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Crude oil and equity markets in major European countries: New evidence

Ramzi Benkraiem
Audencia Business School, France

Thi hong van Hoang
Montpellier Business School and Montpellier Research in Management, France

Amine Lahiani
LEO, University of Orleans, France

Anthony Miloudi
La Rochelle Business School & CRIEF University of Poitiers, France

Abstract

This article aims at studying the relationship between oil prices and stock indexes in four major European countries, i.e. United Kingdom (UK), Germany, France, and Italy using monthly data over the 1999–2016 period. We employ the Quantile Autoregressive Distributed Lags model of Cho et al. (2015) that accounts for distributional asymmetry in the relationship between stock prices and energy prices in the long and short run. Findings show that the distinction between short-run and long-run, between quantiles, and between countries are of particular importance. For the UK, only the long-run relationship between oil and stock prices is significant at medium and high quantiles. For Italy, this is true only at high quantiles. However, for France and Germany, the relationship is significant only in the short run, at low and medium quantiles for France and only at low quantiles for Germany. The results of the quantile Granger causality test of Troster (2018) confirm the importance of distinguishing between quantiles and between countries while investigating the causal relationship between oil prices and stock indexes. These results contribute to understand inconclusive results in previous studies. They also provide important information for investors, portfolio managers, and policymakers.

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Contact: Ramzi Benkraiem - rbenkraiem@audencia.com, Thi hong van Hoang - thv.hoang@montpellier-bs.com, Amine Lahiani - amine.lahiani@univ-orleans.fr, Anthony Miloudi - miloudia@esc-larochelle.fr.
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1. Introduction

Oil is a very important, if not the most important, commodity worldwide. It is involved in all economic activities, both on the supply and on the demand sides. Thus, it is natural that oil prices have a direct impact on not only inflation but also numerous other macroeconomic indicators (such as production, consumption, and financial markets). Oil consumption has been increasing constantly for years (US Energy Information Administration, hereafter EIA). In this context, oil production plays a very important role in the variation of oil prices (e.g., Huang et al. 2017b and Apergis et al. 2016). It is now well documented that a country that is dependent on oil imports is consequently more vulnerable than is a net oil-exporting country (e.g., Rafiq et al. 2016). From this logic, the four countries investigated in this study are all net oil-importing countries, and three of them (Germany, France and Italy) show up in top ten oil-importing countries worldwide, following the EIA (EIA 2012). We include the UK because up to year 2005 British oil production was higher than oil consumption while afterwards UK oil dependency has increased and nowadays UK is an oil importing country (EIA, 2012). This may cause differences in the nexus between oil prices and stock indexes due to specific economic and financial rules of the Eurozone (e.g., Eleftheriadis 2016). Furthermore, the financial markets in these four countries operate differently and are impacted by different events. Thus, it would be interesting to compare how stock indexes respond to world oil prices in these different countries.

The main contribution of this study is related to the use of new econometric methods that allow the analysis of the relationship between these two variables based on different quantile levels of stock prices. This allows understanding of how these relationships evolve, not only in time, but also across quantile levels of stock prices. This investigation is important because it helps understanding, and thus forecasting, the relationship between these two variables depending on the tendency of stock prices to be in high, middle, or low quantiles. Hence, fund managers, investors and policymakers can make reliable forecasts or investment decisions based on the quantiles in which the stock price would be. To do so, we employ the Quantile Autoregressive Distributed Lag (QARDL) model recently developed by Cho et al. (2015). The QARDL methodology is an extension of the linear ARDL to account for distributional asymmetry according to the location of the dependent variable within its distribution. Through the QARDL, we can study the cointegration between different variables in distinguishing between the short run and long run. Furthermore, the QARDL allows the nonlinear relationship between the variables to be taken account in dividing the distribution of the dependent variable into different quantiles. This aspect is important because the estimated parameters may depend on the quantile location of the dependent variable within its distribution instead of only one average coefficient on the whole series. Furthermore, we also test the causality between stock and oil prices by using the quantile causality test developed recently by Troster (2018). To the best of our knowledge, this is the first time that these two methods have been used to study the relationship between oil and stock prices.

The empirical results are interesting. They contribute to explain the current inconclusive literature about the relationship between stock and oil prices. Indeed, the interaction between these two variables depends on the quantile in which the stock price is. Thus, studying their relationship as a whole does not allow the detection of this nonlinearity, and this is one of the reasons for the inconclusive findings in previous studies. Concretely, the results based on the QARDL show that there is a real disparity in the results depending on the quantiles and the country. For the UK, only the long-run relationship is significant at medium and extreme high quantiles. For Italy, this is only true at high quantiles. Meanwhile, for France and Germany, the relationship is significant only in the short run, at low and medium quantiles for France and only at low quantiles for Germany. On the other hand, the results of the quantile Granger causality test of Troster (2018) show that the causal relationship also differs depending on the quantile and country. Future research should, thus, take these aspects into account to obtain accurate results that are important for investors, portfolio managers, and policymakers.

The rest of the paper is organized as follows. Section 2 reviews the literature on the relationship between oil prices and stock prices and introduces some directions for extensions. Section 3 presents the dataset and the methodology used to examine the relationship between oil and stocks in Germany, France, Italy, and the UK. Section 4 discusses the empirical results and analyzes their implications. Section 5 concludes.

2. Literature review

A huge body of academic literature has investigated the interaction between oil prices and financial assets. Hamilton (1983) can be considered as the first study that shows the importance of investigating the relationship between oil prices and economic activities. This study was followed by several others, including Burbridge and Harrison (1984), Gisser and Goodwin (1986), Ferderer (1996), Haung et al. (1996), Jones and Kaul (1996), Sadorsky (1999), Ciner (2001), and Kilian and Park (2009). In general, previous studies show different channels through which oil prices impact stock markets. First, a rise of oil prices can result in higher production costs and higher inflation, leading to a lower production volume and, thus, a lower expected income, a lower dividend, and a lower value of stocks (Jones et al. 2004). Second, an oil price increase can also generate a higher uncertainty in financial markets, a consequent decrease in the confidence on financial investments, and, thus, a decrease in stock values (Filis 2010). For example, Kilian and Park (2009) and Kang et al. (2015) showed a negative linkage between oil prices and stock market returns for the US market, while Cunado and Gracia (2014) demonstrated similar relationship for European markets and Basher et al. (2012) for emerging stock markets. Third, a rise in oil prices due to global economic expansion can have a positive impact on stock prices (Kilian and Park 2007). Fourth, the impact of oil price increases on stock markets can be insignificant (Chen et al. 1986).

