International Journal of Energy Economics and Policy
Vol. 4, No. 3, 2014, pp.442-447
ISSN: 2146-4553
www.econjournals.com

Volatility Transmissions between Oil Prices and Emerging Market Sectors: Implications for Portfolio Management and Hedging Strategies

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ABSTRACT: This paper investigates the mechanisms of return and volatility transmissions between oil prices and five emerging market sector returns. For the empirical method, we utilize a recent and novel technique: Vector Autoregressive-Asymmetric GARCH (VAR-AGARCH) model. We find some significant cross shock and volatility linkages between oil prices and the sectors. However, our results manifest that the sector indices are not affected equally or simultaneously by movements in oil prices. Additionally, we compute the optimal holding weights and hedge ratios for the two-asset portfolio consisting of oil and each sector index. Our empirical findings have potential implications for investors and portfolio managers.

Keywords: Emerging sector indices; oil prices; volatility transmission; optimal weights; hedge ratios
JEL Classifications: C32; G11

1. Introduction

The second half of the 20th century brought out significant developments in world history, as the result of growing global population, world-wide application of improving technologies, expanding mobilization and global trade. Meanwhile, oil has become the main source of energy for both the households and the manufacturing industries that utilize mass-production. Heating and lighting, transportation, and production are all heavily dependent on oil. Thus, the price of oil is a direct determinant of input costs affecting the macroeconomic factors such as inflation, interest rates and foreign exchange rates. Oil price shocks stagnate economic activity with adverse effects on employment and real GDP growth rates. The repercussions of oil prices are transmitted to stock markets through various channels. Firstly, the cash flows of a firm are contingent on oil prices; higher input costs accompanied with reduced household spending as the result of increasing inflation, impact the revenues and costs simultaneously. Secondly, the rise in oil prices amplifies uncertainty and inflation which raise the discount rates in equity pricing.

Arouri et al. (2011) assert that 'oil is used as a pricing benchmark for various financial instruments and plays a crucial role in international asset hedging strategies'. Hence, investigating the return and volatility dynamics between oil prices and financial markets has become pivotal to investors, portfolio managers and policy makers. There is a strand of literature investigating the relationship between oil prices and macroeconomic variables (Hamilton, 1983; Sadorsky, 1999; Park and Ratti, 2008). In recent years, a number of studies analyze the impacts of oil price shocks on stock markets of both developed and emerging economies (Jones and Kaul, 1996; Huang et al., 1996; Driesprong et al. 2008; Narayan and Narayan, 2010). However, the results vary between different markets and time intervals. As a result, researchers make further distinctions between supply-side and demand-side oil shocks to elaborate the effects on stock markets (Kilian and Park, 2009; Filis et al., 2011). Some also distinguish between the stock markets of oil-importing and oil-exporting countries

(Hammoudeh and Aleisa, 2002; Al-Fayoumi, 2009; Al-Janabi et al. 2010). Recently, scholars ponder the divergent effects of oil price shocks on different industries (Sadorsky, 2001; Driesprong et al., 2008; Malik and Ewing, 2009; Elyasiani et al., 2011; Arouri et al. 2011). Mainly, sector disparities arise whether oil products are inputs or outputs of various industries, but additionally, the market infrastructure and the terms of competition are determinants of the varying responses.

In this paper, we are motivated from the growing energy demand of emerging countries in the last years and the heavy dependence of their economic activities on oil price fluctuations. In this regard, we analyze the volatility transmissions between oil prices and sector returns of emerging stock markets applying a recent and novel technique, the VAR-AGARCH model of McAleer (2009). Using the generated conditional volatilities and covariances, we also compute optimal weights and hedge ratios of oil/index portfolios. This paper differs from the existing literature in analyzing the volatility transmission mechanisms between oil prices and emerging sector returns in the context of the VAR-AGARCH model.

2. Empirical Method

We analyze the volatility spillovers between each pair of oil returns and sector VAR (1)-AGARCH (1, 1) model proposed by McAleer et al. (2009).[1] In the model, it is realistically assumed that positive and negative shocks have different impacts on the conditional volatility. The conditional mean of the model is specified as follows:

$$\begin{cases} R_t = \mu + \Phi R_{t-1} + \varepsilon_t \\ \varepsilon_t = \sqrt{H}\eta_t \end{cases} \tag{1}$$

where $R_t = \left(r_t^s, r_t^o\right)'$ denotes the vector of returns on sector indices and oil price at time t, respectively. Φ represents a (2 × 2) matrix of the coefficients. ε_t is a vector of error terms of the conditional mean equations for the returns. η_t is a sequence of *i.i.d.* random errors and H_t is the matrix of sector and oil returns' conditional variances.

