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Full Length Research Paper

News arrival and volatility components: Oil and the stock markets

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This study develops a two step method for investigating the impact of oil shocks on stock returns. Oil price volatility is monitored using structural change and regime switching. The jump model is then used to examine the spillover and asymmetric effects of oil prices on stock returns. Based on cross examination, a conclusive result is obtained, namely, when oil prices fluctuate significantly, asymmetric unexpected changes in oil price negatively impacted the Standard and Poor (S&P500).

Key words: Structural change, regime switch, spillover, asymmetric, autoregressive jump intensity (ARJI) model.

INTRODUCTION

For a financial hedger, portfolio manager, asset allocator, or other financial analyst, understanding volatility spillovers between markets is extremely important. The conditional volatilities of stock market indices change over time. Numerous studies thus have been intrigued by the causes for these changes, and a considerable body of literature exists on the relationship between financial and macroeconomic variables and stock market. In analyzing time-variation of stock returns, this study focuses on oil price volatility spillovers rather than general macroeconomic variables. The choice of oil is motivated by the extensive literature regarding the relationship between oil prices and macroeconomy. Previous studies suggest that, oil price variations have strong consequences on economic activity. Higher oil prices increase production costs have a negative effect on investment and thus reduce investment. If oil affects real output, increases in oil price would lower the expected earnings of stock market. This study thus focuses specifically on the association between oil price shocks and stock returns.

Most time series models experience two phenomena when applied to real life data, namely structural-changes and regime-switching. Estimation and inference that does not acknowledge these facts may result in unreliable results. Regime-switches are designed to capture discrete changes of states in the data generating economic mechanism, while structural change determines the break locations.

This study develops a two step method for investigating the impact of oil shocks on stock returns. Consistent results are obtained by comparing structural changes and regime switching while simultaneously considering the jump model[1]. This study assumes that stock returns are affected by shocks in oil prices and oil price volatility is affected by the state of the shocks in oil prices. Oil price volatility is examined based on structural change and regime switching. Using the jump model, Maheu and McCurdy (2004), the spillover and asymmetric effects of oil prices on stock returns are then examined. Cross examination yields a conclusive result, namely, when oil prices fluctuate significantly, asymmetric unexpected changes in oil prices [West Texas Intermediate (WTI)] negatively impact the S&P500.

LITERATURE REVIEW

A growing body of research exists on the relationship

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[1] See, Maheu, J. M. and T. H. McCurdy, 2004.

between energy prices and stock prices. Chen et al. (1986), Hamao (1989) failed to find a phenomenon of oil price risk being rewarded by the stock market. However, Kaneko and Lee (1995) found evidence of oil prices influencing stock returns. Furthermore, Ferson and Harvey (1995) found evidence of oil price risk factor statistically significantly and differentially influencing 18 equity markets. Additionally, Huang et al. (1996) found that oil futures returns lead stock returns of certain individual oil companies, but found no significant influence of oil futures on broad based market indices such as the S&P500. Jones and Kaul (1996) demonstrated that changes in oil prices that granger-precede most economic series, but also influence output and real stock returns in the U.S. Sadorsky (1999) showed that oil price movements explain the bulk of forecast error variance in real stock returns than do interest rates; oil price volatility shocks thus exert asymmetric economic effects. Faff and Brailsford (1999) found that oil prices positively and significantly influenced the oil and gas and diversified resource industries and negatively and significantly impacted paper and packaging and transportation industries. Meanwhile Papapetrou (2001) suggest that changes in oil prices affect real economic activity and employment. Oil prices are important in explaining stock price movements and stock returns do not cause changes in real activity and employment. Sadorsky (2003) demonstrated that the conditional volatilities of industrial production, oil prices, the federal funds rate, default premium, consumer price index and foreign exchange rate all significantly impact the conditional volatility of technology stock prices. Furthermore, the only study to find a bi-directional relationship between oil prices and stock prices was that of Hammoudeh and Eleisa (2004) on the Saudi Arabian Stock Market. Chaudhuri and Smiles (2004) found evidence of long-term relationships between real stock prices and measures of aggregate real activity. Using daily and weekly data for the petroleum complex, Pindyck (2004) developed a structural model of inventories, spot and futures prices that explicitly explains volatility. Regardless of the direction of global capital markets, Hammoudeh and Li (2005) suggest that investors should view the systematic risk as more important than oil sensitivity in pricing oil-sensitive returns. Kaufmann and Laskowski (2005) confirmed that price asymmetries can be generated by efficient markets, meaning there is little justification for policy interventions to reduce or eliminate price asymmetries in the motor gasoline and home heating oil markets. While most studies agree that energy prices influence stock prices, few studies have investigated the long-run equilibrium between stock and oil markets.

