2231]	0.0074 (0.027) [0.7873]
	S. return	5.1193	4.7202	0.4747 (0.0832) [0.0000]	0.4535 (0.0532) [0.0000]	0.4497 (0.0343) [0.0000]	0.3502 (0.0138) [0.0000]	0.4440 (0.0195) [0.0000]	0.4959 (0.027) [0.0000]
New Zealand	Return	1.4186	1.3775	0.1855 (0.0828) [0.0251]	0.04020 (0.0519) [0.4392]	0.0742 (0.0331) [0.0249]	0.0108 (0.0138) [0.4337]	0.0518 (0.0195) [0.0082]	0.0531 (0.027) [0.0551]
	S. return	5.1646	4.9082	0.3587 (0.0829) [0.0000]	0.36897 (0.0527) [0.0000]	0.3552 (0.0352) [0.0000]	0.3944 (0.0138) [0.0000]	0.4210 (0.0195) [0.0000]	0.4617 (0.027) [0.0000]
USA	Return	1.7790	1.8428	0.0636 (0.0519) [0.2210]	0.0636 (0.0519) [0.2210]	0.0659 (0.0331) [0.0465]	-0.0394 (0.0138) [0.0044]	-0.0140 (0.0195) [0.4748]	0.0576 (0.027) [0.0377]
	S. return	9.3680	8.3862	0.5658 (0.0828) [0.0000]	0.4876 (0.0521) [0.0000]	0.4319 (0.0336) [0.0000]	0.2794 (0.0138) [0.0000]	0.4100 (0.0195) [0.0000]	0.4396 (0.027) [0.0000]

Variable	Data	Hurst-Mandelbrot's Classical R/S Statistic	Modified R/S Statistic	GPH test			GPS test		
				$M = T^{0.5}$	$M = T^{0.6}$	$M = T^{0.7}$	M = T/4	M = T/8	M = T/16
Japan	Return	1.1226	1.1406	0.1389 (0.0828) [0.0935]	-0.0059 (0.0519) [0.9088]	0.0128 (0.0331) [0.6972]	-0.0255 (0.0138) [0.0649]	-0.0141 (0.0195) [0.4696]	0.0034 (0.027) [0.9021]
	S. return	3.9652	3.6694	0.2431 (0.0828) [0.0033]	0.2896 (0.0521) [0.0000]	0.4417 (0.0340) [0.0000]	0.3819 (0.0138) [0.0000]	0.4456 (0.0195) [0.0000]	0.4523 (0.027) [0.0000]
Oil	Return	1.4463	1.4302	0.01659 (0.0828) [0.8412]	0.04077 (0.0519) [0.4328]	0.0341 (0.0331) [0.3027]	0.0082 (0.0138) [0.5520]	-0.0073 (0.0195) [0.7066]	0.0219 (0.027) [0.4288]
	S. return	4.3102	4.0736	0.5786 (0.0841) [0.0000]	0.47452 (0.0520) [0.0000]	0.3128 (0.0334) [0.0000]	0.2462 (0.0138) [0.0000]	0.2723 (0.019) [0.0000]	0.3545 (0.027) [0.0000]

Note: M denotes the bandwidth used for the GPH and GPS tests. T is the total number of observations. The associated p-value are reported in [] and standard errors in (). S. return denotes squared returns.

The results of Hurst-Mandelbrot's Classical R/S and modified R/S statistics support no long-range dependence for all stock market and oil returns, at a significance level of 1%. However, both tests support long-range dependence in all squared returns at a significance level of 1%. These findings mean the long memory behaviour is present in the second moment of the returns series. In other words, the volatilities of studied stock and oil markets are characterized by long-range dependence.

The results of the GPH and GPS tests, estimating the fractional differencing parameter (d) for daily stock and oil returns and stock and oil squared returns are in line with the R/S and modified R/S tests. These tests test the null hypothesis of short memory $(H_0\text{: } d = 0)$ against long-memory alternatives $(H_1\text{: } d > 0)$ for a range of bandwidth (M). For squared returns, the two long memory tests (GPH and GPS) conclude favourably in the presence of a long-memory component at a significance level of 1%. The estimates of parameter (d) range from 0.6778 to 0.2109 and are statistically significant at the 1% level, thus rejecting the null of short memory in the squared returns of all studied series. These results indicate a long-memory property exists in the volatility of studied series.

3.3. Estimation of dynamic correlation

To analyse the volatility spillovers between oil and stock markets, we estimate a c-DCC-FIAPARCH specification. We start by estimating a FIAPARCH specification for all markets. As suggested by Davidson (2008), several specifications are estimated using the maximum likelihood estimation (MLE) and using a Student-t distribution for the stock market return innovations. The results are presented in Table 3.