The VAR-AGARCH specification of McAleer et al. (2009) is expressed as:

$$\begin{aligned} &\Phi(L)(Y_t - \mu) = \psi(L)\varepsilon_t \\ &\varepsilon_t = D_t\eta_t \\ &H_t = W + \sum_{i=1}^{r} A_l \vec{\varepsilon}_{t-l} + \sum_{i=1}^{r} C_i I(\eta_{t-l})\vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} B_l H_{t-l} \end{aligned} \tag{2}$$

where $D_t = diag\left(\sqrt{h_{i,t}}\right)$, $H_t = \left(h_{1t}, \ldots, h_{mt}\right)'$. $\Phi(L) = I_m - \Phi_1 L - \ldots - \Phi_p L^p, \psi(L) = I_m - \psi_1 L - \ldots - \psi_q L^q$ are polynomials in L, $\vec{\varepsilon} = \left(\varepsilon_{1t}^2, \ldots, \varepsilon_{mt}^2\right)$. A_l matrix coefficients for $l = 1, \ldots, r$ quantify past own and cross shock dependence of conditional volatility, while B_l matrix coefficients for $l = 1, \ldots, s$ measure the sensitivity of conditional volatility to past own and cross volatilities. Hence, equation (2) allows us to examine transmission mechanisms of shocks and volatilities between emerging sector indices and oil markets. $I_t = diag\left(I_{1t}, \ldots, I_{mt}\right)$ given in equation (2) is an indicator function given as:

$$I(\eta_{it}) = \begin{cases} 0, & \varepsilon_{it} > 0 \\ 1, & \varepsilon_{it} \le 0 \end{cases} \tag{3}$$

If $m = 1$, equation (3) collapses to the asymmetric GARCH or GJR-GARCH model.

We can also write the conditional covariance between sector and oil returns, h_t^{so} as:

$$h_t^{so} = \rho\sqrt{h_t^s}\sqrt{h_t^o} \tag{4}$$

where ρ denotes the constant conditional correlation.[2]

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[1] Other multivariate GARCH models, such as BEKK specifications could be employed. However, the over-parameterized models suffer from the curse of dimensionality problems and hence computational complications.

[2] McAleer et al. (2009) consider constant conditional correlations for the model. As far as we know, the model with the time-varying correlations have not developed yet.

3. Data

For this paper, we use weekly data for Morgan Stanley Capital International (MSCI) emerging market sector indices and Brent oil prices.[3] All the price series are denominated in US dollars and converted to log-returns. The data is retrieved from Bloomberg. Our data covers the period from January 6, 1995 to December 27, 2013. In Table 1, we report the summary statistics of the return variables. The non-normality is evidenced by Jarque-Bera tests statistics, the values of skewness and kurtosis. This brings us a motivation to make use of the Student-t distribution. The results from Ljung-Box tests applied to the raw and squared residuals up to 10th lag demonstrate serial correlations. Employing ARCH-Lagrange Multiplier tests, the null hypotheses of no ARCH effects are rejected at the 1% level. The existence of unit-roots and stationarity is checked by ADF and KPSS tests, which differ in their null hypotheses. While we reject the null hypotheses of a unit-root for ADF tests, we fail to reject the null hypotheses of stationarity in the context of KPSS tests.

Table 1. Summary Statistics of the returns

	Brent	Financials	Energy	Telecom.	Materials	Industrials
Mean	0.195	0.078	0.137	0.089	0.066	-0.027
Std. Dev.	4199	3368	4107	3342	3670	3430
Skew.	-0.373	-0.810	-0.607	-0.534	-0.638	-1000
Kurt.	2.350	4.938	5.602	4.145	7.300	6.802
J-B	250.94^a	1114.4^a	1355.8^a	756.14^a	2266.0^a	2074.1^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH (10)	6.415^a	19.506^a	34.365^a	13.972^a	49.598^a	23.017^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q (10)	61.226^a	25.141^a	27.478^a	32.004^a	34.720^a	34.649^a
	(0.000)	(0.005)	(0.002)	(0.000)	(0.000)	(0.000)
Q^2 (10)	105.723^a	370.126^a	664.732^a	259.272^a	885.394^a	393.330^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF	-15.919^a	-16.921^a	-17.354^a	-17.170^a	-17.024^a	-16.755^a
KPSS	0.036	0.105	0.103	0.069	0.156	0.314

Notes: (a), (b) and (c) denote statistical significance at the 1%, 5% and 10%, levels. The associated p-values are given in the parentheses. *Q* represents the Ljung-Box test and ADF unit-root and KPSS stationarity tests are applied to the return series.

