Non-integrated companies in the oil supply chain and time-varying correlations of stock returns

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Abstract

This paper uses the DCCGARCH model to investigate the existence of time-varying correlations among stock returns of companies in upstream and downstream sectors of the global oil supply chain. The goal is to understand whether investors and fund managers should worry about time-varying conditional correlations of returns stocks returns in the two sectors. The study uses a sample of 2820 daily observations of stock returns from 12 oil-related companies from the two sectors. The results show high levels of dynamic conditional correlations among stocks returns of companies in both sectors. This result implies that investors and fund managers should not expect inter-sector diversification strategy to lead to a significantly improvement in their portfolios' risk-return profile.

Keywords: stock returns, volatility, DCC, oil supply chain, upstream and downstream sectors

JEL Classification: C32, G10, Q40

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1. Introduction

Non- integrated firms in global oil and gas industry usually operate in one of two broad sectors in the supply chain: viz upstream and downstream.[3] Companies in Drilling and Exploration (D&E) and Equipment and Services (E&S) are typically classed as upstream companies; while those in construction of Pipelines (PIP) and Retail and Marketing (R&M) are downstream companies. Large vertically integrated oil companies like Exxon Mobil and BP undertake diversified range sets of operations across the supply chain (Lin and Su, 2008). They are involved in exploring, drilling, transporting, refining and marketing of oil and gas products and by products in various locations around the world. However, integrated firms tend to outsource or sub-contract specialized or highly technical operations such as seismic scanning and offshore drilling, which require specific skills and equipment, to relatively small specialized non-integrated firms which specialize in upstream and downstream operations in the supply chain. The fundamental question examined here is: should investors and fund managers consider about time-varying conditional correlations between volatility of returns on stocks of non-integrated firms in upstream and downstream sectors of global oil supply chain?

A plethora of empirical evidence shows that the oil industry is subject to high levels of stock price and returns volatility. Regnier (2007) notes that oil and natural gas prices are more volatile than 95 percent of all primary products sold domestically

[3] This categorization is based on S&P classification of oil industry stock indices

in United States. During the period of 1984-1994, crude oil price shows more volatility than nine other commodities (Plourde and Watkins, 1998). Optimal portfolio diversification requires a clear understanding of the nature and scope of correlations among returns on stocks of firms in both sectors of the oil and gas supply chain. Stock prices of companies operating in upstream or downstream sectors of the oil industry are strongly influenced by volatility of oil prices. However, it is not clear whether significant differences exist between stock returns volatility of companies that operate in downstream and upstream sectors of the oil supply chain. According to Markowitz (1959), the asset selection process should focus on identifying stocks that eliminate firm-specific risks while isolating the impact of market-risk on the overall return of the portfolio. Such analyses are vital to avoiding naive diversification, dealing with idiosyncratic risk and minimizing the all risks associated with of the portfolio. Thus, a well-diversified portfolio is not simply a collection of 'good' dissimilar assets, but a collection of assets that minimize the total risk of portfolio. An understanding of nature and scope of time-varying volatility of correlations among returns on stocks in the oil sector is useful to portfolio risk management.

Moreover, the global oil supply chain and the business environments that govern it are complex. Firms in different sectors of the oil industry face different challenges. For example, petrochemical and oil refineries face challenges that are different from those faced by firms in the other sectors. On one hand, increasing oil prices would cause the cost of production (or operation) of petrochemical and oil refinery companies to increase which would negatively affect their profitability. On the other hand, drilling and exploration companies make record profits during periods of high oil prices. This contrasting situation makes us think that the correlation between stock returns of companies in these sectors could be different, or even depend on cash flows and expected profit. Therefore, stock returns of companies belonging to one particular oil sector could exhibit similar levels of DCCs.