Table 3. Results for the c-DCC-FIAPARCH parameters

	Cst(M)	AR(1)	d-Figarch	ARCH (Phi1)	GARCH (Beta1)	APARCH (Gamma1)	APARCH (Delta)
France	0.0002**	0.0290**	0.3354***	0.2851***	0.5313***	0.5920***	1.4743***
	(0.0001)	(0.0128)	(0.0666)	(0.0618)	(0.0737)	(0.1234)	(0.0895)
UK	0.0002**	0.0324**	0.4224***	0.3101***	0.6229***	0.4910***	1.4041***
	(0.0001)	(0.0133)	(0.0672)	(0.0431)	(0.0496)	(0.1344)	(0.1202)
Canada	0.0003***	0.0370***	0.3630***	0.2809***	0.5821***	0.5290***	1.7079***
	(0.0001)	(0.0142)	(0.0481)	(0.0367)	(0.0484)	(0.1337)	(0.0980)
Finland	0.0004**	0.0427***	0.3819***	0.3584***	0.6520***	0.3982***	1.8641***
	(0.00015)	(0.0164)	(0.0521)	(0.0451)	(0.0527)	(0.1017)	(0.0890)
Ireland	0.0006***	0.0537***	0.3080***	0.1535	0.3902***	0.3718***	1.9153***
	(0.00015)	(0.0154)	(0.0503)	(0.1034)	(0.1209)	(0.1258)	(0.1116)
Italy	0.00015	-0.0367**	0.3227***	0.2618***	0.5148***	0.6051***	1.7017***
	(0.00014)	(0.0166)	(0.0661)	(0.0442)	(0.0700)	(0.1654)	(0.1036)
Netherlands	0.0003***	0.0143	0.3526***	0.2705***	0.5415***	0.6152***	1.3970***
	(0.0001)	(0.0122)	(0.0529)	(0.0424)	(0.0575)	(0.1195)	(0.0840)
Spain	0.00015	0.0179	0.3477***	0.2921***	0.5728***	0.9749***	1.2776***
	(0.00015)	(0.0158)	(0.0893)	(0.0353)	(0.0866)	(0.2516)	(0.1129)
Denmark	0.00048***	0.0520***	0.2550***	0.1874**	0.3578***	0.4205***	1.9656***
	(0.00014)	(0.0150)	(0.0392)	(0.0848)	(0.1005)	(0.1095)	(0.1143)
Norway	0.0007***	0.0141	0.2953***	0.3307***	0.5122***	0.4695***	1.8106***
	(0.00014)	(0.0148)	(0.0437)	(0.0650)	(0.0735)	(0.0902)	(0.0725)
Sweden	0.00027**	-0.0225	0.3512***	0.2900***	0.5661***	0.6024***	1.7064***
	(0.00013)	(0.0148)	(0.0545)	(0.0424)	(0.0591)	(0.1314)	(0.0936)
Switzerland	0.00004	0.0345	0.4011***	0.3038***	0.5998***	0.9341***	1.1664***
	(0.0001)	(0.0127)	(0.0731)	(0.0451)	(0.0625)	(0.1840)	(0.0927)
Australia	0.0002**	0.0415***	0.3411***	0.3065***	0.5526***	0.6116***	1.2932***
	(0.0001)	(0.0124)	(0.0498)	(0.0576)	(0.0799)	(0.0816)	(0.0922)
Germany	0.00045***	0.0270**	0.2711**	0.2593***	0.4730***	0.8883	1.5441***
	(0.00014)	(0.0134)	(0.1115)	(0.0609)	(0.0890)	(0.5972)	(0.2691)
New Zealand	0.00046***	0.0488***	0.2269***	0.2350*	0.4085***	0.2489**	2.2553***
	(0.00014)	(0.0151)	(0.0370)	(0.1427)	(0.1532)	(0.0970)	(0.1166)
Japan	-0.000032	-0.0098	0.3536***	0.1806***	0.4392***	0.3570***	1.7358***
	(0.0001)	(0.0125)	(0.0453)	(0.0717)	(0.0959)	(0.0579)	(0.1341)
USA	0.00065***	-0.0395**	0.2507***	0.2414***	0.4267***	0.7471***	1.6769***
	(0.00015)	(0.0148)	(0.0608)	(0.0761)	(0.1060)	(0.2742)	(0.1602)
Oil	0.00019	0.0308**	0.2485***	0.1186	0.3127**	0.3726***	2.1422***
	(0.00025)	(0.0146	(0.0354)	(0.1324)	(0.1416)	(0.0939)	(0.1013)