Thus, the literature survey shows the heterogeneity of the results that can be explained by different factors, such as economic sectors (Henriques and Sadorsky 2007, Arouri 2011, Bondia et al. 2016); the geographical situation of the country (Arouri and Rault 2010, Mohanty et al. 2011, Cunado and Gracia 2014); and the oil position of the country, whether importing or exporting (Park and Ratti 2008, Wang et al. 2013, Guesmi and Fattoum 2014, Phan et al. 2015). The methodology used can also explain this heterogeneity. This includes methods that take into account the nonlinearity (Naifa and Dohaiman 2013, Ahmed 2017); methods that take into account the asymmetry (Ramos and Veiga 2013, Raza et al. 2016); and methods that take into account the time-varying property (Kollias et al. 2013, Chkili et al. 2014, Tsai 2015, Jammazi et al. 2017). Various other methods have also been used, such as methods focusing either on tail dependence or copulas (Ding et al. 2016, Mensi et al. 2017); on time-scale dependence or wavelet (Khalfaoui et al. 2015, Huang et al. 2017a); on cointegration and/or causality (Ghosh and Kanjilal 2016; Bouri et al. 2017); on the VAR system (Diaz and Gracia 2017, Gupta and Wohar 2017); or on the VAR-GARCH system (Guesmi and Fattoum 2014, Jouini and Harrathi 2014, Jain and Biswal 2016). The quantile technique has been used for time series. In particular, Koenker and Xiao (2006) introduced the quantile autoregressive model (QAR) which becomes increasingly popular and there is a growing number of studies dealing with the QAR approach; see, for example, Sim and Zhou 2015, Roboredo and Ugolini 2016, Zhu et al. 2016, and Peng et al. 2017. In this paper, we extend the existing research by applying the QARDL model (Cho et al. 2015) and the quantile

Granger causality test (Troster 2018). Thus, the use of these recently developed methods may bring new insights into the relationship between oil and stock prices.

Within this huge literature, we will detail some recent studies first before focusing on those based on the quantile framework, which is the principal purpose of our paper. Chen (2010) studied whether higher oil prices push the stock market into bear territory, using time-varying transition-probability Markov-switching models in the US. The results show that an increase in oil prices leads to a higher probability of being in a bear market. Arouri (2011) was interested in European stocks, through the DJ Stoxx 600 index covering 12 different sectors in European countries over the 1998–2010 period. His findings, using GARCH models and an asymmetric Granger-causality test, show that the strength of the relationship between oil and stocks' prices depends on the economic sector. Ramos and Veiga (2013) also focused on the asymmetric aspect in distinguishing between oil-importing and oil-exporting countries over the 1989–2009 period. The results of panel data regressions show that oil prices have asymmetric impacts on stock prices in oil-importing countries only. Furthermore, oil price volatility has a negative impact on stock prices in oil-importing countries, while it is the opposite in oil-exporting countries. Jouini and Harrathi (2014) investigated GCC countries (Gulf Cooperation Council) over the 2005–2011 period. The authors took the asymmetry into account by using the BEKK–GARCH process. Their results show that the spillover effects run more from stock markets to oil prices than the inverse.

The quantile approach has attracted increasing attention. In this regard, Meligkotsidou et al. (2014) state that the quantile regression models are particularly suitable for forecasting stock returns. Indeed, this approach does not look only at the conditional mean but also consider the lower, medium or/and upper quantiles of the return series, which is likely to reveal interesting financial characteristics. Chuang et al. (2009) examine the dynamic relationship of the quantiles of stock returns and trading volume and find a heterogeneous causal effect of volume across quantiles. Sim and Zhou (2015) used the quantile-on-quantile approach (or QQ) to investigate the case of US stocks. Their results show that oil shocks in low quantiles affect US stocks positively in their high quantiles. Inversely, oil shocks in high quantiles have a weak impact on US stocks. This shows the importance of distinguishing between different quantiles of oil and stock prices. Also, in the quantile framework, Reboredo and Ugolini (2016) examined the impact of oil prices in different quantiles on stock returns based on conditional and unconditional quantile distribution functions of stock returns. Using data in BRICS countries, the UK, the US, and the countries in the Economic and Monetary Union over the 2000–2014 period, the authors found that the downside spillover effects are larger than are the upside spillover effects. In low quantiles of oil prices, there is no impact on any quantiles of stock returns. Zhu et al. (2016) based on the quantile regression developed by Koenker and Bassett (1978) study the interaction between oil and stock prices from different industry sectors in China over the 1994–2014 period. Their results show that there is dependence in low quantiles but that this changes when considering structural breaks. Finally, Peng et al. (2017) investigate the relationship between oil and stock prices across extreme lower and upper quantiles using data of 8 stocks of petroleum firms in China over the 2001–2015 period. The results show that oil shocks affect the synchronicity in the upper quantiles differently based on the firm size. In extreme low quantiles, the synchronicity responds to oil shocks significantly.

To summarize, the review of the literature shows that the results can differ depending on countries, sectors, and econometric methods. However, there have been few studies that focus on the quantiles of the stock price series (Sim and Zhou 2015, Roboredo and Ugolini 2016, Zhu et al. 2016, and Peng et al. 2017). The results of these studies underline the importance of taking this aspect into account. However, none of these studies has taken into account either the cointegration at different quantiles or the causality at different quantiles. The Quantile Autoregressive Distributed Lag model (QARDL), introduced recently by Cho et al. (2015), and the quantile Granger causality test proposed by Troster (2018) are employed in this paper to fill this gap. To the best of our knowledge, these two methods have not been used in previous studies about the oil–stock nexus.

3. Data and Methodology

3.1. Data and statistic properties

Our sample data consist of monthly time series for the West Texas Intermediate (WTI) crude oil price,[1] expressed in USD per barrel, and four major European stock market indexes. The four 'blue ships' indexes are FTSE All-Share for the UK, MIB 30 for Italia, CAC All Tradable (the new name of the SBF 250 index since 2011) for France, and DAX 30 for Germany. The monthly values of these stock indexes are collected from Bloomberg. WTI oil prices are collected from the EIA, and we cover the period from January 1999 to September 2016. This long study period allows us to take into account the impact of different crisis times, such as the dotcom bubbles in 2001–2002, the global financial crisis in 2007–2008, and the European debt crisis in 2010–2012. This heterogeneity occurring in the study period suggests that a nonlinear framework should be used to better understand the interaction between crude oil price changes and stock market prices in various quantiles of the latter over both the short run and the long run. Finally, the monthly frequency is chosen because it allows the estimation procedure to be performed over a high number of observations, 201 in total. This high sample size provides accurate estimations in econometric models.

