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Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management

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A B S T R A C T

In this article we take a recent generalized VAR-GARCH approach to examine the extent of volatility transmission between oil and stock markets in Europe and the United States at the sector-level. The empirical model is advantageous in that it typically allows simultaneous shock transmission in the conditional returns and volatilities. Insofar as volatility transmission across oil and stock sector markets is a crucial element for portfolio designs and risk management, we also analyze the optimal weights and hedge ratios for oil-stock portfolio holdings with respect to the results. Our findings point to the existence of significant volatility spillover between oil and sector stock returns. However, the spillover is usually unidirectional from oil markets to stock markets in Europe, but bidirectional in the United States. Our back-testing procedures, finally, suggest that taking the cross-market volatility spillovers estimated from the VAR-GARCH models often leads to diversification benefits and hedging effectiveness better than those of commonly used multivariate volatility models such as the CCC-GARCH of Bollerslev (1990), the diagonal BEKK-GARCH of Engle and Kroner (1995) and the DCC-GARCH of Engle (2002).

1. Introduction

It is common in theory that stock prices are equal to the sum of discounted values of expected future cash flows at different investment horizons. Market participants must therefore identify the factors

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affecting these discounted cash flows to support their decision making. In view of the crucial role of oil in the global economy and its spectacular price fluctuations in recent years, it is naturally opportune to ask questions about the impact of the price of oil on stock prices. Research in the energy finance literature has documented several channels through which oil shocks are transmitted to stock markets, but the most important one may be the financial link between oil prices, corporate cash flows, and the discount rate used in stock-valuation models. We can see easily that the latter two factors depend on economic conditions (changes in the consumer price index, interest rates, industrial production costs, economic growth rates, investor and consumer confidence, and so on) that are significantly influenced by changes in the price of oil (Jones and Kaul, 1996; Sadorsky, 1999; Park and Ratti, 2008; Apergis and Miller, 2009). It is thus obvious that a change in oil prices of either sign (positive or negative) may move stock prices.

Although understanding the causal relationships between oil price changes on stock markets is crucial for energy policy planning, portfolio diversification and energy risk management, and other such issues, it is only recently that these relationships have been examined[1] Moreover, the focus was essentially on broad market indices (national and/or regional stock market indices). One of the earliest pieces, done by Kling (1985), studies oil shocks and US stock market behavior, and shows that stock market returns are negatively associated with the rise of crude oil prices. Jones and Kaul (1996) use a standard present value model to examine the response of four developed stock markets (Canada, Japan, the United Kingdom, and the United States) to oil shocks and find that changes in stock returns can be partially accounted for by the effect of oil price movements on current and future cash flows. Subsequent studies including, for example, those by Huang et al. (1996), Sadorsky (1999), Park and Ratti (2008), and Apergis and Miller (2009) rely on such methods as vector autoregressive models, international multifactor asset pricing models, cointegration tests, and vector error-correction models and reach similar conclusions. As to emerging stock markets, several papers have shown that changes in the price of oil have significant effects on stock returns over both the short and the long-term (Papapetrou, 2001; Basher and Sadorsky, 2006; Narayan and Narayan, 2010). But it must be emphasized that both the magnitude and sign of the effects differ from one market to another, depending on whether the market is more dependent on petroleum-related products or less so.

Some studies have examined the extent of oil price impacts on stock prices from a sector-by-sector perspective. For instance, Sadorsky (2001) and Boyer and Filion (2007) show that the stock returns of Canadian *Oil & Gas* companies are positively related to oil price increases. El-Sharif et al. (2005) obtain similar findings for *Oil & Gas* returns in the United Kingdom, whereas non-*Oil & Gas* sectors are weakly linked to oil price changes. Nandha and Faff (2008) study the short-term relationship between oil prices and thirty-five global industries covered by Datastream International and show that the rise of oil prices has a negative impact on all industries but not *Oil & Gas*. The work of Nandha and Brooks (2009) focuses on the reaction of the transport sector to oil prices in thirty-eight countries around the world and shows that oil prices do play a role in determining the transport sector returns in developed countries. For the Asian and Latin American countries in their sample, however, there appears to be no such evidence. In a more recent attempt, Arouri and Nguyen (2010) shift attention to short-term links between oil and stock prices in the aggregate as well as sector-by-sector in Europe. Their findings, obtained through various econometric techniques, suggest that the sensitivity of sector stock returns to oil price changes differs greatly from one sector of activity to another. More interestingly, their out-of-sample analysis shows that there are substantial diversification benefits to adding the oil asset to a diversified portfolio of stocks, as doing so significantly improves the portfolio's risk-return characteristics. This finding is consistent with those of several other papers, for which using futures contracts on traded commodities as part of existing portfolios of stocks improves overall returns (Satyanarayan and Varangis, 1996; Geman and Kharoubi, 2008).

As we can see, almost all of the abovementioned papers look at price spillover in oil and stock markets, whereas little has been done on possible volatility spillover. Using different specifications of

[1] Most earlier contributions to the understanding of oil effects focus on the links between oil price changes and real economic variables (Hamilton, 1983, 2003; Hutchison, 1993; Amano and van Norden, 1998; Kilian, 2008) following the major oil price events of the 1970s. Most of these studies find that oil price shocks significantly affect economic activity in both developed and emerging economies.

Engle and Kroner (1995)'s multivariate BEKK-GARCH models, some very recent papers document significant volatility spillover between oil and stock markets (Agren, 2006; Malik and Hammoudeh, 2007; Malik and Ewing, 2009; Tansuchat et al., 2009). For example, Malik and Hammoudeh (2007) show that Gulf equity markets are sensitive to volatility from the oil markets, while stock market volatility spills over into the oil markets only in Saudi Arabia. For their part, Malik and Ewing (2009) investigate volatility spillover between oil prices and five US equity sector indices (*Financials*, *Industrials*, *Consumer Services*, *Health Care*, and *Technology*) and conclude in favor of significant transmission of return and volatility shocks. In firm-level analysis, Tansuchat et al. (2009) find no volatility spillover between WTI (West Texas Intermediate) crude oil futures returns and the stock returns of ten worldwide oil companies.

Our study extends the research into volatility spillover between oil and stock markets. Specifically, we look at Europe and the United States over the period from 1998 to 2009 and do a thorough analysis of how shocks and volatility are transmitted from oil markets to the stock market sectors and from the stock markets to the oil markets. There are several reasons for this particular study. First, most previous work focuses on the oil-stock return links and often neglects the volatility spillover between these two markets, even though understanding volatility transmission mechanisms provides insight into means of building accurate stock-valuation models and accurate forecasts of the volatility of both markets. The information contained in empirical results also provides empirical bases from which to address issues regarding hedging strategies, optimal portfolio allocation, and derivatives management in the presence of energy risk. Second, our review of the literature indicates that little attention has been paid to the interaction of the volatility of oil prices and stock market sectors. Indeed, some sectors may be more severely affected by oil price volatility than others, depending on whether oil and oil-related products are an input or an output for the industry, on the indirect effect of oil prices on the industry, on the degree of competition and concentration in the industry, and on the capacity of the industry to transfer oil price shocks to its customers. The industry breakdown is even more important in that it would make it possible to counter biases inherent to the use of aggregate market indices that may mask the characteristics, not necessarily uniform, of several sectors. Here, the results of such studies based on national stock market indices as that of Park and Ratti (2008) may reflect differences in industrial structure from one country to another. Third, unlike previous studies that mostly report either country-specific or industry-specific results for oil-stock sector relationships, our research considers both the European and US industrial sectors. By doing so we are able to compare the volatility transmission mechanisms between two of the most influential trading blocs in the global economy as well as to compare our results with previous findings on this matter. Finally, we also examine the transmission of volatility between oil prices and aggregate stock market indices to perform a robustness check on our sector-level results.

At the empirical stage, we employ a multivariate vector autoregressive-generalized autoregressive conditional heteroscedasticity (VAR-GARCH) model recently developed by Ling and McAleer (2003). This model offers the possibility to explore the conditional volatility dynamics of the series considered as well as the conditional cross effects and volatility spillover between series. It also provides meaningful estimates of the model's parameters with fewer computational complications than several other multivariate GARCH specifications, such as the full-factor GARCH model. Furthermore, the findings can be used to analyze the diversification and hedging effectiveness across oil asset and sector equity. Some papers have taken the VAR-GARCH approach to investigate volatility spillover and hedging strategies among Gulf Arab equity sectors (Hammoudeh et al., 2009), between previous metals and exchange rates (Hammoudeh et al., 2010), and between crude oil spot and futures returns of the Brent and WTI oil price benchmarks (Chang et al., in press).

