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Conditional correlations in the returns on oil companies stock prices and their determinants

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Abstract The identification of the forces that drive stock returns and the dynamics of their associated volatilities is a major concern in empirical economics and finance. This analysis is extremely important for determining optimal hedging strategies. This paper investigates the stock prices' returns and their financial risk factors for several integrated oil companies, namely Bp (BP), Chevron-Texaco (CVX), Eni (ENI), Exxon-Mobil (XOM), Royal Dutch (RD) and Total-Fina Elf (TFE). We measure the actual co-risk in stock returns and their determinants "within" and "between" the different oil companies, using multivariate cointegration techniques in modelling the conditional mean, as well as multivariate GARCH models for the conditional variances. The distinguishing features of this paper are: (i) focus on the determinants of the market value of each company using the cointegrated VAR/VECM methodology; (ii) specification of the conditional variances of VECM residuals with the Constant Conditional Correlation (CCC) multivariate GARCH model of Bollerslev [(1990) Review of Economics and Statistics 72:498–505] and the Dynamic Conditional Correlation (DCC) multivariate GARCH model of Engle [(2002) Journal of Business and Economic Statistics 20:339–350]; (iii) discussion of the performance of

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optimal hedge ratios calculated with the DCC estimates. The "within" and "between" DCC indicate time-varying interdependence between stock return volatilities and their determinants. Moreover, DCC models are shown to produce more accurate hedging strategies.

Keywords Constant conditional correlations · Dynamic conditional correlations · Multivariate GARCH models · Stock price indexes · Brent oil prices · Spot and futures prices · Multivariate cointegration · Hedge ratios

JEL classification C32 · G10 · Q40

Introduction

The identification of the forces that drive stock returns and the dynamics of their associated volatilities is a major concern in empirical economics and finance. The assessment of the volatility of stock price returns and their determinants is particularly important in the Oil & Gas sector (O&G), since O&G is one of the largest industries in the world, involving different companies and business in the different chains of production, distillation and distribution.

Recent empirical work has focussed on the analysis of the leading factors which determine the level of stock prices for the most important world oil corporations. For instance, Lanza et al. (2004) investigate the dynamics of oil stock prices and their associated volatilities and correlations. In particular, this study analyzes the long-run relationship among the market value of a single oil company, the spread between spot and future oil prices, the relevant stock market index and the exchange rate. By using a company-specific VECM approach, the paper shows that: (i) major financial variables are significant in explaining oil stock prices; (ii) either the spread between spot and future oil prices or the stock market index are found to be exogenous variables in the econometric specification; (iii) it cannot be established a priori whether a rise in oil prices will lead to an increase of the oil stocks' value; (iv) the long-run elasticity of the oil stock price with respect to the stock market index is generally positive; (v) the stock price of an European oil company decreases when the dollar appreciates relative to the local currency.

The study of oil stock prices, return volatilities and correlations is also extremely important for portfolio analysis. Actually, it is well known that the strategy of minimizing risk exposure can be achieved by taking opposite positions in assets which are affected by the same kind of shocks. More specifically, if two assets are positively correlated, the ratio between the number of units of short positions and long positions held in a given portfolio is defined as hedge ratio. The simplest approach to risk hedging assumes a one-to-one ratio. That is, for any long position in one asset, an equal amount of short positions in the other asset should be undertaken to reduce risk. In contrast, the portfolio approach determines the hedge ratio by minimizing the portfolio variance. In this case, the optimal hedge is equal to the covariance between the two assets' returns divided by the variance of the stock return in which the short position is held. The conventional way calculates the optimal ratio as the estimated coefficient of an OLS regression, under the implicit assumption of constant second moments. However, it is widely acknowledged that financial time series exhibit conditional heteroskedasticity. Multivariate GARCH (MGARCH) models allow to take into account dynamic conditional variances, and therefore represent a very convenient way to evaluate portfolio volatilities and to calculate optimal hedge ratios (see, among others, Brooks et al. (1999); Lien and Tse (2002)).