Table 1: Descriptive statistics

	FTSE	DAX	CAC All Tradable	MIB	WTI
Mean	2895.768	3167.617	3010.023	3000.783	61.372
Maximum	3861.580	6225.240	4354.420	5015.640	133.880
Minimum	1760.310	1227.340	1762.240	1753.530	12.010
Std. Dev	498.570	1050.500	608.741	788.993	29.731
Skewness	-0.251	0.725	0.261	0.615	0.196
Kurtosis	2.337	3.294	2.192	2.413	1.868
JB	5.778*	18.325***	7.762**	15.567***	12.012***
ZA	-2.937	-3.413	-3.051	-2.734	-4.121
ZA (1st diff)	-8.511***	-7.985***	-7.918***	-7.892***	-7.766***

Notes: JB and ZA denote the empirical statistics of the Jarque-Bera test for normality and Zivot and Andrews (1992) unit root test taking structural breaks into account, respectively. ***, **, * indicate rejection of the null hypothesis of normality and unit root test at 1%, 5% and 10% significance levels, respectively. The ZA critical values are -5.57, -5.08 and -4.82 at the significance levels of 1%, 5% and 10%, respectively.

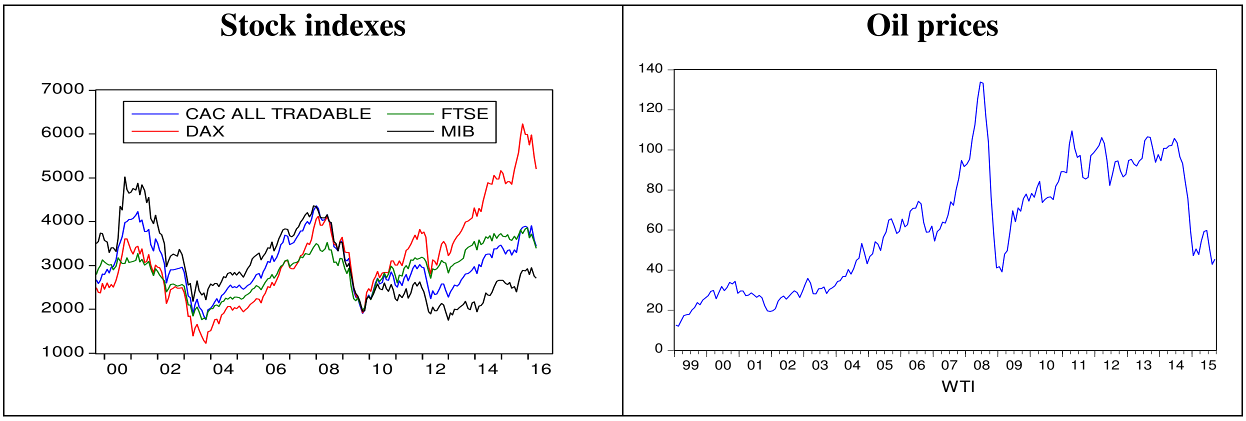
The descriptive statistics and stochastic properties of crude oil prices (WTI) and the four European stock indexes are summarized in Table 1. The figures indicate that the monthly average price was approximately $61 per barrel over the study period. The FTSE is negatively skewed (or skewed to the left) and shows no excess kurtosis. In contrast, all the other series are positively skewed (or skewed to the right) and present a kurtosis lower than 3, indicating that their distributions have thin tails. The Jarque–Bera test indicates the non-normality of all

[1] The WTI and Brent prices are closely related through time.

the series at the 1% and 5% significance levels, except for the FTSE. The unit root test of Zivot and Andrews accounts for structural breaks in the time series. Our findings show that European stock indexes and the WTI crude oil price are non-stationary in level, but their first differences are stationary. Thus, they are integrated at order 1. Figure 1 shows the dynamics of the considered series over the study period.

The observation of Figure 1 shows that the time trend of the four studied European stock indexes is quite homogenous over the sample period. However, there has been more disparity since the global financial crisis that began in 2008. The DAX index had the highest increasing tendency since 2011. The oil price reached its peak in March 2008, when the price of the barrel was almost $140. In 2016, the price of a barrel was much lower, at approximately $45. This disparity shows the instability of the oil price over time. The comparison of the graph on stock indexes with that on oil prices also indicates the heterogeneity in the relationship between the two variables. In some periods, they can evolve in the same sense while they can involve inversely in other periods. This again shows the importance of taking into account the nonlinearity, and the quantile analysis can help explaining this nonlinearity in the complex relationship between oil and stock prices.

Figure 1: Time trend of stock indexes and oil prices from 1999 to 2016



3.2. Methodology

This methodology section is divided into two parts. Part 1 focuses on the cointegrating relationship through the QARDL model of Cho et al. (2015). Part 2 explains the quantile causality proposed by Troster (2018). The QARDL model allows us to simultaneously investigate the long-run relationship and short-run dynamics by accounting for any potential asymmetric and nonlinear linkages between the considered variables. The analysis of quantile causality in the Granger sense allows us to complete the analysis regarding the ability to use past oil prices to forecast future values of European stock indexes, and vice versa.

Quantile ARDL

Cho et al. (2015) extended the linear ARDL model to account for locational asymmetry and introduced the QARDL model. The use of the quantile ARDL methodology has several advantages compared to the ARDL methodology and the quantile regression methodology. In fact, while accounting for cointegration between variables, the ARDL model only allows for linear relationship between variables, while the quantile regression model allows for locational asymmetries. This is important because the parameters may depend on the location of stock prices.

The QARDL (p,q) model is written as follows:

$$Y_t = \alpha(\tau) + \sum_{i=1}^{p} \delta_i(\tau) Y_{t-i} + \sum_{i=0}^{q} \theta_i(\tau)' X_{t-i} + \varepsilon_t(\tau) \tag{1}$$

where ε_t is the error term, defined as $Y_t - Q_{Y_t}(\tau / \Omega_{t-1})$, with $Q_{Y_t}(\tau / \Omega_{t-1})$ is the τ^{th} quantile of Y_t conditional on the smallest $\sigma-$field generated by $\{X_t', Y_{t-1}, X_{t-1}', ...\}$. We define $Z_t = \Delta X_t$, $\lambda(\tau) = \sum_{i=0}^{q} \theta_i(\tau)$ and $w_i(\tau) = -\sum_{j=i+1}^{q} \theta_i(\tau)$. Eq. (2) can be rewritten as:

$$Y_t = \alpha(\tau) + \sum_{i=1}^{p} \delta_i(\tau) Y_{t-i} + \sum_{i=0}^{q-1} Z_t' w_i(\tau) + X_t' \lambda(\tau) + \varepsilon_t(\tau) \tag{2}$$