Most previous studies examining the traditional time series model assumed that the underlying variables exhibited a linear and symmetrical adjustment processes, but in reality, most macro variables exhibit asymmetrical adjustment. Pippenger and Goering (1993), Balke and Fomby (1997), Enders and Granger (1998) and Enders and Siklos (2001) have demonstrated the limited usefulness of traditional co-integration tests in situations involving asymmetric adjustment. To overcome the problem of the low power of asymmetric adjustment, various studies have applied nonlinear techniques to capture this asymmetry effect during the adjustment of the variable toward its long-run equilibrium.

Unlike the existing literature, this study considers expected, unexpected, and negative-unexpected fluctuation of oil prices in the model of stock returns. Additionally, to examine the behavior of the discrete changes of states in the economic mechanism that generates the data and locate the breaks[2], Chiou and Lee (2009), the ARJI model with structural-change and regime-switching consideration of the influence of oil prices on S&P500 returns is applied.

METHODOLOGY

Structural change

Based on the principle of dynamic programming and the requirement of least-squares operations for any number of breaks, Bai and Perron (2003) comprehensively analyze multiple structural change models. A multiple linear regression system with *m* breaks (*m+1* regimes) may be expressed in matrix form as:

$$Y = \beta X + \delta \bar{Z} + U, \quad (1)$$

where $Y = (y_1,...,y_T)'$, $X = (x_1,...,x_T)'$, $U = (u_1,...,u_T)'$, $\delta = (\delta_1', \delta_2',...,\delta_{m+1}')'$, and $\bar{Z}$ is the matrix which diagonally partitions Z at $(T_1,...,T_m)$. $\delta^0 = (\delta_1^{0'},...,\delta_{m+1}^{0'})'$ and $(T_1^0,...,T_m^0)$ are used to denote, respectively, the true values of the parameters δ and the true break points. The matrix $\bar{Z}^0$ is the one which diagonally partitions Z at $(T_1^0,...,T_m^0)$. Hence, the data-generating process is assumed to be:

$$Y = \beta^0 X + \delta^0 \bar{Z}^0 + U. \quad (2)$$

Assume $\delta_i^0 \neq \delta_{i+1}^0 \ (1 \le i \le m)$, the unknown coefficients $(\beta^0, \delta_1^0,...,\delta_{m+1}^0, T_1^0,...,T_m^0)$ are estimated. The regression parameter estimates can be obtained by using the associated least-squares estimates at the estimated *m*-partition $\{\hat{T}_j\}$, that is, $\hat{\beta} = \hat{\beta}(\{\hat{T}_j\})$, $\hat{\delta} = \hat{\delta}(\{\hat{T}_j\})$. The break points are discrete parameters and can only take a finite number of values.

Markov regime-switching

Consider the time series $y_t = \mu_{s_t} + \varepsilon_t$, where $\varepsilon_t \overset{iid}{\sim} N(0, \sigma^2)$,

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[2] See, Chiou, J. S. and Y. H. Lee, 2009.

$s_t = 1$, …., N indicates the market regime at time t. Note that the variable $s_t = i$, which can be referred to as a regime indicator, is a random variable with its own distribution and cannot be observed. We begin with the case where $N = 2$[3]. Two states of the market are provided through a first-order Markov process with the following transition probabilities matrix:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \quad (3)$$

where $\mathbf{P}$ transition probabilities matrix and the transition probability P_{11} and P_{12} (P_{21} and P_{22}) gives the probability that state 1 (4) will be followed by state 1 and 2 (2 and 1). The $\boldsymbol{\eta}_t$ show the two density function:

$$\boldsymbol{\eta}_t = \begin{bmatrix} f(y_t \mid s_t = 1, \mathbf{Y}_{t-1}; \boldsymbol{\theta}) \\ f(y_t \mid s_t = 2, \mathbf{Y}_{t-1}; \boldsymbol{\theta}) \end{bmatrix} = \begin{bmatrix} \dfrac{1}{\sqrt{2\pi}\sigma_1} \exp\left\{ \dfrac{-(y_t - \mu_1)^2}{2\sigma_1^2} \right\} \\ \dfrac{1}{\sqrt{2\pi}\sigma_2} \exp\left\{ \dfrac{-(y_t - \mu_2)^2}{2\sigma_2^2} \right\} \end{bmatrix}$$

