AN EMPIRICAL INVESTIGATION INTO THE RELATION OF OIL TO STOCK MARKET PRICES

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ABSTRACT
This paper investigates the relationship between oil and stock market returns for the United States using cointegration techniques and the modified VECM. The results reveal that the oil and stock market returns are cointegrated. The results from the modified VECM suggest that causality runs from stock market to oil market but not vice versa. Taken together, the results provide evidence in support of the notion that the two markets are integrated rather than segmented. The finding of integration between oil price and stock market returns implies that investors cannot benefit from diversification by holding assets in oil and stock markets simultaneously.

Keywords: Cointegration, Oil Price, Stock markets, VECM,
JEL Classification: C32, E32

I. INTRODUCTION

Recent turmoil in oil and changes in stock market sparked interest in studying the interaction among them. "Stocks Rebound on Good Profit Data, But Rise in Oil Prices Limits the Gain." The Wall Street Journal on January 20, 2006. Oil prices still matter to the stock market. In this paper we investigate the causal nexus and its direction(s) between oil price and stock markets. Stock market integration has been extensively investigated in the literature. Early studies focused on correlations among different national markets [Levy and Sarnat, (1970), Agmon, (1972), Solnik, (1974) and Panton et al., (1976)]. Their findings suggested that possibilities exist to diversify portfolios internationally. However, evidence from short-term cross-country correlations may be misleading if investors have long horizons and stock markets share a common stochastic trend, see Kasa, (1992).

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Some other studies have used variations of ARCH and time-varying parameter models to investigate short horizon aspects of stock markets integration associated with time-varying risk and volatility spillovers [Eun and Shim, (1989), Hamao *et at,*. (1990), Koch and Koch, (1991), Roll, (1992), Chan et al., *(*1992b), Lin et al., *(*1994), Susmel and Engle, (1994), Bekaert and Harvey, (1995), Koutmos and Booth, (1995), Login and Solnik, (1995), Booth et al., *(*1997) and Santis and Gerard, (1997)].

Studies of stock market integration using cointegration techniques are numerous. Some of them are Taylor and Tonk, (1989), Jeon and Chiang, (1991), Beckers et al., (1992). Chan et al., (1992a), Kasa, (1992), Malkamaki, (1992), Arshanapalli and Doukas, (1993). Chorhay et al., (1993), Blackman *et al*., (1994), Arshanapalli et al., (1995), Richards, (1995), Choudhry, (1996), Masih and Masih, (1997), Serletis and King, (1997), Roca, (1999), Ghosh et al., (1999) and Pan et al., (1999). Taylor and Tonk, (1989) were the first to apply bivariate cointegration to the UK and US markets to test integration after the abolition of the foreign exchange controls in 1979. Arshanapalli and Doukas, (1993) used bivariate cointegration to study the dynamic interactions among national stock market indices following the October 1987 market crash. Kasa, (1992) applied multivariate cointegration methods to five major international stock markets to determine the number and relative importance of common stochastic trends driving the long-run co-movement of market prices and dividend payments. Kasa's findings indicated the presence of a single common stochastic trend driving prices (and dividends), thus casting doubts over the benefits of long horizon international portfolio diversification.

Recent work on stock market integration using cointegration techniques includes Masih and Masih, (2000), Chang, (2001), Ostermark, (2001), Chen et al., (2002), Sharma and Wongbangpo, (2002). Compared to earlier applications of multivariate cointegration, these studies report fewer cointegration vectors among equity markets around the world and therefore a larger number of common stochastic trends. For example, Masih and Masih, (2000) found there was a single cointegrating vector among price indices of South Asian stock markets. Chen et al., (2002) also reported the presence of a single cointegration vector among indices from a number of Latin American stock markets.

Heimonen, (2002) found one cointegration vector between the US, UK, German, Japan and Finnish stock markets. His results suggested that the UK and German stock markets have accommodated changes in US stock prices, whereas the Finnish and Japanese stock markets appear to be segmented. He also suggested the benefits from international diversification may have been overestimated. Manning, (2002) studied eight stock markets in South East Asia and reported that increasing convergence trends were evident during the 1990s. He draws attention to the sensitivity of the cointegration rank results to the choice of the VAR lag length, ranging from rank one when the VAR lag is one to six cointegration vectors when a twenty-six period lag is used.

