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Relationships among U.S. oil prices and oil industry equity indices

Shawkat Hammoudeh[a,*], Sel Dibooglu[b], Eisa Aleisa[c]

[a] *Department of Economics and International Business, Bennett S. LeBow College of Business, Drexel University, 3141 Chestnut Street, Philadelphia, PA 19104-2875, USA*

[b] *Southern Illinois University at Carbondale, Carbondale, IL 62901, USA*

[c] *Saudi Arabian Monetary Agency, Riyadh, Saudi Arabia*

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Abstract

The cointegration analysis suggests that the pure oil industry equity system and the mixed oil price/equity index system offers more opportunities for long-run portfolio diversification and less market integration than the pure oil price systems. On a daily basis, in the oil price systems all oil prices with the exception of the 3-month futures can explain the future movements of each other. In the mixed system, none of the daily oil industry stock indices can explain the daily future movements of the New York Mercantile Exchange (NYMEX) futures prices, whereas these prices can explain the movements of independent companies engaged in exploration, refining, and marketing. The spillover analysis of oil volatility transmission suggests that the oil futures market has a matching or echoing volatility effect on the stocks of some oil sectors and a volatility-dampening effect on the stocks of others. The policy implication is that, during times of high oil volatility, traders should choose the S&P oil sector stocks that match their tolerance for volatility and use the right financial derivative to hedge against or profit from this volatility. The day effect for volatility transmission suggests that Friday has a calming effect on the volatility of oil stocks in general. The effect for Monday is not significant.

JEL classification: C22; F3; Q49

Keywords: Oil prices; S&P oil sector stock indices; Cointegration; Spillover effects; Day effect

1. Introduction

Changes in crude oil prices affect a national economy at large and impact certain sectors of this economy more than others. The most affected sectors include the oil-related industries (oil exploration,

* Corresponding author. Tel.: +1-215-895-6673; fax: +1-215-895-6975.

E-mail address: hammousm@drexel.edu (S. Hammoudeh).

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production, refining, etc.), the highly oil sensitive transportation industries (airlines, trucking, railroads, etc.) and the highly oil intensive manufacturing industries (aluminum, steel, polymer, etc.). Although higher oil prices usually have a positive impact on most companies of the oil industry, this impact is less favorable on the independent oil refineries, which use crude oil as their input, and is also negative on the other oil-sensitive industries such as the airlines, trucking, etc. Those prices affect the companies' earnings and their bottom lines, which in turn affect their dividends, retained earnings, and the prices of their stocks.

There has been a large volume of work investigating the links among international financial markets,[1] and some work has also been devoted to the relationships among petroleum spot and futures prices.[2] In contrast, little work has been done on the relationship between oil spot/futures prices and stock indices, particularly the ones related to the oil industry, and in most of this work this relationship was examined within a framework of a macroeconomic model using low-frequency data. Jones and Kaul (1996) investigated the reaction of the U.S., Canadian, Japanese, and UK stock prices to oil price shocks using quarterly data. Utilizing a standard cash-flow dividend valuation model, they found that this reaction could completely be accounted for by the impact of the oil shocks on real cash flows. The results for Japan and the UK were not as strong. Huang, Masulis, and Stoll (1996) used a VAR model to examine the relationship between daily oil futures returns and daily U.S. stock returns. They found that oil futures returns lead some individual oil company stock returns but they do not have much impact on the broad-based market indices such as the S&P 500. In a more recent study, Sadorsky (1999), utilizing an unrestricted VAR and using monthly data (January 1947–April 1996) for oil prices proxied by the wholesale price index for fuels, stock returns represented by the S&P 500, short-term interest rate, and industrial production, examined the links among these variables. In contrast with Huang et al.'s result, Sadorsky found that oil price movements are important in explaining movements in broad-based stock returns. Papapetrou (2001), using an error-correction representation of a VAR macroeconomic model and using a monthly data for Greece for the period January 1989–June 1999, concluded that oil prices are important in explaining stock price movements.

Our study distinguishes itself from previous ones in the oil and financial literatures in that it examines the spillover effects, day effects and dynamic relationships among five S&P oil sector stock indices and five oil prices for the U.S. oil markets using daily data for the available period July 17, 1995 to October 10, 2001. The U.S. oil markets include the West Texas Intermediate (WTI)-Cushing spot and the New York Mercantile Exchange (NYMEX) 1- to 4-month futures prices. The U.S. oil industry includes companies engaged in the various phases of oil production and processing, operating domestically and internationally. Those companies are grouped into five categories: oil exploration and production; oil and gas refining and marketing; oil-domestic integrated; oil-international integrated; and oil composite. This categorization is based on the classification of the S&P oil industry sector stock indices. The S&P indices for the overall economy are divided in general into 11 economic sectors and 118 industry groups and include all stocks in the S&P 1500 supercomposite.

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[1] Most of the financial literature examined the international equity markets separately from the oil markets. See, for example, Choudhry (1997), Eun and Shim (1989), Francis and Leachman (1998), Hamao, Masulis, and Ng (1990), Jeon and von Furstenberg (1990), Kasa (1992), and Longin and Solnik (1995).

[2] In the petroleum literature, see Crowder and Hamid (1993), Gulen (1999), Schwartz and Szakmary (1994), Serletis and Banack (1990), Silvapulle and Moosa (1999), and Xiaowen and Tamvakis (2001). For a brief review of this literature, see Hammoudeh, Li, and Jeon (2003).

This paper will concentrate on the effects of changes in both the levels and volatility of crude oil prices on the different sector stock indices of the U.S. oil industry using daily data. It will specifically examine whether there are long-run relationships or comovements among the U.S. oil prices and the U.S. oil industry's sector stock indices as classified by S&P. It will also investigate the relative magnitude and the favorability of the volatility spillover effects from the oil markets to those different sector stock indices as a result of shocks in the oil markets. Additionally, it will investigate whether the trading day effect is more significant in explaining the relationships and transmission for specific days of the week, using changes in volatility instead of changes in levels of the oil and equity prices.

The results of the study should be useful to the various oil companies who are engaged in different phases of this industry and whose shares are traded on those stock exchanges. They should also be useful to the individual investors, hedgers, and arbitrageurs who buy the shares of these companies and wish to understand how the stocks of the different companies react to changes in the level and volatility of the oil spot/futures prices. If an increase in the oil price leads to a decrease in the stock index of another group of companies, say refiners, this increase should be a precursor for the investors to avoid these stocks. Moreover, the presence of long-run relationships among the different oil sector stock indices has implications for whether the sector stock markets are integrated or segmented, and whether there are potential benefits from the long-run portfolio in these markets. The volatility spillover effects from the oil markets to those stock markets should also provide insightful investment information to those who are volatility averse and who hedge against volatility and those who gain from trading on volatility. The financial literature has also pointed out the importance of the day-of-the-week effect in determining the behavior of the stock prices. Economic news is announced on Mondays and Fridays, which have special characteristics.[3] Is a Monday or a Friday trading effect relevant for changes in the levels or changes in volatility of both the oil and oil stock prices?

The main findings of this paper are as follows: (1) The oil price systems have a few number of common trends, suggesting little potential for long-run portfolio diversification. (2) In the S&P oil sectors stock index system, the five indices are not cointegrated, suggesting no index integration and strong opportunities for gains from diversification. (3) On a daily basis, none of the oil industry stock indices explains the future movements of the NYMEX oil futures prices, while these prices can explain the movements of independent oil companies engaged in exploration, refining, and marketing, confirming our results that the oil exploration companies and refiners take their cues from the oil market. (4) The autoregressive conditional heteroskedasticity (ARCH)/GARCH analysis suggests that the oil futures market's volatility has a matching resonant or volatility-echoing effect on the stocks of the oil exploration, production, and domestic integrated companies, and a volatility-dampening effect on the stocks of oil international integrated and oil and gas refining and marketing companies. (5) The day effect with oil volatility transmission suggests that Friday has a calming effect on the volatility of the oil stocks. The policy implication is that, at times of oil volatility, traders should choose the trading day and the S&P sectors that match their tolerance for volatility and use the right financial derivative to profit from this volatility.

[3] Rumor has it that traders formulate their strategies during the weekends while partying to implement them on Mondays. Moreover, the triple witching hour occurs on Fridays.

The paper is organized as follows. Section 2 provides a description of the WTI oil spot/NYMEX futures prices and S&P oil sector stock index series used in carrying out this study and also presents the descriptive statistics for these series. Section 3 examines empirical results for integration, cointegration, and causality among the oil prices and the different sector stock indices. Section 4 examines the relative magnitude and the favorability of the volatility spillover effects from the oil markets to the equity markets in univariate ARCH/GARCH models. Section 5 analyzes this oil volatility using a multivariate GARCH model that allows for considerable dynamics in the interactions among the oil spot price, the 3-month futures price and one of each of the S&P sector stock indices. Section 6 offers summary and conclusions.

2. The oil/equity data

In this section, we present an institutional description of the five oil spot/futures prices and the five S&P oil sector stock indices. Moreover, we will also analyze the descriptive statistics of the data for these series. The daily data series utilized in this paper over the available period from July 17, 1995 to October 10, 2001 are for five crude oil spot/futures prices and five S&P oil sector stock indices (see Figs. 1 and 2).

The spot price is the WTI price quoted for immediate delivery of crude oil in Cushing, Oklahoma, trading center. The oil futures prices are prices quoted for delivering a specified quantity of any of WTI crude oil at a specific time and place in the future in the NYMEX. The trading oil futures contracts range from 1 to 4 delivery months. The prices of crude oil are U.S. dollars per barrel.

WTIS (as denoted in this paper) is the crude oil spot price of the WTI-Cushing, which is a crude stream produced in Texas and southern Oklahoma. The futures prices NYCOF1, NYCOF2, NYCOF3, and NYCOF4 are the prices for contracts ranging from 1 month to 4 months, respectively, traded on the NYMEX and having their underlying physical asset WTI deliverable at the end of the domestic pipeline at the Cushing, Oklahoma, center.