All the parameters measuring short-run dynamics in Eq. (2) are estimated for any value of τ in [0,1] through minimization of $\sum_t \rho_t \left(Y_t - \alpha - \sum_{j=1}^{p} \delta_i Y_{t-i} - X_t' \lambda - \sum_{i=0}^{q-1} Z_t' w_i \right)$ with $\rho_\tau(u) = u(\tau - I(u<0))$ is the check function. The long-run parameter β is obtained by using the plug-in principle and is computed as follows:

$$\hat{\beta}(\tau) = \hat{\lambda}(\tau)\left(1 - \sum_{i=1}^{p} \delta_{\mathrm{i}}(\tau)\right)^{-1}$$

We reformulate Eq. (2) using the property $E\left(\rho_t(\varepsilon_t(\tau))\right) = 0$, as argued by Kim and White (2003):

$$Q_{\Delta Y_t}(\tau|.) = \alpha(\tau) + \rho(\tau)\left(Y_{t-1} - X_{t-1}'\beta(\tau)\right) + \sum_{i=1}^{p-1} \pi_i(\tau) Y_{t-i} + \sum_{i=0}^{q-1} Z_{t-i}' \varphi_i(\tau) + \varepsilon_t(\tau) \tag{3}$$

where $\varphi(\tau) = \sum_{j=1}^{p} \delta_j(\tau) - 1$, $\varphi_0(\tau) = \lambda(\tau) + w_0(\tau)$, and $\hat{\pi}_i(\tau) = -\sum_{j=i+1}^{p} \phi_i(\tau)$, and $\varphi_i(\tau) = -\sum_{j=i+1}^{q} w_i(\tau)$, for $i = 1,2, ...$

In the model represented in Eq. (3) there are four parameters of interest: (i) ρ: the error correction parameter (ECM), measuring the speed of adjustment toward the long-run equilibrium between oil prices and stock prices, (ii) β: the long-run cointegrating parameter, (iii) π_*: the cumulative short-run effect of past variations of SP on the current variations of SP, and (iv) φ_*: which represents the cumulative short-run effect of contemporaneous and past variations of *WTI* on the current variations of SP. The ECM parameter ρ should be significantly negative for the variables to be cointegrated. We then use the Wald test with the null hypothesis of parameter constancy across quantiles. The Wald test asymptotically follows a chi-squared distribution. Finally, prior to estimating the QARDL model in Equation (3), we first determine the optimal lag length orders p and q using the Schwarz Information Criterion (SIC). Then, we use the conventional delta method to determine the respective standard errors of π_* and φ_* to measure the respective cumulative short-run effects of past variations of *SP* and current and past variations of *WTI* on current variations of *SP*.

Quantile Granger causality test

The recent econometric methodology developed by Troster (2018) consists of testing the Granger causality running from European stock market prices to WTI crude oil prices in different quantiles, and vice versa. The standard Granger causality test between stock prices

(*SP*) and oil prices (*WTI*) is based on the estimation of a bivariate Vector Autoregression (VAR) model, as defined below:

$$SP_t = c_1 + \sum_{i=1}^{p} \alpha_i SP_{t-i} + \sum_{i=1}^{p} \beta_i WTI_{t-i} + \varepsilon_{1t}$$

$$WTI_t = c_2 + \sum_{i=1}^{p} \gamma_i SP_{t-i} + \sum_{i=1}^{p} \theta_i WTI_{t-i} + \varepsilon_{2t} \tag{4}$$

To check whether *WTI* does not Granger cause *SP*, we test the null hypothesis $\beta_1 = \beta_2 = \cdots = \beta_p = 0$ against the alternative $\exists i/\beta_i \neq 0$. Similarly, we accept the null that *SP* does not Granger cause *WTI* if $\gamma_1 = \gamma_2 = \cdots = \gamma_p = 0$, while *SP* is said to Granger cause *WTI* if $\exists i/\gamma_i \neq 0$.

Given that a distribution is completely determined by its quantiles, the Granger non-causality in distribution can also be expressed in terms of conditional quantiles. The quantile causality is defined as *SP* does not Granger cause *WTI* in the τ quantile with respect to the available information at time *t*, $\Omega_t = \{SP_{t-1}, SP_{t-2}, ..., SP_{t-p}, WTI_{t-1}, WTI_{t-2}, ..., WTI_{t-p}\}$ if:

$$Q\tau\{WTI_t / WTI_{t-1}, WTI_{t-2}, ...WTI_{t-p}, SP_{t-1}, SP_{t-2}, ...SP_{t-p}\}$$
$$= Q\tau\{SP_t / SP_{t-1}, SP_{t-2}, ...SP_{t-p}\} \tag{5}$$

and *SP* Granger causes *WTI* if :

$$Q\tau\{WTI_t / WTI_{t-1}, WTI_{t-2}, ...WTI_{t-p}, SP_{t-1}, SP_{t-2}, ...SP_{t-p}\}$$
$$\neq Q\tau\{WTI_t / WTI_{t-1}, WTI_{t-2}, ...WTI_{t-p}\} \tag{6}$$

where $Q\tau\{WTI_t / .\}$ is the τ quantile of WTI depending on time t and $0 < \tau < 1$.

Similarly, *WTI* does not Granger cause *SP* in the τ quantile with respect to the available information at time *t*, as defined above, if:

$$Q\tau\{SP_t / WTI_{t-1}, WTI_{t-2}, ...WTI_{t-p}, SP_{t-1}, SP_{t-2}, ...SP_{t-p}\}$$
$$= Q\tau\{SP_t / SP_{t-1}, SP_{t-2}, ...SP_{t-p}\} \tag{7}$$

while *WTI* causes *SP* if:

$$Q\tau\{SP_t / WTI_{t-1}, WTI_{t-2}, ...WTI_{t-p}, SP_{t-1}, SP_{t-2}, ...SP_{t-p}\}$$
$$\neq Q\tau\{SP_t / SP_{t-1}, SP_{t-2}, ...SP_{t-p}\} \tag{8}$$

where $Q\tau\{SP_t / .\}$ is the τ-quantile of SP depending on time t and $0 < \tau < 1$.

4. Results and discussions

To facilitate the reading, we divide the results into three different parts. In sub-section 4.1., we focus on the QARDL results. In sub-section 4.2., the Wald test on the constancy of the QARDL coefficients in different quantiles is performed. In the last sub-section, we present the results on the quantile Granger causality.

4.1. QARDL results

The results of the QARDL estimation for each European stock market index are provided in Tables 2 to 5. Each table is composed of two panels (A and B). The first panel contains the results of the linear ARDL model, while the second presents those from the QARDL model. Most of the coefficients related to the WTI variable (coefficient θ, corresponding to past oil prices) in the linear ARDL are not significant, and the results can vary depending on the stock index. These findings thus suggest that the linear ARDL specifications may be insufficient to capture the long- and short-run relationship between oil prices and stock indexes. This result from the linear model confirms our analysis from Figure 1 that the relationship between oil and stock prices is not linear (see Section 2).