Jones and Kaul, (1996) tested whether the reaction of international stock markets to oil shocks could be justified by current and future changes in real cash flows and changes in expected returns. They find that in the postwar period, the reaction of the United States and the Canadian stock prices to oil shocks can be completely accounted for the impact of these shocks on real cash flows alone.

Hammoudeh and Choi, (2005) examined the relationships among five Gulf Cooperation Council's stock markets and their links to three global factors – the WTI oil prices, the U.S. 30-months Treasury bill rate and the S&P Index - using weekly data over the period February 15, 1994 to December 28, 2004. They did not find any direct effect of oil price on the S&P 500 index.

Muellbauer and Nunziata (2001) derived a comprehensive one year ahead forecasting model of U.S. per capita GDP for 1955-2000. They used interest rates, credit conditions, the stock market, oil prices and the yield gap to forecast the GDP and they found all, except the last, are found to matter. Using the vector autoregression (VAR) analysis, Maghyereh, (2004) examines the dynamic linkages between crude oil price shocks and stock market returns in 22 emerging economies. The findings indicate that oil shocks have no significant impact on stock index returns in emerging economies.

This paper examines the dynamic linkages between stock markets and oil price and attempts to generate superior forecasts of stock markets by incorporating long-run information present in the cointegrating vector along with short-run directional information contained in the error correctional model. This topic merits an in-depth investigation for several reasons which include (i) recent turmoil in oil markets has sparked interest in studying the linkages between oil price and stock markets and (ii) changes in oil prices predict future stock market returns.

The remainder of the paper is organized as follows. Section II describes the data and provides descriptive statistics. Section III outlines the methodology used in this paper. Section IV reports empirical results. Finally, section V offers Summary and Policy Implications.

II. DATA AND SUMMARY STATISTICS

The daily data of S&P 500 stock price index, Dow Jones Industrial Averages (DJIA), and NYMEX Light Crude Oil price for the period of January 1993 – August 2006. The Stock Price data are obtained from Yahoo! Finance and NYMEX Crude Oil price data are obtained from Energy Information Administration website. Table 1 reports descriptive statistics for S&P 500, DJIA and oil price. The mean value for percentage changes in DJIA, S&P 500, and oil price are 0.05, -0.01, and 0.04 respectively. The maximum and minimum values are 10.15 and -22.61 percent for DJIA. Percentage changes in oil prices varied from a maximum of 15.29 to a minimum value of -100.00 percent. Percentage changes in S&P 500 ranged from a minimum of -20.47 to a maximum value of 9.10 percent. The standard deviations are 1.05, 3.25, and 1.04 percent, respectively for DJIA, oil prices, and S&P 500. From the reported standard deviations, it can be deduced that oil prices showed greater dispersion from the mean than DJIA and S&P 500.

Table 1. Descriptive Statistics.

	ΔDJIA	ΔOP	ΔSP
Mean	0.05	-0.01	0.04
Maximum	10.15	15.29	9.10
Minimum	-22.61	-100.00	-20.47
Std. Dev.	1.05	3.24	1.04
Observations	5897	5897	5897

DJIA = Dow Jones Industrial Average, OP = Oil price, S&P500 = Standard and Poor 500. Δ represents first difference operator.

Table 2 displays the Parson's correlation coefficients between the series used in the study. The results in Table 2 reveal that the correlation coefficient (0.49) between DJIA and OP is statistically significant. Similarly, the correlation coefficient (0.45) between OP and S&P 500 is statistically significant at the 1 percent level. As expected the correlation coefficient (0.99) between the DJIA and S&P is high and statistically significant at the 1 percent level. Figure 1 plots the data employed by the study. It appears though that the DJIA, oil prices, and S&P 500 trended upward for the period under investigation.