where $\boldsymbol{\theta} = (\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{11}, p_{22})'$, μ_1 and σ_1^2 (μ_2 and σ_2^2) are the conditional mean and variance on state 1 (4), and P_{12} and P_{21} are transition probability. Collect these forecast in a vector $\hat{\xi}_t$, which is a vector whose *j*th element represent $P(s_t = j \mid \mathbf{Y}_{t-1}; \boldsymbol{\theta})$ for j = 1, 2. Thus, $\hat{\xi}_{t+1|t}$ is defined as:

$$\hat{\xi}_{t+1|t} = \mathbf{P} \cdot \hat{\xi}_t = \begin{bmatrix} P(s_{t+1} = 1 \mid \mathbf{Y}_t; \boldsymbol{\theta}) \\ P(s_{t+1} = 2 \mid \mathbf{Y}_t; \boldsymbol{\theta}) \end{bmatrix} = \begin{bmatrix} P_1 \\ P_2 \end{bmatrix} \quad (5)$$

Autoregressive jump intensity (ARJI)

This study follows Chan and Maheu (2002) in using the ARJI model, which postulates that the jump intensity obeys an autoregressive moving average (ARMA) process and incorporates the generalized autoregressive conditional heteroscedasticity (GARCH) effect of returns series. Given the set of returns at time $t-1$ and the two stochastic innovations, $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$, the time-series model of returns can be expressed as follows:

$$R_t = \mu + \sum_{i=1}^{p} \phi_i R_{t-i} + \varepsilon_{1,t} + \varepsilon_{2.t} \quad (6)$$

where $\varepsilon_{1,t}$ is a mean-zero innovation with a normal stochastic process, and is assumed to be:

$\varepsilon_{1,t} = h_t z_t$, $z_t \sim NID(0,1)$ and

$$h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \quad (7)$$

$\varepsilon_{2,t}$ denotes a jump innovation assigned to be a conditional zero-mean value, and conditionally mean zero. $\varepsilon_{1,t}$ is contemporaneously independent of $\varepsilon_{2,t}$.

From Equation 6 it shows that the returns series includes the normal stochastic process and the jump stochastic process. The poisson distribution with parameter λ_t conditional on Ω_{t-1} is assumed to describe the arrival of a discrete number of jumps, where $n_t \in \{0,1,2,\cdots\}$ over the interval $[t-1, t]$. The conditional density of n_t is as follows:

(4)

$$P(n_t = j \mid \Omega_{t-1}) = \frac{e^{-\lambda_t} \lambda_t^j}{j!} \qquad j = 0,1,2,\cdots \quad (8)$$

The conditional jump intensity λ_t is the expected number of jumps conditional on the information set Ω_{t-1}, which is parameterized as:

$$\lambda_t = \lambda_0 + \rho\lambda_{t-i} + \gamma\zeta_{t-j} \quad (9)$$

λ_t is related to the conditional jump intensity and ζ_{t-1} which is defined as:

$$\zeta_{t-1} \equiv E[n_{t-1} \mid \Omega_{t-1}] - \lambda_{t-1} = \sum_{j=0}^{\infty} j\, P(n_{t-1} = j \mid \Omega_{t-1}) - \lambda_{t-1}$$

where $P(n_{t-1} = j \mid \Omega_{t-1})$, called the filter, is the *ex post* inference on n_{t-1} given the information set Ω_{t-1}, and $E[n_{t-1} \mid \Omega_{t-1}]$ is the *ex post* judgment of the expected number of jumps from $t-2$ to $t-1$ and λ_{t-1} is the conditional expectation of $n-1$ given the information set Ω_{t-2}. Therefore, ζ_{t-1} represents the change in the conditional forecast of n_{t-1} by the econometrician as the information set is updated. From this definition, ζ_t is a martingale difference sequence with respect to information set Ω_{t-1}. Therefore $E[\zeta_t] = 0$ and $Cov(\zeta_t, \zeta_{t-i}) = 0$, i >0. Consequently, the intensity residuals in a specified model should not show any autocorrelation. Hence, the ARJI model can be rewritten as follows:

$$\lambda_t = \lambda_0 + (\rho - \gamma)\lambda_{t-1} + \gamma E[n_{t-j} | \Omega_{t-j}] \quad (11)$$

where $\lambda_t > 0$, and $\lambda_0 > 0$, $\rho \geq \gamma$, $\gamma \geq 0$.

[3] Limiting the number of the regimes to two improves the model's tractability and, intuitively, a two-state process corresponds to periods of high- and low-volatility in the markets.

Table 1. Descriptive statistics.