In Panel B of Tables 2 to 5, all the QARDL coefficients are provided, along with their associated standard errors in brackets. We are interested in the five following parameters related to equation (5): α, ρ, β, φ, and θ. For the short-run coefficients φ and θ, we present only the lagged coefficients that are statistically significant. Thus, the number of coefficients presented for each stock can be different depending on their significance. The ECM parameter $\rho(\tau)$ measures the speed of adjustment towards the long-run equilibrium at quantile τ. Its negative value shows the cointegration between oil prices and stock indexes. β_{WTI} is the long-run parameter or the cointegrating coefficient between oil and stock prices. The short-run coefficient φ_* represents the cumulative impact of contemporaneous and past values of stock prices on current stock prices. In the same vein, the short-term parameter θ_* reflects the cumulative impact of current and past values of *WTI* crude oil prices on stock prices.

Table 2: Linear and quantile estimation results for the FTSE stock market index

Panel A: Linear ARDL

α_*	ρ_*	β_{WTI}	φ_1
0.272^{*} (0.138)	-0.040^{**} (0.019)	0.297^{*} (0.153)	0.012^{*} (0.153)

Panel B: Quantile ARDL

Quantile index (τ)	α_*	ρ_*	β_{WTI}	φ_1
0.05	-0.800 (0.526)	0.095 (0.070)	0.081 (0.096)	0.110 (0.118)
0.10	-0.336 (0.439)	0.034 (0.056)	-0.040 (0.362)	0.180 (0.117)
0.20	0.117 (0.372)	-0.017 (0.050)	-0.122 (0.909)	0.075 (0.082)
0.30	0.199 (0.224)	-0.031 (0.031)	0.256 (0.219)	0.059 (0.064)
0.40	0.367^{*} (0.214)	-0.054^{*} (0.029)	0.267^{**} (0.102)	0.029 (0.071)
0.50	0.478^{**} (0.185)	-0.065^{**} (0.025)	0.172^{*} (0.101)	0.002 (0.061)
0.60	0.427^{***} (0.125)	-0.057^{***} (0.018)	0.169^{**} (0.084)	-0.015 (0.048)
0.70	0.344^{***} (0.102)	-0.045^{***} (0.015)	0.213^{**} (0.099)	0.001 (0.042)
0.80	0.299^{*} (0.160)	-0.037^{*} (0.022)	0.190 (0.148)	-0.010 (0.054)
0.90	0.614^{**} (0.247)	-0.076^{**} (0.022)	0.145 (0.112)	0.060 (0.050)
0.95	0.736^{***} (0.167)	-0.092^{***} (0.022)	0.148^{**} (0.063)	0.053 (0.037)

Notes: This table reports OLS (equation 1) and quantile regressions' (equation 3) coefficients. The first column presents different quantiles going from 5% (0.05) to 95% (0.95). α is the constant, ρ is the ECM coefficient, β_{WTI} is the cointegrating parameter, φ is the coefficient for the short-run effect from past *SP* to current *SP*, and θ is the coefficient for the short-run effect from past *WTI* on current *SP*. Standard errors are between brackets. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively. *p* and *q,* the lag lengths in equation 2 selected using the Schwartz Information Criterion (SIC) are p=1, q=1.

Table 3: Linear and quantile ARDL estimation results for the DAX stock market index

Panel A: Linear ARDL				
α_*	ρ_*	β_{WTI}	φ_1	θ_0
0.148 (0.107)	-0.026* (0.015)	0.597* (0.358)	0.164** (0.072)	0.016 (0.010)

Panel B: Quantile ARDL					
Quantile index (τ)	α_*	ρ_*	β_{WTI}	φ_1	θ_0
0.05	-0.381 (0.245)	0.021 (0.032)	-1.445 (2.733)	0.481*** (0.174)	0.162 (0.150)
0.10	-0.027 (0.242)	-0.020 (0.035)	1.483 (2.083)	0.486*** (0.174)	0.128 (0.082)
0.20	-0.037 (0.133)	-0.007 (0.020)	1.993 (4.472)	0.328*** (0.108)	-0.006 (0.072)
0.30	-0.056 (0.111)	-0.003 (0.017)	4.829 (24.285)	0.260*** (0.091)	0.028 (0.078)
0.40	0.045 (0.178)	-0.017 (0.024)	1.203 (1.504)	0.206$_{*}$ (0.111)	0.028 (0.078)
0.50	0.196 (0.172)	-0.026 (0.023)	0.218 (0.280)	0.107 (0.097)	-0.052 (0.076)
0.60	0.249 (0.162)	-0.036 (0.024)	0.398* (0.225)	0.095 (0.117)	-0.036 (0.074)
0.70	0.151 (0.149)	-0.010 (0.022)	-0.960 (3.381)	-0.010 (0.091)	-0.028 (0.052)
0.80	0.174 (0.154)	-0.011 (0.023)	-0.846 (2.681)	-0.008 (0.090)	0.014 (0.052)
0.90	0.335 (0.214)	-0.029 (0.031)	-0.254 (0.679)	-0.100 (0.093)	-0.031 (0.082)
0.95	0.513** (0.243)	-0.052 (0.033)	-0.078 (0.238)	-0.075 (0.141)	-0.066 (0.113)

Notes: This table reports OLS (equation 1) and quantile regressions' (equation 3) coefficients. The first column presents different quantiles going from 5% (0.05) to 95% (0.95). α is the constant, ρ is the ECM coefficient, β_{WTI} is the cointegrating parameter, φ is the coefficient for the short-run effect from past *SP* to current *SP*, and θ is the coefficient for the short-run effect from past *WTI* on current *SP*. Standard errors are between brackets. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively. *p* and *q,* the lag lengths in equation 2 selected using the Schwartz Information Criterion (SIC) are p=1, q=1.