Figure 1: Nymex Futures Prices of Crude Oil, S&P 500 and DJIA

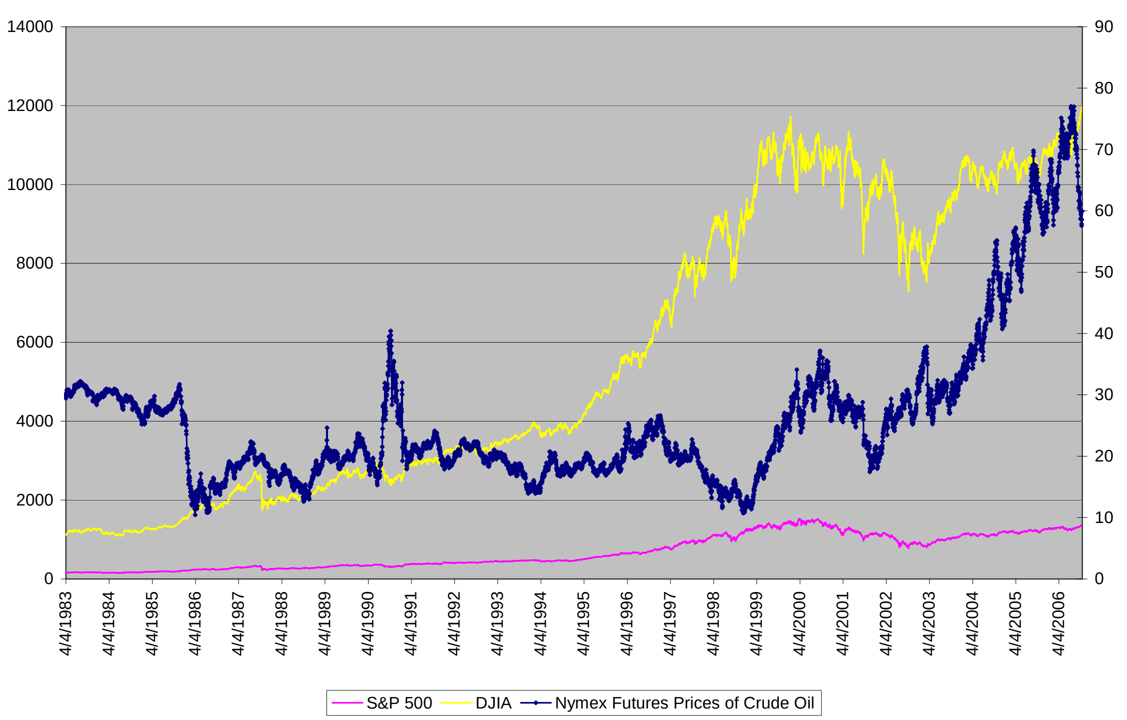

Table 2. Pearson Correlation

	DJIA	OP	SP500
DJIA	1.00		
OP	0.49***	1.00	
SP500	0.99***	0.45***	1.00

*** indicates that the correlation coefficient is statistically significant at the 1 percent level. DJIA = Dow Jones Industrial Average, OP = Oil price, S&P500 = Standard and Poor 500.

III. METHODOLOGY

Using the cointegration and error-correction methodology, this paper studies the causal nexus and its direction(s) between oil market and stock markets. In particular, the empirical exercise consists: (1) testing for a unit root, I (1), in each series; (2) testing for the number of cointegrating vectors in the system; (3) estimating and testing for the cointegrating relationship in the framework of a vector error correction model (VECM); and (4) incorporating the long-run information present in the cointegrating vector along with short-run directional information contained in the error correction model to obtain forecast of stock prices.

A univariate analysis is conducted to investigate the stationary properties for each time series by implementing the modified DF (Dickey-Fuller) test proposed by Elliot et al., (1996). A time series is said to be nonstationary if: i) its variance is time-variant and it goes to infinity as time approaches infinity, ii) it depicts no long-run mean-reversion, and iii) theoretical autocorrelations do not decay but the sample correlogram dies out slowly in finite samples.