4. Empirical Results

We document the empirical results of VAR (1) - AGARCH (1, 1) model in Table 2.[4] The results for the mean equation in the VAR framework reveal that current returns of materials, financials and industrials indices are affected by their own past realizations, indicating the possibility of predicting current returns by using the past values. Besides, past oil returns have a positive and significant impact on all current returns of the indices. For the materials index, we document the highest elasticity to oil price fluctuations. However, we do not validate the return transmission from the indices to oil prices.

The results of variance equations manifest that past own shocks (news) affect the current conditional volatility of only the telecommunication index. The sensitivity to own past volatilities are statistically significant at the 1% level for all indices and Brent oil. Examining the cross shocks and volatilities, it is observed that the sector indices are not impacted co-equally or simultaneously by variations in oil prices. We depict a negative and uni-directional shock transmission from oil market to

[3] Emerging markets include Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand and Turkey. The sector indices under investigation are the materials, telecommunications, financials, energy and industrials.

[4] We select the lag lengths according to Schwartz information criterion (SIC).

financials and energy indices while negative and bi-directional shock transmissions exist between the oil market and the industrials index.

Table 2. VAR (1) - AGARCH (1, 1) Model Results

	Materials	Oil	Telecom	Oil	Financials	Oil	Energy	Oil	Industrials	Oil
Mean Eq.										
Constant	0.057	0.258[b]	0.209[b]	0.256[b]	0.158[c]	0.217[c]	0.243[b]	0.262[b]	0.095	0.224[b]
	(0.496)	(0.018)	(0.016)	(0.022)	(0.070)	(0.052)	(0.019)	(0.017)	(0.233)	(0.043)
Index (1)	0.088[b]	0.015	0.021	-0.010	0.063[c]	0.007	0.048	0.024	0.123[a]	0.033[c]
	(0.011)	(0.470)	(0.546)	(0.652)	(0.074)	(0.733)	(0.163)	(0.388)	(0.000)	(0.098)
Oil (1)	0.129[a]	0.208[a]	0.090[b]	0.215[a]	0.083[b]	0.220[a]	0.125[a]	0.193[a]	0.105[a]	0.217[a]
	(0.000)	(0.000)	(0.012)	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Variance Eq.										
Constant	-0.017	0.212	0.268	0.080	0.273[c]	0.034	0.232	0.218	0.127	0.061
	(0.867)	(0.198)	(0.149)	(0.611)	(0.082)	(0.810)	(0.306)	(0.258)	(0.329)	(0.580)
$(\varepsilon_{it-1})^2$	0.038	0.027	0.087[b]	-0.006	0.003	0.019	0.039	0.029	0.012	0.047[b]
	(0.142)	(0.170)	(0.017)	(0.805)	(0.903)	(0.363)	(0.197)	(0.288)	(0.660)	(0.013)
$(\varepsilon_{ot-1})^2$	-0.038	0.049[c]	-0.029	0.036	-0.052[b]	0.042[c]	-0.040[c]	0.054[c]	-0.067[a]	0.034
	(0.162)	(0.060)	(0.245)	(0.168)	(0.020)	(0.058)	(0.088)	(0.073)	(0.001)	(0.107)
h_{it-1}	0.833[a]	0.321[b]	0.718[a]	0.625	0.791[a]	0.547[c]	0.778[a]	0.360[b]	0.750[a]	0.579[b]
	(0.000)	(0.033)	(0.000)	(0.138)	(0.000)	(0.093)	(0.000)	(0.046)	(0.000)	(0.035)
h_{ot-1}	0.227	0.892[a]	0.795[b]	0.857[a]	0.607[c]	0.887[a]	0.249[c]	0.858[a]	0.484[b]	0.901[a]
	(0.198)	(0.000)	(0.029)	(0.000)	(0.078)	(0.000)	(0.093)	(0.000)	(0.023)	(0.000)
CCC	0.192[a]		0.147[a]		0.132[a]		0.294[a]		0.154[a]	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
γ	0.195[a]	0.026	0.106[b]	0.024	0.152[a]	0.025	0.085[b]	0.035	0.195[a]	0.026
	(0.000)	(0.327)	(0.019)	(0.428)	(0.000)	(0.354)	(0.014)	(0.303)	(0.000)	(0.327)
Student-t	8.830[a]		9.901[a]		10.133[a]		8.125[a]		8.830[a]	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Q^2 (10)	5.708	3.747	7.645	3.662	8.647	4.467	11.743	3.468	4.100	4.400
	(0.839)	(0.958)	(0.663)	(0.961)	(0.565)	(0.923)	(0.302)	(0.968)	(0.942)	(0.927)
ARCH (10)	0.568	0.364	0.750	0.343	0.876	0.419	1233	0.350	0.408	0.421
	(0.840)	(0.961)	(0.676)	(0.969)	(0.554)	(0.937)	(0.265)	(0.966)	(0.943)	(0.936)