Table 4: Linear and quantile ARDL and quantile estimation results for the CAC All Tradable stock market index

Panel A : Linear ARDL						
α_*	ρ_*	β_{WTI}	φ_1	φ_2	φ_3	θ_0
0.329** (0.147)	-0.042** (0018)	0.043 (0.176)	0.155** (0.073)	-0.024 (0.074)	0.159** (0.073)	0.002 (0.007)

Panel B : Quantile ARDL							
Quantile index (τ)	α_*	ρ_*	β_{WTI}	φ_1	φ_2	φ_3	θ_0
0.05	0.119 (0.421)	-0.023 (0.051)	-0.107 (0.553)	0.556** (0.0230)	0.053 (0.213)	0.318** (0.156)	0.049 (0.106)
0.10	0.090 (0.218)	-0.022 (0.026)	0.219 (0.496)	0.538*** (0.156)	0.072 (0.161)	0.348** (0.145)	0.080 (0.097)
0.20	0.086 (0.192)	-0.012 (0.025)	-0.604 (1.587)	0.477*** (0.153)	-0.145 (0.169)	0.318** (0.143)	-0.002 (0.095)
0.30	0.235 (0.211)	-0.031 (0.027)	-0.066 (0.288)	0.250* (0149)	0.054 (0.141)	0.263** (0.127)	0.017 (0.082)
0.40	0.311* (0.178)	-0.040* (0.023)	0.050 (0.175)	0.196* (0.108)	-0.004 (0.103)	0.242** (0.107)	-0.057 (0.075)

0.50	0.394** (0.156)	-0.048** (0.021)	-0.013 (0.143)	0.198* (0.108)	0.031 (0.092)	0.107 (0.080)	-0.027 (0.057)
0.60	0.298* (0.154)	-0.034* (0.020)	-0.043 (0.189)	0.142 (0.118)	-0.049 (0.063)	0.057 (0.072)	-0.026 (0.056)
0.70	0.411** (0.174)	-0.049** (0.021)	0.030 (0.135)	0.013 (0.095)	-0.033 (0.071)	0.045 (0.088)	-0.064 (0.064)
0.80	0.503*** (0.155)	-0.057*** (0.019)	-0.009 (0.121)	-0.102 (0.072)	-0.038 (0.096)	-0.001 (0.119)	0.002 (0.088)
0.90	0.525*** (0.157)	-0.057*** (0.021)	-0.060 (0.188)	-0.136* (0.075)	-0.126 (0.111)	-0.026 (0.124)	0.042 (0.090)
0.95	0.632*** (0.146)	-0.064*** (0.020)	-0.187 (0.242)	-0.023 (0.117)	-0.155 (0.128)	-0.020 (0.100)	0.004 (0.080)

Notes: This table reports OLS (equation 1) and quantile regressions' (equation 3) coefficients. The first column presents different quantiles going from 5% (0.05) to 95% (0.95). α is the constant, ρ is the ECM coefficient, β_{WTI} is the cointegrating parameter, φ is the coefficient for the short-run effect from past *SP* to current *SP*, and θ is the coefficient for the short-run effect from past *WTI* on current *SP*. Standard errors are between brackets. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively. *p* and *q,* the lag lengths in equation 2 selected using the Schwartz Information Criterion (SIC) are p=1, q=1.

Table 5: Linear and quantile ARDL and quantile estimation results for the MIB stock market index

Panel A: Linear ARDL

α_*	ρ_*	β_{WTI}	φ_1	φ_2	φ_3	θ_0
0.329** (0.147)	-0.038** (0.016)	-0.202 (0.203)	0.027 (0.070)	-0.010 (0.070)	0.182** (0.070)	-0.008 (0.008)

Panel B: Quantile ARDL

Quantile index (τ)	α_*	ρ_*	β_{WTI}	φ_1	φ_2	φ_3	θ_0
0.05	0.188 (0.566)	-0.030 (0.062)	-0.339 (0.604)	0.081 (0.240)	0.098 (0.260)	0.245 (0.222)	0.150 (0.113)
0.10	-0.282 (0.510)	0.026 (0.058)	-0.012 (0.728)	0.123 (0.191)	0.127 (0.163)	0.289** (0.141)	0.099 (0.079)
0.20	0.227 (0.234)	-0.030 (0.026)	-0.214 (0.425)	0.023 (0.151)	-0.073 (0.145)	0.243** (0.123)	0.085 (0.095)
0.30	0.233 (0.213)	-0.028 (0.025)	-0.308 (0.258)	0.007 (0.075)	0.087 (0.108)	0.223** (0.097)	0.078 (0.086)
0.40	0.158 (0.216)	-0.021 (0.025)	0.033 (0.423)	0.021 (0.089)	-0.062 (0.106)	0.130 (0.119)	0.058 (0.094)
0.50	0.198 (0.195)	-0.028 (0.023)	0.249 (0.339)	0.058 (0.076)	-0.118 (0.106)	0.151 (0.124)	-0.003 (0.087)
0.60	0.424*** (0.155)	-0.048*** (0.017)	-0.127 (0.144)	0.031 (0.092)	-0.100 (0.115)	0.070 (0.090)	-0.020 (0.077)
0.70	0.404** (0.179)	-0.045** (0.020)	-0.063 (0.153)	-0.059 (0.079)	-0.220* (0.112)	0.006 (0.084)	-0.033 (0.055)
0.80	0.411*** (0.144)	-0.045*** (0.016)	-0.031 (0.201)	-0.071 (0.076)	-0.156* (0.081)	0.019 (0.057)	-0.049 (0.046)
0.90	0.683*** (0.190)	-0.067*** (0.019)	-0.341** (0.168)	-0.032 (0.077)	-0.097 (0.095)	-0.055 (0.096)	-0.019 (0.038)
0.95	0.714** (0.284)	-0.063** (0.025)	-0.554* (0.328)	0.021 (0.168)	-0.123 (0.172)	-0.037 (0.218)	-0.16 (0.089)

Notes: This table reports OLS (equation 1) and quantile regressions' (equation 3) coefficients. The first column presents different quantiles going from 5% (0.05) to 95% (0.95). α is the constant, ρ is the ECM coefficient, β_{WTI} is the cointegrating parameter, φ is the coefficient for the short-run effect from past *SP* to current *SP*, and θ is the coefficient for the short-run effect from past *WTI* on current *SP*. Standard errors are between brackets. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively. *p* and *q,* the lag lengths in equation 2 selected using the Schwartz Information Criterion (SIC) are p=1, q=1.

In the long run, the ECM parameter $\rho(\tau)$ and cointegrating parameters β_{WTI} are found to behave differently across quantiles. Concerning the dynamics between the FTSE and oil prices (Table 2), the ECM coefficients are significant and negative only for the medium and high quantiles (from 0.4 to 0.95 quantiles). Furthermore, the higher the quantile, the higher the coefficient. This result means that the adjustment to the long-run equilibrium is faster, as the quantile of stock prices is higher for the UK. The same result is found for the CAC All Tradable index for France (Table 4). On the other hand, a closer comparison between these two countries shows that the value of the parameters is higher for the UK than for France (9.2% for the 0.95 quantile for the UK and 6.4% for France). This finding indicates that the adjustment speed is higher for the UK than for France. As for the Italian MIB index (Table 5), the ECM coefficients are significantly negative only for high quantiles (from 0.6 to 0.95 and not for quantiles 0.4 and 0.5, like for France and the UK). This shows that, in Italy, oil and stock prices are cointegrated only at high quantiles. In contrast, no ECM significant coefficient is found for the German stock index (DAX, Table 3).