Note: $Q(20)$ *and* $Q^2(20)$ *denote the* 20^{th} *order Ljung-Box tests for serial correlation of standardized and squared standardized residuals, respectively. The numbers between () are standard errors. ***, **, and * represent significance level at the 1%, 5%, and 10% levels, respectively.*

The results of the FIAPARCH parameterization show important findings. Table 3 shows that the power term δ is statistically different from 2, whereas the estimated asymmetry coefficients are significant and positive. Spain and Italy display different results, with a negative γ. This implies that negative shocks predict higher volatility than positive shocks and positive correlation between returns and volatility. The test statistic, which is asymptotically χ^2-distributed with two degrees of freedom (when the null hypothesis is true), clearly rejects the constraints implied by the FIGARCH-type adaptation at the 1% significance level.

Our analysis unveils the following main trends. First, during sub-period 2008–2010, the coefficients of correlation are generally positive regarding the period of global crisis. The main event of this phase is the US subprime crisis, which contaminated the entire world. Particularly, this crisis is characterized by American mortgage exportation to different financial places in the world, such as asset-backed securities, considered by the International Energy Agency (2009) as an aggregate demand-side oil shock. Our results are in line with those of Filis *et al.* (2011), who explain the positive correlation between oil prices and stock markets by bearish stock markets to enter territories and cause oil prices to fall sharply during the subprime crisis. Second, around 2006, our results show high correlation coefficients for Spain, Germany, and France. This correlation pattern between stock and oil markets is explained through the increase of both oil demand and housing industry, as worldwide interest decreases. According to Kilian and Park (2009) and Filis *et al.* (2011),[3] aggregate demand-side oil price shock was expected to have a positive effect on oil importing countries.

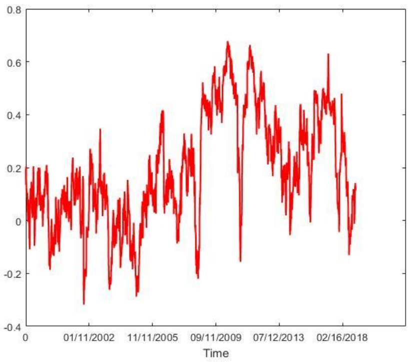
To better interpret the results, we regrouped countries with similar characteristics. This geographical clustering is illustrated in Figures 2a–2e, showing the time-varying correlation coefficients between each stock market index and crude oil prices. Figures 2a–2e represent five groups of countries. Figure 2a displays the dynamic correlations between oil and stock markets in the United Kingdom, Australia, and Japan; Figure 2b for New Zealand, Spain, and the USA; Figure 2c for Denmark, Norway, Sweden, and Switzerland; Figure 2d for Ireland, Italy, and the Netherlands; finally, Figure 2e presents the dynamic correlations between Canada, Finland, France, and Germany.

[3] The period 2006–2008 is characterized by high oil prices due to the rising demand, triggered by global economic growth.

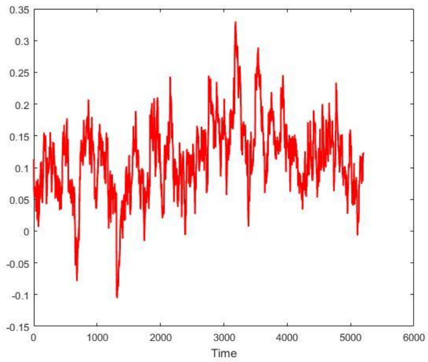
The first group of countries (United Kingdom, Australia, and Japan) is characterized by a series of correlations that are stationary. The average correlations range from 0.09 to 0.12 during the period. In other words, the correlations of this group of countries exhibit a unique regime, characterized by clustering volatility, but a lower interaction between stock and oil markets.

For this first group, we observe transitory upward and downward movements of the correlation during periods of financial turmoil and/or period oil shocks. For example, we observe an upward increase of the correlation during oil demand increases, such as housing market in 2000, global financial crisis in 2008, and global debt crisis in 2010. For oil supply shocks, the correlation is negative during the Iraq war, generating precautionary demand, and during the PdVSA workers' strike, affecting supply. These findings are in line with those of Forbes and Rigobon (2002), showing a significant change of correlations during financial turmoil.