On the whole, we find evidence of significant volatility cross effects between oil and equity sector indices in Europe and the United States over the study period. Past oil shocks are found to play a crucial role in explaining the time-dynamics of conditional volatility of sector returns and should thus be accounted for when making volatility forecasts of future stock returns. On the other hand, portfolio analysis suggests that adding the oil asset to a well-diversified portfolio of European and US stocks improves its risk-adjusted performance and that oil risk exposures can be effectively hedged in portfolios of sector stocks over time. In addition, we show that among the models considered, the VAR-GARCH is the best model for optimal portfolio designs and hedging effectiveness. But there are several differences between Europe and the United States. First, for Europe, transmission of volatility is greater from oil to stocks than from stocks to oil, whereas for the United States it seems to be bidirectional. Second, the oil risk premium appears not to be relevant to international asset pricing models for European stocks as past values of oil price volatility do not significantly affect stock market volatility, whereas it is for the *Automobile and Parts*, *Basic Materials*, and *Utilities* sectors in the United States.

The remainder of the article is structured as follows. Section 2 introduces our empirical methodology. Section 3 presents the sample, data sources, and some preliminary analysis. Section 4 reports and discusses the empirical findings. Section 5 makes concluding remarks.

2. Empirical method

The GARCH-type approach has received a special interest from almost all previous papers dealing with the issue of volatility modeling and forecasting of commodities prices. When the objective is to investigate volatility interdependence and transmission mechanisms among different time-series, multivariate settings such as the CCC-MGARCH model of Bollerslev (1990), the BEKK-MGARCH model of Engle and Kroner (1995), or the DCC-MGARCH model of Engle (2002) are more relevant than univariate models. Empirical results reported in Hassan and Malik (2007), Agnolucci (2009), and Kang et al. (2009), among others, confirm the superiority of these models and show that they satisfactorily capture the stylized facts of the commodity-price conditional volatility and the dynamics of volatility interaction.

Since in this article we attempt to examine the volatility spillover between oil prices and stock market sectors in Europe and the US, as well as to derive the implications of the results on optimal weights and hedge ratios for oil-stock portfolio holdings, the abovementioned models are naturally suitable for our research question. But, they are excessive in parameters and often encounter convergence problem during estimation processes especially when additional exogenous variables are introduced to the conditional mean and variance equations. For these reasons, the multivariate VAR(k)-GARCH(p,q) model proposed by Ling and McAleer (2003) represents an interesting alternative. Its main advantage is that it is flexible enough to deal with the conditional cross effects and volatility transmission between the series under consideration with fewer computational complexities than other volatility spillover models. In particular, the ability of the VAR(1)-GARCH(1,1) specification to capture cross-market volatility interaction has been confirmed by recent research (Chang et al., in press).

We use the univariate and bivariate AIC and BIC information criteria to respectively choose the optimal lag length of the univariate GARCH process (i.e., values of p and q) and that of the bivariate VAR-GARCH model (i.e., value of k) for each pair of oil and stock sectors. Similar to previous studies, our results also select one lag for both conditional mean and variance equations for the majority of market pairs we study. Therefore, we decide to opt for the bivariate VAR(1)-GARCH(1,1) to compare empirical results across different stock/oil pairs.

In what follows we present the bivariate framework of the VAR(1)-GARCH(1,1) model and three competing models (CCC-, DCC- and diagonal BEKK-GARCH(1,1)). The former is considered our benchmark model, and the latter are used especially to compare the results of diversification and hedging effectiveness.

2.1. Bivariate VAR(1)-GARCH(1,1)

For each pair of stock returns (sector or market returns) and oil returns, the bivariate VAR(1)-GARCH(1,1) model of Ling and McAleer (2003) has the following specification for the conditional mean:

$$\begin{cases} R_t = \mu + \Phi R_{t-1} + \varepsilon_t \\ \varepsilon_t = H_t^{1/2} \eta_t \end{cases} \tag{1}$$

where $R_t = (r_t^S, r_t^O)'$ is the vector of returns on the stock (sector or market) index and the oil price index respectively. Φ refers to a (2×2) matrix of coefficients of the form $\Phi = \begin{pmatrix} \phi_1 & 0 \\ 0 & \phi_2 \end{pmatrix}$. $\varepsilon_t = (\varepsilon_t^S, \varepsilon_t^O)'$ is the vector of the error terms of the conditional mean equations for stock and oil returns respectively.

$\eta_t = (\eta_t^s, \eta_t^o)'$ refers to a sequence of independently and identically distributed (*i.i.d*) random errors; and $H_t = \begin{pmatrix} h_t^S & h_t^{SO} \\ h_t^{SO} & h_t^O \end{pmatrix}$ is the matrix of conditional variances of stock and oil returns. h_t^S, h_t^O and h_t^{SO} are specified as follows:

$$h_t^S = C_S^2 + \beta_{S1}^2 \times h_{t-1}^S + \alpha_{S1}^2 \times \left(\varepsilon_{t-1}^S\right)^2 + \beta_{S2}^2 \times h_{t-1}^O + \alpha_{S1}^2 \times \left(\varepsilon_{t-1}^O\right)^2 \tag{2}$$

$$h_t^O = C_O^2 + \beta_{O1}^2 \times h_{t-1}^O + \alpha_{O1}^2 \times \left(\varepsilon_{t-1}^O\right)^2 + \beta_{O2}^2 \times h_{t-1}^S + \alpha_{O1}^2 \times \left(\varepsilon_{t-1}^S\right)^2 \tag{3}$$

Obviously, Eqs. (2) And (3) assume that negative and positive shocks of equal magnitude have identical effects on conditional variances. The volatility transmission across the oil and stock markets over time is governed through the cross values of error terms, $(\varepsilon_{t-1}^O)^2$ and $(\varepsilon_{t-1}^S)^2$, which capture the impact of direct effects of shock transmission, as well as those of lagged conditional volatilities, h_{t-1}^O and h_{t-1}^S, which directly accounts for the transfer of risk between markets. To guarantee stationarity, the roots of the equation $|I_2 - AL - BL| = 0$ must be outside the unit circle, where L is a lag polynomial, I_2 is a (2×2) identity matrix, and

$$A = \begin{pmatrix} \alpha_{S1}^2 & \alpha_{S2}^2 \\ \alpha_{O2}^2 & \alpha_{O1}^2 \end{pmatrix} \text{ and } B = \begin{pmatrix} \beta_{S1}^2 & \beta_{S2}^2 \\ \beta_{O2}^2 & \beta_{O1}^2 \end{pmatrix}$$

Let ρ be the constant conditional correlation; the conditional covariance between stock and oil returns is modeled as:

$$h_t^{SO} = \rho \times \sqrt{h_t^S} \times \sqrt{h_t^O} \tag{4}$$

As specified previously, our empirical model simultaneously allows long-run volatility persistence as well as shock and volatility transmissions between the oil and stock markets under consideration. Of course, the assumption of constant conditional correlation may be viewed as restrictive given changing economic conditions, but the statistical properties of a VAR-GARCH model accounting for dynamic conditional correlations have not yet been analyzed theoretically. The parameters of the above bivariate model are obtained by quasi-maximum likelihood estimation (QMLE), which is robust to any departure from normality conditions (Ling and McAleer, 2003).

2.2. Bivariate AR(1)-GARCH(1,1) models

Let us define here again the vector of the returns on stock (sector or market) index and oil price index, $R_t = (r_t^S, r_t^O)'$, and let $H_t = [h_t^{ij}], i,j = S,O$ be the conditional variance-covariance matrix of the returns which follows a bivariate GARCH(1,1) process, the conditional mean of the bivariate AR(1)-GARCH(1,1) can be specified as:

$$\begin{cases} R_t = \mu + \Phi R_{t-1} + \varepsilon_t \\ \varepsilon_t = H_t^{1/2} \eta_t \end{cases} \tag{5}$$

where $H_t^{1/2}$ is a (2×2) symmetric positive definite matrix and $\eta_t = (\eta_t^s, \eta_t^o)'$ is the vector of *i.i.d.* random errors with $E(\eta_t) = 0$ and $Var(\eta_t) = I_N$. The matrix of coefficients in the mean equations is defined as in the VAR-GARCH model, i.e., $\Phi = \begin{pmatrix} \phi_1 & 0 \\ 0 & \phi_2 \end{pmatrix}$, to permit the comparison across the benchmark and competing models. Different specifications for H_t thus lead to different multivariate GARCH-type models.

The diagonal BEKK-GARCH(1,1) of Engle and Kroner (1995), in which the parameters of the covariance equations (h_t^{ij}, $i \neq j$) are the products of the parameters of the variance equations (h_t^{ii}), is defined as follows:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B \tag{6}$$

where C, A, and B are (2×2) matrices of parameters, C is upper triangular, and A and B are diagonal. Accordingly, the conditional variance and covariance processes take the following forms:

$$\begin{cases} h_t^S = C_S + \alpha_S^2 \left(\varepsilon_{t-1}^S\right)^2 + \beta_S^2 h_{t-1}^S \\ h_t^O = C_O + \alpha_O^2 \left(\varepsilon_{t-1}^O\right)^2 + \beta_O^2 h_{t-1}^O \\ h_t^{SO} = C_{SO} + \alpha_S \alpha_O \varepsilon_{t-1}^S \varepsilon_{t-1}^O + \beta_S \beta_O h_{t-1}^{SO} \end{cases} \tag{7}$$

where h_t^s and h_t^o are the conditional variances of r_t^S and r_t^O. Eq. (7) thus shows that direct volatility transmission between oil and stock returns is not possible since the conditional volatility of each market depends only on its own shocks and its long-run persistence. This volatility model is covariance stationary when $\alpha_S^2 + \beta_S^2 < 1$, $\alpha_O^2 + \beta_O^2 < 1$ and $|\alpha_S \alpha_O + \beta_S \beta_O| < 1$.