The above results on the ECM coefficients reveal important information about the relationship between oil and stock prices in the European countries under study. First, this relationship depends on the quantiles in which the values of stock prices are. In our case, the variables are cointegrated only at medium and high quantiles of stock prices for France, the UK, and Italy, while at low quantiles for Germany. Second, this relationship also depends on the country in which stocks are quoted. Third, the speed of adjustment to the long-run equilibrium varies depending on the country and the quantiles. These results thus confirm the complex and nonlinear nature of the nexus between oil and stock prices demonstrated by previous studies (e.g., Reboredo and Ugolini 2016, Zhu et al. 2016, Sim and Zhou 2015, Peng et al. 2017). Conclusions drawn recently by Reboredo and Ugolini (2016) are also in accordance with our results, as these researchers find that, the stock market response to crude oil price changes is not significant at low quantiles. This means that small oil price movements have no impact on the stock market prices.

The cointegrating parameters β_{wti} are found to be significant for the UK, Italy, and Germany. These results clearly indicate that only the medium and high quantiles provide significant ECM and long-term coefficients, especially for the UK and Italy. For the UK, the long-run coefficients β_{wti} are positive, indicating that an increase of 1% in the crude oil price provokes an increase ranging from 14.8% to 26.7%, depending on the quantile (ranging from 0.4 to 0.95). It is worth noting that the higher the quantile, the lower the coefficient. Contrary to the situation for the UK, the beta coefficients are negative for Italy and are significant only at very high quantiles (0.9 and 0.95). This result means that, for Italy, an increase of 1% in oil prices causes stock prices to decrease by 34% and 55% at the 0.9 and 0.95 quantiles, respectively. This difference between Italy and the UK may be explained by the fact that the UK is out of the Eurozone and its stocks may behave differently to variations in oil prices than do those of Italy, which is in the Eurozone. Similarly to Italy, a negative relationship between oil and stock prices is also found in Cunado and Gracia (2014) in most of 12 European stock indexes market returns over the period 1973–2011 on a quarterly basis and in Park and Ratti (2008) for 10 of 12 European countries being studied. In an asymmetric setting, Ramos and Veiga (2013) also depict a negative relationship for oil-importing countries. As for Germany, only one coefficient is significantly positive at the 0.6 quantile (with a value of 0.39). This result means that, for Germany, an increase of 1% in oil prices contributes to a rise of stocks' prices of 39% only at the 0.6 quantile. This implies that the relationship between oil and stock prices in Germany is weak and that they interact only at certain levels of quantiles.

As for France, none of the long-term coefficients is significant. This implies that there is no long-term interaction between oil and stock prices in France at any level of quantile. Zhang (2017) recently corroborates this fact by investigating the impact of oil shocks on six major international stock markets. He finds that oil shocks (beyond the large shocks) are not fundamental in explaining stock market index reactions. In the same vein, Lee et al. (2012) demonstrate that oil price shocks have a weak influence on the composite index of G7 countries, while the UK and the US react more to oil price changes. This result confirms our findings about the specificity of the UK compared to other European countries.

In the short run, past changes of stock market prices (corresponding to φ coefficients) affect current stock prices as follows: for the DAX at lag 1 and at low quantiles (from 0.05 to 0.4), for CAC All Tradable at lags 1 and 3 at low quantiles (from 0.05 to 0.4), and for the MIB at lags 2 and 3 at low quantiles (from 0.1 to 0.3). However, there is no short-run impact of past stock prices on current stock prices for the FTSE. As for the impact of past oil prices on current stock prices (corresponding to θ coefficients), no coefficient is found to be significant for any index at any quantile. This finding implies that short-term changes in oil prices fail to explain the stock price changes. This may be explained by the fact that changes in oil prices need time to have significant impacts on the activities of firms and, thus, on their stock prices.

4.2. Robustness check: Wald tests on the constancy of parameters in different quantiles

To test the robustness of the previous results on the cointegration between oil and stock prices at various quantiles, we follow Cho et al. (2015) to check the constancy of the parameters through various quantiles. For this purpose, the Wald test is applied on ρ, β, π_i, and φ_i. For each parameter, we compare their values in all pairs of quantiles. The null hypothesis posits that the coefficients are constant in all quantiles. The acceptance of the null hypothesis indicates the constancy of parameters across quantiles and, hence, potential nonlinearities and locational asymmetries are rejected. On the other hand, the rejection of the null hypothesis confirms that the transmission of oil price shocks to the related stock market index is nonlinear and asymmetric.

Table 6: Results of the Wald test for the constancy of parameters

	FTSE	DAX	CAC All Tradable	MIB
ρ_*	1.850* [0.055]	1.370 [0.197]	0.830 [0.597]	0.730 [0.698]
β_{WTI}	0.470 [0.905]	0.910 [0.522]	0.440 [0.925]	1.010 [0.437]
φ_1		2.880*** [0.002]	3.110*** [0.001]	0.590 [0.821]
φ_2			1.300 [0.232]	6.240*** [0.000]
φ_3			2.180** [0.020]	0.610 [0.808]
φ_4			1.640* [0.097]	
θ_0	2.480*** [0.008]	3.320*** [0.000]	1.210 [0.286]	0.620 [0.797]

Notes: This table reports the results of the Wald test for the parameter constancy between all the quantiles, at the selected lags defined in previous tables. ρ is the ECM coefficient, β_{WTI} is the cointegrating parameter, φ is the coefficient for the short-run effect from past *SP* to current *SP*, and θ is the coefficient for the short-run effect from past *WTI* on current *SP*. P-values associated to the Chi² values are reported between brackets. ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

Table 6 suggests the rejection of the null of parameter constancy for coefficients φ that shows the short-run impact of stock prices and its current level. This is true for all the four stock indexes and at different lags, varying from 1 to 4. As for the short-run effect of past oil price changes on current stock prices (coefficientsφ_i), the Wald test rejects the constancy across different quantiles for the FTSE and DAX indexes. This means that, for these two indexes, there is nonlinearity in the way that oil prices impact them in the short-run, while this is not the case for the CAC All Tradable and MIB indexes. The previous results strongly confirm the presence of nonlinearities and asymmetries in the short-run linkages between oil and stock prices. However, there is no significant nonlinearity in the long-run relationship between oil prices and stock prices, as the Wald test fails to reject the null of parameter constancy for the β parameter for all four indexes. This is also the case for the ECM coefficient ρ, except for the FTSE index. The above results thus indicate that the distinction between quantiles is very important when investigating the short-run and long-run relationship between oil and stock prices.

4.3. Quantile Granger causality results

The previous results on the quantile cointegration between oil and stock prices lead us to further analyze the quantile Granger causality between these variables. While the cointegration analysis allows examination of the adjustment of the two variables to achieve their long-run equilibrium, the Granger causality allows us to understand whether past values of one variable predict the other variable. Table 7 shows the results of the causality test for each pair of variables (country stock index and oil prices) over different quantiles as proposed by Troster (2018).