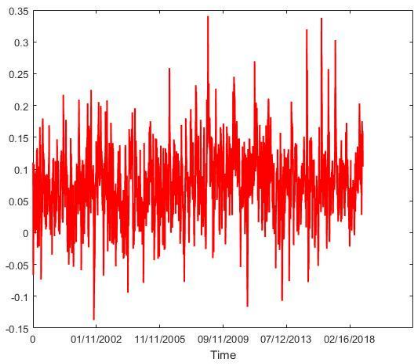
Figure 2a. Dynamic conditional correlations of the United Kingdom, Australia, and Japan with oil prices



UK



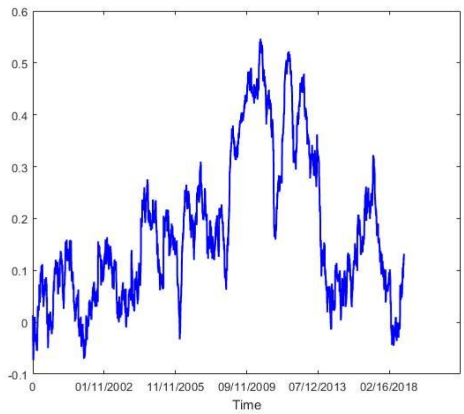
Australia



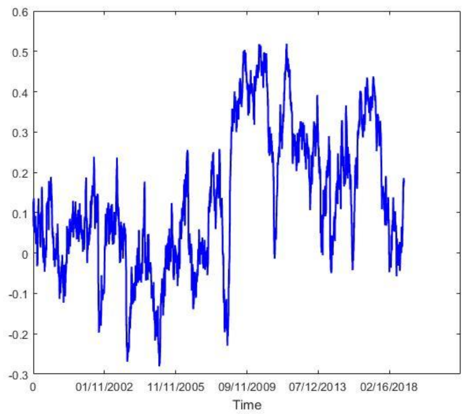
Japan

For the second group of countries, composed of New Zealand, Spain, and the USA (Figure 2b), the conditional dynamic correlation exhibits two regimes.[4] The first regime is characterized by negative correlation, on average, for Spain and the USA and slightly above zero (on average) for New Zealand from 1998 to 2008. The second regime starts with the subprime crisis (2007–2008) and lasts until 2018, with a positive and relatively higher correlation, ranging from 0.22 to 0.3 across countries.

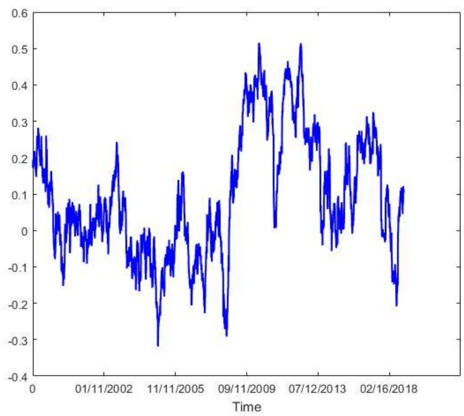
Figure 2b. Dynamic conditional correlations of New Zealand, Spain, and the USA with oil prices



NZ



Spain

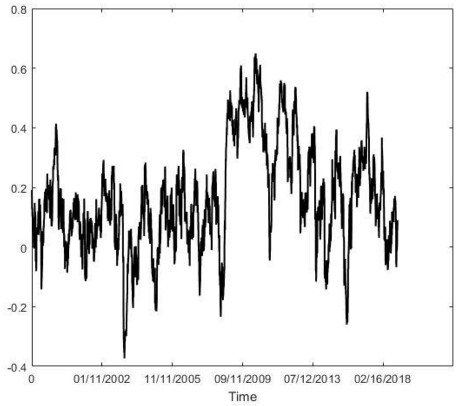


USA

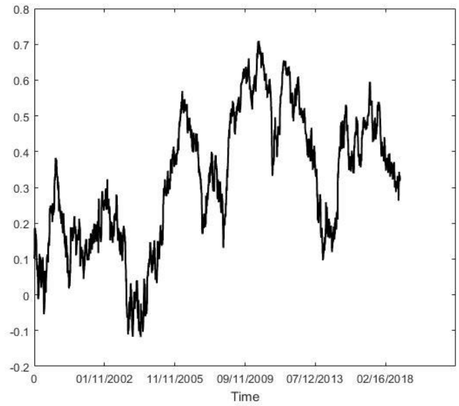
[4] The two regimes are verified based on the unit root tests and structural break tests of Bai and Perron (1998, 2003). To save space, the results of these tests are available upon request.

The third group of countries (Denmark, Norway, Sweden, and Switzerland, Figure 2c) has a similar pattern of correlation to group 1, but the main difference is around the level of correlation. Indeed, the dynamic correlations for this group of countries exhibit a unique regime during the studied period and, on average, range from 0.16 to 0.32 across countries.