Iterm	Oil future	S&P500
Mean	0.0409	0.0197
Standard deviation	2.7096	1.2735
Maximum	23.6680	10.9571
Minimum	-23.5883	-9.4695
Skewness	-0.2245***	-0.1472 ***
Kurtosis	8.4888***	8.0206 ***
Jarque-Bera	12070.9152***	10760.4517 ***
Ljung-Box Q(25)	87.3455***	115.6621 ***
Ljung-Box Q^2(25)	703.2014 ***	6127.8350 ***

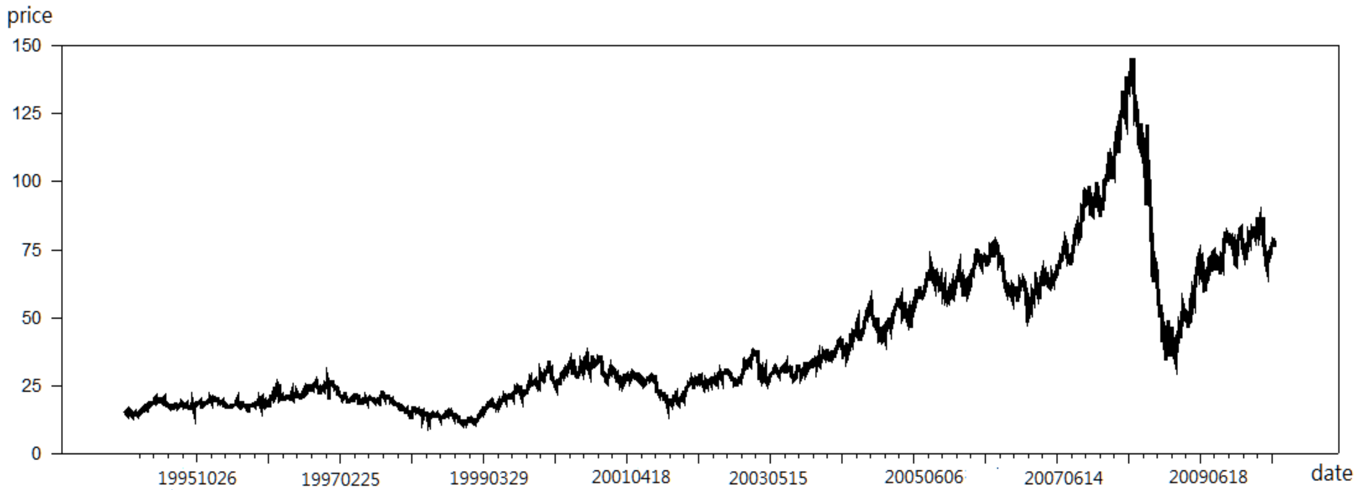

Figure 1. Price of WTI oil futures.

The jump size, $\pi_{t,k}$, is assumed to be independently drawn from a normal distribution. The jump-size distribution is:

$$\pi_{t,k} \sim NID\left(\theta, \delta^2\right) \tag{12}$$

and the jump component influencing returns from $t-1$ to t is:

$$J_t = \sum_{k=1}^{n_t} \pi_{t,k} \tag{13}$$

Therefore, the jump innovation associated with period t is expressed as:

$$\varepsilon_{2,t} = J_t - E\left[J_t \mid \Omega_{t-1}\right] = \sum_{k=1}^{n_t} \pi_{t,k} - \theta\lambda_t \tag{14}$$

The conditional variance of returns is decomposed into two components: A smoothly developing conditional variance component related to the diffusion of past news impacts and the conditional variance component associated with the heterogeneous information arrival process which generates jumps. The conditional variance of returns is:

$$Var\left(R_t \mid \Omega_{t-1}\right) = Var\left(\varepsilon_{1,t-1} \mid \Omega_{t-1}\right) + Var\left(\varepsilon_{2,t-1} \mid \Omega_{t-1}\right)$$
$$= h_t + \left(\theta^2 + \delta^2\right)\lambda_t$$

THE DATA AND EMPIRICAL RESULTS

The sample period ran from January 1, 1994 to June 30, 2010. Daily S&P500 and West Texas Intermediate (WTI) Oil transaction data were gathered and transformed into daily returns, yielding 4,140 observations. Daily data were obtained from the Bloomberg. Returns were defined as the logarithm in the form $R_t = \ln(P_t/P_{t-1}) \times 100$, where P_t denotes the closing price at time t.