The DF-GLS unit root test is based on the following equation:

$$\Delta Y_t^k = \alpha_0 Y_{t-1}^k + \sum_{j=1}^{p} \alpha_j \Delta Y_{t-j}^k + \varepsilon_t , \qquad (1)$$

where p represents the optimal lag, Y_t^k is the locally detrended series of Y_t [i.e. $Y_t^k = Y_t - z_t\tilde{\alpha}$, where zt=(1,t) and $\tilde{\alpha}$ is the regression of $\hat{Y}$ on $\hat{z}$]. The null hypothesis under the DF-GLS unit root test is that $\alpha_0 = 0$, in equation (1). The alternative on the other hand is that $\alpha_0 < 0$. The null hypothesis is rejected if the test statistic is significantly different from zero.

To test for cointegration all variables must have the same order of integration (Engle and Granger, 1987). In this study, cointegration is examined for stock price (S&P 500 and DJIA) and oil price in a bivariate context using the maximum likelihood procedure suggested by Johansen and Juselius, (1990) and Johansen, (1991). This procedure detects the number of cointegrating vectors (rank of the matrix *Π*) present in the nonstationary time series.

The cointegration tests are based on the following equation:

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \dots + \Gamma_{k-1}\Delta Y_{t-k+1} + \Pi\, Y_{t-1} + \mu + \varepsilon_t \qquad (2)$$

where Δ is the first-difference operator, k denotes lag length, Y_t is a vector of m non-stationary endogenous (stock price) variables, Γt and Π are a matrix of coefficients, μ is a vector of constants, and ε_t is a vector for errors. The lag length, k, is chosen to ensure that the errors are independent and identically distributed. Based on the assumption of well-behaved disturbance terms if sufficient lags are utilized, the Trace and the maximum eigenvalue (*λ-max*) tests are used to determine the existence of cointegrating vectors. If a non-zero vector is indicated by these tests, a stationary long-run relationship between the relevant variables is implied.

To account for the possibility of structural break in the data, the study next applies the Gregory and Hansen, (1996) cointegration test procedure that allows for structural break in the mean to ascertain the long run relationship between consumption and income. The Gregory and Hansen, (1996) advanced three models including model C, model C/T, and model C/S, also known as 'regime shift' model. Model C allows for a level shift. Model C/T allows for a level shift and a time trend. Model C/S allows a shift in both intercept and slope. The Gregory-Hansen framework involves two steps. The first step involves the estimation of the following multiple regression equation:

$$Y_t = \alpha + \beta TR + \gamma DU_i(\lambda) + \phi DU_i(\Phi) + \theta X_t + \varpi_t \text{, for t=1,……,T} \qquad (3)$$

where DU is a dummy variable, $Du_t(\lambda) = 1$ for $t > T\lambda$, and $Du_t(\lambda) = 0$ for $\leq T\lambda$; $\lambda = T_B/T$ is the location of the structural break; TR is the time trend, T is the total sample size; T_B represents the break date, X consists of a vector of independent variables, θ is the slope before the break and $(\theta + \phi)$ represents the slope after the break.

The second step involves testing the residual from equation (3) for stationarity. The recovered residual is used to formulate the following regression equation:

$$\Delta \varepsilon_t = \alpha\, \varepsilon_{t-1} + \sum_{i=1}^{n} \beta_i \Delta \varepsilon_{t-i} + \mu_t \qquad (4)$$

The ADF or Phillips-Perron (PP) unit root test procedure is applied to equation (4). The null and alternative hypotheses are as follows:

$$H_o\colon \alpha = 0 \qquad Ha\colon \alpha < 1. \qquad (5)$$

We reject the null hypothesis of no cointegration in equation (4) if α is statistically significant and negative. The ADF and the PP test statistics are defined by:

$$ADF^* = \inf_{\tau \varepsilon T} ADF(\tau) \qquad (6)$$

$$Z^*_\tau = \inf_{\tau \varepsilon T} Z_\tau(\tau) \qquad (7)$$

Cointegration implies that the transitory components of the series can be given a dynamic error correction representation; one that allows for flexibility in the short-run dynamics but constraints the model to return to

long-run equilibrium (see Engle and Granger, 1987). If there is evidence of a cointegrating relationship, causal inferences can be made by estimating the parameters of the following vector error correction model (VECM) equation.