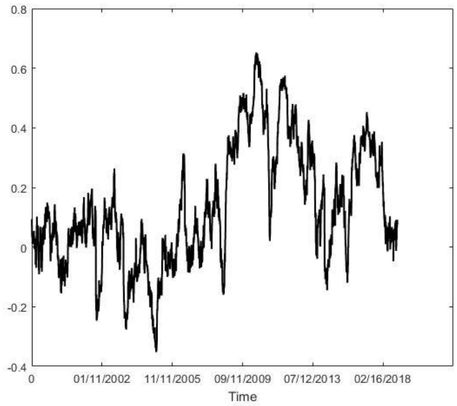
Figure 2c. Dynamic conditional correlations of
Denmark, Norway, Sweden, and Switzerland with oil prices



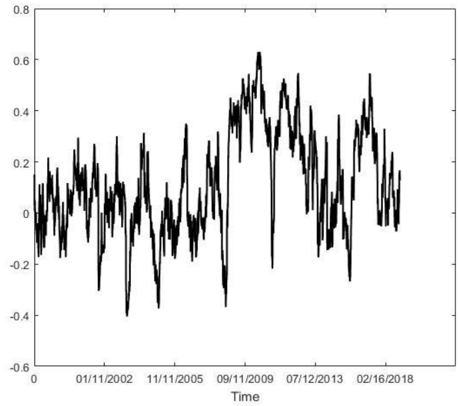
Denmark



Norway



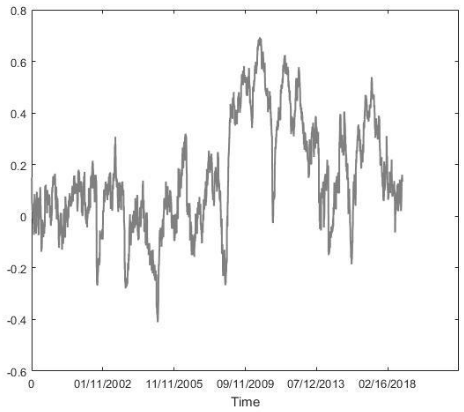
Sweden



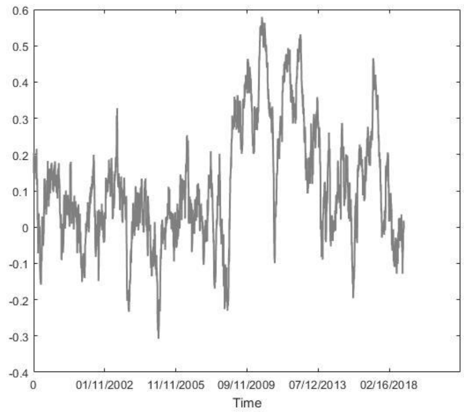
Switzerland

The dynamic correlations for Ireland, Italy and the Netherlands (Figure 2d) show a double regime. The first regime exhibits a lower correlation from 1998 to 2007. This first regime is characterized by troughs and peaks, troughs during periods of turmoil, such as a negative correlation in 2001 (US terrorist attack), 2003 (Iraq War), and during the subprime crisis (2007–2008). The second regime is characterized by a higher correlation, ranging on average between 0.22 to 0.41 during more recent years. This trend might be explained by the implementation of several European policies aiming at reducing oil dependency.

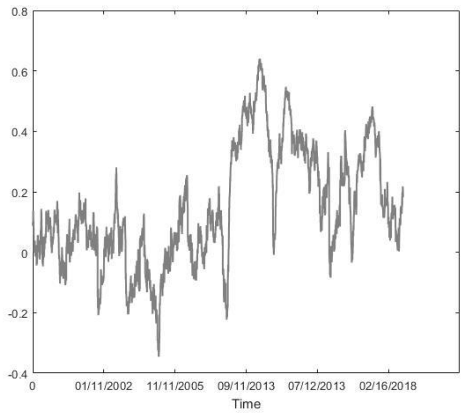
Figure 2d. Dynamic conditional correlations of Ireland, Italy, and the Netherlands with oil prices