We now shift our attention to another class of GARCH processes that model the conditional correlations rather than the conditional covariance matrix H_t. The economic rationale for doing so is to obtain the intuitive and meaningful interpretations of the correlation coefficients. The most well known and commonly used specifications are the CCC-GARCH of Bollerslev (1990) and the DCC-GARCH of Engle (2002).

As to our research problem, the bivariate CCC-GARCH(1,1) is defined as follows:

$$H_t = D_t P D_t \tag{8}$$

where $D_t = \text{diag}(\sqrt{h_t^S}, \sqrt{h_t^O})$, and $P = (\rho_{ij})$ is the (2×2) matrix containing the constant conditional correlations ρ_{ij} with$\rho_{ii} = 1, \ \ \forall i = S, O$. The conditional variances and covariance are given by

$$\begin{cases} h_t^S = C_S + \alpha_S \left(\varepsilon_{t-1}^S\right)^2 + \beta_S h_{t-1}^S \\ h_t^O = C_O + \alpha_O \left(\varepsilon_{t-1}^O\right)^2 + \beta_O h_{t-1}^O \\ h_t^{SO} = \rho \sqrt{h_t^S h_t^O} \end{cases} \tag{9}$$

Bollerslev (1990) shows that the positiveness of the ARCH and GARCH coefficients is not necessary to get a positive definite matrix P. This process is covariance stationary when the roots of $\det(I_2 - \lambda A - \lambda B) = 0$ are outside the unit circle of the complex plan, where I_2 is a (2×2) identity matrix and

$$A = \begin{pmatrix} \alpha_S & 0 \\ 0 & \alpha_O \end{pmatrix} \text{ and } B = \begin{pmatrix} \beta_S & 0 \\ 0 & \beta_O \end{pmatrix}$$

The DCC-GARCH(1,1) of Engle (2002) remedies the restrictive assumption of the constant conditional correlations by allowing the conditional correlation matrix to vary over time. That is,

$$P_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{10}$$

where the (2×2) symmetric positive definite matrix $Q_t = (q_t^{ij})$ is given by:

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha \eta_{t-1} \eta_{t-1}' + \beta Q_{t-1} \tag{11}$$

In Eq. (11), α and β are non-negative scalars such that $\alpha + \beta < 1$, $\overline{Q}$ is the (2×2) matrix of unconditional correlations of the standardized errors η_t. The conditional variances are specified as univariate GARCH(1,1) processes, similar to those of the CCC-GARCH model. Engle (2002) indicates that specifying dynamic conditional correlation structure is no obstacle to model estimation.

On the whole, compared to the VAR-GARCH model, the bivariate GARCH models presented above do not explicitly allow for the cross-sectional dependency of conditional volatilities between oil and stock markets.

3. Data and preliminary analysis

Our sample data for the equity segments cover seven industrial sectors in Europe (Dow Jones Stoxx 600 sector indices) and the United States (S&P sector indices): *Automobile & Parts*, *Financials*, *Industrials*, *Basic Materials*, *Technology*, *Telecommunications*, and *Utilities*. Two market-wide indices, the Dow Jones (DJ) Stoxx Europe 600 index and the S&P 500 index, are also included to compare the empirical results across sector and market levels. All stock market data are gathered from the Datastream International database.

The S&P 500 index has been widely viewed as the best single benchmark of the US stock markets since its release in 1957. The index is actually broken down into ten sectors according to the global industry classification standard (GICS). The DJ Stoxx Europe 600 index is derived from the DJ Stoxx Europe Total Market Index (TMI) and measures the performance of 600 large-, medium- and small-capitalization companies in eighteen European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The DJ Stoxx 600 sector indices, for their part, were introduced in 1998 and provide investors information on the performance of the 600 largest European companies in each of the most important industries. By design, the sector indices offer an alternative view of the performance of the European and US stock markets.

For the crude oil market, we use the Brent crude oil price, taken from the Energy Information Administration (EIA) database. Brent crude is sourced from the North Sea, usually refined in northwestern Europe, and currently used to price about two-thirds of the world's internationally traded crude oil.

As suggested by Arouri and Nguyen (2010), weekly data are used in this study since they appear to capture the interaction of oil and stock prices. The use of weekly data in the analysis also makes it possible to counter potential biases that may arise from using daily data (e.g., the bid-ask effect and non-synchronous trading days) and monthly data (e.g., time aggregation and strong compensation effects for the positive and negative shocks). By considering the sample period from January 01, 1998, to December 31, 2009, we can examine the sensitivity of European and US sector returns to the recent oil price boom following the 1997–1998 Asian financial crisis. As usual, stock market, sector, and oil returns are computed by taking the natural log of the ratio between two successive prices. Note finally that all data are expressed in euro inasmuch as our primary focus is on Europe where the links between oil prices and European sector returns have received only little attention. The euro/dollar exchange rate from the Datastream International database was used to perform any conversion to euro.

Table 1 shows selected descriptive statistics for log return series we have previously calculated. The crude oil market experienced higher returns than both European and US equity segments over our study period. European equity sectors appeared to perform better than those in the United States. *Basic Materials* has the highest sector returns in Europe (0.14%); the best performing sector for the United States is *Technology* (0.03%). Two sectors in Europe (*Financials* and *Technology*) and five in the United States post negative average returns (*Automobile & Parts*, *Financials*, *Industrials*, *Telecommunications*, and *Utilities*). One possible explanation for the worse performance of the US sectors is the more severe effect of the 2007–2009 global financial crisis on the US economy.

Oil returns, however, post the second-highest volatility (4.77%), just after the European *Technology* sector (4.93%) and US *Automobile & Parts*. Skewness coefficients are negative for all cases, except for the European *Automobile & Parts* sector. Kurtosis coefficients are significantly greater than three. These findings indicate that the distributions of almost all return series are typically asymmetric, and that the probability of observing large negative returns is higher than that of a normal distribution. As a result, the Jarque–Bera test statistics (JB) clearly confirm the rejection of the null hypothesis of normality for all return series. Results from the Ljung–Box (LB) test indicate the presence of serial correlations for eleven of seventeen return series. Finally, we find strong evidence of ARCH effects for all series considered, which thus supports our decision to employ a GARCH modeling approach to examining volatility transmission between oil and stock markets.

We also compute the unconditional correlation of equity and oil returns. It varies substantially across industries: from 0.06 (*Automobile & Parts*) to 0.19 (*Basic Materials*) for Europe and from 0.02 (*Financials* and *Telecommunications*) to 0.11 (*Basics Materials* and *Technology*) for the United States. On average, however, the values are weak and surprisingly positive. This finding suggests that oil price increases over the last decade may be indicative of higher expected economic growth and corporate earnings. The correlation of returns on the DJ Stoxx Europe 600, the S&P 500 index, and sector indices, shown in the last column of Table 1, is positive and relatively high, findings that suggest, in theory, that there is little short- or long-term benefit to diversifying over industry sectors.

Table 1
Descriptive statistics of return series.