SPOCI is the S&P Oil Composite index and is designed to represent a cross section of widely held corporations involved in various phases of the oil industry (see Appendix A for the names of companies included in each index). SPODI is the S&P Oil Domestic Integrated index, which includes five domestic oil companies engaged in the exploration, production, refinement and distribution of oil and gas products in the United States. SPOEP is the Oil and Gas Exploration index for companies engaged in the exploration and production of oil and gas not classified elsewhere. This index includes the stock of seven companies that are exclusively engaged in the first (upstream) phase of the oil industry and thus should give special cues to stocks of companies engaged in later phases. SPOGRM is the S&P Oil and Gas (Refining and Marketing) index, which is comprised of companies engaged in the refining and marketing of oil and gas products and are not classified in the Integrated Oil and Gas subindustry. This index includes the stock of companies that are exclusively engaged in the last (downstream) phase of the oil industry. SPOII is the S&P Oil-International Integrated index, which includes multinational integrated oil companies engaged in the exploration, production, refinement, and distribution of oil and gas products in the Unites States and abroad.

FD is the dummy variable for the day-of the-week effect for Fridays. The series for this variable takes on one for Fridays and zero for the other trading days of the week. MD is the dummy variable for the Monday day effect.

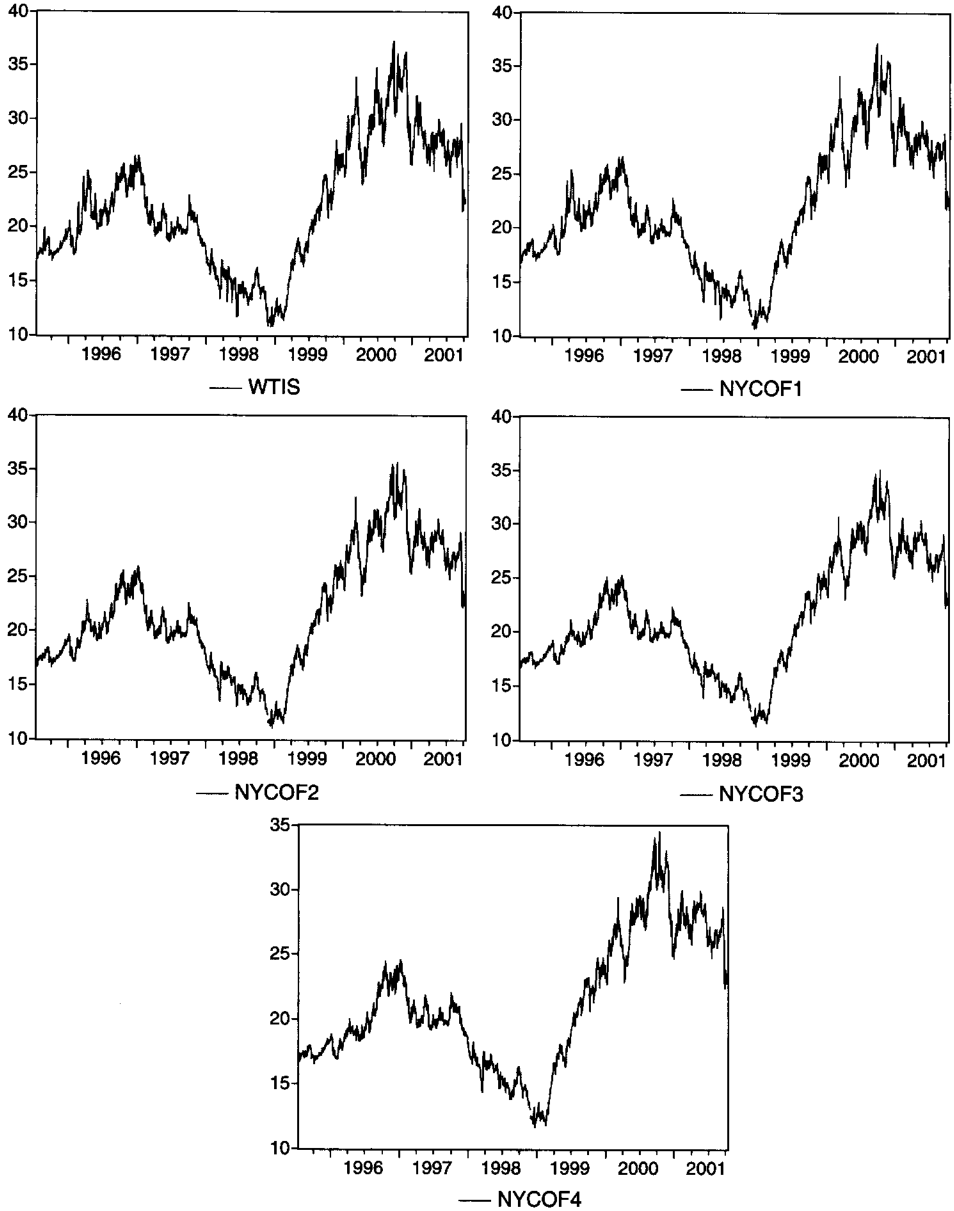

Fig.1. The daily oil spot and futures prices.

All of the displayed oil spot/futures prices and the S&P oil sector stock indices have nonsymmetric distributions as represented by the kurtosis and the skewness statistics.[4] The negative skewness statistics for the stock indices imply that their data series have a thicker lower tail than the upper one, and thus

[4] A detailed table that includes the descriptive statistics for all series can be requested from the authors.

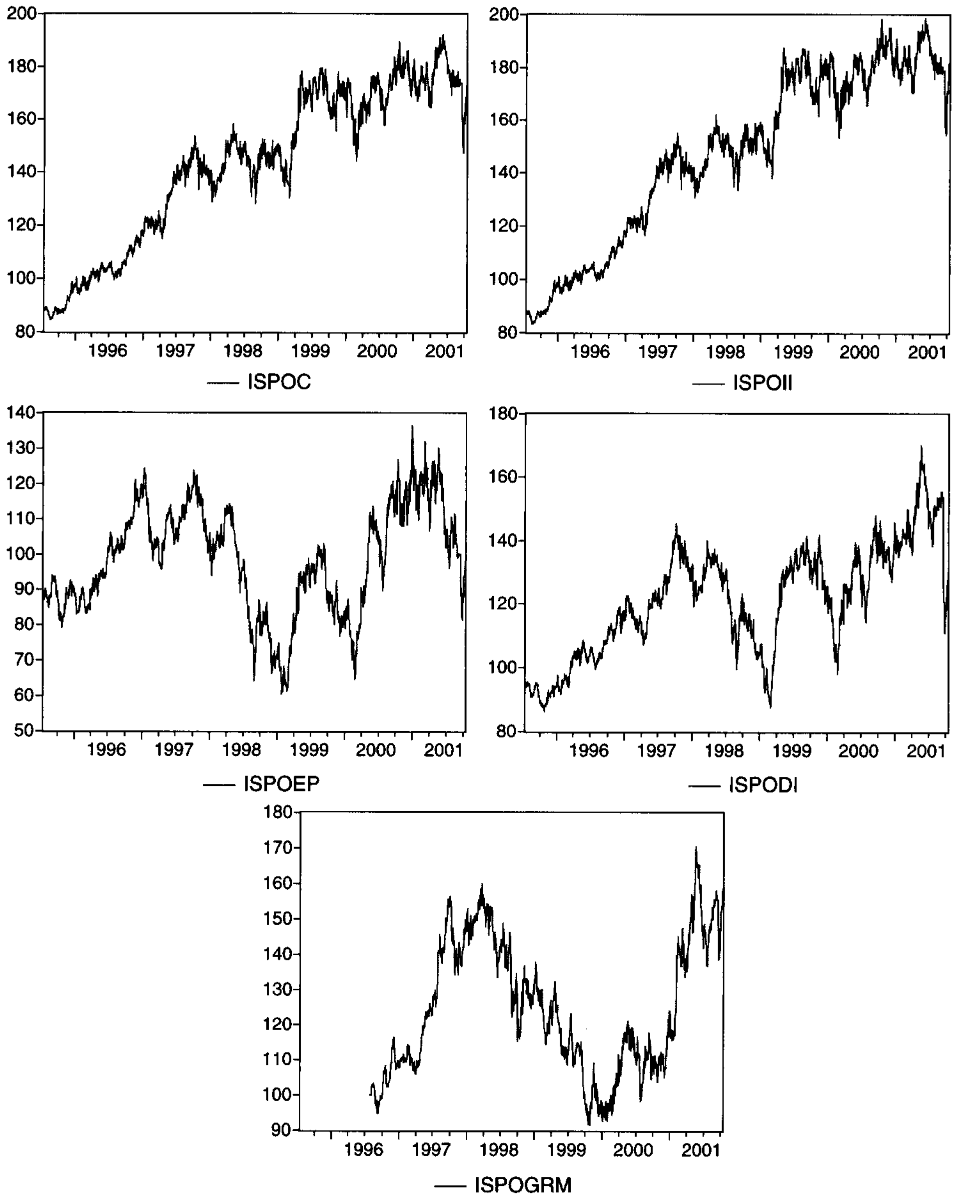

Fig. 2. The daily S&P oil sector stock indices.

skewed to the left. However, the oil spot/futures prices are skewed to the right, as suggested by their positive skewness statistics, and the distributions of the futures prices become more skewed as contract maturity increases.

Kurtosis (K) provides a measure of the "peakedness" of a distribution relative to the normal distribution. For the normal distribution, K is equal to 3. All the distributions of both the sector stock indices and oil prices are less than 3, suggesting that they are less peaked than the normal distribution. For crude oil futures, K exhibits a pattern similar to that of their means, with K decreasing as the length of futures contracts increases. The Jarque–Bera statistics confirm the nonnormal distribution of all of the S&P sector stock index and oil price data series, which is not an unusual finding because prices are bounded below at zero.