In this paper we use the DCCGARCH model developed by Engle (2002) to estimate and examine the dynamic conditional correlations between stock return volatilities of upstream and downstream sectors of the oil and gas industry. The paper is organized as follow. Section 2 contains a brief literature review for both the theoretical advancements and empirical applications of the DCCGARCH model. Section 3 outlines the model as well as the approach and data used. Section 4 presents and discuses results obtained from the application of the model. Section 5 provides some concluding remarks.

2. The literature

The original DCCGARCH model proposed by Engle (1999) offers both the flexibility of univariate GARCH models and the simplicity of parametric correlation in the model. Engle and Sheppard (2001) further extended the model to accommodate large time-varying covariance matrices. They estimated the conditional covariance of up to 100 assets in the S&P 500 and the Dow Jones Industrial Average. Their results show that the new model performed considerably well. Two different versions of the DCCGARCH model were also developed, by Tse and Tsui (2002) and Christodoulakis and Satchell (2002).

The issue of risk reduction through diversification in portfolio selection has been the focus of a good number of GARCH-type models. In particular, Alexander (2001) applied a multivariate-GARCH model to portfolios by splitting the estimation process into two steps. Hlouskova, *et. al* (2004) further used multi-step multivariate GARCH models to predict portfolio values for fund mangers. Lee, *et. al.* (2006) used the DCCGARCH model to estimate the value-at-risk of a portfolio of assets. Pelagatti and Roudena (2004) used an extension of Engle's (1999) two step estimation of DCCGARCH model to evaluate the value-at-risk of realistic portfolios. Garlappi, *et al*. (2005) examined portfolio selection with parameter and model uncertainty.

Two clear frontiers have recently emerged in the development and application of the DCCGARCH models. The first approach attempts to improve the original model's performance and capability by addressing issues such as simplicity, asymmetry and flexibility. The second involves application of DCCGARCH framework to real-life data such as modelling the DCCGARCH of volatility between bond and equity returns or the modelling the volatility associated with the performances of the Euro and non-Euro currencies. Simplifying the DCCGARCH model's application process has been the focal point of several studies. Kearney and Poti (2003) showed that the parameters of the DCCGARCH model can easily be derived from estimated parameters of a VARMA model of average conditional correlation. Moreover, a DCCGARCH model with elliptical distributions was proposed by Pelagatti and Roudena (2004). They suggested an extension to Engle's two- step DCCGARCH model to elliptical conditional distributions. A simplified DCCGARCH model has also been developed by joining the univariate GARCH model with an easy to interpret dynamic correlation estimator, by Lee, Shiou and Lin (2006).

To deal with the original DCCGARCH model's limitations in dealing with asymmetric effects, especially between blocks of assets, Capiello, Engle and Sheppard (2003) introduced asymmetry in DCCGARCH model. In modelling bond and equity returns across a wide range of markets, they found that national equity index returns exhibit strong asymmetry compared to returns on the bond index. However, a recent paper by Vargas (2006) notes that Capiello, Engle and Sheppard (2003) looked only at the average dynamic correlation of individual variables as representatives of regional dynamic conditional correlations. Vargas suggests a new model to deal more effectively with the issue of asymmetric effects. This new model is an extension of the Block Dynamic Conditional Correlation (BDCC) model developed by Billio, Caporin and Gobbo (2003). That BDCC model has also been extended to deal with the issue of flexibility. In a recently published paper, they have introduced the Flexible Dynamic Conditional Correlation (FDCC) multivariate GARCH model. The original DCCGARCH model has constraints that make all dynamics equal for all correlations. The FDCC allows each correlation to have different dynamics (Billio, Caporin and Gobbo, 2006).

Modelling co-movements and correlation of currencies is one of the areas in which the DCC has been applied extensively. Applications of the DCC model(s) have been appearing in many academic papers. Dijk, Munandar and Hafner (2005) have used the DCCGARCH model to analyze the relationship between several European currencies and the Euro. Their paper documents the existence of a large structural break in the unconditional correlation between these currencies. Hautsch and Inkmann (2003) use the DCCGARCH model to find the optimal hedge ratio of multiple currency exchange risk exposure. These applications are not limited to developed markets. For example, interest rate-exchange rate dynamics in the emerging market of the Philippines have been analyzed using the DCC model (Bautista, 2003).

