Economics Bulletin

Volume 32, Issue 4

Oil-stock volatility transmission, portfolio selection and hedging

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Abstract

We employ a bivariate VAR-GARCH model of Ling and McAleer (2003) to examine the volatility transmission between oil prices and stock market sectors in the United States. We also compute the optimal weights and hedge ratios for oil-stock portfolio holdings and show how they can be used to build effective diversification and hedging strategy. Using daily data over the period from January 2, 1995 to December 17, 2010, we find evidence of significant volatility spillovers in both directions, from oil market to stock sectors and from stock sectors to oil market. Moreover, investors can improve the risk-adjusted performance of their portfolios of sector stocks by adding the oil asset. These results are crucial for portfolio management in the presence of the oil risk and the implementation of sector-specific policy actions.

Citation: Mohamed El Hédi Arouri and Amine Lahiani and Duc Khuong Nguyen, (2012) "Oil-stock volatility transmission, portfolio selection and hedging", *Economics Bulletin*, Vol. 32 No. 4 pp. 2768-2778.
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Submitted: March 15, 2012. **Published:** October 08, 2012.

1. Introduction

Theoretically, oil price changes may affect economic activity and financial markets through various channels. Hamilton (1983), Jones *et al.* (2004), and Gogineni (2010), among others, show that oil price fluctuations may have effects on the basic production input availability and investment costs (supply-side effects), on the terms of trade and wealth transfer from oil consumers to oil producers, on the firm's production structures and unemployment, on monetary policies, interest rates and inflation, and on consumption opportunities, costs and consumer demand and sentiment (demand-side effects). Moreover, not all the economic sectors respond similarly to the changes in oil prices as some sectors may be more sensitive to these changes than the others. In particular, oil prices may affect several companies in certain sectors from the supply side but the others from the demand side. A sector's sensitivity to oil prices depends on whether oil serves as its input or output, its exposure to indirect oil price effects, competition and concentration, and its capacity to absorb and pass on the oil price risk to its consumers. Therefore, the supply-side and demand-side dependence on oil can be used to categorize sectors as oil-intensive and non-oil intensive, and to better understand the effects of oil price changes on stock return dynamics across sectors (Lee and Ni, 2002; Gogineni, 2010).

The empirical relationship between oil prices and stock sectors has been recently examined by several studies. Sadorsky (2001) and Boyer and Filion (2007) show that oil price increases positively affect stock returns of Canadian *Oil & Gas* companies. El-Sharif *et al.* (2005) focus on the *Oil & Gas* sector returns in the United Kingdom and reach similar findings. Their results also point to a weak link between non-*Oil & Gas* sectors and oil price changes. Using data of thirty-five global industries, Nandha and Faff (2008) provide evidence that the rise in the price of oil has a negative impact on all industries but not *Oil & Gas*. The results of Nandha and Brooks (2009) suggest that changes in oil prices are an important determinant for stock returns of the transport sectors in developed countries of their sample, but not in the Asian and Latin American countries. More recently, Arouri and Nguyen (2010) investigate the links between oil prices and twelve stock sectors in Europe. They show that the reaction of sector returns to changes in oil prices is sensitively different across sectors and that the inclusion of the oil assets into a portfolio of sector stocks permits to improve the portfolio's risk-return characteristics.

The issue of volatility transmission between oil prices and stock sectors receives, however, little attention, while it is crucial for portfolio diversification, energy risk management, and specific-sector energy policy actions. In the present study we attempt to fill in this gap by examining how volatility is transmitted from oil market to U.S. stock sectors and from U.S. stock sectors to oil market over the period 1995-2010. We also draw practical implications for optimal portfolio designs in the presence of the oil risk and policy actions which permit to improve the well functioning of equity sectors. Unlike many previous studies which have looked at oil-stock return and volatility spillovers at the market-wide level (e.g., Malik and Hammoudeh, 2007; Park and Ratti, 2008; Choi and Hammoudeh, 2010), a sector investigation is of particular importance because it would allow us to better understand the dynamics of different industries in response to oil price movements as well as to avoid the compensation effects owing to the use of aggregate market indices. The purpose of our study is directly related to that of Malik and Ewing (2009) who investigate volatility spillover between oil prices and five US equity sector indices.[1] We differ however from them in three main aspects. First, we consider a broader range of stock sectors, provided by Standard &

[1] Malik and Ewing (2009) consider the following U.S. Dow Jones equity sectors: *Financials*, *Industrials*, *Consumer Services*, *Health Care*, and *Technology*.