Notes: (a), (b) and (c) denote statistical significance at the 1%, 5% and 10%, levels. The associated p-values are given in the parentheses 'Student-t' is the degrees of freedom parameter of the student-t distribution.

The GARCH coefficients, which measure own volatility dependence show that own one-period lagged volatilities have a great impact on the current conditional volatilities for all the markets. We elaborate bi-directional volatility transmissions in general, except for the pairs of materials-oil and telecommunications-oil. The markets which are exposed to the highest and lowest spillovers from the oil market are telecommunications and energy indices, respectively. As suggested by Driesprong et al. (2008), the industries that are less dependent on oil exhibit a more pronounced oil effect, while oil related industries instantaneously incorporate any changes in oil prices. It is surprising that one-lagged volatility of the materials index is significant on the current volatility of oil returns, however, the opposite is not valid. This can be attributed to the composition of the index which includes materials, mining, chemicals and construction companies. As a result of the surge in global business activity, the production of these companies increase, which also inclines the demand for oil. Moreover, the asymmetric effects (γ) are present for all the sectors. However, an asymmetric reaction to the negative and positive shocks is not empirically found for the oil market. The constant conditional correlations range from 0.132 for financials-oil pair to 0.294 for energy-oil pair. These low correlations can advocate the possible benefit of investing in oil to reduce the sector specific risk in a portfolio.

Table 2 also displays the Student-t distribution degrees of freedom and residual diagnostics. The results provide the evidence of capturing the fat-tails and hence the suitability of the Student-t distribution. As confirmed by Ljung-Box tests applied to standardized squared residuals and ARCH-LM tests, all VAR (1)-AGARCH (1, 1) models are correctly specified.

5. Optimal Portfolio Designs and Hedging Strategies

In the last section, we compute the weights and hedging ratios of an optimal portfolio consisting of each index and oil together. For this, we consider the portfolio in which an investor aims minimizing the risk without lowering the expected returns. Following Kroner and Ng (1998), we determine the optimal weight of oil in a one-dollar portfolio of Brent oil/ sector index at time *t* as follows:

$$w_t^{os} = \frac{h_t^s - h_t^{os}}{h_t^o - 2h_t^{os} + h_t^s} \tag{5}$$

and

$$w_t^{os} = \begin{cases} 0, & if \ \ w_t^{os} < 0 \\ w_t^{os}, & if \ \ 0 \le w_t^{os} \le 1 \\ 1, & if \ \ w_t^{os} > 1 \end{cases} \tag{6}$$

where w_t^{os} is the weight of oil in a one-dollar portfolio at time *t*, h_t^s, h_t^0 represent conditional variances of sector indices and oil returns and h_t^{os} is the conditional covariance between the two assets, generated from the VAR-GARCH models.

Kroner and Sultan (1993) calculate the optimal hedge ratios of a two asset portfolio. To minimize risk, a long position of one dollar in the oil market must be hedged by a short position of β_t^{os} dollars in the sector index. β_t^{os} can be computed as:

$$\beta_t^{os} = \frac{h_t^{os}}{h_t^s} \tag{7}$$

In Table 3, we present the average values of optimal weights and hedge ratios for the portfolios. The results show that the weights vary between 0.340 for industrials and 0.448 for energy index. This implies that, in one dollar of oil/industrials portfolio, the optimal holdings of oil and industrials index are 34 cents and 66 cents, respectively. The weight of oil is the highest in the oil/energy index portfolio, which is also substantiated by the highest correlation coefficient between these two assets. For the hedge ratios, the values range from 0.177 for the financials to 0.326 for the energy, suggesting that one-dollar long in oil should be shorted by 17. 7 cents and 32.6 cents in these sector indices, respectively. Our results suggest that in emerging markets, adding a portion of oil to the portfolio of sector indices reduces the risk without lowering expected returns. However, the portion of the index in the portfolio should be greater than that of oil.