Netherlands



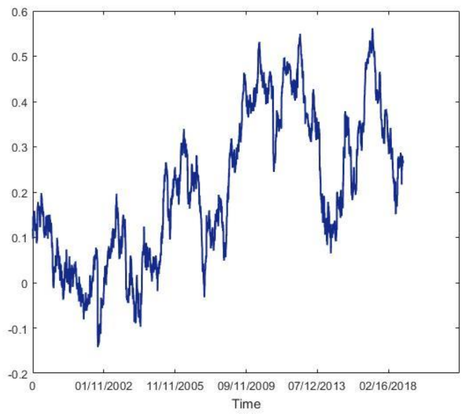
Ireland



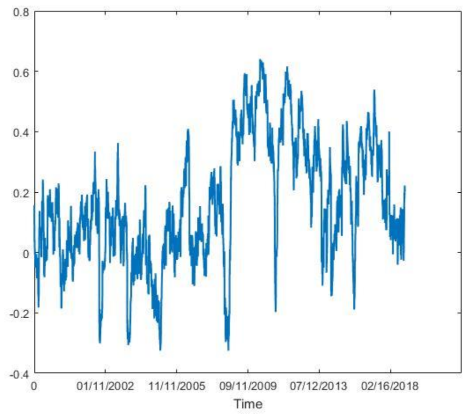
Italy

The last group of countries (i.e. Canada, Finland, France, and Germany, Figure 2e) has a level of correlation between oil and stock market of around 20%. The patterns of correlation for this last group exhibit a unique regime around the mean of 20%. This result is confirmed by the Bai and Perron (1998, 2003) test and the unit root test.

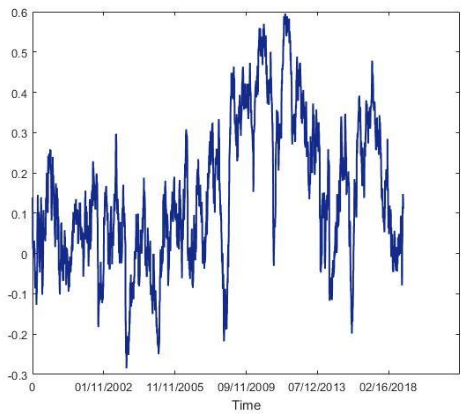
Figure 2e. Dynamic conditional correlations of
Canada, Finland, France, and Germany with oil prices



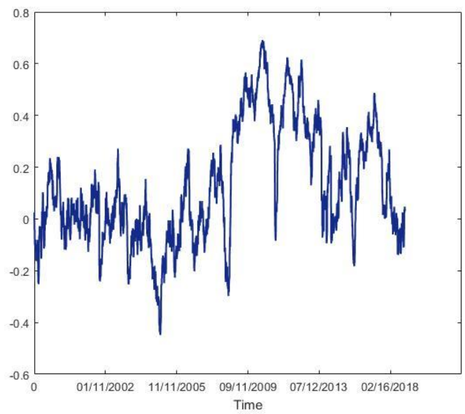
Canada



France



Finland



Germany

Our analysis reveals two main findings on the interaction between oil and stock markets. We highlight the important impact of oil price shocks on the relationship between oil and stock markets and this impact is more pronounced during periods of global turmoil. Our analysis contributes to the literature by identifying the main determinants of correlation signs between stock and oil markets. In line with Kilian and Park (2009) and Filis *et al.* (2011), our results identify a negative trend, that is, we consider that the war in Iraq (2003) and US terrorist attack (2001) are the main sources of the negative correlation between oil and stock markets. The positive trend is identified during other periods coinciding with aggregate demand-side oil price shocks, such as the Asian crisis (1997–1998), Chinese economic growth (2002), and the global financial crisis (2007–2008) or European energy policies during more recent years. Our results highlight the repercussions of these phenomena are not symmetric for the entire sample, as we did not identify a proper 'contagion effect'. However, some trends appear among the countries whose stock markets exhibit positive correlations.

3.4. Statistical analysis of correlation coefficients in different phases of geopolitical and financial crises

The literature on the linkages between markets support that the periods of turmoil and geopolitical events play an important role in explaining the connection between markets (Chkili *et al.* 2011, Aloui and Jammazi, 2009). We thus explain the pattern of dynamic correlation through periods of turmoil and geopolitical events. Formally, we follow the methodology proposed by Chkili *et al.* (2011), as follows:

$$\rho_{ij,t} = \omega_0 + \sum_{p=1}^{P} \phi_p \rho_{ij,t-p} + \sum_{k=1}^{K} \beta_k DM_{k,t} + \vartheta_{ij,t}, \tag{7}$$

where ρ_{ij} is the pairwise conditional correlation calculated from c-DCC-FIAPARCH between the oil *(j)* and stock markets *(i)*. The dummy variables denoted $(DM_{k,t})$ are introduced to control for turmoil periods and geopolitical events. $DM_{k,t}$ takes the value 1 during geopolitical and/or turmoil periods, and 0 otherwise.