$$\Delta Y_t = \alpha + B(L)\Delta Y_{t-1} + B(L) X_{t-1} + \delta z_{t-1} + \varepsilon_t \qquad (8)$$

where, Y_t represents n x t vector of endogenous (stock prices) variables, X_t stands for n x t vector of exogenous (oil price) variable, α is n x 1 vector of constants, B(L) represents n x n matrices of the polynomial expression in the lag operator (L), δ is n x 1 vector of constants, z_{t-1} represents n x t vectors of error correction terms, and ε_t stands for n x t vector of residuals

The VECM model allows us to differentiate between the short- and long-run dynamic relationships, and tests for the hypothesis that the coefficients of lagged variables and the error correction terms calculated from the cointegrating regression are zero. If the coefficients in the system are jointly significant, then the lagged variables in the system are important in predicting current movements of the dependent variables (i.e., the short run dynamics), and the dependent variables in the equation adjust to the previous period's equilibrium error.

IV. EMPIRICAL RESULTS

This study implements the DF-GLS to ascertain the time series properties of the Dow Jones Industrial Average (DJIA), oil price (OP), and the S&P 500. Table 3 presents the unit root test results from the DF-GLS. The maximum lags were determined by the application of the modified Akaike Information Criterion (MAIC) (Ng and Perron, 2001). The unit root tests included a constant and time trend. The results suggest that three time series including the DJIA, OP, and S&P 500 are not stationary in their levels. Nevertheless, they are stationary at the 5 percent level of significance after first differencing. In all, the unit root tests indicate one order of integration for DJIA, OP, and S&P500.

Since the DJIA, OP, and S&P500 are series have one order of integration, the study next implements the Johansen and Juselius, (1990) and Johansen, (1991) cointegration procedures.

Table 3. Modified Dickey-Fuller (DF-GLS) Unit Root Test Results.

Series	Level	Lags	Difference	Lags
DJIA	-2.11	33	-15.14***	33
OP	-1.83	14	-19.93***	13
S&P500	-1.75	33	-14.45**	33

*** R and ** Rejection of the null hypothesis of a unit root at the 1 and 5% level, respectively. The 5% critical value is -3.96 and -3.41. The modified Akaike Information Criterion was used to determine the lag lengths. The null hypothesis is that the series has a unit root. DJIA = Dow Jones Industrial Average, OP = Oil price, S&P500 = Standard and Poor 500.

This study uses the two variants of the Johansen cointegration tests including the trace and the maximum eigenvalue (λ-max) to determine the number of cointegrating vectors in the system. In the trace test, the null hypothesis that there are at most r cointegrating vectors is tested against the general alternative, whereas in the maximum eigenvalue test the null hypothesis of r cointegrating vectors is tested against the alternative of at least (r+1) cointegrating vectors. Table 4 presents results from the Johansen and Juselius cointegration tests. The trace and maximum eigenvalue cointegration test results presented in Panel A of Table 4 fail to reject the null hypothesis of no cointegration (i.e. r=0) between the Dow Jones Industrial Average and oil price for the period under consideration. The computed test statistics 11.81 and 7.75, respectively for the trace and maximum eigenvalue statistics are less than the critical values of 20.26 and 15.89 at the 5 percent level of significance. Similarly, the results presented in Panel B of Table 4 suggest that oil prices and the S&P 500 are not cointegrated as the computed values 10.26 and 6.36 respectively for the trace and maximum eigenvalue tests are less than the critical values of 20.26 and 15.89. These results suggest that oil prices are neither cointegrated with the DJIA nor the S&P 500. However, one of the limitations of the Johansen cointegration tests is that they do not account for structural breaks in the data.

To this effect, the study further applies the Gregory-Hansen cointegration tests to further explore the long run relationship between the series in the system. Table 5 displays the results obtained from the three models (i.e. C, C/T, and C/S) of the Gregory-Hansen cointegration procedure. The maximum lag of 20 used in the calculation of the Gregory-Hansen cointegration tests were obtained through the AIC.

Table 4. Johansen Bivariate Cointegration Tests.