Europe	Mean (%)	Std. dev. (%)	Skew.	Kurt.	JB	ARCH	LB	Corr. with Oil	Corr. with DJ Stoxx
Brent	0.25	4.77	−0.40	4.81	101.9^{+++}	21.45^{+++}	38.23^{+++}	1.00	0.16
DJ Stoxx Europe 600	0.01	2.67	−0.59	5.82	243.8^{+++}	75.56^{+++}	10.34^{+}	0.16	1.00
Automobile & Parts	0.02	4.54	0.34	15.39	4019.5^{+++}	145.45^{+++}	11.45^{+}	0.06	0.69
Financials	−0.04	3.69	−0.62	7.60	593.2^{+++}	156.56^{+++}	9.34	0.12	0.91
Industrials	0.03	3.07	−0.51	6.61	368.5^{+++}	78.56^{+++}	12.45^{++}	0.15	0.91
Basic Materials	0.14	3.64	−0.72	6.90	452.3^{+++}	156.67^{+++}	7.56	0.19	0.79
Technology	−0.07	4.93	−0.24	4.78	89.3^{+++}	78.67^{+++}	13.59^{++}	0.10	0.80
Telecommunications	0.01	3.53	−0.09	4.11	33.1^{+++}	78.56^{+++}	15.45^{++}	0.07	0.72
Utilities	0.07	2.37	−1.37	10.62	1713.3^{+++}	27.74^{+++}	3.99	0.13	0.73

United States	Mean (%)	Std. dev.	Skew.	Kurt.	JB	ARCH	LB	Corr. with Oil	Corr. with S&P 500
Brent	0.25	4.77	−0.40	4.81	101.9^{+++}	21.45^{+++}	38.23^{+++}	1.00	0.16
S&P 500	0.02	2.20	−0.82	8.38	826.2^{+++}	61.08^{+++}	21.60^{+++}	0.16	1.00
Automobile & Parts	−0.16	5.04	−0.37	9.90	1256.4^{+++}	54.74^{+++}	14.39^{++}	0.10	0.65
Financials	−0.11	4.73	−0.99	16.71	5005.8^{+++}	138.31^{+++}	54.10^{+++}	0.02	0.69
Industrials	−0.02	3.40	−0.70	7.94	687.9^{+++}	50.84^{+++}	3.68	0.03	0.71
Basic Materials	0.01	3.58	−0.55	8.53	828.4^{+++}	70.78^{+++}	13.49^{++}	0.11	0.61
Technology	0.03	4.77	−0.60	4.69	111.5^{+++}	58.75^{+++}	6.17	0.11	0.64
Telecommunications	−0.12	3.73	−0.62	7.69	614.2^{+++}	47.66^{+++}	11.42^{+}	0.02	0.55
Utilities	−0.03	3.09	−0.76	7.13	505.1^{+++}	56.43^{+++}	4.16	0.05	0.44

The table reports the basic statistics of return series, including mean (Mean), standard deviations (Std. dev.), skewness (Skew.), and kurtosis (Kurt.). ARCH refers to the empirical statistics of the statistical test for conditional heteroscedasticity of order six. LB are the empirical statistics of the Ljung–Box tests for autocorrelations of order six applied to raw return series. JB are the empirical statistics of the Jarque–Bera test for normality based on skewness and excess kurtosis. Corr. refers to the correlation coefficients. $^{+}$, $^{++}$, and $^{+++}$ indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5%, and 1% levels respectively.

4. Results and portfolio implications

In this section we first present the empirical results from estimating our bivariate VAR(1)-GARCH(1,1) model for all pairs of oil and stock market (sector) returns in Europe and the United States. We discuss the extent of volatility transmission. The competing models (CCC-, DCC-, and diagonal BEKK-GARCH) are also estimated, but the results are not shown here.[2] We then show how estimation results of all models considered can be used to compute the optimal weights and hedge ratios of an oil-stock portfolio. Finally, we empirically compare the diversification and hedging effectiveness across models in order to assess the real ability of the VAR(1)-GARCH(1,1) specification to model and forecast volatility transmission between oil and stock market sectors.

4.1. Volatility cross effects in oil and stock markets

Tables 2 and 3 show the estimation results of our bivariate VAR(1)-GARCH(1,1) model for the eight pairs of oil-stock market returns in Europe and the United States, together with statistical tests applied to standardized residuals. Taking a close look at mean equations for both regions, we find that the one-period lagged oil returns, denoted by AR(1) coefficients, significantly affect current oil returns in all cases. This finding thus indicates some evidence of short-term predictability in oil price changes through time and reinforces the conclusion of some recent papers, according to which the weak-form informational efficiency of international oil markets is rejected most of the time (Shambora and Rossiter, 2007; Elder and Serletis, 2008; Arouri et al., 2010). On the contrary, none of the autoregressive terms in the return-generating process for stock markets is significantly different from zero, except for the US aggregate stock market index (S&P 500), where we find evidence of return

[2] They are, however, available on request.

Table 2
Estimates of VAR(1)-GARCH(1) model for oil and stock sectors in Europe.

Variables	DJ Stoxx Europe 600		Automobile and parts		Basic materials		Financials		Industrials		Technology		Tele-communications		Utilities	
	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock
Conditional mean equation																
Constant	0.0046^{a}	0.0020^{b}	0.0027	0.0030^{b}	0.0047^{a}	0.0027^{b}	0.0044^{b}	0.0023^{b}	0.0033^{b}	0.0033^{a}	0.0041^{b}	0.0019	0.0035^{b}	0.0014	0.0041^{b}	0.0020^{b}
AR(1)	0.2254^{a}	−0.0455	0.2307^{a}	−0.0560	0.2290^{a}	0.0131	0.2306^{a}	−0.0572	0.2265^{a}	−0.0292	0.2179^{a}	−0.0299	0.2235^{a}	−0.0611	0.2136^{a}	0.0199
Conditional variance equation																
Constant	9.84E-5^{c}	4.81E-5^{b}	7.45E-5	−1.81E-6	0.0001^{b}	0.0001^{b}	1.35E-4^{b}	5.58E-5^{a}	0.0001	0.0001^{b}	6.48E-5	7.42E-5^{b}	6.41E-5	2.59E-5^{a}	6.51E-5^{b}	2.83E-5
$(\varepsilon^{S}_{t-1})^2$	0.0390	0.1358^{a}	−0.0171	0.2510^{a}	0.0412	0.1923^{a}	0.0560^{b}	0.1614^{a}	0.0094	0.1515^{a}	−0.0025	0.1172^{a}	−0.0255	0.0596^{a}	0.0909^{a}	0.1269^{a}
$(\varepsilon^{O}_{t-1})^2$	0.0376^{c}	0.0564^{a}	0.0389^{a}	−0.0293	0.0419^{b}	0.0970^{a}	0.0373^{b}	0.0857^{a}	0.0492^{b}	0.0470^{c}	0.0531^{b}	0.0497^{b}	0.0586^{a}	0.0247^{b}	0.0163^{c}	0.0653^{a}
h^{S}_{t-1}	0.5729	0.7923^{a}	7.5368	0.2531	0.1441	0.7173^{a}	37.5959	0.7924^{a}	0.6478	0.8042^{a}	0.6984	0.9239^{a}	2.0470	0.9620^{a}	−0.7458	0.6168^{a}
h^{O}_{t-1}	0.8777^{a}	−0.0675	0.7994^{a}	2.4053	0.8908^{a}	−0.4044	0.8780^{a}	−3.5215	0.8425^{a}	−0.5150	0.8689^{a}	−1.2407	0.8517^{a}	−0.9019	0.9774^{a}	1.1696
JB	60.55^{+++}	100.97^{+++}	49.92^{+++}	155.10^{+++}	68.10^{+++}	151.38^{+++}	37.71^{+++}	96.46^{+++}	67.10^{+++}	128.78^{+++}	34.91^{+++}	20.83^{+++}	33.05^{+++}	5.29^{+}	74.60^{+++}	78.63^{+++}
ARCH(12)	7.47	17.21	8.58	5.62	6.70	6.37	5.25	17.52	6.30	11.67	7.00	15.20	5.93	9.09	6.98	5.08
LB(12)	21.78^{++}	10.02	7.50	6.37	22.57^{++}	7.61	22.02^{++}	6.73	22.07^{++}	18.06	21.09^{++}	16.43	20.91^{+}	16.53	22.74^{++}	7.84
$LB^2(12)$	8.96	14.59	10.16	21.70^{++}	7.90	6.29	6.48	15.34	7.64	10.95	14.28	7.76	6.59	8.57	7.96	5.63
CCC	0.1031^{b}		0.0190		0.0984^{b}		0.0004		0.1170^{a}		0.0640		0.0404		0.0843^{b}	
AIC	−7.9731		−7.6789		−7.6789		−7.5213		−7.3394		−6.7930		−7.4366		−8.1795	

Oil, stock, and CCC are oil price returns, stock market (sector) returns, and conditional constant correlation respectively. The superscripts a, b, and c indicate significance at 1%, 5%, and 10% respectively. The AIC criterion measures the relative goodness of fit of the estimated model. JB, ARCH(12), LB(12), and $LB^2(12)$ refer to the empirical statistics of the Jarque–Bera test for normality based on skewness and excess kurtosis, the Engle (1982) test for conditional heteroscedasticity of order 12, and the Ljung–Box tests for autocorrelations of order 12 applied to standardized residuals in levels and squared standardized residuals respectively. $^{+}$, $^{++}$, and $^{+++}$ indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5%, and 1% levels respectively.

Table 3
Estimates of VAR(1)-GARCH(1) model for oil and stock sectors in the United States.