Descriptive statistics

Table 1 (also refers to Figure 1-4) lists descriptive

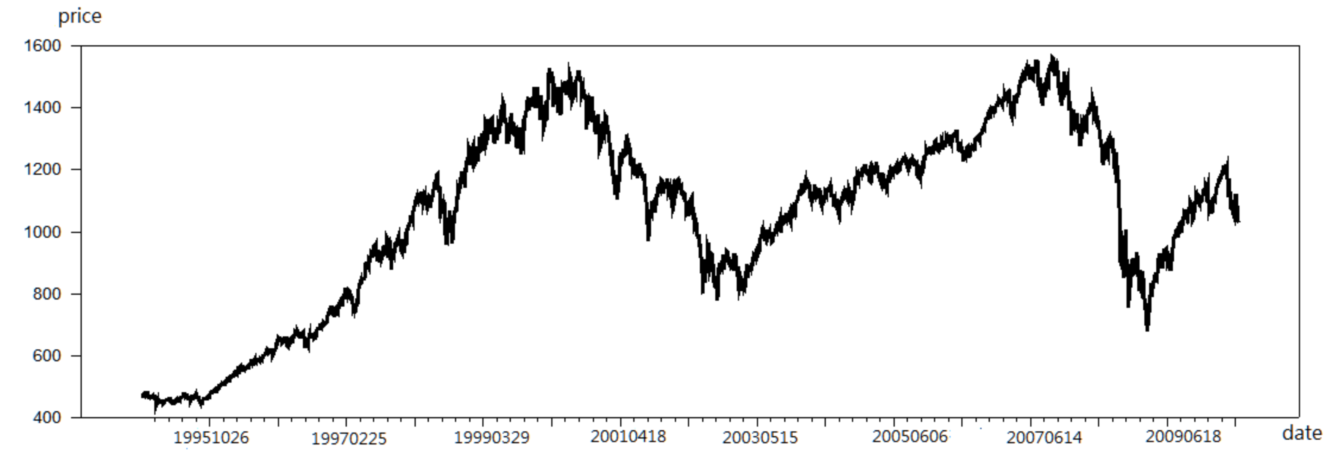

Figure 2. Price of S&P500 index.

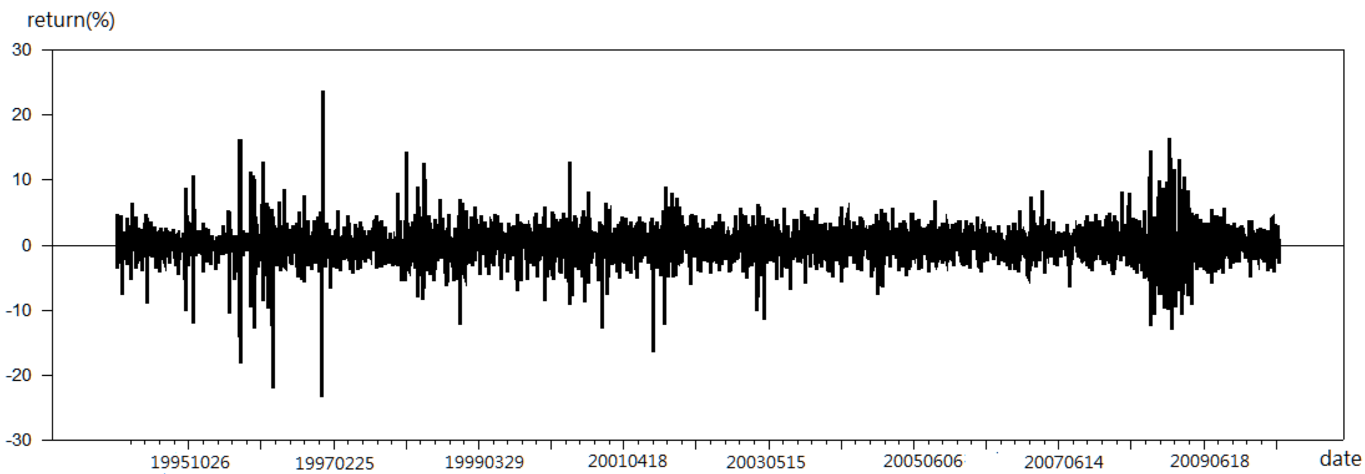

Figure 3. Returns of WTI oil futures.