In our analysis, we consider three important financial and geopolitical events. The first one $(DM_{1,t})$ concerns the period from August 1998 to December 1999, related to the Brazilian and Russian economic crises. The second event is related to the period between September and December 2001, related to the terrorist attack ($DM_{2,t}$). The last event concerns the subprime and global financial crisis ($\mathrm{DM}_{3,\mathrm{t}}$), from August 2007 to March 2009.

$$h_{ij,t} = \alpha_0 + \alpha_1 h_{ij,t-1} + \alpha_2 \vartheta_{ij,t-1}^2 + \alpha_3 I_{t-1} \vartheta_{ij,t-1}^2 + \sum_{k=1}^{K} \lambda_k DM_{k,t}, \tag{8}$$

where $I_{t-1} = \begin{cases} 1 \text{ if } \vartheta_{ij,t-1} < 0 \\ 0 \text{ if } \vartheta_{ij,t-1} > 0 \end{cases}.$

Table 4. Results of the effects of main events (geopolitical events and crises) on the dynamic correlations between crude oil and stock markets

	Mean equation				
	$\boldsymbol{\omega_0}$	$\boldsymbol{\rho_{t-1}}$	$\boldsymbol{\beta_1}$**(DM1)**	$\boldsymbol{\beta_2}$**(DM2)**	$\boldsymbol{\beta_3}$**(DM3)**
France	- 1.4291***	1.0003***	0.0004***	0.0015***	0.0148***
	- 4.630	118.1	4.222	7.116	1.849
UK	0.2099	0.9977***	- 0.0045	0.0128	0.0272
	0.7545	354.2	- 4.720	1.203	0.2029
Canada	0.2960***	0.9990***	- 0.0071***	0.0097***	- 0.008***
	1.175	145.8	-8.531	6.345	- 2.317
Finland	0.2497***	0.9921***	0.0040***	- 0.0019	0.0215***
	2.842	426.9	5.379	- 0.1493	4.398
Ireland	0.2286**	0.9915***	- 0.0113***	0.0054***	0.0049**
	0.9608	10.83	- 2.864	8.047	1.5798
Italy	0.0157**	0.9841***	0.0011***	- 0.0301***	0.0040***
	1.251	83.34	2.3934	- 6.1197	1.3290
Netherlands	0.0142**	0.991***	0.0020***	- 0.0045***	0.0207**
	1.969	102.045	4.1152	- 5.166	1.020
Spain	0.0124**	1.0028***	0.0016***	- 0.0024***	0.0024***
	1.083	473.1	2.8197	- 4.1246	2.1089
Denmark	- 0.5396***	1.0008***	- 0.0281***	- 0.0045***	0.0218***
	- 1.193	61.863	- 8.3321	- 1.837	1.932
Norway	0.0498***	1.0069***	0.0045***	0.00941***	0.0036***
	4.570	113.4	3.3865	7.039	2.879
Sweden	0.0116***	1.0139***	- 0.0021***	- 0.0016***	- 0.0020**
	2.115	81.07	- 4.1143	- 6.165	- 1.008
Switzerland	0.1760***	0.9902***	0.0032***	- 0.0777***	0.0569***
	5.792	72.382	9.637	-1.420	13.52
Australia	0.2339***	0.976***	0.0233***	0.0450***	0.0091
	5.945	61.130	7.815	4.014	0.6052
Germany	- 0.1944***	0.9981***	0.0080***	- 0.0463***	0.0233***
	- 9.145	73.732	5.0617	- 2.0660	1.183
New Zealand	0.0121**	1.0027***	0.0197**	0.0020***	0.0021***
	7.006	74.64	5.711	1.9503	3.0998
Japan	0.4554***	1.00096***	0.0301***	0.0384***	0.0347***
	3.7943	81.278	3.7625	4.0176	3.3184