Table 3. Optimal Portfolio Weights and Hedge Ratios

	Oil/Materials	Oil/Telecom	Oil/Financials	Oil/Energy	Oil/Industrials
w_t^{os}	0.371	0.357	0.359	0.448	0.340
β_t^{os}	0.256	0.195	0.177	0.326	0.219

6. Conclusion

In this paper, we analyze the return and volatility transmission mechanisms between oil prices and emerging market sector returns, applying VAR (1) - AGARCH (1, 1) model over the period January 6, 1995 to December 27, 2013. Overall, we posit some significant shock and volatility transmissions at varying magnitudes. The sectors which are not heavily dependent on oil as an input, such as the telecommunications, show a more notable oil effect while oil related industries efficiently incorporate any changes in oil prices. We also compute the optimal weights and hedge ratios for the oil/index portfolios. We adduce that all the optimal portfolios should be dominated by sector indices. The hedge ratios are low, remarking the hedging effectiveness of taking a long position in oil. Our results provide insights for investors and portfolio managers to effectively implement diversification and hedging strategies.

References

Al-Fayoumi, N.A. (2009). Oil prices and stock market returns in oil importing countries: the case of Turkey, Tunisia and Jordan. *European Journal of Economics, Finance and Administrative Sciences*, *16*, 86-101.

Al Janabi, M.A., Hatemi-J, A., Irandoust, M. (2010). Modeling time-varying volatility and expected returns: Evidence from the GCC and MENA regions. *Emerging Markets Finance and Trade*, *46*(5), 39-47.

Arouri, M.E.H., Lahiani, A., Nguyen, D.K. (2011). Return and volatility transmission between world oil prices and stock markets of the GCC countries. *Economic Modelling*, *28*(4), 1815-1825.

Driesprong, G., Jacobsen, B., Maat, B. (2008), Striking Oil: Another Puzzle? *Journal of Financial Economics*, 33, 3-56.

Elyasiani, E., Mansur, I., Babatunde, O. (2011), Oil Price Shocks and Industry Stock Returns, *Energy Economics*, 33(5), 33-52.

Filis, G., Degiannis, S., Floros, C. (2011), Dynamic Correlation between Stock Market and Oil Prices: The Case of Oil-Importing and Oil-Exporting Countries, *International Review of Financial Analysis*, 20(3), 152-164.

Hamilton, J.D., (1983), Oil and Macroeconomy since World War II, *Journal of Political Economy*, 91(2), 228-248.

Hammoudeh, S., Aleisa, E. (2002). Relationship between Spot/Futures Prices of Crude Oil and Equity Indices for Oil-Producing Economies and Oil-Related Industries. *Arab Economic Journal*, *11*(27), 37-62.

Huang, R.D., Masulis, R.W., Stoll, H.R. (1996), Energy Shocks and Financial Markets, *Journal of Futures Markets*, 16(1), 1-27.

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

Kilian, L., Park, C. (2009), The Impact of Oil Price Shocks on the US Stock Market, *International Economic Review*, 50, 1267-1287.

Kroner, K.E., Ng, V.K. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies*, *11*(4), 817-844.

Kroner, K.F., Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, *28*(04), 535-551.

Malik, F., Ewing, B.T. (2009). Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis*, *18*(3), 95-100.

McAleer, M., Hoti, S., Chan, F. (2009). Structure and asymptotic theory for multivariate asymmetric conditional volatility. *Econometric Reviews*, *28*(5), 422-440.

Narayan, P.K., Narayan, S. (2010). Modelling the impact of oil prices on Vietnam's stock prices. *Applied Energy*, *87*(1), 356-361.

Park, J., Ratti, R.A. (2008). Oil price shocks and stock markets in the US and 13 European countries. *Energy Economics*, *30*(5), 2587-2608.

Sadorsky, P. (1999), Oil Price Shocks and Stock Market Activity, *Energy Economics*, 21, 449-469.

Sadorsky, P. (2001), Risk Factors in Stock Returns of Canadian Oil and Gas Companies, *Energy Economics*, 23, 17-28.