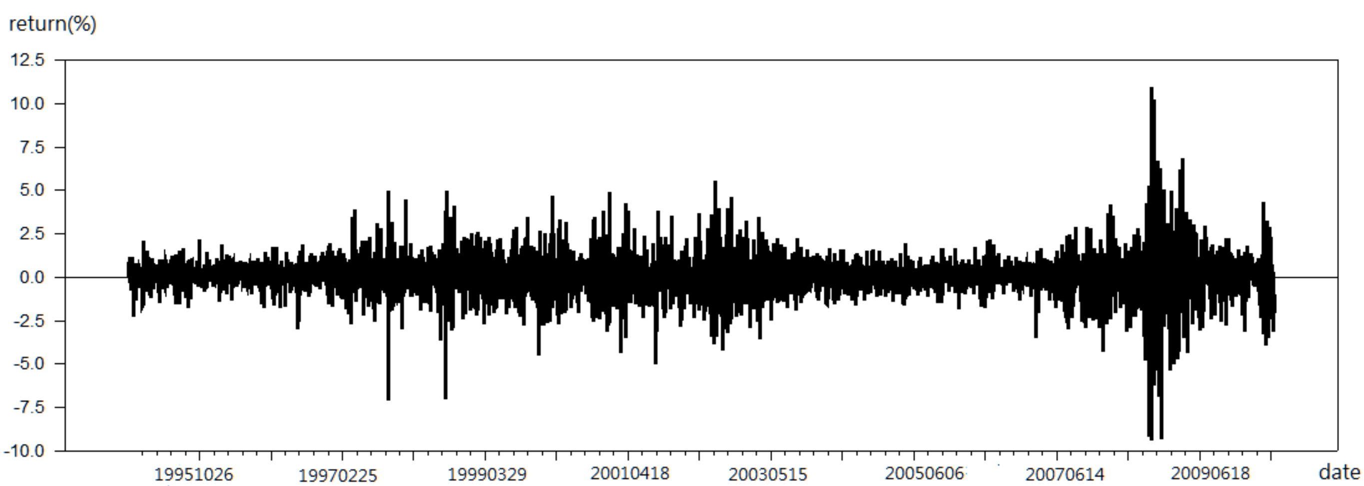

Figure 4. Returns of S and P500 index.

Table 2. Unit root and stationarity tests for stock price indexes.

Item	Model	ADF		PP		KPSS	
		level	diff	level	diff	level	Diff
S&P500	C	-2.0536	-49.5273***	-2.0512	-68.6749***	3.1673***	0.2767
	C / T	-1.5058	-49.5540***	-1.4956	-68.7397***	0.9168***	0.0628
Oil futures	C	-1.1551	-48.5385***	-1.2038	-67.3704***	5.8281***	0.0511
	C / T	-2.4389	-48.5334***	-2.5091	-67.3629***	0.6629***	0.0426

1) *** denotes significance at the 1% level. 2) The ADF and P-P critical values are based on the applicable test statistic reported by Mackinnon (1991) and those for the KPSS are based on Kwiatkowski et al. (1992).

statistics for the returns of oil futures and the S&P500. Based on the statistics of JB, Skewness, and Kurtosis West Texas Intermediate (WTI) crude oil exhibit GARCH effect, indicating that GARCH families are plausible for the modeling. Table 2 lists the results of applying the Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) unit tests[4] to prices, as well as the first order differences with respect to the S&P500 and oil prices futures. The table also lists the results of Kwiatkowski et al. (1992) Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity tests. The joint use of the stationarity and unit root tests is known as confirmatory data analysis. The results of the non-stationary for the level using the augmented Dickey–Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were identified, respectively. The results of the stationary were obtained for the 1st difference using ADF, PP, and KPSS respectively. The results indicate that all of series are non-stationary in levels but stationary in first order differences, suggesting that all the series are integrated and have an order of one, I(1).

Structural change test and ARJI model

The structural change test of Bai and Perron (2003) was performed on oil futures contracts, and as a result several intervals were separated and formed based on the dates of statistically significant structural changes. For each interval, expected (E_t), unexpected (up_t), and negative-unexpected (up_t^-) were constructed as follows:

$$R_{oil,t} = \mu_{oil} + \sum_{i=1}^{p} \phi_{oil,i} R_{oil,t-i} + \sqrt{h_{oil,t}}\,\varepsilon_{oil,t}\,, \quad \varepsilon_{oil,t} \sim NID(0,1)$$

$$h_{oil,t} = \omega_{oil} + \sum_{i=1}^{p} \beta_{oil,i} h_{oil,t-i} + \sum_{j=1}^{q} \alpha_{oil,j} \varepsilon^2_{oil,t-j}$$

$$up_t = \frac{\varepsilon_{oil,t}}{\sqrt{h_{oil,t}}}$$

shown in Table 1, daily returns of futures contracts for

$$up_t^- = Min\left(up_t, E(up_t)\right)$$

$$E_t = \mu_{oil} + \sum_{i=1}^{p} \phi_{oil,i} R_{oil,t-i}$$

Table 3 lists the results of structural change tests for oil futures contracts. Based on Sup FT(K), UD max, and WD max statistics, structural changes were identified in futures oil contract prices at the 1% significance level. Sequence test (Sup FT(2|1) and Sup FT(3|2)) and LWZ test were used to determine the break counts and break dates.