To our knowledge, this work is the first attempt to use the DCCGARCH model to examine dynamic conditional correlation of stock returns of companies in the upstream and the downstream sectors of global oil supply chain.

3. Model and approach

Engle (2002) simplified the DCCGARCH model estimation process in two steps. In this paper, the first step involves the estimation of a univariate GARCH model of k stock returns that are assumed to be conditionally multivariate normal.[4] Thus, time-varying conditional volatility of returns on stock *i* at time *t*, (denoted by $r_{i,t}$) is given by the following GARCH model:[5]

$$h_{i,t} = \omega_i + \sum_{j=1}^{p} \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{i=1}^{q} \beta_{ij} \; h_{i,t-j} \qquad i = 1, 2, ..., k \tag{1}$$

where $\varepsilon_t = \eta_t \sqrt{h_{it}}$ is the error term of a *d*-dimensional model, and η_t is a sequence of independently and identically distributed random variables with zero mean and variance of one, $h_{i,t}$ is the conditional variance of returns on stock *i* at time *t*, and α_i and β_i are ARCH and GARCH effects respectively (Manera, *et al*. 2006,).

In the second step, we characterize ε_t as a diagonal matrix and a time-varying correlation matrix as expressed below:[6]

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[4] These returns can either have a mean zero or simply residuals from a filtered time series (Engle and Sheppard, 2001).

[5] We used the continuously compounded stock returns $r_{i,t} = \ln(P_{i,t} / P_{i,t-1})$ and the ARCH representation: $r_{it} = \varphi_0 + \sum_{i=1}^{k} \phi_i \; r_{i,t-k} + \varepsilon_t$

[6] See Baustista, (2003) and Andersson *et al*, (2007)

$$r_{i,t}|\Psi_{t-1} \sim \mathrm{N}(0, H_t)\,,\ \ H_t \equiv D_t \Gamma_t D_t$$

$$\varepsilon_t = D_t \eta_t\,,\ E_{t-1}(\varepsilon_t \varepsilon_t') = \Gamma_t \tag{2}$$

where H_t denotes a positive definite conditional covariance matrix, $r_{i,t}$ is normally distributed with zero mean, Ψ_{t-1} denotes information set available at $t-1$, and D_t is a k x k diagonal matrix of time-varying residuals obtained from step 1 with $\sqrt{h_{it}}$ on the i^{th} diagonal,

$$D_t = \begin{pmatrix} \sqrt{h_{11,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22,t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{h_{mn,t}} \end{pmatrix} \tag{3}$$

These residuals are standardised and applied to Equation (2). Γ_t is a k x k time varying correlation matrix that can be expressed as:

$$\Gamma_t = (diag(Q_t))^{-1}.Q_t.(diag(Q_t))^{-1} \tag{4}$$

Thus, we can express the DCC structure as follows:

$$Q_t = (1-\delta_1-\delta_2)\overline{Q} + \delta_1(\varepsilon_{t-m}\varepsilon'_{t-m}) + \delta_2 Q_{t-n} \tag{5}$$

where $\overline{Q}$ is the matrix of unconditional covariances of the standardized errors obtained in first step. As the residuals from the Equation (1) are standardised and used in the second step, the resulting dynamic correlation coefficient matrix is $\Gamma_t = Q^{*-1}\ Q_t\ Q_t^{*-1}$; Q_t* is a diagonal matrix consisting of the square root of diagonal elements of Q_t and is expressed as:

$$Q_t{*} = \begin{pmatrix} \sqrt{q}_{11} & 0\cdots\cdots & 0 \\ 0 & \sqrt{q}_{22}\cdots & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0\cdots\cdots & \sqrt{q}_{kk} \end{pmatrix} \tag{6}$$

The elements of Γ_t can be calculated using $\rho_{12,t} = \dfrac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}}$, where $\rho_{12,t}$ is the conditional correlation of the two stocks. $\varepsilon_{t-m}\varepsilon'_{t-m}$ is the unconditional covariance of the standardised residuals.