Examining intraoil relative volatilities for the oil market, as represented by the coefficient of variation, the WTI spot price commands the greatest relative volatility compared to the futures prices, whereas the 4-month futures price exhibits the lowest volatility. These relative volatilities decrease with the increasing length of the futures contracts.

The intra relative volatilities for the S&P sector stock indices show that the index for the oil integrated international companies (ISPOII) is the most volatile, whereas the index for the oil domestic integrated companies (ISPODI) is the least volatile. This finding is perhaps due to the double exposure of the multinational oil companies to economic and political events both at home and in the pertinent oil-producing third world countries where these companies have interests. Surprisingly, the volatilities of the indices for oil and gas exploration and production (ISPOEP) and for oil and gas refining and marketing (ISPOGRM) are identical.

3. Empirical results: integration, cointegration and causality

The empirical analysis of the relationships among the oil price series and the five S&P oil sector stock index series requires that several time series tests be conducted. The unit root test should be conducted first to determine whether the individual series are nonstationary in the levels and whether they are stationary in the first differences. Then the cointegration test is conducted to determine whether those nonstationary series of two or more have common long-run relationships and whether causality exists in at least one direction. Examination of the directional causality among the cointegrated series is then conducted through the use of the error-correction model.

3.1. Integration

Integration of individual time series is tested by means of the unit root tests that investigate the presence of a stochastic trend in those individual series. If the series has a stochastic trend, then a shock that hits it will have permanent effects (Hendry & Juselius, 2000).

The main unit root test employed in this investigation is the augmented Dickey–Fuller (ADF) test, but the Phillips and Perron (1988) (PP) test is also used to double-check the integration results. According to Banerjee, Dolado, Galbraith, and Hendry (1993), DeJong, Nankervis, Savin, and Whiteman (1992), and Schwert (1989), the ADF test provides more robust results than any other unit root test in the presence of autoregressive errors. Moreover, according to Said and Dickey (1984), this test is valid for a general ARMA process in the error terms.

For the study under consideration, the ADF test is conducted for all the spot and futures prices and the S&P oil sector stock indices taking into account all possible deterministic components and lag lengths. The test was first conducted in levels on all the series, and the number of the lagged level terms was chosen based on the AIC and SBC information criteria. Table 1 presents the results from the ADF test, which shows that all the 10 variables are nonstationary in (log of) levels at the 5% significance level. The test was then conducted again in first differences, and the results show that all the individual series are stationary, that is, contain a single root, and thus are integrated of degree one, $I(1)$. The PP test was also

Table 1
The ADF test for the S&P oil sector stock indices and the oil prices

Variables	Level			First difference		
	ADF statistic	Lag	Critical value	ADF statistic	Lag	Critical value
ISPOC	−2.972[a]	2	−3.415	−31.467[b]	1	−2.863
ISPOII	−2.860[a]	2	−3.415	−31.893[b]	1	−2.863
ISPODI	−3.122[a]	1	−3.415	−28.709[b]	1	−2.863
ISPOEP	−2.587[b]	1	−2.864	−28.713[b]	1	−2.863
ISPOGRM	−1.699[b]	1	−2.864	−25.971[b]	1	−2.864
NYCOF1	−1.726[b]	2	−2.864	−31.150[b]	1	−2.863
NYCOF2	−1.733[b]	2	−2.864	−30.635[b]	1	−2.863
NYCOF3	−1.656[b]	2	−2.864	−30.550[b]	2	−2.863
NYCOF4	−1.583[b]	2	−2.864	−30.786[b]	1	−2.863
WTIS	−1.880[b]	2	−2.864	−30.461[b]	1	−2.863

The length of lags is decided by AIC and SBC. The critical values are for the 5% significance level. The Phillips–Perron (PP) test was also conducted on each of the series and this test confirmed the ADF's results that all the individual series are $I(1)$. All variables are expressed in logarithmic form.

[a] Indicates intercept and trend.

[b] Indicates intercept only.

conducted on each of the series and this test confirmed the ADF test results that all the individual series are $I(1)$.[5]

3.2. Cointegration

A system of two or more time series, which are nonstationary in levels and have individual stochastic trends, can share common stochastic trend(s); in this case those series are said to be cointegrated. Thus, two or more nonstationary time series are cointegrated if a linear combination of these variables is stationary, that is, converges to equilibrium over time. The stationary linear combinations are called cointegrating equations, and may be interpreted as long-run equilibrium relationships among the variables. The idea behind cointegration is that there are common forces that comove the variables over time. In general, the less common trends (i.e., the more integrating vectors) are in the system, the more stable the system is (Crowder & Wohar, 1998).[6] Additionally, more cointegration implies more convergence among markets.[7] Under these circumstances, there is less potential gain from diversification.

Cointegration tests not only allow us to examine the long-run comovements or relationships among oil markets and oil industry stock indices, but they also may be interpreted as tests of the weak form of the efficient market hypothesis (Richards, 1985). In fact, the presence of cointegration between markets implies that at least one of them can be used to help forecast other markets because a valid causal relationship based on the error-correction model exists. Therefore, the implication of the presence of

[5] The PP test's results can be obtained from the authors upon request.

[6] If a five variable system has, say four cointegrating vectors (one common trend or one unit root), then there are four directions where the variance is finite (i.e., stable) and one direction in which the variance is infinite (because the variance of a unit root is infinite). If the system has only one cointegrating vector (four common trends or unit roots), then it can deviate in four independent directions and is stable in one direction (Crowder & Wohar, 1998, p. 195).

[7] We are thankful to Katarina Juselius for this comment.

cointegration would limit the potential benefits that can be derived from long-run diversification. On the contrary, the absence of cointegration suggests some degree of market segmentation, whereas its presence indicates a greater degree of market integration.

There are many possible tests for cointegration; the most general of them is the multivariate test based on the autoregressive representation discussed in Johansen (1988) and Johansen and Juselius (1990). This procedure provides more robust results when there are more than two variables (Gonzalo, 1994) and when the number of observations is greater than 100 (Hargreaves, 1994). The Johansen method provides two different likelihood ratio tests, the trace test and the maximum eigenvalue test, to determine the number of cointegrating vectors (Hendry & Juselius, 2001). This paper will use the critical values for the trace statistics. The finding of the presence of cointegration paves the way for using the error-correction model that is described in Section 3.3.

As mentioned above, the study contains two different systems of variables: the oil system, which includes the five oil spot/futures prices, and the equity system, which contains the five S&P oil sector stock indices. The cointegration test will first be applied to each of the two systems separately, and then it will be conducted on five mixed oil/equity systems where each mixed system contains one of the five oil prices, and the five stock indices. The selection of the lag lengths is based on the AIC criterion. The selection of the deterministic components relies, in addition to the results of the AIC criterion, on the preponderance of evidence of whether to include or exclude time trends, linear or quadratic, by examining the graphs of the series in Figs. 1 and 2. The results are given in Table 2[8].

The cointegration test applied to several VAR combinations of the oil prices indicates that cointegration exists regardless of the number of the oil prices included in each oil VAR. As indicated before, the more cointegrating vectors (i.e., the less common trends) are in the system, the more convergence among the variables. The number of cointegrating vectors or long-run equilibrium relationships for the different oil VARs are: one vector for the bivariate oil VARs (Oil-SF1 to Oil-SF4), which each contains the spot price and one of the four futures prices; three vectors for the Oil-F4 VAR which contains the four NYMEX futures prices, and four vectors for the multivariate VAR (Oil-5) which includes all the five oil prices.[9]

An interesting hypothesis with regards to the oil spot and each of the futures prices is whether the current futures price is an efficient predictor of the future spot price (the so-called unbiasedness hypothesis). If information is processed efficiently, the futures prices and the appropriately lagged spot price should be cointegrated with a normalized cointegrating vector of $(1, -1)$. The upper portion of Table 2 (Oil-SF1 to Oil-SF4) indicates that the futures prices and the appropriately lagged spot price are indeed cointegrated. This table also presents a likelihood ratio test attesting that the restricted cointegrating vector is $(1, -1)$. The $\chi^2(1)$-distributed test statistics indicate that the restriction cannot be rejected for all four maturity levels, confirming that the oil markets are efficient. The point

[8] Great care was given to the selection of deterministic trends. For each lag, ranging from 1 to 10, we ran the cointegration tests for the five specifications of the deterministic components using different time periods. For the oil systems, the evidence does not support the selection of time trends over the last 20 years. The graphs of the series strongly support no time trends. In the equity system, the issue of including or excluding time trends is not an issue because there is no cointegration under all five specifications of deterministic components. Finally, the mixed systems show only one cointegrating relation and cointegration stops when the linear deterministic trend is included. This procedure is similar in spirit to the Pantula (1989) principle, which was followed by Johansen (1992). We are indebted to one of the referees for pointing this out to us.

[9] For economic explanation of the cointegrating vectors, see Hammoudeh et al. (2003).