Variables	S&P 500 index		Automobile and parts		Basic materials		Financials		Industrials		Technology		Telecommunications		Utilities	
	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock
Conditional mean equation																
Constant	0.0034^{b}	0.0016	0.0030^{c}	0.0010	0.0028	0.0015	0.0030c	0.0002	0.0030	0.0011	0.0039^{b}	0.0012	0.0035^{b}	0.0005	0.0035^{c}	0.0012
AR(1)	0.2678^{a}	0.1289^{a}	0.2301^{a}	−0.0199	0.2248^{a}	−0.0460	0.2291^{a}	−0.0627	0.2160^{a}	0.0128	0.2187^{a}	−0.0240	0.2287^{a}	−0.0554	0.2342^{a}	−0.0023
Conditional variance equation																
Constant	7.91E-4^{a}	1.35E-5^{b}	6.49E-4^{a}	9.75E-4^{a}	0.0004^{b}	0.0002	1.08E-3^{b}	−6.06E-5^{c}	0.0001^{b}	7.94 E−5	7.83E-5^{c}	7.33E-5^{a}	6.33E-5^{b}	8.97E-6	0.0007^{a}	5.46E-5^{b}
$(\varepsilon^{S}_{t-1})^2$	0.1506^{a}	0.1374^{a}	0.1023^{a}	0.0588^{a}	0.0122	0.1226^{a}	0.1171^{a}	0.1305^{a}	0.0679^{a}	0.2495^{a}	0.0044	0.0713^{a}	−0.0367	0.0919^{a}	0.1579^{a}	0.1510^{a}
$(\varepsilon^{O}_{t-1})^2$	0.0849^{a}	0.0460^{a}	0.0767^{a}	0.0702^{b}	0.0604^{a}	−0.0355^{b}	0.0981^{b}	0.0113^{b}	0.0791^{a}	−0.0207	0.0637^{a}	0.0517^{a}	0.0838^{a}	0.0073^{b}	0.1182^{a}	0.0003
h^{S}_{t-1}	0.0473	0.8345^{a}	0.8492	0.7442^{a}	0.7575	0.8350^{a}	−1.4828	0.7355^{a}	−0.5152	0.3790^{b}	0.8533	0.9772^{a}	−1.2280	0.8812^{a}	−0.5732	0.6181^{a}
h^{O}_{t-1}	0.7219^{a}	−0.0187	0.6886^{a}	0.1725^{a}	0.7768^{b}	0.0751^{a}	0.7327^{a}	−2.3745	0.8060^{a}	−1.1361	0.7666^{a}	−0.8540	0.8118^{a}	−1.0765	0.7941^{a}	−0.0603^{b}
JB	44.29^{+++}	55.20^{+++}	46.40^{+++}	52.18^{+++}	48.28^{+++}	98.35^{+++}	44.19^{+++}	736.19^{+++}	48.10^{+++}	204.40^{+++}	38.00^{+++}	25.13^{+++}	41.94^{+++}	162.70^{+++}	38.00^{+++}	25.13^{+++}
ARCH(12)	7.85	11.16	5.78	9.45	7.89	10.36	6.58	15.86	6.80	3.80	6.50	19.22^{+}	7.44	10.07	6.50	19.22^{+}
LB(12)	25.40^{++}	11.10	25.81^{++}	18.16	22.19^{++}	4.89	24.47^{++}	9.14	21.27^{++}	4.85	20.88^{+}	7.55	20.91^{+}	5.61	20.88^{+}	7.55
$LB^2(12)$	9.36	2.57	13.71	9.15	14.56	11.15	9.31	16.40	12.48	4.08	7.04	18.88^{+}	8.45	10.85	7.04	18.88^{+}
CCC	0.0707^{c}		0.0607^{a}		0.0759^{a}		−0.0738^{c}		−0.0499		0.0495		−0.0198		−0.0420	
AIC	−8.4809		−6.7729		−7.6789		−7.1288		−7.3394		−6.8808		−7.2577		−7.6747	

Oil, stock, and CCC are oil price returns, stock market (sector) returns, and conditional constant correlation respectively. The superscripts a, b, and c indicate significance at 1%, 5%, and 10% respectively. The AIC criterion measures the relative goodness of fit of the estimated model. JB, ARCH(12), LB(12), and $LB^2(12)$ refer to the empirical statistics of the Jarque–Bera test for normality based on skewness and excess kurtosis, the Engle (1982) test for conditional heteroscedasticity of order 12, and the Ljung–Box tests for autocorrelations of order 12 applied to standardized residuals in levels and squared standardized residuals respectively. $^{+}$, $^{++}$, and $^{+++}$ indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5%, and 1% levels respectively.

predictability at the 1% level. This finding suggests that in almost all cases past realizations of stock returns do not help predict stock returns.

As for the estimates of ARCH and GARCH coefficients, which capture shock dependence and volatility persistence in the conditional variance equations, common patterns are observed for both Europe and the United States. Indeed, these coefficients are highly significant in most cases. The volatility sensitivity to past own conditional volatility (GARCH terms) is significant for all oil and stock return series at the 1% level, except for *Automobile & Parts*, for which an ARCH(1) model seems to be more appropriate. In addition, the statistical significance of the coefficients related to ARCH terms suggests that changes in the current conditional volatility of both oil and stock returns depend on past own shocks affecting return dynamics (i.e., $(\varepsilon^O_{t-1})^2$ and $(\varepsilon^S_{t-1})^2$) as well. At the same time, dependence is stronger for sector stock returns, especially for Europe.

In general, the estimated conditional volatility series do not change very rapidly under the impulsion of return innovations given the small size of ARCH coefficients. They tend instead to evolve gradually over time with respect to substantial effects of past volatility, as indicated by the large values of GARCH coefficients. Accordingly, investors and fund managers seeking profit from trading oil assets and equity sectors of both regions may consider active investment strategies based on volatility persistence and current market trends. It would be advisable, for example, to increase the portfolio investment if markets are actually rising and to decrease it if they are falling, all while keeping in mind that the viability of such strategies depends on the stability and the strength of performance between successive periods.

Regarding the extent of volatility transmission between oil and stock markets in Europe and the United States, the results show that in the aggregate the conditional volatility of the returns on the DJ Stoxx Europe 600 index is significantly affected by unexpected changes in the Brent oil market, $(\varepsilon^O_{t-1})^2$. An oil shock, regardless of its sign, thus implies an increase in the volatility of European stock markets. On the other hand, oil's past volatility, represented by h^O_{t-1}, has no significant effects on stock markets. As for the opposite direction, the impact of past changes (shock and volatility) in the European stock market (i.e., $(\varepsilon^S_{t-1})^2$ and h^S_{t-1}) on the conditional volatility of oil market is statistically insignificant. The results for the oil and S&P 500 index pair are broadly similar to those for the DJ Stoxx Europe 600 index because past oil shocks account for changes in the volatility of US stock markets; at the same time there is no evidence to suggest that there are cross effects of conditional volatility between oil and US markets. A difference is however observed in that oil price volatility responds significantly to unexpected shocks affecting US stock market returns.

The results for stock sectors offer many interesting insights. In general, past volatility of stock returns does not significantly affect the current volatility of the oil market in all cases, leading us to conclude that there are no long-term volatility cross effects. The one-period lagged return shocks of only two sectors in Europe (*Financials* and *Utilities*), but four sectors in the United States (*Automobile & Parts*, *Financials*, *Industrials*, and *Utilities*), generate significant influences on oil market volatility. In addition, past oil shocks tend to raise stock sector volatility for all but the *Automobile & Parts* sector in Europe and *Industrials* and *Utilities* in the United States. *Basic Materials* (Europe) and *Automobile & Parts* (United States) experienced the largest response to oil shocks, whereas for both regions the smallest response is found in *Telecommunications*. Nor do we find any spillover from changes in oil market volatility to the European stock sectors under consideration, whereas the volatility of three stock sectors in the US is highly sensitive to past oil volatility (*Automobile & Parts*, *Basic Materials*, and *Utilities*). Finally, the effects of past oil shocks on stock sector volatility are only moderate because the associated coefficients are much smaller than those related to past own shocks and volatility. In what follows, as it happens, we shed light on the volatility interaction for each stock sector.

The European *Automobile & Parts* sector and the oil markets experience no significant direct cross-volatility effects. Their conditional volatility depends only on own past return innovations and own past volatility. The results for the US *Automobile & Parts* sector are completely different: significant bilateral volatility spillover is observed. In fact, past oil shocks and volatility are found to drive volatility changes in stock sectors, whereas unexpected changes in sector returns influence oil volatility. There are two possible reasons for these findings. First, the specificity of European legislation, which encourages more fuel-efficient vehicles, as well as government aid to the automobile industry during the recent crisis, plays an important role in reducing the sensitivity of this sector to oil shocks (Cameron and Schulenburg, 2009). Moreover, companies operating in the *Automobile & Parts* industry in Europe may manage oil risk more effectively than their counterparts in the United States, although they have somewhat similar exposure to oil price fluctuations.

The results for oil and basic materials models in Europe and the United States are similar in that there is evidence that one-period lagged oil market news makes a significant impact on the conditional volatility of *Basic Materials* stocks at least at the 5% level and that spillover effects in the opposite direction are insignificant. An apparent difference observed between the two regions is the significant increase in the volatility of the US *Basic Materials* sector with respect to changes in past oil volatility. The relatively heavy use of oil in the *Basic Materials* sector is, in our opinion, a key determinant of the oil effects. Indeed, the rise in oil prices may intensify the sector return volatility through changes in the oil supply for this industry as well as consumer demand for its manufactured products. To minimize the unfavorable impact of rising oil prices, an effective hedging strategy is thus of great interest.