Poor's, over a more recent period. This choice thus enables not only the comparison of our empirical results with theirs, but also the better understanding of the oil-stock links during periods of important oil price variations, essentially since the 1997 Asian crisis. Second, instead of using a bivariate BEKK-GARCH model of Engle and Kroner (1995) as in Malik and Ewing (2009), we take a bivariate VAR-GARCH approach which allows for direct return and volatility cross effects between oil and sector returns. Finally, we analyze the optimal weights and hedge ratios for oil-stock portfolio holdings and show how empirical results can be used to build effective diversification and hedging strategy.

We mainly find evidence that: *i*) conditional volatility significantly spills over from oil market to stock sectors. The volatility transmission also runs from stock rectors to oil market; *ii*) the sensitivity of sector returns to oil shocks varies across sectors of activity; *iii*) investors can hedge the risk of their portfolios of stocks with the oil asset and improve the risk-return trade-off of the oil-stock portfolios by investing from 53.5% to 63% of their wealth in the oil asset.

We organize the remainder of the article as follows. Section 2 introduces the VAR-GARCH model. Section 3 presents the data used and discusses empirical results. Section 4 concludes the article.

2. The model

The multivariate VARMA-GARCH model of Ling and McAleer (2003) generalizes the vector autoregressive moving average (VARMA) process to the case where model's errors are allowed to follow some multivariate GARCH representations. However, due to the lack of theoretical contributions on the statistical properties of VARMA-GARCH with dynamic conditional correlations, the multivariate CCC-GARCH representation of Bollerslev (1990) where correlations between system shocks are assumed to be constant is frequently used to ease the estimation and inference procedure.

In this paper we employ a bivariate VAR(1)-GARCH(1,1) to explore the volatility spillovers between oil and sector returns.[2] Let Y_t denote the vector of stock sector returns (r_t^s) and crude oil returns (r_t^o), and H_t the conditional variance-covariance matrix of the return processes, the VAR(1)-GARCH(1,1) model can be specified as

$$\begin{aligned} Y_t &= \mu + \phi Y_{t-1} + \varepsilon_t \\ \varepsilon_t &= H_t^{1/2}\eta_t, \;\; \eta_t \to i.i.d(0, I_2) \\ H_t &= W + A\vec{\varepsilon}_{t-1} + BH_{t-1} \end{aligned} \tag{1}$$

where $\phi = \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix}$ and $\vec{\varepsilon}_{t-1} = \left((\varepsilon_t^s)^2, (\varepsilon_t^o)^2\right)$. W, A and B are (2×2) matrices with typical elements ω, α and β. 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. By construction, the conditional variance of the stock sector (h_t^s) depends not only on its own past volatility and return residuals, but also on those of the oil market. Inversely, the oil's conditional variance (h_t^o) is affected by its own past volatility and return residuals as well as by those of the stock sector. This particular feature thus allows for the direct transmission of vol-

[2] This model has been found to satisfactorily capture the empirical stylized facts of conditional volatility of various financial variables including crude oil returns, stock returns and exchange rate returns (see, e.g., Hammoudeh *et al.*, 2009; 2010).

atility from one market to another. Let ρ be the conditional constant correlation, the conditional covariance is defined as

$$h_t^{so} = \rho (h_t^s)^{1/2} (h_t^o)^{1/2} \tag{2}$$

Note that if A and B are diagonal, the system (1) reduces to the CCC-GARCH model of Bollerslev (1990). To estimate the vector of unknown parameters, we use the quasi-maximum likelihood estimation (QMLE) method which is robust even in case where the return series are not normally distributed.

Once the VAR(1)-GARCH(1,1) is estimated, we can use the obtained conditional variance and covariance series to compute the optimal weights and optimal hedge ratios of a hedged portfolio. Formally, let's consider a hedged portfolio composed of oil and stocks. A stock investor should have interest to hold this hedged portfolio if investing in the oil asset offers substantial diversification benefits. Putting differently, the said investor wishes to know the proportion of wealth he must invest in the oil market in order to minimize the risk of his stock portfolio without reducing its expected returns. Kroner and Ng (1998) show that the optimal weight of oil asset ($w_{os,t}$) in a one-dollar oil-stock portfolio is given by[3]

$$w_{os,t} = \frac{h_t^s - h_t^{os}}{h_t^o - 2h_t^{os} + h_t^s} \tag{3}$$

and,

$$w_{os,t} = \begin{cases} 0, & if \quad w_{os,t} < 0 \\ w_{os,t}, & if \quad 0 \le w_{os,t} \le 1 \\ 1, & if \quad w_{os,t} > 1 \end{cases}$$

Optimal hedge ratios for the above oil-stock hedged portfolio can be determined as follows (Kroner and Suktan, 1993)

$$\beta_{os,t} = \frac{h_t^{os}}{h_t^o} \tag{4}$$

The risk of the hedged portfolio is minimal if a long position of one dollar in the stock market sector at the time t is hedged by a short position of $\beta_{os,t}$ dollars in the crude oil market, through for example selling oil futures contracts. The lower the hedge ratio the higher is the degree of hedging effectiveness because of the low costs incurred in the hedging operations.