Table 2
Johansen cointegration test, deterministic components, and CEs for the pure oil, pure equity, and mixed oil/equity VARs

Specifications	Oil-SF1	Oil-SF2	Oil-SF3	Oil-SF4	Oil-F4	Oil-5	Equity-5
AIC—none[a]	−9.2610*	−9.5162*	−8.0326*	−9.8147*	−25.0456	−31.1686	−38.2264
AIC—intercept[b]	−9.2598	−9.5152	−8.0325	−9.8137	−25.0494*	−31.1714*	−38.2352*
AIC—linear trend[c]	−9.2586	−9.5139	−8.0313	−9.8125	−25.0470	−31.1691	−38.2327
AIC—linear trend[d]	−9.2574	−9.5129	−8.0307	−9.8115	−25.0446	−31.1655	−38.2304
No. of lags	2	2	3	2	2	2	1
No. of CEs[e]	1	1	1	1	3	4	0
Arbitrage hypothesis, $\chi^2(1)$	0.042 (0.84)	0.517 (0.47)	1.073 (0.30)	0.512 (0.47)	–	–	–
Observations	1595	1573	1548	1529	1621	1621	1356

Specifications	Mixed-0	Mixed-1	Mixed-2	Mixed-3	Mixed-4
AIC—none[a]	−42.7991	−42.9324	−43.1920	−41.5280	−43.5140
AIC—intercept[b]	−42.8051*	−42.9387*	−43.1975*	−41.5323*	−43.5182*
AIC—linear trend[c]	−42.8019	−42.9346	−43.1934	−41.5288	−43.5141
AIC—linear trend[d]	−42.8001	−42.9329	−43.1917	−41.5269	−43.5120
No. of lags	1	1	1	2	1
No. of CEs[e]	1	1	1	1	1
Observations	1353	1353	1353	1351	1353

All variables are expressed in natural logarithms. The exogenous variables are DM and DF.
Lags from 1 to 5 were tried and the selected lag is based on the minimum AIC.
Oil-SF1 VAR: NYCOF1, WTIS; Oil-SF2 VAR: NYCOF2, WTIS; Oil-SF3 VAR: NYCOF3, WTIS; Oil-SF4 VAR: NYCOF4, WTIS; Oil-F4 VAR: NYCOF1, NYCOF2, NYCOF3, NYCOF4; Oil-5 VAR: WTIS, NYCOF1, NYCOF2, NYCOF3, NYCOF4; Equity-5 VAR: ISPOC, ISPOII, ISPODI, ISPOEP, ISPOGRM; Mixed-0 VAR: WTIS+Equity-5; Mixed-1 VAR: NYCOF1+Equity-5; Mixed-2: NYCOF2+Equity-5; Mixed-3: NYCOF3+Equity-5; and Mixed-4: NYCOF4+Equity-5.

[a] Data has no deterministic trend and the cointegrating equations do not have intercepts.
[b] Data has no deterministic trend but the cointegrating equations have intercepts.
[c] Data has linear trend but the cointegrating equations have intercepts only.
[d] Both data and the cointegrating equations have linear trends.
[e] CEs stands for number of cointegrating equations, and the selection is based on the trace test.
* Refers to the selected deterministic component specification.

estimates of the normalized cointegrating vectors is (1, −0.99) in all four cases (see the upper portion of Table 3).

The cointegration test is then conducted on the equity system, Equity-5 VAR, which comprises the five S&P sector stock indices. The estimates show no cointegration among these five variables (see Table 2). This surprising result is perhaps due to the intended composition of those indices. Two of them include stocks of only integrated companies that are either domestic (e.g., Amerada Hess, Conoco, Phillips Petroleum, etc.) or international (e.g., Chevron, Exxon Mobile, Texaco, etc.) as shown in Appendix A. On the other hand, two other indices, ISPOEP and ISPOGRM, include small independent upstream companies (e.g., Anadarko Petroleum, Apache, Burlington Resources, Devon Energy) and downstream companies (e.g., Ashland, Sunoco, Tosco, etc.), respectively, which both cannot be classified with the integrated companies. The forces that comove the integrated companies are basically guided by the fundamental factors, whereas those that comove the independent exploration and production are particularly geared by investment capital, new oil field concessions, and a definite increasing trend in

Table 3
Johansen multivariate cointegration equation normalized parameter estimates

VAR	WTIS	NYCOF1	NYCOF2	NYCOF3	NYCOF4	ISPOC	ISPOII	ISPODI	ISPOEP	ISPOGRM	Constant[a]
Oil-SF1	−0.99[a]	1.00									
Oil-SF2	−0.99[a]		1.00								
Oil-SF3	−0.99[a]			1.00							
Oil-SF4	−0.99[a]				1.00						
Oil-F4		1.00	−4.62	6.22	−2.58						−0.070
			(−21.79)	(23.40)	(−10.88)						(−0.95)
Oil-5	1.00	−1.82	2.99	−3.53	1.33						0.042
		(−6.85)	(6.12)	(−23.06)	(5.45)						(0.93)
Mixed-0	1.00					197.80	−170.28	−25.88	−0.10	1.41	−17.10
						(6.83)	(−6.81)	(−7.12)	(0.23)	(4.97)	(6.17)
Mixed-1		1.00				191.42	−164.78	−25.17	−0.04	1.40	−16.62
						(6.78)	(−6.76)	(−7.11)	(−0.09)	(5.09)	(−6.16)
Mixed-2			1.00			183.06	−157.50	−24.29	0.03	1.30	−15.51
						(6.73)	(−6.71)	(−7.12)	(0.06)	(4.89)	(−5.96)
Mixed-3				1.00		171.85	−147.87	−22.84	−0.019	1.19	−14.15
						(6.79)	(−21.85)	(−7.20)	(−0.05)	(4.83)	(−5.84)
Mixed-4					1.00	165.30	−142.26	−21.92	−0.06	1.09	−13.36
						(6.81)	(−6.79)	(−7.21)	(−0.16)	(4.62)	(−5.76)

All variables are expressed in logarithm form and the numbers are elasticities.
Numbers in parentheses are t statistics.
The VAR Mixed-0: WTIS, ISPOC, ISPOII, ISPOEP, ISPODI, ISPOGRM; other Mixed VARs are defined similarly to Mixed-0 but each starts with a futures price ranging from NYCOF1 to NYCOF4 (see notes of Table 2).

[a] Intercept (no trend) in CE but no intercept in the VAR.

Table 4
Significance of zero restrictions on coefficients of normalized cointegrating equations

VAR	WTIS	NYCOF1	NYCOF2	NYCOF3	NYCOF4	ISPOC	ISPOII	ISPODI	ISPOEP	ISPOGRM
Oil-F4		99.18*	116.42*	656.9*	112.6*					
Oil-5	432.8*	321.6*	127.3*	657.9*	115.34*					
Mixed-0	3.63**					7.32*	7.24*	8.04*	0.01	4.49**
Mixed-1		4.35**				8.56*	8.46*	9.57*	0.00	5.27**
Mixed-2			3.99**			8.23*	8.13*	9.29*	0.00	4.92*
Mixed-3				14.82*		11.27*	11.41*	10.41*	6.38*	10.41*
Mixed-4					3.06***	6.61*	6.53*	7.30*	0.00	73.94

The null hypothesis is that the *i*th endogenous variable does not enter the cointegrating equation significantly. The test statistic is chi-square. Other notes are similar to Table 3 notes.

* Rejection of the null hypothesis at 1% significance level.

** Rejection of the null hypothesis at 5% significance level.

*** Rejection of the null hypothesis at 10% significance level.

both the oil price and production. The downstream companies are also affected by refinery margins and distribution power. Thus, perhaps those five S&P oil sector stock indices do not share long-run relationships that can be exploited by policymakers. Contrary to the oil markets, this finding implies that those five indices have the potential for gains from long-run portfolio diversification.[10]

Additionally, we perform the cointegration test on the five mixed systems (VAR Mixed-0 to VAR Mixed-4), which each contains one of the oil spot and futures prices and the five S&P sector stock indices as shown in Table 2. The estimates suggest that there is only one cointegrating equation at the 5% significance in any of these mixed VARs regardless of the type of the oil price included in the system. It is worth noting that adding oil price to the uncointegrated five stock indices has brought out a force that could comove the system, which includes these six variables. This force is likely to be either the global business cycle or OPEC's oil production and pricing policy. The resultant five stochastic trends include the incidental factors that affect the oil industry such as changes in oil inventories, refinery margins, the weather, political events, and companies' own unsystematic risk.

The significant cointegrating vectors can be given economic meaning using normalization on the parameters of the cointegrating equations for the mixed VARs. The normalized vectors represent the implied long-run effects imposed by the variables. In the VAR Oil-5, the largest coefficient in the cointegrating equation normalized on the oil spot price, WTIS, belongs to the NYMEX 3-month futures price and the smallest is on the NYMEX 4-month futures price (see Table 3). This finding represents the fact that the 3-month futures contracts are the oldest, best known, and have the largest market share at the NYMEX, whereas the 4-month contracts have the smallest market share. In each of the five mixed oil/equity VARs, the cointegrating equation normalized on the pertinent oil price shows that the largest coefficient is on the overall S&P composite index (ISPOC), followed by the integrated international index (ISPOII) and the integrated domestic index (ISPODI) in this sequence. The smallest is on the coefficient of the unintegrated exploration and production index (ISPOEP). Again, the sizes of these coefficients reflect the market shares of the companies comprising these indices.

[10] For more information on the linkages between cointegration and diversification, see Crowder and Wohar (1998). We are indebted to one of the referees for this comment.

We then investigated whether the oil/equity variables enter statistically significantly into the cointegrating vectors for the two comprehensive oil VARs, Oil-F4 and Oil-5, and the five mixed VARs. The results of the likelihood ratio test for those two oil VARs indicate that all the oil prices enter statistically significantly into the cointegrating vectors (Table 4). For all the five mixed VARs, only the S&P stock index for exploration and production does not enter significantly into these VARs. As mentioned before, the companies in this index are small and not integrated and they may lack new oil field concessions, capital, and other resources to increase exploration and production. Additionally, exploration usually does not take place unless both oil price and production ascend an upward trend.