For the oil-financials sector model, we essentially find bidirectional shock transmissions for both regions. In Europe, this spillover is significant at the 1% level from oil markets to *Financials* in Europe, and at the 5% in the opposite way. In the United States, the impact from oil market on *Financials* sector is significant at the 5% level, and the spillover in the reverse direction is significant at the 1% level. This result is expected, as rising oil prices are likely to strongly influence consumer and investor sentiment, and consequently their appetite for financial products. The appreciation of *Financials* stocks reflects, on the other hand, greater oil consumption resulting from increasing production.

The results for the oil-industrials model reveal only a volatility reaction of European *Industrials* sector to unexpected changes in oil returns, significant at the 10% level. The same impact is insignificant for US *Industrials*. Changes in the US *Industrials* sector returns, however, exerts a significant impact on oil volatility. On the whole, the findings for oil market effects are somewhat surprising because the *Industrials* sector of the stock markets is a heavy user of petroleum and related products. Our results are indeed consistent with those of Malik and Ewing (2009), who focus only on the United States and find no evidence that oil makes an impact on *Industrials*. As these authors note, the development of effective hedges against the effects of oil price changes is the most likely explanation of their findings.

The VAR(1)-GARCH(1,1) models display similar results of volatility transmission for the *Technology* and the *Telecommunications* sectors in Europe and the United States. They indicate significant spillover only from oil to stock sector volatility. We think that this link is primarily the result of the direct impact of oil price fluctuations on uncertainty over demand for the products of companies in *Technology* and *Telecommunications* sectors. For example, oil price increases may give incentives to the development of new technologies or new energy sources, depressing the market performance of *Technology* and *Telecommunications* firms and making their stocks riskier.

The oil-utilities sector models for Europe and the US show significant transmission of volatility sparked by cross innovations effects. Oil return volatility varies significantly at the 1% level only when US *Utilities* sector returns increase unexpectedly. These facts are not surprising because the *Utilities* industry contains mainly electricity and water firms, and integrated providers that use petroleum-related products as an input.

Turning to the estimates of constant conditional correlations (CCC), we find that sector returns in Europe are all positively correlated with oil returns, but they are weak in general. The CCC estimates are significant in three out of seven cases (*Basic Materials*, *Industrials*, and *Utilities*). US sector returns are negatively correlated with oil returns in four out of seven cases, but negative CCC estimates are significant in only one (*Financials*). The two other sectors positively and significantly correlated with oil returns are *Automobile & Parts*, and *Basic Materials*. As in Europe, oil and US sector return correlations are very weak. In view of these results, one may expect substantial gains from investing in both stock sectors and oil assets. It is obvious, however, that the significant volatility cross effects we show previously require portfolio managers to quantify the optimal weights and hedging ratios to deal properly with oil risk.

Lastly, the results of diagnostic tests based on standardized residuals ($\varepsilon_t^s = H_t^{-1/2}\varepsilon_t$) are shown in Tables 2 and 3. We find that departure from normality and autocorrelation are greatly reduced than they are in Table 1 which report statistical properties of raw returns. More importantly, there are no ARCH effects. Therefore, the bivariate VAR(1)-GARCH (1,1) model we use is flexible enough to capture the dynamics of oil and stock returns for both Europe and the United States.

In summary, our results point to the existence of widespread direct spillover of volatility between oil and stock sector returns whatever the region considered. The volatility cross effects run only from oil to stock sectors in Europe, whereas bilateral spillover effects are found in the United States. Moreover, the intensity of "oil to stock" volatility transmission varies from one industry to another, variation that confirms our intuition that the degree with which stock sector returns are sensitive to oil volatility (risk) depends on several industry-specific factors such as the degree of oil consumption, competition and concentration in the industry, and the effectiveness of hedging oil risk. Oil-related products, for example, closely linked to oil price movements, have a direct impact on sectors such as *Industrials* and *Utilities*. Oil price changes may also have indirect effects on such sectors as *Financials*, which is sensitive to oil price increases, especially through the effects of these increases on monetary and fiscal policies, investor sentiment, employment, and consumer confidence. Obviously, oil price changes and how the oil shocks spillover into industrial sectors are particularly important for better forecasting stock market volatility and making appropriate capital budgeting decisions.

4.2. Optimal portfolio designs and hedging ratios in the presence of oil assets

The subsection 4.1 shows that the volatility spillover between oil and stock sectors is fairly similar for the Europe and the United States, but the sensitivity to oil shocks differs across stock sectors. Investors in some stock sectors (*Automobile & Parts*, *Financials*, and *Utilities* in the United States) may need to hedge oil risk more effectively than they have to if they hold stocks of companies in other sectors.

To illustrate the implications of our findings on optimal portfolio design and oil risk hedging, we consider a hedged portfolio of oil and stocks in which an investor attempts to hedge exposure to crude oil price movements. The investor's objective is then to minimize risk of his oil-stock portfolio without reducing its expected returns. Let h_t^O, h_t^S, and h_t^{so} be respectively the conditional volatility of the oil market, the conditional volatility of the stock market (sector), and the conditional covariance between oil and stock returns at time t, all estimated from our benchmark bivariate VAR(1)-GARCH(1,1) model and three alternative bivariate AR(1)-GARCH(1,1) models–the optimal holding weight of oil in a one-dollar portfolio of crude oil/stock sector at time t, according to Kroner and Ng (1998), is given by

$$w_t^{SO} = \frac{h_t^S - h_t^{SO}}{h_t^O - 2h_t^{SO} + h_t^S} \tag{12}$$

under the condition that

$$w_t^{SO} = \begin{cases} 0, & if \ \ w_t^{SO} < 0 \\ w_t^{SO}, & if \ \ 0 \le w_t^{SO} \le 1 \\ 1, & if \ \ w_t^{SO} > 1 \end{cases}$$

By design, the weight of the stock market (sector) index in the oil-stock portfolio is equal to $(1 - w_t^{SO})$. Alternative GARCH-type models we consider include the CCC-, DCC-, and diagonal BEKK-GARCH(1,1), presented in Section 2. Considering them enables us to discuss the empirical results in terms of optimal weights and hedging ratios from a comparative perspective. We also have the possibility to compare the performance across models used in terms of diversification and hedging effectiveness in the next subsection.

As to the optimal hedge ratios, Kroner and Sultan (1993) consider a two-asset portfolio, equivalent to a portfolio composed of oil and the stock market (sector) index in our study. To minimize the risk of this hedged portfolio, a long position of one-dollar on the stock segment must be hedged by a short position of β_t^{SO} dollars on the oil asset, where β_t^{SO} is given by

$$\beta_t^{SO} = \frac{h_t^{SO}}{h_t^O} \tag{13}$$

We report in Table 4 the average values of realized optimal weights w_t^{SO} and hedge ratios β_t^{SO}. A glance at the coefficients shows that the optimal weights for the oil asset in the hedged portfolios vary

Table 4
Optimal portfolio weights and hedge ratios for pairs of oil and stock sectors.

Portfolio	Europe				United States			
	VAR-GARCH	BEKK-GARCH	DCC-GARCH	CCC-GARCH	VAR-GARCH	BEKK-GARCH	DCC-GARCH	CCC-GARCH
DJ Stoxx Europe 600/oil								
w_t^{SO}	0.205	0.201	0.202	0.204				
β_t^{SO}	0.201	0.174	0.194	0.223				
S&P 500 index/oil								
w_t^{SO}					0.149	0.138	0.142	0.145
β_t^{SO}					0.184	0.142	0.155	0.199
Automobile & Parts/oil								
w_t^{SO}	0.418	0.421	0.411	0.407	0.481	0.455	0.473	0.491
β_t^{SO}	0.025	0.019	0.027	0.021	0.064	0.049	0.055	0.053
Basic Materials/oil								
w_t^{SO}	0.334	0.349	0.338	0.328	0.350	0.353	0.352	0.354
β_t^{SO}	0.160	0.122	0.163	0.181	0.102	0.086	0.098	0.081
Financials/oil								
w_t^{SO}	0.321	0.328	0.325	0.318	0.415	0.421	0.413	0.417
β_t^{SO}	0.001	0.005	0.009	0.002	0.095	0.109	0.084	0.109
Industrials/oil								
w_t^{SO}	0.263	0.278	0.226	0.295	0.334	0.319	0.338	0.315
β_t^{SO}	0.165	0.152	0.175	0.174	0.074	0.057	0.068	0.049
Technology/oil								
w_t^{SO}	0.481	0.483	0.478	0.480	0.454	0.464	0.470	0.457
β_t^{SO}	0.069	0.066	0.079	0.083	0.057	0.047	0.040	0.068
Telecommunications/oil								
w_t^{SO}	0.328	0.337	0.336	0.333	0.372	0.375	0.362	0.371
β_t^{SO}	0.062	0.066	0.046	0.063	0.022	0.024	0.025	0.027
Utilities/oil								
w_t^{SO}	0.173	0.193	0.180	0.181	0.286	0.283	0.280	0.291
β_t^{SO}	0.176	0.122	0.131	0.159	0.083	0.057	0.089	0.010