	Trace Test		Maximum Eigenvalue Test		
Null Hypothesis	Test Statistic	Critical Value	Null hypothesis	Test Statistic	Critical Value
Panel A: Cointegration Results between Oil Price and Dow Jones Industrial Average					
r=0	11.81	20.26	r=0	7.75	15.89
r≥1	4.06	9.16	r≥1	4.06	9.16
Panel B: Cointegration Results between Oil Price and S&P 500					
r=0	10.25	20.26	r=0	6.36	15.89
r≥1	3.88	9.16	r≥1	3.88	9.16

The order of VAR (20) is determined MAIC.

Panel A of Table 5 presents the cointegration tests between oil prices and S&P 500. The results from both the ADF and Phillips-Perron tests based on the Gregory-Hansen cointegration procedures reveal that oil prices and S&P 500 are cointegrated at the 5 percent level. The computed values in all of the cases exceed the critical value at the 5 percent level. For example, the computed values for the ADF (-10.60) and the Phillips-Perron [i.e. -13.11 and -334.01, respectively for $Z_{(t)}$ and $Z_{(\alpha)}$ tests] based on the 'regime shift' model (C/S) exceed the critical value of -4.95 at the 5 percent significance level. These results indicate that oil prices and the S&P 500 variables are cointegrated.

The cointegration results between the DJIA and oil prices are presented in Panel B of Table 5. Once again, the results from the Gregory-Hansen models reveal that the null hypothesis of no cointegration between the DJIA and oil prices should be rejected at the 5 percent significance level. The computed values in all of the three cases exceed the critical values. After accounting for structural break in the data, the study finds evidence in support of cointegration between oil and the two market indexes including the DJIA and the S&P 500 for the period under consideration. The existence of cointegration suggests that oil prices and the stock market indexes share long run relationship. It is interesting to observe that the C, C/T, and C/S Gregory-Hansen models indicate that a structural break occurred sometime in 1992 (41% location of the data).

Table 5. Gregory-Hansen Cointegration Results.

Model	ADF	Z(t)	Z(α)	Lag(s)
Panel A: Cointegration between Oil Price and S&P 500				
C	-10.60(0.41)**	-13.11(0.41)**	-334.01(0.41)**	20
C/T	-11.04(0.41)**	-13.35(0.42)**	-346.74(0.41)**	20
C/S	-10.60(0.41)**	-13.11(0.41)**	-334.01(0.41)**	20
Panel B: Cointegration between Oil Price and S&P 500				
C	-10.41(0.41)**	-12.98(0.41)**	-327.78(0.41)**	20
C/T	-10.72(0.41)**	-13.20(0.41)**	-338.69(0.41)**	20
C/S	-10.53(0.41)**	-13.16(0.41)**	-336.46(0.41)**	20

** indicates rejection of the null hypothesis of no cointegration at the 5% level of significance. The 5% critical value for ADF and Z(t) is -4.95. The critical values are taken from Table 1 of Gregory and Hansen, (1996). C/S indicates that the model allows for regime shift. The numbers in parentheses are the break points expressed as percentage of the sample size. The lags are determined by the MAIC.

Table 6. Bivariate Granger-Causality Tests between the Dow Jones Industrial Average and Oil Prices based on Modified VECM (*F-Statistics*).

	INDEPENDENT VARIABLES			
	z_{t-1}	DM92	ΣΔDJIA	ΣΔOP
Equation for ΔDJIA	0.81	1.36	2.88***	0.73
Equation for ΔOP	1.88*	0.73	0.86	3.31***

*, **, *** associated with the *F-statistics* represent statistical significance at the 10%, 5% and 1% level respectively. The standard *t-test* is used to determine the level of marginal significance for the error correction term (z_{t-1}) and the dummy variable (DM92. The optimal lag lengths are determined by the AIC. DJIA = Dow Jones Industrial Average, OP = Oil price, DM92 = dummy variable that takes the value 0 prior to 1992 and 1 thereafter.