In this paper we extend the existing empirical research in this area along three different dimensions. First, we focus on the determinants of the market value of each company using the cointegrated VAR/VECM methodology of Johansen and Juselius (1990). Second, we specify the conditional variances of VECM residuals with the Constant Conditional Correlation (CCC) multivariate GARCH model of Bollerslev (1990) and the Dynamic Conditional Correlation (DCC) multivariate GARCH model of Engle (2002). Third, we extend previous empirical research by using the DCC estimates to calculate optimal hedge ratios which allow for time-varying conditional volatilities and correlations. Our approach considers both a ‘‘within’’ and a ‘‘between’’ perspective. With the former, we study the interdependence among each oil company stock price and ‘firm-specific’ variables, whereas with the latter we investigate the relationship among different oil companies’ stock prices. In this way, we are able to capture the degree of co-risk across markets and across companies operating in the oil industry.

The rest of the paper is organized as follows. Section 2 contains a brief review of the relevant literature. The data set is discussed in Section 3. In Section 4 we model the determinants of the stock price returns of different oil companies, as well as their associated volatilities. In Section 5 the main empirical results are presented and the economic implications of our findings discussed. Section 6 concludes.

Previous work

There has been much empirical research on the identification of risk factors affecting companies’ stock value, which can be classified in at least three broad groups of contributions.

The first strand of literature studies whether stock prices are affected by the value of their underlying financial determinants. Jorion (1990), for instance, estimates exchange rate exposure of US multinationals over the period from January 1971 to December 1987. Statistical tests are performed to determine whether the exposure coefficients differ across firms. The hypothesis of equal coefficients is strongly rejected for multinationals, but not for domestic firms without foreign operations. The determinants of exchange rate exposure are therefore analysed, and a direct relation between exchange rate sensitivity and the percentage of foreign operations is assessed.

Blose and Shieh (1995) examine the impact of gold prices’ changes on the returns of gold mining stocks. The authors derive a model where the gold price elasticity is related to the level of gold prices, the quantity of reserves, the cost of production and the amount of non-gold activities. The gold price sensitivity of a mining stock is found to be grater than one. The hypothesis of unity gold price sensitivity is not rejected using monthly data over the period 1981–1990 for a sample of commonly traded companies.

Tufano (1998) studies gold price exposures of North American gold mining firms. Data from January 1990 to March 1994 show that gold mining stocks respond more than proportionally to gold price changes, and that exposures vary considerably over time and across firms.

The second group of works investigates the conditional volatilities and correlations of returns. For example, Flannery and James (1984) analyse the effect of interest rate changes and volatility on common stock returns of financial institutions. Using a sample of commercial banks, stock savings and loan associations from January 1976 to November 1980, common stock returns are found to be correlated with both interest rate changes and volatility. Cross-sectional differences in the results arise from discrepancies in the maturity composition of nominal assets: the longer the maturity of bank's nominal assets, the larger the interest rate sensibility.

Elyasani and Mansur (1998) analyse the sensitivity of banks stock returns to changes in interest rates and their corresponding volatilities. It is employed a GARCH-M specification that includes interest rates' volatility and allows for shifts in the stochastic process due to changes in monetary policy regimes. This model seems to be statistically adequate on monthly data for the period 1970–1992. In particular, the degree of persistence in shocks and the effect of interest rate volatility are substantial and depend on the nature of bank portfolio and on the prevailing monetary policy regime.

To examine the relation between exchange rate variability and stock returns volatility, Bartov et al. (1996) consider two 5-year periods around the 1973 switch from fixed to floating exchange rates. A significant generalised increase in the volatility of equity returns during the second period is found. Moreover, this increase is significantly larger for US multinationals than for other US firms, and only multinationals show a significant increase in market risk corresponding to the increase in exchange rate volatility.