We are interested in estimating the DCCGARCH of returns of non-integrated firms operating in upstream and downstream sectors of global oil supply chain. Our leading hypothesis is that dynamic correlations of stock returns of companies within the same sector (intra-sector pairs) are significantly different from those between the sectors (inter-sector pairs.) Inter-sector pairs contain two stocks listed in two different sectors (namely upstream and downstream) .Specifically, we hypothesise that DCC of stock returns of intra-sector pairs of companies are statistically significantly different from DCC of inter-sector pairs

The data set consists of daily stock prices returns of 12 oil companies, three stocks from each of the following sectors: D&E, E&S, PIP and R&M. The daily time series start from October 4, 1995 to the December 12, 2006. We have a total of 2820 observation for each stock. Table 1 report some company-specific financial information used in this study.

4. Results and Discussion

Table 1 contains a list companies examined and summaries of key financial information on them. Tables 2 and 3 contain estimates of DCC values δ_2 and δ_1 respectively. We used Berndt, *et al* (1974) algorithms to obtain quasi-maximum likelihood estimates of δ_1 and δ_2. The results in Table 2 show high DCC coefficient between stock returns in downstream and upstream sectors. The table further shows high DCC coefficients for intra-sector and inter-sector pairs of stocks that are generally higher than 0.90. These high DCC coefficients show that volatility correlations between stock returns are not generally affected by sector affiliation. Estimated DCC values, δ_1 and δ_2, satisfy the $0 \leq (\delta_1, \delta_2) \leq 1$ condition of for the conditional correlation matrix is positive semi- definite.

A perusal of DCC estimates reveals no noticeable differences between companies in upstream and downstream sectors of the oil industry. Therefore, we cannot identify any statistical evidence to support the hypothesis that stock returns of firms in different sectors of the oil supply chain are significantly different. High DCC values among stock returns imply that inter-sector diversification in the oil industry, if not synonymous to naive diversification, confers no significant risk reduction benefit. These results suggest that investors and fund managers should not expect to gain a significant risk-reduction benefit by merely picking assets of companies in different sectors of the oil supply chain. When considering time-varying correlations of stock returns, fund managers should view the whole oil industry as similar class of assets in terms of risk and expected return.

However, noticeable aberrations are visible in DCC values of Diamond Offshore Incorporated which are significantly lower for both intra-sector and inter-sector pair combinations. These DCC values could be the results of company-specific factors like level of debt or type of operation.

We proceed to estimate contemporaneous correlations between stock returns of the 12 companies to identify common patterns. The results listed in Table 4 shows low negative to moderate positive levels of correlation (-0.063 and 0.50). However, three companies, HAL, BHI, and NE do exhibit a relatively high levels of correlation among themselves (i.e. HAL & BHI = 0.66, NE & BHI = 0.72, and NE & HAL = 0.64) but not with other stocks. RIG & SLB also exhibits also a moderately high level of correlation. The moderately high stock returns correlations are restricted to few companies in the upstream sector of the supply chain; and returns correlations among downstream companies were generally low. These exceptions could be the results of the companies' exposure to similar market-related factors. Investors and fund mangers may view these companies differently from the others due to the type and scale of their business operations. For instance, they may compete in close cooperation or rival with one another in pursuing international opportunities; which cause the market to value them as similar companies.

5. Concluding Remarks

We used the DCCGARCH model to estimate the DCC between stock volatilities in the upstream and downstream sectors of the oil industry. The upstream sector consisted of two sub-sectors: the D & E and E & S sectors; while downstream sector is divided into PIP and R & M. An understanding the nature and scope of correlations between stocks of different sectors of the oil industry is important in creating a well-diversified portfolio of assets; as well as perceiving their the way the responses to challenges in the marketplace .