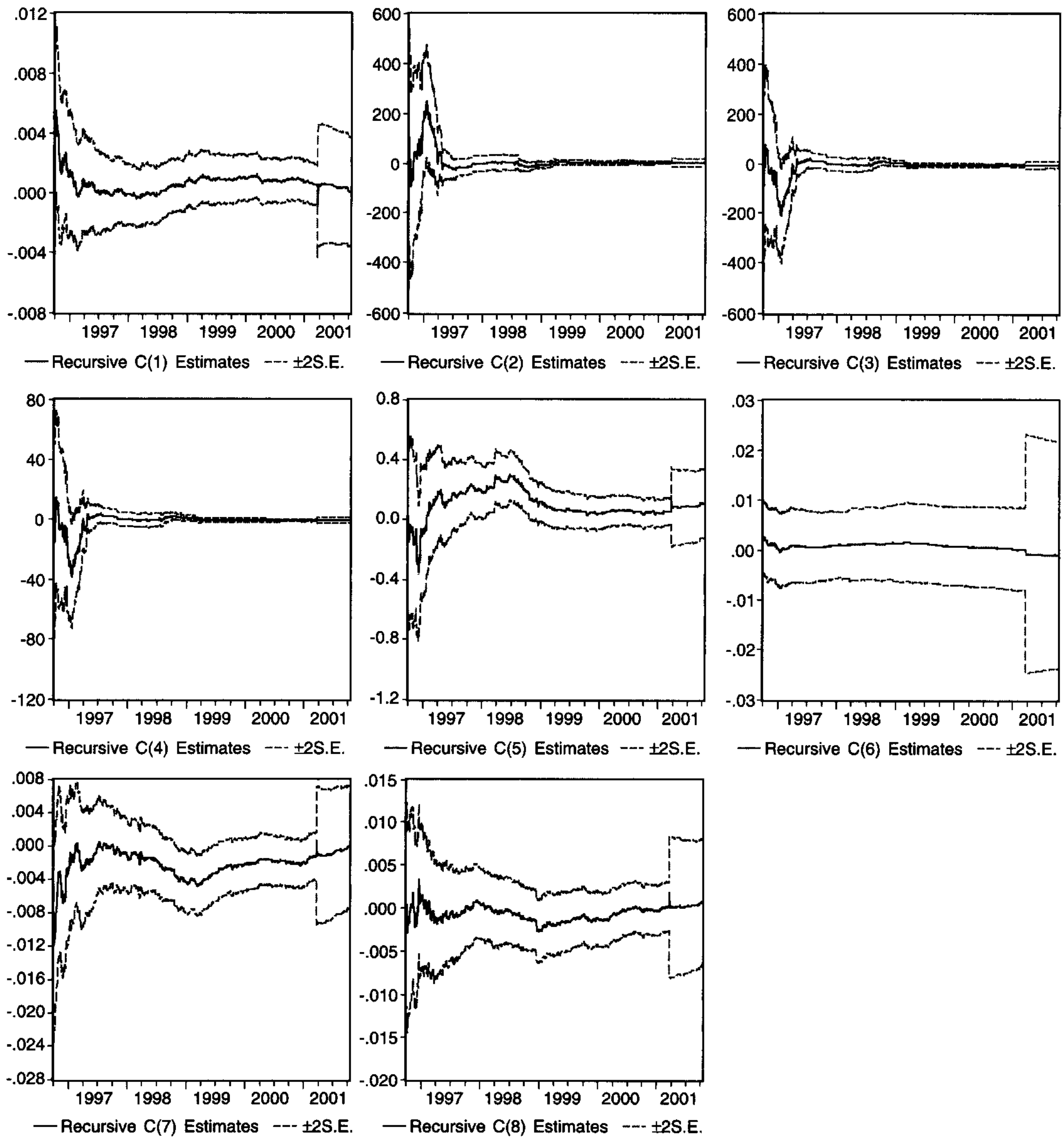

Fig. 3. The recursive stability test for the mixed oil/equity VAR 3.

Table 5
The VEC model for VAR Oil-5

Error correction	D(LWTIS)	D(LNYCOF1)	D(LNYCOF2)	D(LNYCOF3)	D(LNYCOF4)
ECT1	−0.4596*	0.8593***	0.0669	0.0583	0.0485
ECT2	0.4355*	−0.2623*	−0.0999	−0.2536**	−0.0802
ECT3	0.0605	0.3034*	0.0618	0.8188*	0.0672
ECT4	−0.0092	−0.0271	−0.0230	−1.0151*	−0.0121
D(LWTIS(−1))	0.2437*	0.1379**	0.1293*	0.1081	0.0912**
D(LNYCOF1(−1))	−0.0570	0.1454	0.2418**	0.2840***	0.1296***
D(LNYCOF2(−1))	−0.6174*	−0.6745*	−0.8125*	−0.7029**	−0.5482*
D(LNYCOF3(−1))	−0.0077	−0.0025	−0.0006	−0.0039	−0.0031
D(LNYCOF4(−1))	0.5352*	0.5009*	0.5424*	0.4003	0.3852**
DM	0.0015	0.0011	0.0006	0.0017	0.0005
DF	0.0023***	0.0013	0.0011	0.0022	0.0009
Log likelihood			25,351.21	Skewness	3,844.37*
AIC			−31.01	Kurtosis	1,660,915.0*
SC			−30.85	Normality	1,664,760.0*
Portmanteau test (up to 12 lags)			6 Lags	White test	2,087.36*

VAR Oil-5: WTIS, NYCOF1, NYCOF2, NYCOF3 and NYCOF4.

* Significant at the 1% level.

** Significant at the 5% level.

*** Significant at the 10% level.

Moreover, S&P has also classified them as a separate index because they do not fit into the other indices.

Finally, the recursive coefficients stability test, which we employed to check whether the estimated regression equations are stable throughout the sample period, supports the structural stability of the estimated regressions for mixed VARs as represented by the mixed VAR, Mixed-3 (see Fig. 3).[11]

3.3. Causality and error correction models

The finding of the presence of cointegration sets the stage for using the error-correction model. If a set of nonstationary variables is cointegrated then an unrestricted vector autoregression model (VAR) comprised of the first differences of these variables will be misspecified. The reason is that the first differences of nonstationary variables impose too many unit roots, and information on long-run equilibrium relationships among the variables will be lost. Then in this case the error-correction model (VECM) must be used. This model includes a vector of error terms that represents deviations from the long-run equilibrium and lagged short-term deviations.

[11] In this procedure, the equations are estimated repeatedly, using ever larger subsets of the sample data. If there are k coefficients, then the first k observations are used to form the first estimate of the parameter vector. The next observation is then added to the data set, and k+1 observations are used to compute the second estimate of the parameters. This process is repeated until all the T sample points have been used.

Table 6
Weak exogeneity tests for various VEC models

VAR	WTIS	NYCOF1	NYCOF2	NYCOF3	NYCOF4	ISPOC	ISPOII	ISPODI	ISPOEP	ISPOGRM
Oil-F4		8.98**	0.99	515.07*	0.75					
Oil-5	77.15*	13.40*	3.77	517.68*	2.76					
Mixed-0	2.88***					5.83*	6.88*	0.22	0.37	2.73***
Mixed-1		3.43***				5.75*	6.85*	0.16	0.25	2.76***
Mixed-2			3.22***			5.10**	6.14*	0.05	0.12	2.35
Mixed-3				14.47*		0.85	0.85	0.33	0.53	1.97
Mixed-4					2.67***	4.35**	4.18**	0.00	0.07	1.45

The null hypothesis is that the *i*th endogenous variable is weakly exogenous with respect to the β parameters. The test statistic is chi-square. Other notes are similar to Table 3 notes.

* Rejection of the null hypothesis at 1% significance level.

** Rejection of the null hypothesis at 5% significance level.

*** Rejection of the null hypothesis at 10% significance level.

We estimated three VEC models: one for Oil-F4, which includes the four NYMEX futures; one for Oil-5, which contains the five spot and futures prices; and the last one is for Mixed-3 which comprises the 3-month futures and the five S&P oil sector stock indices. The 3-month futures price was chosen because it showed more causal relationships with the stock indices than the other oil prices. We also add dummy variables for Fridays and Mondays to all the VEC models to account for the day-of-the week effect. Both days are associated with the release of important economic indicators, and Friday may coincide with triple option expiration. In order to estimate those VEC models, we have to determine the number of lags in each equation of the series. The lag lengths were selected based on the likelihood ratio (LR) test supplemented by the AIC information criterion.[12]

Table 5 shows the estimates for Oil-5 VEC model.[13] In this model, those estimates show that the error-correction terms in each equation, which measure the long-run disequilibrium are not significantly different from zero for the 2- and 4-month futures prices, implying that those two prices do not have the tendency to restore equilibrium and take the brunt of the shocks to the system (Urbain, 1992). The Wald tests for the error correction terms in this oil VEC model indicate that at all three significance levels these two futures prices are weakly exogenous (see Table 6). This suggests that there is no long-run relationship between these two prices and the spot, 1-month, and 3-month futures prices. Moreover, on a daily basis, there are bidirectional causal relationships among all the oil prices with the exception of the maverick 3-month futures price, which is geared by more forces than the other prices.

Table 7 shows the estimates for the Mixed-3 VEC model. In this model, the estimates show that the error-correction terms are statistically significant in the cases of the 3-month oil futures price, ISPOEP and ISPOGRM but are not in the case of the integrated indices (namely ISPOC, ISPOII, and ISPODI), implying that those integrated indices do not have the tendency to restore equilibrium and

[12] The selected lag lengths have also been consistent with the shortest lag adequate to produce serially uncorrelated residuals as shown by the LM and Portmanteau tests.

[13] A VEC model for the VAR Oil-F4, which contains all four futures prices, was also estimated and gave results similar to those of the Oil-5 VEC model. Those results are not reported in this version of the paper.