The table reports average optimal weight of oil and hedge ratios for an oil-stock portfolio using conditional variance and covariance estimated from four competitive volatility spillover models for each pair of oil/stock markets: VAR(1)-GARCH(1,1), BEKK-GARCH(1,1), DCC-GARCH(1,1), and CCC-GARCH(1,1). VAR(1)-GARCH(1,1) is our benchmark model. For all models considered, the conditional mean equations contain a constant term and an autoregressive component. The oil asset is represented by the Brent crude oil index, whereas investment in stocks is represented by the European-wide market index, the S&P 500, or each of seven stock sector indices in Europe and the United States.

substantially across sectors and markets (Europe and the United States), but they are only slightly different across models used. At the aggregate market level, we observe that, to maximize the risk-adjusted return of the same one-dollar oil-stock portfolio, US investors should hold, on average, fewer oil assets than their European counterparts. The optimal weight of oil suggested by our VAR-GARCH benchmark model is 20.5% for stock markets in Europe and 14.9% for those in the United States. This finding suggests that the oil risk is substantially greater for the United States than for Europe, and any change in the price of oil could lead to unfavorable effects on the performance of hedged portfolios. Comparatively, for both Europe and the United States, VAR-GARCH models point to the highest oil holding weights, followed by CCC-GARCH, DCC-GARCH, and diagonal BEKK-GARCH models.

By sector, the optimal weight for oil ranges from 17.3% (*Utilities*) to 48.1% (*Technology*) from VAR-GARCH models for European sector-based portfolios. This result suggests that for *Utilities* the optimal allocation for oil in a one-dollar oil-stock portfolio should be 17.3 cents, with the remainder, 86.3 cents, invested in the *Utilities* stock sector index. For *Technology*, these optimal investments are 48.1 cents for oil and 51.9 cents for stocks. Similar patterns are obtained from competing models with slight differences in the oil weights. The VAR-GARCH models for the United States reveal that the smallest weight for oil is 28.6% (*Utilities*), whereas the largest is 48.1% (*Automobile & Parts*). As in Europe, no significant difference in terms of optimal weights for oil is found across models. There is, for example, a high of 47.3% for *Automobile and Parts* and a low 28% for *Utilities* from the DCC-GARCH model.

On the whole, our results show that, to minimize the risk without lowering the expected return, investors in Europe and the US should have more stocks than oil in their portfolios.

A glance at the average optimal hedge ratios (β_t^{SO}), shown in Table 4, offers several insights for short hedgers. First, the low ratios suggest that stock investment risk can be hedged by taking a short position in oil markets or oil futures markets. The largest ratio, 0.223, is for the oil and DJ Stoxx Europe 600 pair from the CCC-GARCH model, meaning that one-dollar long (buy) in the European stock market index should be shorted (sell) by 22.3 cents of oil futures. Second, similar to the optimal weights, the optimal hedge ratios differ greatly across sectors, but for a particular sector they vary only slightly across models. For example, *Financials* in Europe has an optimal hedge ratio of 0.001, whereas that of *Utilities* is 0.176. Furthermore, the following hedge ratios of 0.176, 0.112, 0.131 and 0.159 are obtained for European *Utilities* from VAR-GARCH, diagonal BEKK-GARCH, DCC-GARCH, and CCC-GARCH respectively. These numbers thus mean that VAR-GARCH and CCC-GARCH models require more oil assets than the others to minimize the risk for investors with stock holdings in the *Utilities* sector. Finally, we identify three sectors in Europe with relatively higher hedge ratios and thus higher hedging costs (*Basic Materials*, *Industrials*, and *Utilities*), and two sectors in the United States (*Basic Materials* and *Financials*).

Taken together, our findings for optimal hedge ratios are consistent with the view that oil assets should be an integral part of a diversified portfolio of stocks and help increase the risk-adjusted performance of the hedged portfolio.

4.3. Diversification and hedging effectiveness

We now look into diversification and hedging effectiveness by actually running the portfolio simulations with our optimal portfolio designs and hedging ratios.[3] We use the estimates of four GARCH-based models (a benchmark and three alternatives) to build two portfolios: a portfolio of stocks (PF I) and a weighted oil-stock portfolio with the optimal weights calculated in Subsection 4.2 (PF II). The effectiveness of the portfolio diversification is judged by comparing the realized risk and return characteristics of the considered portfolios. The effectiveness of hedging across constructed portfolios can be evaluated by examining the realized hedging errors, which are determined as follows (Ku et al., 2007)

$$HE = \left(\frac{Var_{unheged} - Var_{hedged}}{Var_{unheged}}\right) \tag{14}$$

where the variances of the hedge portfolio (Var_{heged}) are obtained from the variance of the return on the oil-stock portfolios (PF II), whereas the variance of the unhedged portfolio (Var_{unheged}) is the variance of the return on the portfolio of stocks (PF I). A higher *HE* ratio indicates greater hedging effectiveness in terms of the portfolio's variance reduction, which thus implies that the associated investment method can be deemed a better hedging strategy.

The results from portfolio simulations in Table 5 show that adding the oil asset to the diversified portfolios improves their risk-adjusted return ratios. More importantly, this result holds for all cases and for all models we consider. The role of the oil asset appears to be more marked for the United States, whose stock sectors were more heavily affected by the recent global financial crisis than European sectors. More often than not, different GARCH-based models return similar results. The benchmark VAR-GARCH model provides the best risk-adjusted return ratios in seven out of sixteen pairs of oil/stock markets, followed closely by the diagonal BEKK-GARCH and CCC-GARCH–each prevails in four out of sixteen cases.

We focus next on Table 6, in which portfolio variance and hedging effectiveness (*HE*) ratios are reported. The results show that hedging strategies involving oil and stock assets make it possible to reduce portfolio risk (variance) considerably. When only the models that provide the best hedging effectiveness for each pair of markets are considered, the variance reduction ranges from 21.15% (*Telecommunications*) to 39.29% (*Utilities*) in Europe and from 23.39% (Technology) to 39.84% (*Basic*

[3] We are particularly grateful to an anonymous reviewer for this very interesting suggestion.

Table 5
Portfolio designs and diversification in presence of the oil asset.