	Variance equation						
	α_0	α_2	α_1	α_3	λ_1(DM1)	λ_2 (DM2)	λ_3 (DM3)
France	0.0041***	0.1425***	- 0.411***	- 0.167***	- 0.0029***	- 0.0026***	- 0.0029***
	2.064	1.353	- 3.115	- 1.635	- 5.847	- 1.354	- 5.837
UK	0.0020**	0.0564**	0.2218	- 0.061***	- 0.0050***	0.000245	0.000036***
	1.696	2.518	- 0.4339	- 2.956	- 4.198	1.180	- 3.045
Canada	0.002742	- 0.1873***	-0.455615	0.021477	- 0.0018***	0.002159	- 0.0018***
	6.477	- 2.742	2.967	3.143	- 1.592	9.604	- 1.115
Finland	0.0032***	0.2790***	- 0.132***	- 0.313***	- 0.0027***	- 0.0023***	- 0.0027***
	2.6415	1.623	- 8.456	- 1.821	- 3.110	- 1.204	- 8.794
Ireland	0.0027***	0.1249**	0.2018***	- 0.241***	- 0.0020***	- 0.0015***	- 0.0089***
	4.797	4.1499	13.97	- 4.150	- 1.3633	- 1.7469	- 1.579
Italy	0.0012***	0.1007**	0.7969***	0.0989**	- 0.0047***	0.0042***	0.0049***
	7.391	2.154	5.491	3.785	- 7.006	9.284	7.3091
Netherlands	0.0016***	0.1003***	0.7943***	0.0106***	- 0.0014***	- 0.0037***	- 0.00164***
	4.2352	3.482	7.454	1.141	- 9.1943	- 6.8549	- 5.7210
Spain	0.0024***	0.1000***	0.7999***	0.0099***	- 0.0023***	- 0.0024***	- 0.0025***
	2.416	3.431	4.566	2.7625	- 8.3416	- 8.125	- 3.463
Denmark	0.0018***	0.2289***	- 0.125***	- 0.269***	- 0.0012***	- 0.0011***	- 0.0010***
	8.1124	2.8612	- 4.6825	- 2.8777	- 7.461	- 8.133	- 6.1415
Norway	0.0028***	0.1062***	0.8011***	0.0097***	0.00116***	- 0.0044***	0.0096***
	5.022	4.103	6.121	3.022	7.946	- 4.074	4.961
Sweden	0.0019***	0.10028***	0.7983**	0.0091***	- 0.0017***	0.0047	- 0.0014***
	3.210	4.306	1.060	6.599	- 9.140	7.531	- 8.115
Switzerland	0.0034***	0.1599***	- 0.235***	- 0.174***	- 0.0027***	- 0.0017***	- 0.0019***
	7.725	7.614	- 1.280	- 2.091	- 6.256	- 3.940	- 4.376
Australia	0.00488***	0.1355***	0.8357***	0.0100	0.0050***	0.0012***	0.0058***
	5.945	3.185	6.376	0.0451	3.169	- 1.304	6.697
Germany	0.0051***	0.1244***	- 0.164***	- 0.179***	- 0.0044***	- 0.0026***	- 0.0040***
	8.1329	3.5131	- 2.0799	- 3.5040	-2.068	- 4.450	- 1.049
New Zealand	0.0014***	0.1066***	0.8001***	0.0997**	- 0.0012***	- 0.0015***	0.0025**
	6.066	4.661	1.670	6.897	- 2.786	- 3.732	1.510
Japan	0.0083***	- 0.0144***	- 0.004***	0.0289***	- 0.0083****	- 0.0083***	- 0.0083***
	6.5811	- 7.5960	- 4.827	8.2784	- 4.2719	- 6.552	- 5.653

*Note: *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

Table 4 presents the estimation results related to specifications (7) and (8). The results show a significant effect of both the financial crisis and geopolitical events on the pattern of the dynamic conditional correlation between oil and stock markets. Interestingly, the results (lower part of Table 4) show this effect is more pronounced in the second than in the first moment. In other words, the volatility of the dynamic conditional correlation reacts strongly to such events rather than the level of the dynamic conditional correlation.

4. Conclusion

In this paper, we investigate the return spillover effects between oil and stock markets, analysing, particularly, mean and volatility transmissions phenomena. This paper contributes to the literature by proposing an empirical model that considers both asymmetry and persistence. We use the c-DCC-FIAPARCH model. Further, we add to the literature by proposing a multivariate case study through an investigation of 17 OECD countries from March 1998 to February 2018.

Our results show that the dynamic correlations between oil and stock markets exhibit an increase in co-movement, which in some cases has even started with negative values. Consequently, diversification opportunities are generally decreasing in all countries studied. Further, our multivariate analysis allows us to identify five groups of countries based on the shape of the dynamic conditional correlation, where the dynamic correlations between oil and stock markets are similar. This finding highlights that the relationship between oil and stock markets is segmented geographically. In addition, we show there is a form of spillover effect among all markets. Therefore, the diffusion of shocks and volatility does not show contagion.

Our findings have several policy implications for both investors and policy makers. For investors, it is important to learn the nature of the relationship between oil and stocks because the changes in the co-movement have consequences on portfolio weight. Therefore, as our results highlight that the co-movement between two markets is segmented geographically, each region can gain some useful insights on the construction of optimal portfolio diversification strategies. For example, vulnerable countries can create a diversification strategy for their optimal portfolio with other lesser sensitive groups. For policy makers, our results can be helpful in energy risk planning and risk management. Based on our results, each group must establish an appropriate surveillance system having the ability to monitor market situations to address accurate and relevant responses to oil volatility shocks, specifically in periods of turmoil, as suggested, for instance, by Stiglitz (2009) and Blanchard *et al.* (2010) in the context of monetary policy stability objectives.

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