The results in this paper show that almost all selected stocks have high levels of dynamic conditional correlation among them. However, inter-sector pairs and intra-sector pairs showed very similar level of DCC. Therefore, stocks belonging to different oil sectors should be viewed as similar assets in term of time-varying correlations conditional correlation. This pattern of DCC indicate that fund managers in search of new stock to diversify portfolio should view non-integrated firms in both sectors similar class of assets.. No additional reduction in a portfolio's overall risk is expected to result from selecting stocks from different sectors of the oil industry. Instead, the fund manger should look at the wider range of non-integrated oil company stocks industry regardless of the sector to which it relates.

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Table 1: Summary financial information companies in sample (U.S. $ as of 31/12/2006)

	Sector	Stock*	Company	Market Cap. (Billion)	Revenue (Billion)	Profit Margin%	ROA%
Upstream	DE	DO	Diamond Offshore Drilling Inc.	13.47	2.21	35.50	17.96
		NE	Noble Corp.	12.64	2.28	36.63	14.26
		RIG	Transocean Inc.	29.06	4.39	39.43	9.18
	ES	BHI	Baker Hughes Inc.	27.40	9.44	26.01	15.90
		HAL	Halliburton Co.	33.31	22.99	10.49	13.43
		SLB	Schlumberger Limited	92.82	20.46	20.38	16.31
Downstream	Pip	EP	El Paso Corp.	11.90	3.97	18.86	2.97
		KMP	Kinder Morgan Energy Partners	12.79	8.72	10.79	6.59
		WMB	Williams Companies Inc.	19.27	11.81	2.61	2.97
	RM	IMO	Imperial Oil Ltd	44.31	21.86	13.90	16.10
		MRO	Marathon Oil Corp.	43.79	56.37	9.17	N/A
		SSL	Sasol Ltd	21.59	9.72	15.66	13.31

*As listed in NYSE

Table 2: The DCC (δ_2) values of pairs of stock returns.

			Upstream						Downstream					
			DE			ES			Pip			RM		
			RIG	DO	NE	SLB	HAL	BHI	WMB	KMP	EP	MRO	IMO	SSL
Upstream	DE	RIG	**1**											
		DO	0.481 (0.334)	**1**										
		NE	0.975 (0.005)	0.3194 (0. 197)	**1**									
	ES	SLB	0.97 (0.028)	0.173 (0. 296)	0.976 (0.003)	**1**								
		HAL	0.984 (0.005)	0.000 (0. 492)	0.916 (0.062)	0.98 (0.005)	**1**							
		BHI	0.975 (0.005)	0.000 NA	0.965 (0.020)	0.974 (0.005)	0.987 (0.031)	**1**						
Downstream	Pip	WMB	0.984 (0.003)	0.000 (0. 842)	0.988 (0.002)	0.988 (0.004)	0.991 (0.006)	0.989 (0.002)	**1**					
		KMP	0.985 (0.004)	0.615 (0.129)	0.989 (0.003)	0.985 (0.069)	0.991 (0.0035)	0.991 (0.002)	0.992 (0.002)	**1**				
		EP	0.993 (0.002)	0.87 (0.077)	0.989 (0.004)	0.995 (0.001)	0.762 (0.061)	0.987 (0.010)	0.981 (0.010)	0.992 (0.002)	**1**			
	RM	MRO	0.98 (0.006)	0000 (0.004)	0.984 (0.004)	0.984 (0.003)	0.995 (0.003)	0.989 (0.004)	0.984 (0.004)	0.992 (0.002)	0.986 (0.005)	**1**		
		IMO	0.988 (0.005)	0.000 (0.958)	0.976 (0.010)	0.989 (0.004)	0.997 (0.004)	0.982 (0.005)	0.986 (0.004)	0.994 (0.003)	0.998 (0.001)	0.984 (0.006)	**1**	
		SSL	0.987 (0.010)	0.964 (0.010)	0.992 (0.003)	0.992 (0.002)	0.984 (0.006)	0.991 (0.004)	0.994 (0.010)	0.996 (0.002)	0.992 (0.006)	0.987 (0.003)	0.993 (0.002)	**1**

Notes: Values in brackets are standard errors of DCC coefficients

Table 3: The DCC (δ_1) values of pairs of stock returns.