Table 7: Quantile Granger causality test

Quantiles index (τ)	*0.05*	*0.10*	*0.20*	*0.30*	*0.40*	*0.50*	*0.60*	*0.70*	*0.80*	*0.90*	*0.95*
FTSE does not cause WTI	0.715 [0.238]	1.125 [0.131]	1.700^{**} [0.045]	1.746^{**} [0.041]	1.988^{**} [0.024]	2.396^{***} [0.009]	1.825^{**} [0.035]	1.856^{**} [0.032]	1.295^{*} [0.098]	0.671 [0.251]	0.514 [0.514]
WTI does not cause FTSE	0.928 [0.177]	0.788 [0.216]	0.953 [0.171]	1.008 [0.157]	1.115 [0.133]	1.616^{*} [0.054]	2.110^{**} [0.018]	1.456^{*} [0.073]	1.204 [0.115]	0.847 [0.199]	0.434 [0.332]
DAX does not cause WTI	0.617 [0.269]	0.914 [0.181]	1.637^{*} [0.052]	2.167^{**} [0.016]	2.251^{**} [0.013]	2.525^{***} [0.006]	2.051^{**} [0.021]	1.883^{**} [0.031]	1.215 [0.113]	0.773 [0.220]	0.483 [0.315]
WTI does not cause DAX	0.840 [0.201]	1.166 [0.122]	1.445^{*} [0.075]	1.403^{*} [0.081]	1.243 [0.108]	1.582^{*} [0.058]	1.136 [0.128]	1.099 [0.137]	1.403^{*} [0.081]	1.079 [0.141]	0.637 [0.262]
CAC All Tradable does not cause WTI	0.749 [0.227]	0.746 [0.228]	1.955^{**} [0.026]	2.499^{***} [0.007]	2.440^{***} [0.008]	2.237^{**} [0.013]	1.676^{**} [0.048]	1.772^{**} [0.039]	0.912 [0.181]	0.601 [0.274]	0.476 [0.317]
WTI does not cause CAC All Tradable	0.660 [0.255]	0.869 [0.193]	1.409^{*} [0.080]	1.716^{**} [0.044]	1.393^{*} [0.083]	1.293^{*} [0.098]	1.277 [0.101]	1.268 [0.103]	0.960 [0.169]	0.824 [0.205]	0.335 [0.369]
MIB does not cause WTI	1.185 [0.119]	1.368^{*} [0.086]	2.782^{***} [0.003]	3.489^{***} [0.000]	3.283^{***} [0.001]	2.727^{***} [0.003]	1.952^{**} [0.026]	1.872^{**} [0.031]	0.992 [0.161]	0.632 [0.264]	0.555 [0.290]
WTI does not cause MIB	1.111 [0.134]	1.174 [0.121]	1.232 [0.110]	1.594^{*} [0.056]	1.071 [0.142]	1.330^{*} [0.092]	1.234 [0.109]	1.082 [0.140]	0.743 [0.229]	0.778 [0.219]	0.307 [0.379]

Notes: This table presents the estimated coefficients of the Granger causality test by quantiles. The first line indicates the different quantiles. ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively. P-values associated to the F-test values are reported between brackets.

First, Table 7 shows that the results differ depending on the quantiles. This again confirms the importance of distinguishing different quantiles of stock prices distribution when investigating the relationship between oil and stock prices. For the UK, the FTSE stock index

Granger causes oil prices at more quantiles (from 0.2 to 0.8) than the causality from oil prices to stock prices (from 0.5 to 0.7). For Germany, the causality from the DAX index to oil prices is significant at quantiles from 0.2 to 0.7 while it is at 0.2, 0.3, 0.5, and 0.8 for the causality from stock to oil prices. For France, the related quantiles are from 0.2 to 0.7 and from 0.2 to 0.5, respectively. As for Italy, the related figures are from 0.1 to 0.7 and from 0.3 to 0.5, respectively. Second, we notice that stock prices Granger cause oil prices in more quantiles than for the reverse direction. This finding implies that, for the European countries under study, the stock market has higher forecast ability for oil prices than vice versa. Third, the Granger causality is validated in only low and medium quantiles (from 0.1 to 0.8). No causality is found for extreme low and high quantiles (0.05, 0.9 and 0.95). This suggests that there is no Granger causality between these two variables at the tails of the distributions. Fourth, the number of quantiles for which there are significant causalities vary depending on the country. Overall, the causality analysis shows the importance of distinguishing between quantiles as well as between countries. This latter finding is consistent with those of Wang et al. (2013), in the sense that the effect of oil price shocks on stock market returns is less important for oil exporting countries (see also Phan et al. 2015). In the same vein, Sukcharoen et al. (2014) find evidence that the linkage between oil prices and stock indices depends on whether the country is oil-consuming or oil-producing.

5. Conclusion

We have investigated the relationship between oil prices and stock prices in four major European countries, i.e. United Kingdom (UK), Germany, France, and Italy over the 1999–2016 period using monthly data. Representative stock indexes and world oil prices are used in the application of methods developed recently by Cho, Kim, and Shin (2015) and by Troster (2018) which investigate the cointegration (the QARDL model) and Granger causality between variables through different quantiles. To the best of our knowledge, these approaches have not been used in previous studies while very few studies have focused on the use of quantile regressions (Sim and Zhou 2015, Roboredo and Ugolini 2016, Zhu et al. 2016, and Peng et al. 2017). However, none of these studies has taken into account the locational asymmetries and causality at different quantiles as we do in this study.

Overall, the findings of this research show the importance to distinguish between different quantiles, between long-run and short-run analysis and between countries. The QARDL results show that for the United Kingdom, only the long-run relationship between oil prices and stocks prices is significant at medium and extreme high quantiles. For Italy, this is only true at high quantiles. However, for France and Germany, the relationship is significant only in the short run, at low and medium quantiles for France while only at low quantiles for Germany. The quantile Granger causality test shows that past oil prices can be used to forecast future stock prices and inversely, past stock prices can be used to forecast future oil prices. This is particularly valid at low and medium quantiles. Furthermore, the stock market has a higher ability to forecast oil prices than oil prices have to forecast the stock market. This suggests that the performance of listed firms in Europe plays an important role in the level of oil demand and thus in the level of oil prices. These findings imply that the relationship between oil prices and stock prices needs to be investigated, not only taking into account the time period but also looking at the quantile that they are in. Therefore, investors, fund managers, and policymakers can base on the characteristic of the relationship in each quantile of their values to either forecast future levels or choose an appropriate asset allocation strategy. This aspect is important because previous analysis almost focuses on the time-varying character of this relationship, rather than on its distributional character.

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