Table 7
The VEC model for VAR Mixed-3

Error correction	D(LNCOF3)	D(LISPOC)	D(LISPOII)	D(LISPODI)	D(LISPOEP)	D(LISPOGRM)
ECT1	−0.0618*	−0.0044	−0.0046	−0.0028	0.0046	−0.0061***
D(LNCOF3 (−1))	−0.3981*	0.0080	0.0074	0.0129	0.0198***	0.0157**
D(LISPOC (−1))	7.4514	3.4718	3.4893	3.9947***	−0.0863	−0.1056
D(LISPOII (−1))	−6.5042	−3.1868***	−3.2155	−3.5485***	0.0459	0.0779
D(LISPOEP (−1))	0.0790	0.0612**	0.0595***	0.0733**	0.0498	0.0479
D(LISPODI (−1))	−0.8152	−0.3416	−0.3399	−0.4319	0.0789	0.0779
D(LISPOGRM (−1))	0.0087	−0.0332	−0.0356	−0.0140	−0.0092	−0.0658***
DM	−0.0003	0.0003	0.0005	−0.0006	−0.0014	−4.98E−05
DF	0.0027	0.0007	0.0006	0.0015***	0.0019	0.0014
Log likelihood			28,133.76		Skewness	2,261.74*
AIC			−41.46		Kurtosis	3,216.68*
SC			−41.22		Normality	5,478.42*
Portmanteau test (up to 12 lags)			12 Lags		White test	1,821.34*

VAR Mixed-3: NYCOF3, ISPOC, ISPOII, ISPOEP, ISPODI, ISPOGRM.
* Significant at the 1% level.
** Significant at the 5% level.
*** Significant at the 10% level.

take the brunt of the shocks to the system. Again, this finding indicates that these three integrated indices are weakly exogenous with respect to the long-run parameter equations and do not adjust to restore equilibrium. This result may be because these indices are integrated and may have offsetting effects, depending on the type of the company included. The more defined indices ISPOEP and ISPOGRM do not have these problems. On a daily basis, none of the oil industry stock indices can explain the future movements of the NYMEX 3-month futures price, whereas this price can explain the movements of independent companies engaged in exploration, refining, and marketing. This confirms our previous results that the oil exploration companies and refiners take their cues from the oil market.

We used a log-likelihood ratio test to test the deletion of two dummy variables assigned for the beginning of the Asian crisis on July 2, 1997 and the adoption by OPEC of a target zone mechanism for the oil price on February 1, 2000. All the tests conducted on the mixed VEC model reject the null hypothesis of the deletion of the two dummy variables.

4. Univariate ARCH/GARCH model for the mixed system with oil spillover and day effects

The ARCH models were introduced by Engle (1982) and generalized as GARCH by Bollerslev (1986). They are widely used in various branches of econometrics, especially in financial time series analysis, and are specifically designed to model and forecast conditional variances. There is general agreement that capital investors would demand high returns as a compensation for holding risky assets because they generally dislike risk. The investor may thus require a higher risk premium as the degree of market volatility increases, which points to increased investor uncertainty about the future of risky investments and wealth. This, in turn, may lead to lower liquidity and higher transaction costs in the affected markets. Moreover, higher risk premiums and greater uncertainty may also decrease productive direct investment because they may enhance the cost of assets and the cost of new investment projects. If the risk premium is volatile, then the related changes in the returns will cause considerable movement in asset prices. Here, we examine both the mean and volatility spillovers for and between the oil and financial markets.

The standard ARCH model is specified by the mean equation

$$\Delta y_t = \alpha_0 + \sum_{i=0}^{n} \beta_i e_{t-i}, \qquad \text{where } e_t \sim (0, \delta_t^2),$$

and the variance equation

$$\delta_t^2 = \gamma_0 + \sum_{i=1}^{q} \gamma_i e_{t-i}^2$$

where e_{t-i}^2 is the ith ARCH term, q is the order of the ARCH terms, and δ_t^2 is the conditional variance of the residual. The Box–Jenkins methodology is used to identify the order of ARMA in the mean equation.

The LM test is usually conducted to determine whether the ARCH effects are present and that the use of the ARCH/GARCH model is warranted. To account for the spillover effect, the oil ARCH model is first estimated to derive the mean and variance for the 3-month futures price. Then those fitted values for the means and the generated values for the variances of the oil prices in the system are incorporated as regressors in the appropriate mean and variance equations of the ARCH/GARCH model for that the S&P sector stock index system under consideration and their significance is tested. In this case, they are called mean and variance oil spillovers.

$$\Delta y_t = \alpha_0 + \sum_{i=0}^{n} \beta_i e_{t-i} + \text{Mean Spillovers}$$

$$\delta_t^2 = \gamma_0 + \sum_{i=1}^{q} \gamma_i e_{t-i}^2 + \sum_{j=1}^{p} \lambda_j \delta_{t-j}^2 + \text{Variance Spillovers}$$

where δ_{t-j}^2 is the jth GARCH term and p is the order of the GARCH terms. The autoregressive root, which governs the persistence of volatility shocks, is the sum of the ARCH term(s) and the GARCH term(s). If this sum is close to unity, it means that the shocks die out slowly. The ARCH/GARCH order is selected on the criterion of which model has the best fit.

The LM tests for all the oil price and the S&P sector stock indices indicate that the ARCH effects are significant at the 1% level, suggesting the use of the ARCH/GARCH methodology is warranted (see Table 8). Based on the above methodology, we will examine the mixed oil price/ sector stock indices system to examine the volatility spillovers coming from the oil market to the sector stock markets.

The estimates of the GARCH model for the VAR of the four S&P sector stock indices with the 3-month futures oil price's mean and variance spillovers are provided in Table 9. The estimate for the composite index ISPOC is not provided in this table because the GARCH results for this index are not meaningful. For this system, the ARCH and GARCH terms are significant for the most part at the 1%

Table 8
The Lagrange multiplier (LM) test for the three-month futures price and the S&P sector stock indices

	DLISPOC	DLISPOII	DLISPODI	DLISPOEP	DLNYCOF3
Constant	0.0001 (12.31)	0.0002 (6.89)	0.0021 (7.48)	0.0003 (7.24)	0.0013 (1.29)
MA(1)	0.1653 (6.66)	0.8538 (491.20)	0.1185 (4.80)	0.0296 (10.31)	
MA(2)				0.8014 (343.00)	
AR(1)					0.3385 (13.63)
F statistic (probability)	20.00 (.000)	241,281.2 (.000)	23.11 (.000)	62,900.52 (.000)	77.61 (.000)

The null hypothesis is no ARCH.
Numbers in parentheses are *t* statistics.
All ARACH effects are significant at the 1% level.

Table 9
The volatility spillover effects from the NYMEX 3-month futures price to the S&P sector stock indices

Independent variable	DLISPOII	DLISPODI	DLISPOEP	DLISPOGRM
Mean equation				
Constant	0.0071*	0.0121***	0.0255**	−0.0137*
	(6.27)	(1.77)	(2.75)	(−5.53)
NYCOF3 mean spillover	−1.0418*	−1.8385***	−4.0549**	N/S
	(−5.85)	(−1.67)	(−2.72)	
MA(1)	0.0018	0.0541***	0.0588**	0.0462
	(0.06)	(1.83)	(2.07)	(0.37)
ARCH/GARCH variance equation				
Constant	0.0001*	0.0001*	0.0001*	0.0008*
	(13.98)	(12.72)	(10.90)	(7.38)
e_{t-1}^2	0.1002*	0.2281*	0.2125*	0.0883
	(5.42)	(6.95)	(6.28)	(0.78)
δ_{t-1}	0.4372*	0.1031*	0.3715*	0.3953*
	(13.90)	(3.34)	(11.92)	(4.52)
ARCH variance of NYCOF3 with 1-day lag				−0.0001*,[a]
				(−11.95)
DF	−0.0008*	−0.00001	−0.0001*	N/S
	(−6.83)	(−1.38)	(−7.02)	
ARCH variance of NYCOF3 with 2-day lag		0.0279*,[b]	0.0362*	
		(10.59)	(5.88)	
ARCH variance of NYCOF3 with 4-day lag	−2.12E−05*			
	(−21.44)			
Log likelihood function value	4593.11	4602.75	4187.56	2875.737

The estimate of the ARCH/GARCH model for LISPOC was not significant and, thus, is not reported in this table. All variables are first differences of natural logs. *Z* statistics are in parentheses. N/S means not significant.

[a] It is also significant with no lags in ARCH variance of NYCOF3.

[b] It is also significant with a 1-day lag in ARCH variance of NYCOF3.

* Significant at the 1% level.

** Significant at the 5% level.

*** Significant at the 10% level.

level. The autoregressive root, which governs the persistence of volatility in these markets, is between 50% and 60%, indicating that a shock does not die out slowly as is true in the financial literature. Although the oil volatility spillover effect is very small (less than 4%), it is still significant at the 1% level for three indices, namely, ISPOII, ISPOEP and ISPODI. It has a volatility-echoing effect on the stocks of the companies engaged in oil exploration and production, and on the stocks of the oil domestic integrated companies in general. However, it has a volatility-dampening effect on the stocks of the oil international integrated companies and the companies engaged in oil and gas refining and marketing. This negative spillover effect is likely due to crude oil being the main ingredient in the refining process and the inclusion of gas activity in this index. Thus, during times of heightening oil volatility, traders or investors in these oil sector stocks should choose the sectors that fit their tolerance for volatility and use the appropriate financial instruments that profit on volatility if they select more volatile sectors.

Although the day effects for both Monday and Friday are not significant in the VEC models that measure the effects of changes in the variables, the effect for Friday for most sector indices in GARCH models that measure the transmission of volatility is significant at the 1% level, but it is small and negative. This finding for the variance equation suggests that Friday is a calming trading day for the volatility of most of the sectors' stocks in general, and thus is not a good trading day for profiting from volatility. As in the VEC models, the effect for Monday in the GARCH models is not significant and thus is not reported.