	Europe			United States		
	Mean	Std. dev.	Realized risk-adjusted returns (×100)	Mean	Std. dev.	Realized risk-adjusted returns (×100)
DJ Stoxx Europe 600						
PF I	0.0118	2.6723	0.4421			
PF II–VAR-GARCH	0.0609	2.4744	**2.4623**			
PF II–BEKK-GARCH	0.0599	**2.4742**	2.4238			
PF II–DCC-GARCH	0.0602	**2.4742**	2.4334			
PF II–CCC-GARCH	**0.0614**	2.4945	2.4614			
S&P 500 index						
PF I				0.0239	2.1972	1.0898
PF II–VAR-GARCH				**0.0578**	2.1068	**2.7451**
PF II–BEKK-GARCH				0.0553	**2.1049**	2.6287
PF II–DCC-GARCH				0.0562	2.1054	2.6712
PF II–CCC-GARCH				0.0569	2.1060	2.7030
Automobile & Parts						
PF I	0.0173	4.5080	0.3850	−0.1576	5.0366	−3.1295
PF II–VAR-GARCH	0.1151	**3.3925**	**3.3955**	0.0391	3.6464	1.0725
PF II–BEKK-GARCH	**0.1158**	3.4207	3.3852	0.0284	3.6654	0.7769
PF II–DCC-GARCH	0.1135	3.3971	3.3427	0.0358	3.6514	0.9814
PF II–CCC-GARCH	0.1126	3.3999	3.3124	**0.0432**	**3.6412**	**1.1864**
Financials						
PF I	−0.0434	3.6949	−1.1746	−0.1064	4.7338	−2.2495
PF II–VAR-GARCH	0.0512	3.0912	1.6570	0.0420	3.4408	1.2214
PF II–BEKK-GARCH	**0.0532**	**3.0888**	**1.7252**	**0.0441**	3.4948	1.2618
PF II–DCC-GARCH	0.0524	3.0898	1.6960	0.0413	3.4429	1.1999
PF II–CCC-GARCH	0.0503	3.0925	1.6278	0.0434	**3.4367**	**1.2645**
Industrials						
PF I	0.0365	3.0721	1.1901	−0.0193	3.4043	−0.5688
PF II–VAR-GARCH	0.0930	2.7485	3.3858	0.0710	**2.8053**	**2.5332**
PF II–BEKK-GARCH	0.0949	2.7492	3.4553	0.0670	2.8064	2.3874
PF II–DCC-GARCH	0.0851	**2.7543**	3.0901	**0.0721**	2.8654	2.5162
PF II–CCC-GARCH	**0.0999**	2.7547	**3.6278**	0.0659	2.8072	2.3482
Basic Materials						
PF I	0.1408	3.6488	3.8604	0.0114	3.5848	0.3203
PF II–VAR-GARCH	0.1777	**3.1527**	**5.6388**	0.0954	**3.0081**	3.1730
PF II–BEKK-GARCH	**0.1794**	3.1837	5.6350	0.0961	3.0083	3.1967
PF II–DCC-GARCH	0.1782	3.1626	5.6346	0.0959	3.0082	3.1888
PF II–CCC-GARCH	0.1771	3.1531	5.6170	**0.0964**	3.0084	**3.2046**
Technology						
PF I	−0.0712	4.9349	−1.4439	0.0346	4.7732	0.7266
PF II–VAR-GARCH	0.0832	3.6424	2.2847	0.1330	3.5736	3.7235
PF II–BEKK-GARCH	**0.0845**	**3.6032**	**2.3472**	0.1352	3.5690	3.7890
PF II–DCC-GARCH	0.0829	3.6054	2.3010	**0.1365**	**3.5631**	**3.8308**
PF II–CCC-GARCH	0.0836	3.6045	2.3195	0.1337	3.5721	3.7432
Telecommunications						
PF I	0.0057	3.5360	0.1339	−0.1195	3.7285	−3.2064
PF II–VAR-GARCH	0.0856	2.9339	2.9189	0.0184	2.9644	0.6218
PF II–BEKK-GARCH	**0.0878**	**2.9327**	**2.9957**	**0.0195**	**2.9643**	**0.6594**
PF II–DCC-GARCH	0.0876	2.9328	2.9872	0.0147	2.9656	0.4965
PF II–CCC-GARCH	0.0868	2.9331	2.9617	0.0180	2.9645	0.6093
Utilities						
PF I	0.0668	2.3716	2.8185	−0.0338	3.0935	−1.0956
PF II–VAR-GARCH	0.0987	**2.1451**	**4.6012**	**0.0476**	**2.6595**	**1.7933**
PF II–BEKK-GARCH	**0.1024**	2.2275	4.5997	0.0468	**2.6595**	1.7611
PF II–DCC-GARCH	0.1000	2.2241	4.4988	0.0459	2.6596	1.7289
PF II–CCC-GARCH	0.1002	2.2243	4.5067	0.0491	2.6597	1.8468

This table compares the realized risk-adjusted returns, measured by calculating the ratio of each portfolio's mean to its standard deviation, of different portfolios. Figures in boldface indicate the highest mean, standard deviation, and risk-return trade-off. PF I is a portfolio of 100% stocks. PF II is a weighted oil-stock portfolio in which the weights are given by the optimal weights reported in Table 4.

Table 6
Hedging effectiveness.

	Europe		United States	
	Variance (%)	Hedge effectiveness (%)	Variance (%)	Hedge effectiveness (%)
DJ Stoxx Europe 600				
PF I	7.1413	–		
PF II–VAR-GARCH	4.9985	30.0080		
PF II–BEKK-GARCH	**4.9091**	**31.2590**		
PF II–DCC-GARCH	4.9778	30.2972		
PF II–CCC-GARCH	5.0881	28.7527		
S&P 500 index				
PF I			4.8279	–
PF II–VAR-GARCH			3.4220	29.1194
PF II–BEKK-GARCH			**3.3064**	**31.5150**
PF II–DCC-GARCH			3.3362	30.8962
PF II–CCC-GARCH			3.4768	27.9856
Automobile & Parts				
PF I	20.3285	–	25.3679	–
PF II–VAR-GARCH	**12.6532**	**37.7563**	**15.3057**	**39.6650**
PF II–BEKK-GARCH	12.6611	37.7176	15.3255	39.5869
PF II–DCC-GARCH	12.6569	37.7381	15.3168	39.6211
PF II–CCC-GARCH	12.6589	37.7281	15.3196	39.6101
Financials				
PF I	13.6523	–	22.4093	–
PF II–VAR-GARCH	9.4022	31.1309	**15.4911**	**30.8721**
PF II–BEKK-GARCH	9.3911	31.2126	15.5497	30.6102
PF II–DCC-GARCH	**9.3804**	**31.2905**	15.5145	30.7677
PF II–CCC-GARCH	9.3994	31.1517	15.5497	30.6102
Industrials				
PF I	9.4379	–	11.5899	–
PF II–VAR-GARCH	6.4331	31.8375	8.0281	30.7318
PF II–BEKK-GARCH	**6.4166**	**32.0129**	8.0028	30.9501
PF II–DCC-GARCH	6.4542	31.6147	8.0181	30.8178
PF II–CCC-GARCH	6.4517	31.6408	**7.9940**	**31.0257**
Basic Materials				
PF I	13.3142	–	12.8514	–
PF II–VAR-GARCH	8.8389	33.6126	7.7381	39.7872
PF II–BEKK-GARCH	8.8433	33.5796	7.7317	39.8374
PF II–DCC-GARCH	**8.8378**	**33.6207**	7.7359	39.8049
PF II–CCC-GARCH	8.8521	33.5135	**7.7311**	**39.8417**
Technology				
PF I	24.3535	–	22.7839	–
PF II–VAR-GARCH	17.4417	28.3811	**17.4541**	**23.3924**
PF II–BEKK-GARCH	17.4470	28.3590	17.4953	23.2119
PF II–DCC-GARCH	17.4348	28.4094	17.5124	23.1365
PF II–CCC-GARCH	**17.4321**	**28.4203**	17.4737	23.3064
Telecommunications				
PF I	12.5036	–	13.9021	–
PF II–VAR-GARCH	9.8601	21.1416	**9.1192**	**34.4039**
PF II–BEKK-GARCH	9.8625	21.1227	9.1198	34.4000
PF II–DCC-GARCH	**9.8585**	**21.1548**	9.1201	34.3977
PF II–CCC-GARCH	9.8610	21.1349	9.1208	34.3925
Utilities				
PF I	5.6247	–	9.5701	–
PF II–VAR-GARCH	3.5494	36.8968	5.8368	39.0094
PF II–BEKK-GARCH	**3.4145**	**39.2945**	**5.8117**	**39.2715**
PF II–DCC-GARCH	3.4303	39.0135	5.8453	38.9211
PF II–CCC-GARCH	3.4938	37.8838	5.8140	39.2477

This table reports the portfolio variance and hedge effectiveness ratios, computed using Eq. (14). Numbers in boldface indicate the hedged portfolio with lowest variance and the highest variance reduction. PF I is a portfolio of 100% stocks. PF II is a weighted oil-stock portfolio in which the weights are given by the optimal weights reported in Table 4.

Materials) in the US. The lowest and highest *HE* ratios are given by the DCC-GARCH and CCC-GARCH models respectively. Moreover, this variance reduction differs significantly across sectors, but in general it remains relatively stable across the GARCH models. The portfolio variance is reduced most greatly when the VAR-GARCH and diagonal BEKK-GARCH are used. In addition, the diagonal BEKK-GARCH is the best model at the market-wide level. Chang et al. (in press) reach the same conclusion regarding the superior ability of bivariate diagonal BEKK-GARCH over the DCC- and CCC-GARCH when examining the optimal hedging effectiveness between crude oil spot and futures markets.

5. Conclusion

The main purpose of this article was to examine the extent of volatility transmission, portfolio designs, and hedging effectiveness in oil and stock markets in Europe and the United States from a sector perspective. The rationale for doing so is that market-wide indices such as the DJ Stoxx Europe 600 and S&P 500 may mask the industry-specific characteristics, and different industries may react differently to oil shocks as well. Moreover, with respect to portfolio management, studies focusing on sector sensitivities to oil price shocks are of particular interest since they offer insight into sectors that still provide valuable opportunities for international diversification during large swings in oil prices.

Taking the recent VAR-GARCH modeling approach, which permits volatility spillover, we find significant volatility interaction in oil and stock market sectors, although, for Europe, the transmission of volatility is much more apparent from oil to stocks than from stocks to oil. In the US, there is evidence to support the hypothesis of bidirectional volatility spillover. Empirical results also point out to the heterogeneous intensity of volatility cross effects across the seven stock sectors. Finally, our examination of optimal weights and hedge ratios suggests that optimal portfolios in both Europe and the US should have stocks outweigh oil assets and that the stock investment risk can be hedged with relatively low hedging costs by taking a short position in the oil futures markets. In particular, we show that optimally hedged oil-stock portfolios outperform traditional portfolios of stocks regardless of bivariate volatility model, and that our benchmark VAR-GARCH model is the best one when diversification and hedging effectiveness are analyzed. On the whole, oil assets can be considered a dynamic and valuable asset class that helps improve the risk-adjusted performance of a well-diversified portfolio of sector stocks and serves to hedge oil risk more effectively.

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