3. Data and results

3.1 Data

Our sample includes daily index data for eight stock sectors in the United States (S&P sector indices), obtained from the Datastream International database, over the period January 2, 1995 to December 17, 2010: *Consumer Staples*, *Energy*, *Financials*, *Health Care, Industri-*

[3] The optimal weight of the stock market index in the considered portfolio is thus ($1 - w_{os,t}$).

als, *Materials*, *Telecom Services*, and *Utilities*. We also consider the S&P 500 index in order to compare the empirical results for stock sectors with those for market-wide level. The WTI (West Texas Intermediate) crude oil price, taken from the Energy Information Administration database, is used to represent the performance of the oil market. All data are expressed in U.S. dollar and returns are computed by taking the difference between the natural logarithms of two consecutive index prices.

Descriptive statistics and stochastic properties of return series are presented in Table 1. The S&P 500 index has the highest return over the study period (0.055%), followed by the Health Care sector (0.044%) and the WTI crude oil market (0.039%). The oil market experienced the highest unconditional volatility, measured by the standard deviation (2.508). Among the stock sectors, unconditional volatility ranges from 1.011 (*Consumer Staples*) to 2.017 (*Financials*).

Almost all the return series are negatively skewed, two exceptions being *Telecom Services* and *Utilities* sectors. Excess kurtosis is highly significant for all the return series, indicating that return distributions have tails fatter than those of normal distributions. The Jarque-Bera test for normality shows evidence of the departure from normality whatever the series considered. Results from the Ljung-Box test indicate that serial correlations are highly significant. 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.

The unconditional correlation of oil and stock returns varies substantially across industries from -0.015 (*Consumer Staples*) to 0.373 (*Energy*). This finding suggests that there should be diversification benefits from adding the oil asset into the portfolios of sector stocks.

3.2 Empirical results from VAR(1)-GARCH(1,1) model

Table 2 reports the estimation results of the bivariate VAR(1)-GARCH(1,1) models for the nine oil-stock market pairs, of which there is a model at the aggregate market level. We first find that lagged stock returns significantly affect their current values in three out of nine cases (*Energy*, *Financials*, and *Heath Care*). More interestingly, they have significant predictive power for crude oil's future returns in seven out of nine cases. The exceptions include the *Financials* sectors and the aggregate stock market. Whenever the statistical link is significant, it is positive, which means that increases in lagged stock returns are indicative of higher oil returns. This finding is consistent with the view that increased performance in stock markets leads to higher oil prices, and thus higher holding period returns. Neither sector returns nor market-wide returns are influenced by lagged oil returns. The latter only have significant impact on the current values of oil returns in the oil-market (S&P 500) model.

Second, the results indicate the suitability of GARCH(1,1) model for modeling oil and stock return volatility since the estimated coefficients of the conditional variance equations are statistically significant in most cases. This suitability is also confirmed by the results of the specification tests applied to the estimated standardized residuals, in the sense that both autocorrelations and ARCH effects are no longer present. More concretely, stock sector's conditional volatility is a function of both its own past volatility (h^s_{t-1}) and unexpected return residuals $\left(\varepsilon^s_{t-1}\right)^2$. Similar findings are found for oil's volatility since the past volatility (h^o_{t-1}) and unexpected shocks $\left(\varepsilon^o_{t-1}\right)^2$ play a significant and important role in determining the current conditional volatility. The only exception is the volatility model for the S&P index where stock market volatility is significantly affected only by its own past volatility.