Both methods demonstrated four structure breaks in oil futures prices, namely point 708 (Decrmber 20, 1996), point 1475 (March 3, 2000), point 2249 (May 15, 2003), and point 3406 (January 30, 2008). Accordingly, five intervals were constructed and are studied here.

ARJI with structure changes of futures of oil for S&P500

Including expected(E_t), unexpected(up_t), and negative-unexpected(up_t^-) futures changes in the model of stock returns, the results of ARJI with structural consideration of S&P500 returns can then be listed in Table 4.

With regard to fluctuation measurements, the GARCH effects (ω 、α 、β) for the S&P500 are significant for each interval.

Moreover, the returns fluctuation also displays good persistency. The average value of jump θ is significant for 2nd, 3rd, 4th, and 5th interval. However, the jump variance of returns δ^2 is significant for every interval. Regarding jump intensity, λ_0, and ρ all are statistically significant for every interval, meaning the jump intensity is time varying. Consequently, in the third, forth and fifth intervals, unexpected and negative-unexpected incidences significantly impact the S&P500.

[4] See, Hamilton, J. D., 1989.

Table 3. Structural change tests.

Item	Oil future
Sup FT(1)	182.6057***
Sup FT(2)	195.7391***
Sup FT(3)	280.4228***
Sup FT(4)	214.5476***
UD Max	280.4228***
WD-max test	397.8227***
Sup FT(2|1)	173.7172***
Sup FT(3|2)	320.6077***
Sup FT(4|3)	29.1112***
Sup FT(5|4)	0.0000
The number of breaks chosen by LWZ	4
The dates of the breaks are 1	708(1996/12/20)
The dates of the breaks are 2	1475(2000/03/03)
The dates of the breaks are 3	2249(2003/05/15)
The dates of the breaks are 4	3406(2008/01/30)

Table 4. ARJI with structure changes of futures of oil on S&P500.

Variable	First interval 1994.1.1-1996.12.20	Second interval 1996.12.20-2000.3.3	Third interval 2000.3.3-2003.5.15	Forth interval 2003.5.15-2008.1.30	Fifth interval 2008.1.30-2010.6.30
μ	0.1354***	0.1129***	0.1821***	0.2298***	0.2638***
ϕ_1	0.0153	-0.0122	-0.0449	-0.1687***	-0.1688***
ϕ_2	-0.0203	-0.0274	-0.0808***	-0.0989***	-0.1459***
ω	0.1523***	0.0926***	0.0000	0.0000	0.0000
α	-0.0117	0.0485***	0.1171***	0.0565***	0.0656***
β	0.1972**	0.8703***	0.8395***	0.9122***	0.8971***
θ	-0.1153	-1.3444*	-0.2994***	-0.3850***	-0.7393***
δ^2	0.4523***	6.6253**	0.3759***	0.1266***	0.9366***
λ_0	0.0611***	0.0151**	2.0145***	0.4205***	0.0737***
ρ	0.8793***	0.5362**	-0.7147***	0.3623***	0.8887***
γ	0.4488***	0.2206	-0.0677	0.5680***	0.4208***
EE (expected)	-0.0503	-0.0959	0.0743	0.1441	0.2837
SPS(unexpected)	-0.0091	0.0270	0.0595***	0.0227**	0.0447**
SPN(negative unexpected)	0.0162	-0.0348	-0.0834***	-0.0557***	-0.0810***
Ljung-Box Q(25)	30.6913	25.9136	20.7787	46.8620***	37.2167*
Ljung-Box Q^2(25)	47.1241***	72.3194	247.9308	365.4229***	961.1256
Function value	-648.0287	-1198.7860	-1353.3243	-1285.2006	-1124.8336

Significance levels of 10, 5, and 1% are represented by *, **, and ***, respectively.

Investigation of fluctuation

The asymmetrical unexpected fluctuation is found to be the main source of negative influences on oil futures returns. Table 5 reveals that the standard errors in oi futures prices are higher during intervals III and V than that during interval IV. This phenomenon explains the relatively higher fluctuation that causes asymmetrical unexpected oil price events to affect S&P500 returns. The following area thus adopts a switching model for further

Table 5. Standard error of intervals.

Oil price interval	Futures
I	2.90208887610
II	2.69365304309
III	2.7680372121
Ⅳ	2.02662218266
Ⅴ	3.4635408640

Table 6. Markov switch investigation.