Having established the existence of cointegration between oil and the various market indexes, the study next implements the modified version of the VECM. To account for the structural break revealed by the Gregory-Hansen cointegration tests, a dummy variable was added to equation (8). Table 6 displays the Granger-causality test results from the augmented VECM for oil prices and the DJIA. The results reveal that oil prices do not Granger-cause movements in the DJIA as neither the regression coefficient on the error correction (Z_{t-1}) nor the sum of the regression coefficients on OP (ΣΔOP) is statistically significant at the conventional levels. The error-correction term relative to the equation for ΔOP is statistical significant at the 10 percent level. This finding has two important implications. First, it implies that the DJIA adjusts to restore equilibrium in the event of disturbances relative to the relationship between the two markets. Second, it also reveals the presence of causality running from the Dow Jones Industrial Average to oil prices, even though the sum of the regression coefficients on ΔDJIA is not statistically significant. The dummy variable (DM92) in the equations for DJIA and OP is not statistically significant in both cases. From the results presented in Table 6 it can be deduced that causality rums from the DJIA to oil prices but not vice versa.

Table 7 displays the bivariate Granger-causality test between oil prices and the S&P 500. The error-correction term in the equation for ΔOP is statistically significant at the 5 percent level. First, the statistically significant error correction term indicates the S&P 500 adjust to restore equilibrium in its relationship with oil prices. Second, like the DJIA, the S&P 500 Granger-causes oil prices through the statistically significant error correction term, even though the sum of the regression coefficients on ΔS&P500 is insignificant. Turning next to the equation for ΔS&P500, it can be seen that the neither the regression coefficient on the error-correction nor the sum of the regression coefficients on ΔS&P500 is statistically significant at the conventional levels. The dummy variable is not informational in relation to the relationships between oil prices the two stock market indexes. In each case, the DM92 variable is not statistically significant. Taken together, the results presented in Table 7 indicate the existence of unidirectional causality from the S&P 500 series to oil prices, but not vice versa.

Table 7. Bivariate Granger-Causality Tests between Oil Prices and S&P 500 based on Modified VECM (*F-Statistics*).

	INDEPENDENT VARIABLES			
	z_{t-1}	DM92	ΣΔOP	ΣΔS&P500
Equation for ΔOP	1.76**	0.88	3.32***	0.02
Equation for ΔS&P500	0.95	1.27	0.59	4.42***

*, **, *** associated with the *F-statistics* represent statistical significance at the 10%, 5% and 1% level respectively. The standard *t-test* is used to determine the level of marginal significance for the error correction term (z_{t-1}) and the dummy variable (DM92. The optimal lag lengths are determined by the AIC. DJIA = Dow Jones Industrial Average, OP = Oil price, S&P500 = Standard and Poor 500, DM92 = dummy variable that takes the value 0 prior to 1992 and 1 thereafter.

V. SUMMARY AND IMPLICATION OF THE STUDY

This paper has used cointegration analysis and the augmented VECM to examine the long run relationship and the dynamics between oil prices and the two market indexes including the Dow Jones Industrial Average and the Standard and Poor 500 for United States. Specifically, the study applied the DF-GLS unit root procedure to determine the time series properties of DJIA, Oil prices and S&P 500. The modified

VECM was used to examine the dynamic interactions between the DJIA and oil prices on one hand, and between the S&P 500 and oil prices on the other.

The results from the DF-GLS unit root procedures indicate that the DJIA, oil prices, and the S&P 500 are first difference stationary. The results obtained from the Johansen and Juselius cointegration tests suggest that oil prices and the stock markets are not cointegrated for the period under consideration. However, the results from the Gregory-Hansen cointegration tests which allow for structural break in the data revealed that oil and stock markets are cointegrated. The results reveal that risk-reduction through diversification cannot be achieved by holding assets in both the oil and stock markets.

The results from the Granger-causality tests based on the modified VECM suggest that causality runs from the stock markets (i.e. DJIA and S&P 500) to the oil market but not vice versa. The finding that oil prices do not Granger-cause stock markets is consistent with Maghyereh, (2004) who examined the dynamic linkages between crude oil price shocks and stock market returns in 22 emerging economies and concluded that oil shocks have no implications for stock index returns. The major finding of this study is that the oil and stock markets are integrated rather than segmented. From the perspective of investments, risk reduction cannot be achieved by holding assets from both markets in the same portfolio.

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APPENDIX:

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