5. Multivariate models of volatility

In comparison to univariate GARCH models, multivariate models have the advantage that the changes in a stock index (returns) or changes in a price can be modeled to include interactions of this change with all possible variances and covariances. The changes in a stock index are affected by changes in both the spot and futures oil prices. Similarly, changes in stock prices (returns) influence market capitalization and provide future growth potential, in turn influencing oil exploration and supply. Thus, it is important to take into account the interactions among stock prices and volatility stemming from own price movements as well as from the volatility in other markets such as the oil market. These interactions can be summarized in the following conditional mean equations:

$$\begin{aligned} r_{et} &= a_{10} + a_{11}r_{et-1} + a_{12}h_{et} + a_{13}\mathrm{cov}(r_{et}, r_{st}) + a_{14}\mathrm{cov}(r_{et}, r_{ft}) + \varepsilon_{e\tau} \\ r_{st} &= b_{10} + b_{11}r_{st-1} + b_{12}h_{st} + b_{13}\mathrm{cov}(r_{et}, r_{st}) + b_{14}\mathrm{cov}(r_{st}, r_{ft}) + \varepsilon_{e}s \\ r_{ft} &= c_{10} + c_{11}r_{ft-1} + c_{12}h_{ft} + c_{13}\mathrm{cov}(r_{et}, r_{ft}) + c_{14}\mathrm{cov}(r_{st}, r_{ft}) + \varepsilon_{et} \\ [\varepsilon_t] &\sim N(0, [\mathbf{H}_t]) \end{aligned} \tag{1}$$

where r_{et} is the percentage change of returns in an equity index [e.g., r_{et}=DLISPOC, DLISPOGRM, DLISPODI, DLISPOII, DLISPOEP), r_{st} is the percentage change in the spot oil price (DLWTIS), r_{ft} is the percentage change in the 3-month futures oil price (DLNYCOF3), $[\mathbf{H}_t]$ is the 3×3 variance–covariance matrix, and $[\varepsilon_t]$ is the vector of error terms from estimating r_e, r_s, and r_f.

An important step in implementing the model empirically is specifying the dynamics of the conditional variance and covariance. In an extension of the standard (univariate) GARCH-M model given in the previous section, Bollerslev, Engle, and Wooldridge (1988) proposed a multivariate GARCH-M specification, which allows for the influence of the covariance term on the domestic process. For our three-dimensional case (a trivariate GARCH-M process), the conditional variance–covariance specification can be expressed as

$$\mathrm{Vec}[\mathbf{H}_t] = \begin{pmatrix} h_{et} \\ h_{st} \\ h_{ft} \\ \mathrm{cov}(r_{et}, r_{st}) \\ \mathrm{cov}(r_{et}, r_{ft}) \\ \mathrm{cov}(r_{st}, r_{ft}) \end{pmatrix} = \begin{pmatrix} \phi_e \\ \phi_s \\ \phi_f \\ \phi_{es} \\ \phi_{ef} \\ \phi_{sf} \end{pmatrix} + \begin{pmatrix} \alpha_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & \alpha_{22} & 0 & 0 & 0 & 0 \\ 0 & 0 & \alpha_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & \alpha_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & \alpha_{55} & 0 \\ 0 & 0 & 0 & 0 & 0 & \alpha_{66} \end{pmatrix} \begin{pmatrix} (\varepsilon_{et-1})^2 \\ (\varepsilon_{st-1})^2 \\ (\varepsilon_{ft-1})^2 \\ \varepsilon_{et-1}\varepsilon_{st-1} \\ \varepsilon_{et-1}\varepsilon_{ft-1} \\ \varepsilon_{st-1}\varepsilon_{ft-1} \end{pmatrix}$$
$$+ \begin{pmatrix} \gamma_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & \gamma_{22} & 0 & 0 & 0 & 0 \\ 0 & 0 & \gamma_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & \gamma_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & \gamma_{55} & 0 \\ 0 & 0 & 0 & 0 & 0 & \gamma_{66} \end{pmatrix} \begin{pmatrix} h_{et-1} \\ h_{st-1} \\ h_{ft-1} \\ \mathrm{cov}(r_{et-1}, r_{st-1}) \\ \mathrm{cov}(r_{et-1}, r_{ft-1}) \\ \mathrm{cov}(r_{st-1}, r_{ft-1}) \end{pmatrix} + \begin{pmatrix} v_{et} \\ v_{st} \\ v_{ft} \\ v_{est} \\ v_{eft} \\ v_{sft} \end{pmatrix} \quad (2)$$

where Vec(·) is the vector operator that stacks the columns of the matrix $[\mathbf{H}_t]$, and $[\phi]$, $[\alpha]$, and $[\gamma]$ are diagonal coefficient matrices. Moreover, with Eqs. (1) and (2), the dynamic pattern of variances is modeled as GARCH(1,1), as it is a common practice in the literature. French, Schwert, and Stambaugh (1987) contend that it is appropriate to ignore higher order terms of lagged conditional variances or prediction errors as they show that modeling the conditional variance of the expected change or the excess returns as a GARCH(2,1) leads to insignificant results.

The trivariate conditional variance–covariance specification in Eq. (2) allows the conditional variances to depend only on past squared residuals, and covariances to depend on past products of error terms. In other words, cross-market effects are ignored in this specification. It is possible to specify a more general process to capture cross-market spillover effects, but positive semidefiniteness of the conditional covariance matrix in that process is not assured. Baba, Engle, Kraft, and Kroner (1989) (hereafter BEKK) propose the following specification where the $[\alpha]$ and $[\gamma]$ matrices include nonzero, off-diagonal elements, and the positive semidefiniteness of the conditional covariance matrix is guaranteed.

$$[\mathbf{H}_t] = [\mathbf{P}]'[\mathbf{P}] + [\mathbf{F}]'[\mathbf{H}_{t-1}][\mathbf{F}] + [\mathbf{G}]'[\varepsilon_{t-1}][\varepsilon_{t-1}]'[\mathbf{G}] \quad (3)$$

where $[\mathbf{H}_t]$ denotes the 3×3 variance–covariance matrix conditional on information at time t and $[\varepsilon_{t-1}]$ denotes the vector of disturbances from Eq. (1). $[\mathbf{P}]$ is an upper triangular matrix of three coefficients, whereas [F] and [G] are free (square) matrices of coefficients containing nine parameters each. The advantage of this approach over full parameterization is that it economizes on the number of parameters in Eq. (3), and it guarantees positive definite covariance matrices. Moreover, for the covariance to be stationary, the eigenvalues of the expression $\Sigma_q[\mathbf{F}_q]\otimes[\mathbf{F}_q]+\Sigma_p[\mathbf{G}_p]\otimes[\mathbf{G}_p]$ all have to be less than one in absolute value in the respective trivariate GARCH-M processes. The numbers q and p in the expression of eigenvalues are the past lags of conditional variance–covariance, and the product of disturbances, i.e., in the trivariate GARCH(p,q)-M specification, and $\otimes$ denotes the Kronecker product.

The multivariate model above in Eqs. (1) (conditional mean) and (3) (conditional variance) allow for considerable dynamics in the interactions between the S&P oil equity markets and the related oil spot and futures markets.

Table 10 presents the estimation results for the trivariate GARCH model using the BEKK parameterization. This specification relates the changes in each S&P oil sector stock index or returns to the changes in the spot and futures oil prices.

In the mean equations presented for each of the five models, the intercept parameters are either zero or negative for the oil sector stock indices. Of all these negative intercept terms, only the intercept in the S&P Oil and Gas Refining and Marketing (ISPOGRM) equation is significant at the 1% level. Some attribute the negative intercept to the reduced capital gains tax on long-term assets because the tax provides incentives to hold these assets despite otherwise unfavorable rates of returns.[14] The negative intercepts also imply equity holders relative to investors in the commodity markets did consistently worse over the specific sample period under consideration. Note that the intercepts, b_{10}, for the oil spot price change equation and c_{10}, for the changes in oil futures price equation are generally positive, implying that oil traders did consistently better than equity investors over the sample period.

The mean equations also show that the autoregressive term on equity returns (a_{11}) in each model is significant, indicating pronounced serial correlation in equity returns. However, the autoregressive terms on oil spot and futures price changes (b_{11}) and (c_{11}) are not significant. The conditional variance terms on equity returns (a_{12}) are significant for DLISPOC and DLISPOGRF equations. As for the conditional variance terms on oil price changes (b_{12} and c_{12} parameters), all are insignificant except for the DLISPOC model. The lack of significance of the coefficient on the variance is somewhat surprising and implies that time variation in the conditional variance in some returns or price changes is not an important source of variation in those returns or price changes. It is also important to note that this weak premium effect may be due to some diversifiable risk associated with that particular market, or else there is weak evidence of time variation in market risk. Overall, generally, coefficients in the mean equations based on DLISPOC and DLISPOGRM are significant and the rest are not.

The coefficients of the covariance terms indicate that most covariance effects are significant for the equity returns as measured by changes in DLISPOC. Specifically, returns on the ISPOC index depend positively on the covariance of equity returns with the oil spot price changes and oil futures price changes. Is there any effect of the covariance of equity returns with the oil price changes on changes in oil spot and futures prices? The DLISPOC model suggests that the covariance between equity returns and oil spot price changes have a positive effect on the spot oil price changes. Whereas cov(r_{et},r_{ft}) has a positive effect on futures price changes, cov(r_{ft},r_{st}) has a negative effect on futures price changes in the DLISPOC model.

[14] A detailed discussion can be found in Bollerslev et al. (1988), who attribute this to capital gains tax regulation.