The third group of studies concentrates on hedging strategies. Among others, Strong (1991) analyses the ability of oil equities portfolios to hedge oil price risk. In addition to the estimation of exposure coefficients, the author constructs portfolios aimed at maximizing the sensitivity to oil price changes and at diversifying away other risk. Using monthly data over the period 1975–1987, the oil price sensitivity of firms returns appears to be low or not significant, and on average the percentage of oil price changes offset by the returns of the hedge portfolio is only about one-third.

He and Ng (1998) examine the effect of exchange rate fluctuations on stock's returns of Japanese multinationals. About 25% of the considered multinationals show positive exposure over the period from January 1979 to December 1993. The level of export ratio as well as variables that are proxies of the firm's hedging policies are found to affect exchange rate sensitivity. Exposure coefficients are smaller for firms with low liquidity or high financial leverage, and for small Japanese multinationals. Moreover, evidence is provided that industrial grouping is likely to affect hedging needs and exchange rate exposure of firms.

Our paper is an attempt to unify the three strands of literature briefly summarized above. For this purpose, we exploit very recent multivariate techniques in financial econometrics, namely multivariate GARCH models designed to capture the dynamic interdependences in the conditional volatilities and in the conditional correlations (DCC), which we subsequently use to calculate time-varying optimal hedge ratios and efficient hedging strategies.

Data description

We investigate companies from several countries and with different business volumes and targeted markets (global or regional), namely: Bp (BP, UK), Chevron-Texaco (CVX, US), Eni (ENI, Italy), Exxon-Mobil (XOM, US), Royal Dutch (RD, The Netherlands), and Total-Fina-Elf (TFE, France). The stock price series (STOCK) for each company is the closing price quoted in the stock market of the company's country of origin.[1] For the six selected oil companies the relevant stock indexes (INDEX) are: FTSE (UK), Dow Jones (DJ, US), MIB30 (Italy), AEX (The Netherlands) and CAC40 (France).

Moreover, given the presence of companies from UK and countries belonging to the European Monetary Union, we consider the closing quotations of the exchange rates (ER) of the US dollar (USD) against the Euro (EUR) and the British pound (GBP).[2]

The selected crude oil prices are dated Brent for the spot series and futures Brent prices with twelve-month maturities.[3]

The sample period ranges from 23 January 1998 to 4 April 2003, and the frequency of observations is weekly. All prices are log-transformed and expressed in local currencies, with the only exception of crude prices, which are denominated in USD per barrel.

Augmented Dickey–Fuller statistics are used to investigate the time series properties of the data. All variables are integrated of order one, or I(1), most of them with intercept but no trend.[4]

Modelling oil company stock returns and volatility

We consider each company separately and analyze, using a VAR/VECM, the existence of long-run relations and short-run effects among the market value of the company, the difference between 12-month futures price and spot price on Brent (SPREAD), and the relevant stock market index and exchange rate, the latter being only for non-US companies.

Although individually I(1), these series may still form one or more linear combinations which are stationary, or I(0). In this case, there are one or more long-run equilibrium relationships among the variables entering the VAR specification, which are said to be cointegrated.

The Maximum Likelihood method proposed by Johansen (1991) tests the presence of cointegration among the variables in the $m \times 1$ vector X_t by determining the rank of the long-run matrix, Π. If rank(Π) = r, with $0<r<m$, the matrix Π can be decomposed as $\Pi = \lambda\, \beta'$, where λ is a $m \times r$ matrix of adjustment parameters and β is a $m \times r$ matrix containing the r cointegrating relations among the variables X_t. The Johansen approach enables to estimate the β parameters, and to test for the number of I(0) linear combinations among the X_t variables.

With the number r of cointegrating relationships determined, the following VECM can be estimated by OLS:

$$\Delta X_t = \mu_0 + \mu_1 t + \lambda \mathrm{ecm}_{t-P} + \sum_{p=1}^{P-1} A_p \Delta X_{t-p} + \varepsilon_t, \qquad (1)$$

[1] For RD the relevant stock market is the Dutch market.

[2] Reuters is the main source for company stock values, market indexes and exchange rates.