Table 1
Descriptive statistics and stochastic properties of daily returns

	Consumer Staples	*Energy*	*Financials*	*Health Care*	*Industrials*	*Materials*	*Telecom Services*	*Utilities*	S&P 500	WTI
Mean (%)	0.026	0.038	0.017	0.044	0.026	0.020	0.005	0.010	0.055	0.039
Maximum (%)	8.835	16.960	17.201	7.761	9.516	12.425	12.926	12.683	21.276	21.276
Minimum (%)	-9.296	-16.883	-18.638	-9.222	-9.598	-13.164	-10.320	-8.996	-17.216	-17.216
Std. dev.	1.011	1.650	2.017	1.393	1.363	1.529	1.514	1.222	2.506	2.508
Skewness	-0.093	-0.267	-0.069	-0.288	-0.307	-0.304	0.080	0.005	-0.037	-0.038
Kurtosis	11.419	14.023	17.638	7.182	8.750	10.457	9.025	13.096	8.176	8.169
JB	12284	21098	37121	3087	5793	9697	6294	17656	1047	4629
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Q(6)	84.081	64.661	202.152	83.962	154.295	55.772	1112.029	90.106	1784.681	88.864
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH(6)	66.659	55.747	140.878	65.123	119.685	47.061	620.686	69.600	887.225	71.761
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Correlation with the oil returns										
	-0.015	0.373	0.056	0.054	0.070	0.140	0.046	0.100	-0.025	1.000

Notes: This table reports the basic statistics of sample data and their stochastic properties over the period from January 2, 1995 to December 17, 2010. JB, Q(6), and ARCH(6) refer to the empirical statistics of the Jarque-Bera test for normality, Ljung-Box tests for serial correlation with *6* lags, and Lagrange Multiplier test for conditional heteroscedasticity. The numbers in brackets are the associated p-values.

Table 2
Estimation results of bivariate VAR(1)-GARCH(1) models

Variables	Consumer Staples		Energy		Financials		Health Care		Industrials		Materials		Telecom Services		Utilities		S&P 500	
	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil						
Conditional mean equations																		
C	0.039	-0.045	-0.012	0.007	0.045	0.035	0.044	0.030	0.037	0.033	0.015	0.027	0.022	0.012	0.019	0.032	-0.003	-0.048
	(0.155)	(0.075)	(0.042)	(0.033)	(0.034)	(0.029)	(0.032)	(0.025)	(0.034)	(0.027)	(0.038)	(0.028)	(0.045)	(0.035)	(0.037)	(0.025)	(0.248)	(0.157)
Stock(-1)	0.018	0.229***	-0.072***	0.092***	-0.033**	0.049	0.041**	0.097***	-0.004	0.082***	0.0002	0.094***	-0.022	0.082***	-0.003	0.095***	0.164	-0.008
	(0.094)	(0.065)	(0.023)	(0.023)	(0.016)	(0.019)	(0.020)	(0.022)	(0.022)	(0.024)	(0.021)	(0.021)	(0.025)	(0.024)	(0.022)	(0.026)	(0.144)	(0.142)
Oil(-1)	-0.038	0.042	-0.005	0.003	-0.007	-0.004	-0.010	0.015	-0.014	-0.007	-0.008	-0.004	-0.011	-0.001	0.003	-0.003	0.022	0.156**
	(0.056)	(0.028)	(0.019)	(0.014)	(0.014)	(0.011)	(0.014)	(0.010)	(0.013)	(0.011)	(0.015)	(0.010)	(0.016)	(0.013)	(0.015)	(0.010)	(0.110)	(0.071)
Conditional variance equations																		
ω	-0.019	-0.133**	-0.0007	0.208**	-0.008	0.187***	-0.011	-0.120**	0.005	-0.209***	0.0009	0.179**	0.044	-0.203**	-0.0004	0.197**	0.169	0.065
	(2.682)	(0.346)	(19.602)	(0.087)	(1.700)	(0.067)	(0.930)	(0.059)	(2.013)	(0.050)	(17.352)	(0.082)	(0.371)	(0.100)	(36.473)	(0.058)	(0.466)	(1.484)
$(\varepsilon_{t-1}^{s})^2$	0.023***	0.006	0.084***	-0.092***	0.089***	0.095***	0.076***	0.096***	-0.060*	0.139***	0.065**	-0.098***	-0.060**	0.097***	-0.096***	-0.124***	0.195	-0.103
	(0.623)	(2.021)	(0.010)	(0.016)	(0.012)	(0.014)	(0.029)	(0.018)	(0.035)	(0.015)	(0.028)	(0.016)	(0.030)	(0.024)	(0.018)	(0.014)	(0.144)	(0.293)
$(\varepsilon_{t-1}^{o})^2$	-0.002***	0.126***	-0.026	0.082***	0.0001	0.078***	-5.98e-5	0.113***	0.0005	-0.084***	-0.027	-0.067***	-0.0001***	0.075***	-0.001	0.081***	-0.0004	0.138***
	(1.642)	(0.027)	(0.037)	(0.011)	(9.434)	(0.009)	(28.327)	(0.007)	(1.604)	(0.008)	(0.029)	(0.009)	(6.103)	(0.011)	(0.697)	(0.009)	(0.065)	(0.027)
h_{t-1}^{s}	0.949***	0.286*	0.963***	0.0281	0.954***	0.280*	0.932***	0.283***	0.951***	0.288**	0.948***	0.285	0.964***	0.287*	0.931***	0.290*	0.963***	0.277*
	(0.074)	(0.229)	(0.044)	(0.192)	(0.056)	(0.162)	(0.047)	(0.109)	(0.038)	(0.141)	(0.080)	(0.249)	(0.040)	(0.161)	(0.070)	(0.172)	(0.049)	(0.144)
h_{t-1}^{o}	0.283	0.961***	0.223	0.959***	0.246	0.959***	0.288***	0.960***	0.233**	0.961***	0.266	0.960***	0.222*	0.960***	0.278*	0.961***	0.225	0.958***
	(0.207)	(0.057)	(0.152)	(0.044)	(0.175)	(0.037)	(0.105)	(0.021)	(0.098)	(0.026)	(0.219)	(0.056)	(0.133)	(0.036)	(0.152)	(0.033)	(0.194)	(0.044)
Specification tests applied to standardized residuals																		
Q(6)	5.888	9.954	13.269	10.073	6.704	9.953	4.733	9.791	3.774	9.866	2.834	9.597	4.833	9.911	1.673	9.794	661.381	753.782
	[0.435]	[0.126]	[0.038]	[0.121]	[0.349]	[0.126]	[0.578]	[0.133]	[0.707]	[0.130]	[0.829]	[0.142]	[0.565]	[0.128]	[0.947]	[0.133]	[0.000]	[0.000]
ARCH(6)	2.480	9.086	8.132	7.353	4.356	8.857	8.971	8.547	4.880	8.554	5.391	7.924	9.116	8.666	13.826	8.220	6.102	8.103
	[0.870]	[0.168]	[0.228]	[0.289]	[0.628]	[0.181]	[0.175]	[0.200]	[0.559]	[0.200]	[0.494]	[0.243]	[0.167]	[0.193]	[0.031]	[0.222]	[0.411]	[0.230]
Constant conditional correlations																		
CCC		-0.128**		0.302***		-0.033**		0.005		0.006		0.064***		-0.014***		0.047**		-0.309***
		(0.060)		(0.017)		(0.015)		(0.016)		(0.016)		(0.017)		(0.453)		(0.018)		(0.103)
Models' statistics																		
Log-Lik.		-18798		-17066		-17386		-16659.51		-16503.30		-17013.95		-17183.74		-16266.47		-1962.583
AIC		9.052		8.219		8.373		8.023		7.948		8.193		8.275		7.834		8.551
SIC		9.078		8.244		8.398		8.049		7.974		8.219		8.301		7.843		8.703