Table 10
Estimates of the trivariate GARCH model

	Model				
	DLISPOC	DLISPOGRM	DLISPODI	DLISPOEP	DLISPOII

Estimates of the coefficients of the conditional percentage changes:

$$r_{et} = a_{10} + a_{11}r_{et-1} + a_{12}h_{et} + a_{13}\mathrm{cov}(r_{et}, r_{st}) + a_{14}\mathrm{cov}(r_{et}, r_{ft}) + \varepsilon_{e\tau}$$

$$r_{st} = b_{10} + b_{11}r_{st-1} + b_{12}h_{st} + b_{13}\mathrm{cov}(r_{et}, r_{st}) + b_{14}\mathrm{cov}(r_{st}, r_{ft}) + \varepsilon_{e}$$

$$r_{ft} = c_{10} + c_{11}r_{ft-1} + c_{12}h_{ft} + c_{13}\mathrm{cov}(r_{et}, r_{ft}) + c_{14}\mathrm{cov}(r_{st}, r_{ft}) + \varepsilon_{e\tau}$$

	DLISPOC	DLISPOGRM	DLISPODI	DLISPOEP	DLISPOII
a_{10}	0.000	−0.002***	−0.001	−0.004	0.000
a_{11}	−0.062***	0.363***	−0.244***	−0.153***	−0.075***
a_{12}	17.349***	−2.938***	1.271	5.774	−0.542
a_{13}	7.713*	−9.436***	0.022	0.971	−1.681
a_{14}	3.849***	3.197	−0.449	0.666	14.529
b_{10}	0.005**	0.001	0.004	0.004**	0.001
b_{11}	−0.005	−0.003	0.017	−0.001	−0.011
b_{12}	−4.258	3.619	0.012	−0.112	−2.126
b_{13}	91.836***	0.122	0.092	1.245	3.431
b_{14}	0.458	−6.374*	0.048	−0.137	0.490
c_{10}	0.003*	0.002	0.003	0.003	−0.038
c_{11}	0.002	−0.001	−0.003	0.013	0.006
c_{12}	1.779***	1.446	0.028	−0.128	31.412
c_{13}	115.972***	−17.338*	0.462	−0.597	23.796
c_{14}	−9.205**	−7.471	−0.056	−0.539	−20.835

Estimates of the coefficients of the variance–covariance matrix equation:

$$[\mathrm{H}_t] = [\mathrm{P}]'[\mathrm{P}] + [\mathrm{F}]'[\mathrm{H}_{t-1}][\mathrm{F}] + [\mathrm{G}]'[\varepsilon_{t-1}][\varepsilon_{t-1}]'[\mathrm{G}]$$

	DLISPOC	DLISPOGRM	DLISPODI	DLISPOEP	DLISPOII
P_{11}	−0.009***	0.011***	0.015***	0.018***	0.013***
P_{12}	0.001	−0.001	0.003	−0.000	−0.000
P_{13}	0.001	−0.000	0.003	−0.001	0.002
P_{22}	0.004	0.005**	0.021***	0.005	0.001
P_{23}	0.007	0.003	0.017***	0.007	0.022
P_{33}	0.000	0.000	−0.000	0.000	0.027
G_{11}	−0.312***	−1.287***	0.080	−0.049	0.413***
G_{12}	−0.188***	−0.240***	0.027	0.139***	0.158**
G_{13}	0.075***	−0.008	−1.261***	−0.701***	0.128
G_{21}	−0.071***	−0.008	0.065*	−0.011	−0.005
G_{22}	−0.252***	0.231***	−0.007	0.143***	0.363***
G_{23}	0.325***	−0.097***	0.841***	0.924***	0.056
G_{31}	0.005***	0.002	−0.008	−0.005	−0.013
G_{32}	−0.120***	−0.015	0.002	−0.002	−0.091
G_{33}	−1.052***	0.284***	0.229***	0.191***	0.135
F_{11}	−0.689***	0.008	0.213	0.364	0.129
F_{12}	−0.300***	0.181***	0.495	0.793	−0.155
F_{13}	−0.265***	1.251***	0.020	0.700	−0.174

Table 10 (*continued*)

	Model				
	DLISPOC	DLISPOGRM	DLISPODI	DLISPOEP	DLISPOII
F_{21}	0.019	0.060	−0.092	0.061	−0.096
F_{22}	1.064***	−0.873***	0.151	−0.636***	−0.679***
F_{23}	1.027***	−0.387***	0.193	−0.457***	−0.241
F_{31}	0.000	−0.016	−0.005	−0.009	0.017
F_{32}	−0.218***	−0.105***	0.215***	−0.230***	−0.283
F_{33}	−0.874***	−0.155**	−0.012	0.061	−0.297

Each model is based on [r^j_{et}, r_{st}, r_{ft}], where r_{et} is the rate of return on oil related equity indexes; j=SPOC, SPOGRF, SPODI, SPOEP, and SPOII. r_{st} and r_{ft} refer to the returns on oil spot and 3-month oil futures.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

The DLISPOGRM model indicates that equity returns receive volatility from cov(r_{et},r_{st}), while, at the same time, oil spot price changes receive volatility from cov(r_{st},r_{ft}). On the other hand, oil futures price changes appear to receive volatility from cov(r_{et},r_{ft}). The covariance effects in the rest of the models are not significant. These volatility transmissions are summarized in Fig. 4.

Finally, we note that it is hard to directly interpret the coefficient estimates of the variance–covariance matrix equations except that the significance of the diagonal elements of the [**F**] and [**G**] matrix indicate prevalent and strong conditional variance effects. On the other hand, the assumption of cross-market volatility effects can be confirmed by the high degree of significance of the off-diagonal elements. This high degree of significance is consistent with the results of Hamao (1990) that cross-market effects cannot be neglected in volatility analysis.

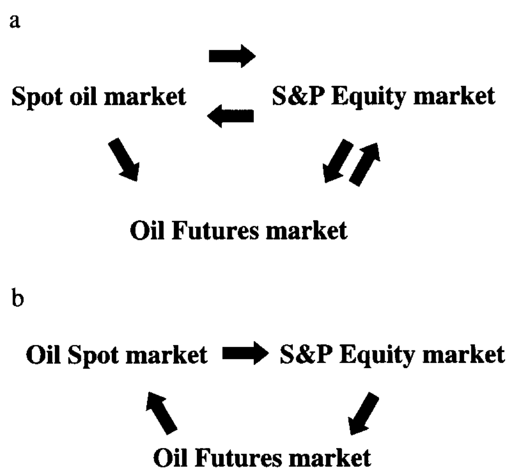

Fig. 4. The pathway of volatility transmission between oil markets and S&P oil sector equity markets. (a) DLISPOC model. (b) DLISPOGRM model.

6. Summary and conclusions

This study investigates the intra- and interlinks for two U.S. markets of oil prices and S&P oil sector stock indices using daily data for the available period July 17, 1995 to October 10, 2001. The oil markets include the WTI spot and 1- to 4-month NYMEX futures prices. The sector stock indices include Oil Exploration and Production, Oil and Gas Refining and Marketing, Oil-Domestic Integrated, Oil-International Integrated, and the overall Oil Composite. The empirical investigation employs unit root tests, cointegration tests, error-correction models with day effects, and univariate and multivariate ARCH/GARCH models with day and oil spillover effects.

The cointegration tests for the mixed oil price/stock index system indicate that these indices have one long-run relationship, suggesting that this system offers more opportunities for long-run diversification than any of pure oil systems, which have more than one cointegrating relationship. Moreover, the VEC model for this mixed system suggests that on a daily basis none of the oil industry stock indices can explain the future movements of the NYMEX 3-month futures prices, while these prices can explain the movements of independent companies engaged in exploration, refining, and marketing. This confirms our previous results that the oil exploration companies and refiners take their cues from the oil market. Therefore, traders and investors in the oil stocks should not use these stocks to forecast the future paths of oil prices. On the contrary, they should use oil futures prices to predict the movements of oil company stock prices, especially those that are engaged in exploration and production (such as Anadarko Petroleum, Apache, Burlington Resources, and Devon Energy) and those that are involved in refining and marketing (such as Ashland, Sunoco, Tosco, etc.).

The spillover analysis in the univariate GARCH for the mixed system suggests that the oil futures market's volatility transmission has a resonant and echoing effect on the volatility of the stocks of the oil and gas exploration, production, and domestic integrated oil companies. It also implies that this oil volatility spillover has a dampening effect on the volatility of the stocks of the oil international integrated, and oil and gas refining and marketing companies. The policy implication for oil volatility transmission is that, at times of oil volatility, traders should choose the S&P oil sector company stocks that match their tolerance for volatility and use the right financial derivative to profit from this volatility. The trading day effect in the spillover analysis indicates that Friday is associated with reducing volatility for most of the sectors' indices. The effect for Monday is not significant.

The multivariate GARCH, which captures simultaneous volatility interactions, indicates that there are two-way interactions between the S&P Oil Composite index, LSPOCI, and the oil spot price and the oil futures price. Moreover, it shows that the transmission of volatility runs from the oil spot price to the 3-month futures price, something that was not revealed by the univariate GARCH model. However, in the case of the refining and marketing index, SPOGRF, there was a circular volatility transmission, starting from the oil spot price to SPOGRF then going to the 3-month futures price. Therefore, both cases hold the spot price to be responsible for more volatility transmission than the futures price.

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Appendix A

S&P: Oil Composite			910
IDD: SP OC 00000267		Oil Composite	
Oil (Domestic Integrated)			
S&P: Oil (Domestic Integrated)			385
IDD: SP OD 00000269		Oil Domestic	
02355110	AHC	Amerada Hess	
20825140	COC B	Conoco	
67459910	OXY	Occidental Petroleum	
71850710	P	Phillips Petroleum	
90290582	MRO	USX-Marathon Group	
S&P: Oil (International Integrated)			390
IDD: SP OI 00000270		Oil International Integrated	
16675110	CHV	Chevron	
30231G10	XOM	Exxon Mobile	
78025770	RD	Royal Dutch Petroleum	
88169410	TX	Texaco	
S&P: Oil and Gas (Drilling and Equipment)			395
IDD: SP OS 00000258		Oil Equipment and Services	
05722410	BHI	Baker Hughes	
40621610	HAL	Halliburton	
62956810	NBR	Nabors Industries	
65504210	NE	Noble Drilling	
77938210	RDC	Rowan Cos	
80685710	SLB	Schulumberger	
G9007810	RIG	Transocean Sedco Forex	
S&P: Oil and Gas (Exploration and Production)			380
IDD: SP OP 00000860		Oil and Gas Exploration and Production	
03251110	APC	Anadarko Petroleum	
03741110	APA	Apache	
12201410	BR	Burlington Resources	
25179M10	DVN	Devon Energy	
26875P10	EOG	EOG Resources	
49238610	KMG	Kerr-McGee	
91528910	UCL	Unocal	
S&P: Oil and Gas (Refining and Marketing)			382
IDD: SP PP 00000E63		Oil and Gas (Refining and Marketing)	
04454010	ASH	Ashland	
86676P10	SUN	Sunoco	
89149030	TOS	Tosco	

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