			Upstream						**Downstream**					
			DE			**ES**			**Pip**			**RM**		
			RIG	**DO**	**NE**	**SLB**	**HAL**	**BHI**	**WMB**	**KMP**	**EP**	**MRO**	**IMO**	**SSL**
Upstream	**DE**	**RIG**	1											
		DO	0.009 (0.041)	1										
		NE	0.024 (0.006)	0.0173 (0.020)	1									
	ES	**SLB**	0.019 (0.017)	0.0129 (0.017)	0.023 (0.003)	1								
		HAL	0.015 (0.005)	0.000 (0.014)	0.038 (0.020)	0.019 (0.005)	1							
		BHI	0.023 (0.004)	0.00 (0.017)	0.024 (0.014)	0.025 (0.005)	0.008 (0.010)	1						
Downstrem	**Pip**	**WMB**	0.014 (0.003)	0.000 (0.064)	0.011 (0.002)	0.011 (0.003)	0.009 (0.005)	0.010 (0.002)	1					
		KMP	0.010 (0.003)	0.0306 (0.014)	0.008 (0.002)	0.009 (0.054)	0.007 (0.025)	0.007 (0.002)	0.007 (0.002)	1				
		EP	0.007 (0.002)	0.017 (0.010)	0.007 (0.003)	0.005 (0.001)	0.066 (0.017)	0.008 (0.004)	0.016 (0.005)	0.006 (0.001)	1			
	RM	**MRO**	0.018 (0.005)	0.00 (0.003)	0.013 (0.003)	0.014 (0.003)	0.004 (0.003)	0.009 (0.003)	0.015 (0.004)	0.006 (0.002)	0.009 (0.003)	1		
		IMO	0.010 (0.004)	0.00 (0.014)	0.015 (0.006)	0.010 (0.003)	0.003 (0.002)	0.013 (0.003)	0.012 (0.004)	0.005 (0.002)	0.002 (0.001)	0.012 (0.004)	1	
		SSL	0.009 (0.004)	0.006 (0.004)	0.007 (0.002)	0.006 (0.002)	0.013 (0.005)	0.008 (0.003)	0.006 (0.002)	0.003 (0.002)	0.007 (0.003)	0.011 (0.003)	0.006 (0.002)	1

Notes: Values in brackets are standard errors of DCC coefficients

Table 4: Contemporaneous correlations of stock returns.

	Upstream						Downstream					
	DE			ES			Pip			RM		
	RIG	*DO*	*NE*	*SLB*	*HAL*	*BHI*	*WMB*	*KMP*	*EP*	*MRO*	*IMO*	*SSL*
RIG	1.000											
DO	-0.042	1.000										
NE	0.213	0.029	1.000									
SLB	0.718	-0.063	0.196	1.000								
HAL	0.198	-0.012	0.643	0.212	1.000							
BHI	0.178	-0.040	0.721	0.214	0.666	1.000						
WMB	0.156	0.018	0.181	0.145	0.215	0.195	1.000					
KMP	0.236	-0.048	0.108	0.267	0.122	0.115	0.131	1.000				
EP	0.150	0.016	0.251	0.140	0.246	0.264	0.357	0.105	1.000			
MRO	0.194	0.013	0.501	0.208	0.460	0.506	0.218	0.101	0.278	1.000		
IMO	0.141	-0.013	0.324	0.149	0.321	0.319	0.147	0.108	0.192	0.401	1.000	
SSL	0.209	-0.014	0.130	0.250	0.136	0.127	0.104	0.145	0.070	0.134	0.124	1.000