Notes: Oil, stock and CCC are oil returns, sector (market) stock returns and constant conditional correlation respectively. Standard errors of the estimates are presented in parenthesis. Q(6) and ARCH(6) refer to the empirical statistics of the Ljung-Box tests for serial correlation with *6* lags and Lagrange Multiplier test for conditional heteroscedasticity, both tests being applied to standardized residuals. The numbers in brackets are the associated p-values. *, **, and *** indicate significance of coefficients at the 10%, 5% and 1% respectively.

Third, the findings regarding the volatility transmission offer several intriguing facts. At a glance, the conditional volatility of the U.S. stock market as a whole is influenced by neither past volatility (h_{t-1}^{o}) nor past shocks $\left(\varepsilon_{t-1}^{o}\right)^2$ in the oil market, but it does have some significant impact on the oil's conditional volatility. A shock affecting the stock market volatility thus leads to increase the oil market volatility.

The results for the volatility transmission between *Consumer Staples* sector and oil market show some evidence of significant direct volatility spillover effects. Past oil shocks significantly affect the sector's conditional volatility at the 1% level. This finding is not unexpected because oil price changes may drive up the earnings variability of consumer services companies, and thus the volatility of their stock returns. Inversely, oil's conditional volatility is driven by past volatility of stock sector returns. Here, higher volatility of the stock sector resulting from changes in consumers' budget for purchases of goods and services would raise the volatility in the oil market, due particularly to unpredicted modifications in the level of demand for oil from the *Consumer Staples* industry. Our results are consistent with those of Malik and Ewing (2009), based on the Dow Jones consumer services sector index.

As to oil-energy model, there is only evidence to suggest the transmission of volatility from energy stock sector to oil market through the significant effects of unexpected stock returns at the 1% level. On the other hand, oil's volatility does not spill over into energy stock sector. This finding is somewhat surprising given that the *Energy* sector includes important oil and gas companies. One potential explanation could be the implementation of effective hedging strategies by energy companies with respect to the oil price risk. Another explanation may come from the US legislation regarding the ability of oil companies to pass higher oil prices into the consumers.