[3] Spot and futures prices of Brent are from Platt's.

[4] Results from Augmented Dickey–Fuller tests, although not reported to save space, are presented in an appendix available from the authors upon request.

where μ_0 is a $m \times 1$ vector of constants, t =1,...,n is a deterministic trend, μ_1 is a $m \times 1$ vector of deterministic linear trend coefficients, ε_t is a $m \times 1$ error vector, and $\mathrm{ecm}_{t-P} \equiv \hat{\beta}' X_{t-P}$ is the $r \times 1$ vector of long-run equilibria among the X_t variables.

Testing the significance of the estimated parameters λ in system (1) determines which variables can be considered as (weakly) exogenous (see Urbain, 1992). Specifically, the dependent variables of equations where the estimated λ are not statistically significant can be treated as exogenous. This results allows us to estimate a parsimonious conditional VECM formed with the equations of the remaining endogenous variables. Each equation is augmented by the full set of exogenous variables in first differences.

Next, we look for the presence of ARCH effects in the errors of the conditional VECM equations, using univariate GARCH(1,1) models of the type:

$$h_{it} = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1}, \tag{2}$$

where i =1,...,m, indicates the i-th equation in the VECM, and h_{it} is the conditional variance of ε_{it}, the error term of the i-th equation. If α_i or α_i and β_i are significant, then ARCH or GARCH effects are present. In order for this test to be meaningful, the necessary and sufficient condition for the existence of the second moments of ε_{it}, namely $\alpha_i+\beta_i < 1$, should be satisfied, since this condition is also sufficient for the Quasi-Maximum Likelihood Estimator (QMLE) to be consistent and asymptotically normal. Jeantheau (1998) showed that the log-moment condition, $E(\log(\alpha_i\, \eta_{it}^2 + \beta_i))<0$, $\eta_{it} = \varepsilon_{it}/\sqrt{h_{it}}$, is sufficient for the QMLE to be consistent for GARCH(1,1).

If conditional heteroskedasticity is found at the single-equation level, a system approach to the analysis of non-constant conditional error variances can be used.

The time-varying behavior of the conditional covariance matrix of the VECM errors, $\varepsilon_t = (\varepsilon_{1t},...,\varepsilon_{mt})'$, can be described using a multivariate GARCH model. Following McAleer (2005), who discusses a wide range of multivariate conditional volatility models, a general expression for heteroskedastic system error terms is:

$$\varepsilon_t = H_t \eta_t, \tag{3}$$

where H_t is the square root of a $m \times m$ symmetric matrix of conditional variances and covariances, and η_t is an $m \times 1$ vector of i.i.d. standardized errors. From expression (3), it follows that $E(\varepsilon_t|\Omega_{t-1}) = 0$ and $E\left(\varepsilon_t \varepsilon_t'|\Omega_{t-1}\right) = H_t$, with Ω_{t-1} denoting the information set at time $t-1$.

A GARCH-type parameterization of the covariance matrix of ε_t should allow H_t to depend on lagged shocks ε_{t-q}, q = 1,...,Q, and on its own past H_{t-p}, p = 1,...,P. However, in this case the number of parameters to be estimated is too large and conditions for H_t to be positive definite can be complicated to impose.

A model which drastically solves these problems is the CCC multivariate GARCH model of Bollerslev (1990). In the CCC specification, $H_t = diag(h_{1t}^{1/2},...,h_{mt}^{1/2})$ and, setting $Q = P = 1$, the conditional variance for each return is assumed to follow the univariate GARCH process (2), that is the conditional variance of the i-th return is assumed to be independent of the conditional variance of the j-th return, i, j = 1,...,m. In order to calculate the constant conditional correlation matrix Γ, whose typical element is ρ_{ij}, i, j = 1,...,m, m univariate GARCH(1,1) models should be estimated with QMLE, the m standardized residuals $\hat{\eta}_{it}$ calculated, and the m correlation coefficients obtained as $\hat{\rho}_{ij} = \sum_{t=1}^{n} \hat{\eta}_{it}\hat{\eta}_{jt}/n$, $i, j = 1,...,m$.