Variable	Futures of oil
P12	0.1389*** (0.0199)
P21	0.0150*** (0.0024)
MU1	-0.4421 (0.3216)
MU2	0.0921*** (0.0348)
SIGMA1	6.1315*** (0.1965)
SIGMA2	2.0120*** (0.0251)
Mean test	2.7274*
Variance test	432.5756***

comparison.

Markov switch model and ARJI model

Repeating the procedure that was discussed earlier but replacing structural changes considerations with Markov switching, high and low fluctuation states are extracted and separated.

Table 6 illustrates the maximum likelihood estimates. The MU1 and SIGMA1 of the first state are (-0.4421, 6.1315) with standard errors (0.3216, 0.1965); moreover the *t*-statistic of SIGMA1 is significantly different from zero, indicating that this state is a high fluctuation regime. The MU1 and SIGMA1 of the second state are (0.0921, 2.0120) with standard errors (0.0348, 0.0251); moreover the *t*-statistic of SIGMA2 is significantly different from zero, indicating that this state is a low fluctuation regime. The bottom half of Table 5 shows the Wald statistics for the null hypothesis. The 1, 5 and 10% critical values for $\chi(1)$ are 6.63, 3.84 and 2.71 respectively. The null hypotheses are rejected and the two-state first-order Markov modeling is thus identified as appropriate.

Incorporating expected(E_t), unexpected(up_t), and negative-unexpected(up_t^-) changes in oil futures prices into the model of stock returns, the results of applying ARJI to S&P500 returns with Markov Switch Investigation are then listed in Table 7. Based on measurements of the fluctuation, the ARCH and GARCH effects (ω、α、β) for S&P500 returns are significant for each interval. The persistency of returns fluctuation also holds. For every interval, the average values of jump θ and the jump variance of returns δ^2 are statistically significant. Furthermore jump intensity, λ_0, ρ, and γ are statistically significant in terms of jump intensity. Therefore, the jump intensity is time varying.

The asymmetrical negative-unexpected incidences of futures of oil price negatively impacted the S&P500 under both the high and low regime state. However, the absolute coefficient value in high regime is greater than that in low regime.

Conclusion

The macroeconomic effects of oil shocks have been debated since the first Organization of the Petroleum Exporting Countries (OPEC) oil embargo during the early 1970s. Most theories regarding the direct effects of oil price shocks include input-cost and income effects. Although, studies have found that oil price shocks influence supply and demand; oil price shocks primarilydecrease the supply for oil-intensive industries and the demand of many other industries, particularly the automobile industry.

Unlike the existing literature, this study incorporates the consideration of expected, unexpected, and negative-unexpected oil price fluctuations into the model of stock returns. Additionally, the ARJI model with structural-change and regime-switching is implemented. The investigation of structural changes found that the

Table 7. ARJI with Markov switching of futures of oil on S&P500.

Variable	High regime of futures of oil	Low regime of futures of oil
μ	-0.0666	0.1007***
ϕ_1	-0.0930***	-0.0546***
ϕ_2	-0.0803**	-0.0272**
ω	0.1519***	0.0035**
α	0.1564***	0.0863***
β	0.7669***	0.8551***
θ	-0.1689	-0.1496***
δ^2	4.7522***	0.7141***
λ_0	0.7366***	1.0035***
ρ	-0.3199***	-0.3708***
γ	0.7167***	0.1482*
EE (expected)	0.2739	0.0521
SPS(unexpected)	0.0435***	0.0149***
SPN(negative unexpected)	-0.0604***	-0.0395***
Ljung-Box Q(25)	69.3518***	77.0725***
Ljung-Box Q^2(25)	6348.5163***	6217.2031***
Function Value	-601.4656	-5256.2558

Significance levels of 10, 5, and 1% are represented by *, **, and ***, respectively.

period of high fluctuation in oil prices caused asymmetrical unexpected oil market events to affect S&P500 returns significantly. Meanwhile, in Markov regime switching investigation, asymmetrical unexpected incidences of oil price futures negatively impact S&P500 returns under the high regime state. Comparing the aforementioned two schemes reveals that when the oil prices are highly fluctuating, asymmetrical unexpected oil market events (the negative-unexpected shocks), negatively impact S&P500 returns.

Based on a cross examination of structural changes and regime switching with consideration of jump modeling, a conclusive result is obtained, namely that when oil prices are in a state of highly fluctuated, asymmetrical unexpected changes of oil price (West Texas Intermediate; WTI) negatively impact S&P500 returns. This evidence indicates that oil price dynamics have changed and that oil price volatility shocks have asymmetric effects on stock returns.

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