The oil-financials sector model shows that volatility transmission runs from stock sector to oil market. Both past unexpected changes and past volatility in the *Financials* sector lead to increase the oil's volatility at the 1% and 10% levels, respectively. This is consistent with the view that the performance of *Financials* sector provides a signal for the level of production activity, and thus degree of oil demand of other industries. Malik and Ewing (2009) reach a conclusion similar to ours according to which financial market stability is fairly decoupled from the shocks affecting the oil market.

The transmission of volatility between oil and *Healthcare* sector is bi-directional. On the one hand, we find a significant impact of oil's past volatility on the current volatility of the *Healthcare* sector. This result suggests that this sector may depend directly on oil prices as some medicines are made from petroleum as well as indirectly via its links to overall economic uncertainties, created by oil price fluctuations. On the other hand, our results indicate that past changes and past volatility in the *Healthcare* sector play a crucial role in explaining the volatility of oil return, which is not consistent with what is found in Malik and Ewing (2009). To the extent that healthcare products are less sensitive to the economic cycle, the rise in the volatility of this sector would inform us of bad times in stock markets, which in turn raises the volatility of oil market owing to unexpected changes in oil consumption.

The results for the oil-industrials model contain a lot of interesting insights. Stock sector volatility reacts significantly to past volatility of the oil market. Spillover effects from stock sector to oil market are however more pronounced as oil volatility is strongly impacted by past news and volatility in the stock sector. This finding is indeed not surprising given that companies that operate in the *Industrials* sector are major consumers of oil-related products. The lesser sensitivity of stock return volatility to that of oil may result from effective hedging strategies with respect to the oil concerns.

Our results for *Materials* sector indicate that the conditional volatility of this sector is not affected by return and volatility shocks in the oil market. Inversely, stock volatility significantly spills over into the oil market. Taken together, these findings suggest that the *Materials* sector seems to have implemented risk management strategies more effective than the *Industrials* sector to hedge against oil price fluctuations.

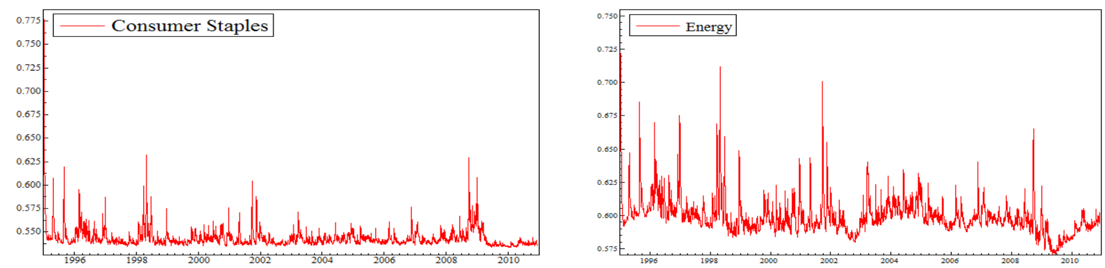
We note, from the model for oil and *Telecom Services* sector, that volatility spillover effects are significant in both directions, from oil market to stock sector as well as from stock sector to oil market. To the extent that the performance of companies in the *Telecom Services* sector is closely tied to overall performance of all other economic sectors, high oil prices lead to greater uncertainty about demand for the products and services they offer to the market, which in turn make their stocks riskier. The above finding clearly requires the implementation of hedging strategies against oil price increases.

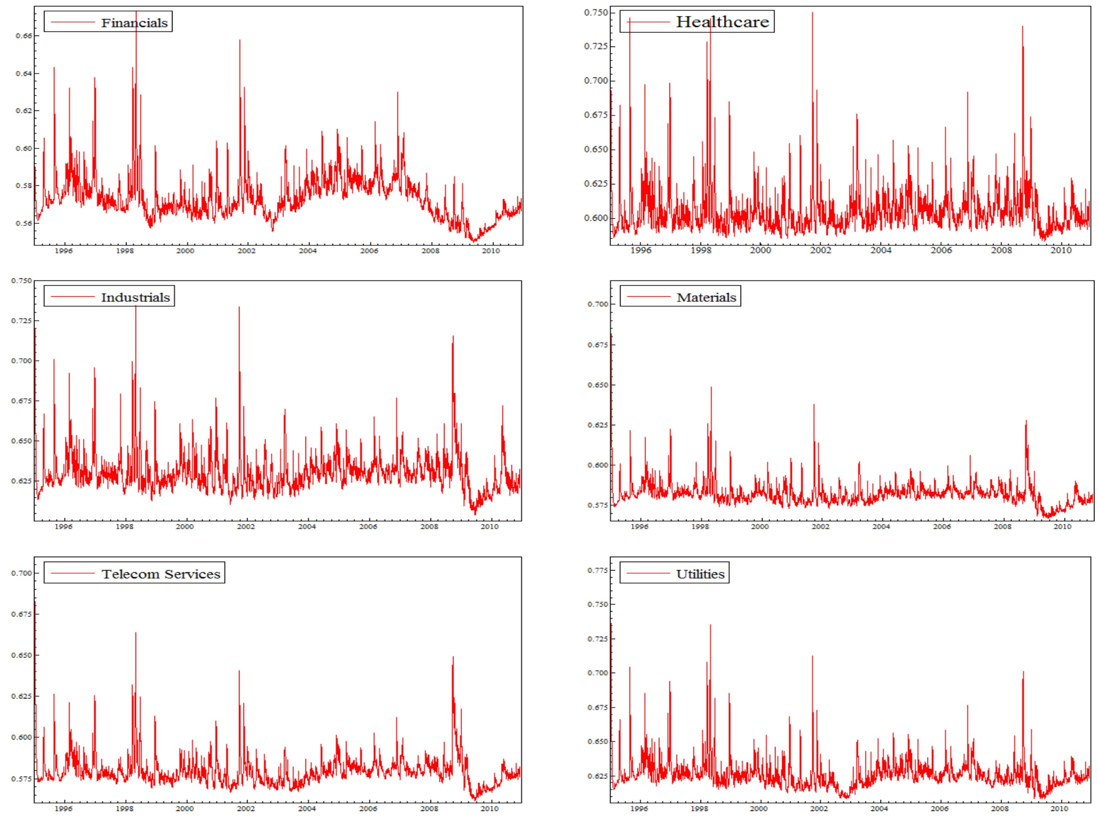
Similar to the case of oil and the *Industrials* sector, the results of the oil-utilities model point to the existence of bi-directional volatility spillovers: oil volatility is significantly impacted by both past residuals and volatility in the stock sector, whereas the volatility of *Industrials* sector only depends on past oil volatility. The observed links are perfectly understandable given that oil is an important input for the *Utilities* industry.

It is finally worth noting that the weak values of the constant conditional correlations (CCC) between oil and stock markets suggest potential diversification gains from adding the oil asset into portfolios of stocks. Moreover, three CCC coefficients with oil market returns are negative (*Consumer Staples*, *Financials*, and *Telecom Services*) and two coefficients are not significant (*Healthcare* and *Industrials* sectors) suggesting higher diversification benefits for these sectors.

We report, in Table 3, the average values of optimal weights of oil in the oil-stock portfolio ($w_{so,t}$) and optimal hedge ratios ($\beta_{so,t}$). The results suggest that investors should invest 53.5% of their wealth in oil asset, and the remaining 46.5% in the S&P 500 market index to minimize the risk of the resulting composite portfolio without lowering its returns. For portfolios of oil and stock sectors, the optimal weights vary on average from 54.3% for *Consumer Staples* sector to 63.0% for *Industrials* sector. It is also important to note that optimal weights of the oil asset vary considerably over time, as shown in Figure 1. In particular, they reached some peaks during periods of financial crisis and turbulences such as the Mexican peso crisis of 1994-1995, the Asian financial crisis of 1997-1998, and the recent global financial crisis of 2007-2008. Altogether, these findings are consistent with the view that investors holding assets in the United States should have more oil than stocks in their diversified portfolios and that oil asset may represent a good hedge against the risk of stock investments during times of turmoil.

Figure 1
Time-varying optimal weights of oil in an oil-stock portfolio





The low values of the optimal hedge ratios suggest a valuable hedge opportunity in the U.S. stock sectors. For example, a hedge ratio of 0.282 implies that one dollar long in the S&P 500 index should be hedged by a short position of 28.2 cents in the crude oil market. For stock sectors, the optimal hedge ratios range from 0.004 (*Healthcare*) to 0.262 (*Energy*). Accordingly, we see that the most effective strategy to hedge the *Healthcare* sector stock risk exposure is thus to take a short position in oil asset.

Table 3
Portfolio optimal weights and hedge ratios

Portfolio	w_t^{so}	β_t^{so}
S&P 500 index/oil	0.535	0.282
Consumer Staples/oil	0.543	0.116
Energy/oil	0.599	0.262
Financials/oil	0.573	0.028
Healthcare/oil	0.604	0.004
Industrials/oil	0.630	0.005
Materials/oil	0.582	0.055
Telecom Services/oil	0.579	0.012
Utilities/oil	0.626	0.037

Notes: The table reports average optimal weight of oil and hedge ratios for an oil-stock market portfolio. Oil asset is represented by the WTI crude-oil index, while investment in stocks is represented by either the S&P 500 market index or each of eight U.S. sector indices.

Overall, our findings show evidence of significant bi-directional volatility spillovers between oil market and eight considered stock sectors. The reaction of stock sector volatility to shocks affecting the oil market varies across sectors depending on their characteristics, especially their degree of dependence on oil. What is interesting to note is that the volatility spillovers are more apparent from stock sectors to oil market in most of the cases. These findings may reflect the different degrees of effectiveness with which companies in various sectors manage their oil risk. The analysis of optimal weights and hedging ratios highlights that adding oil into a diversified portfolio of stocks increases the risk-adjusted performance of the resulting portfolio.

4. Conclusion

In this article we investigate the volatility transmission between oil and stock sectors in the United States. Empirical results from bivariate VAR(1)-GARCH(1,1) models over the period 1995-2010 indicate significant volatility spillover effects, with the volatility transmission being more apparent from stock sectors to oil market. Therefore, to better forecast stock market volatility and make appropriate investment decisions, investors should watch closely on the fluctuations of oil prices. The results also suggest that, in order to improve the risk-return characteristics of their portfolios, investors should hold more oil than stocks. In addition, companies can hedge their exposure to stock risk effectively by taking short positions in the oil market.

References

Arouri, M. and D.K. Nguyen (2010) "Oil prices, stock markets and portfolio investment: evidence from sector analysis in Europe over the last decade" *Energy Policy* **38**, 4528-4539.

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

Choi, K. and S. Hammoudeh (2010) "Volatility behavior of oil, industrial, commodity and stock markets in a regime-switching environment" *Energy Policy* **38**, 4388-4399.

El-Sharif, I., Brown, D., Burton, B., Nixon, B. and A. Russell (2005) "Evidence on the nature and extent of the relationship between oil and equity value in UK" *Energy Economics* **27**, 819-830.

Engle, R.F. and K.F. Kroner (1995) "Multivariate simultaneous generalized ARCH" *Econometric Theory* **11**, 122-150.

Gogineni, S. (2010) "Oil and stock market: An industry level analysis" *Financial Review* **4**, 891-1123.

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

Hammoudeh, S., Yuan, Y. and M. McAleer (2009) "Shock and volatility spillovers among equity sectors of the Gulf Arab stock markets" *Quarterly Review of Economics and Finance* **49**, 829-842.

Hammoudeh, S., Yuan, Y., McAleer, M. and M.A. Thompson (2010) "Precious metals–exchange rate volatility transmissions and hedging strategies" *International Review of Economics and Finance* **19**, 633-647.

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

Jones, D.W., Leiby, P.N. and I.K. Paik (2004) "Oil price shocks and the macroeconomy: What has been learned since 1996?" *Energy Journal* **25**, 1-32.

Kroner, K.F. and V.K. Ng (1998). Modeling asymmetric movements of asset prices. *Review of Financial Studies* **11**, 844-871.

Kroner, K.F. and J. Sultan (1993) "Time-varying distributions and dynamic hedging with foreign currency futures" *Journal of Financial and Quantitative Analysis* **28**, 535-551.

Lee, K. and S. Ni (2002) "On the dynamic effects of oil shocks: A study using industry level data" *Journal of Monetary Economics* **49**, 823-852.

Ling, S. and M. McAleer (2003) "Asymptotic theory for a vector ARMA-GARCH model" *Econometric Theory* **19**, 278-308.

Malik, F. and B.T. Ewing (2009) "Volatility transmission between oil prices and equity sector returns" *International Review of Financial Analysis* **18**, 95-100.

Malik, S. and S. Hammoudeh (2007) "Shock and volatility transmission in the oil, US and Gulf equity markets" *International Review of Economics and Finance* **17**, 357-368.

Nandha, M. and R. Brooks (2009) "Oil prices and transport sector returns: an international analysis" *Review of Quantitative Finance and Accounting* **33**, 393-409.

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

Park, J. and R.A. Ratti (2008) "Oil price shocks and stock markets in the US and 13 European countries" *Energy Economics* **30**, 2587-2608.

Sadorsky, P. (2001) "Risk factors in stock returns of Canadian oil and gas companies" *Energy Economics* **23**, 17-28.