If η_t is not a sequence of i.i.d. random errors, the assumption of constant conditional correlation is no longer valid. In order to model the time-varying behavior of the conditional correlation matrix Γ_t, Engle (2002) introduced the DCC multivariate GARCH:

$$\Gamma_t = (1 - \theta_1 - \theta_2)\Gamma + \theta_1\eta_t\eta_t' + \theta_2\Gamma_{t-1}, \tag{4}$$

where θ_1 and θ_2 are scalar parameters to capture the effects of previous standardized shocks and dynamic conditional correlations on current dynamic conditional correlations, respectively.

Empirical results

According to the Johansen cointegration procedure outlined in the previous section, there is one cointegrating relation among the variables STOCK, SPREAD, INDEX and ER for each of the six oil companies under analysis.[5]

In all models, the significance of the estimated parameters λ (that is, the coefficients of adjustment to the long-run equilibrium) indicates that one or two variables can be considered to be weakly exogenous in the VECM, and that the number of equations can be reduced to form a parsimonious VECM. In particular, the market index seems to be endogenous for those companies (ENI, RD, TFE) whose capitalization is large, compared with the size of the relevant stock market. The spread variable is found to be endogenous for BP, XOM, CVX and RD. Estimates of the loading coefficients which correspond to the exchange rate equations are never significant, confirming the expected exogeneity of ER. The autoregressive structure of the estimated models seems to be statistically adequate, since the null hypothesis of no residual autocorrelation is never rejected by the system.

The univariate estimates of the conditional volatilities in the residuals of each parsimonious VECM system show that four companies of six have significant ARCH(1) or GARCH(1,1) effects in the residuals of all equations forming the parsimonious VECM. Oil company CVX has significant GARCH(1,1) effects in the STOCK equation only, whereas oil company BP does not exhibit significant ARCH(1) or GARCH(1,1) effects in either the STOCK or the SPREAD equation. Both second-moment and log-moment conditions are satisfied, so that the QMLE are consistent and asymptotically normal.

The standardized residuals from each of the estimated univariate GARCH(1,1) models are used to compute the constant conditional correlations reported in Panel a and Panel b of Table 1.

The CCC presented in Panel a of Table 1 are calculated on the standardized residuals of the VECM "within" each company. In four companies the STOCK and SPREAD variables are endogenous according to the VECM specification, namely BP, CVX, RD and XOM. Shocks to volatilities in the returns of STOCK and

[5] For sake of brevity, the results of cointegration tests, VECM and univariate GARCH estimation are not reported. However, the complete set of empirical results is presented in an appendix which is available from the authors upon request.

Table 1 Constant conditional correlations (CCC)

Oil companies	Standardized residuals of VECM equations	CCC				
Panel a. "Within" CCC						
BP	STOCK, SPREAD	−0.120				
		−2.054				
CVX	STOCK, SPREAD	0.070				
		1.206				
ENI	STOCK, INDEX	0.481				
		10.421				
RD	STOCK, SPREAD	−0.143				
		−2.351				
	STOCK, INDEX	0.508				
		11.372				
	SPREAD, INDEX	−0.046				
		−0.727				
TFE	STOCK, INDEX	0.553				
		15.619				
XOM	STOCK, SPREAD	0.053				
		0.922				
Panel b. "Between" CCC						
Std. resid. of VECM eq. STOCK for oil companies	BP	CVX	ENI	RD	TFE	XOM
BP	1.000					
CVX	0.509	1.000				
	11.876					
ENI	0.464	0.280	1.000			
	9.595	5.435				
RD	0.744	0.404	0.546	1.000		
	28.993	7.718	16.045			
TFE	0.680	0.346	0.543	0.732	1.000	
	20.819	6.464	15.756	26.161		
XOM	0.363	0.632	0.262	0.287	0.259	1.000
	7.565	19.547	4.627	5.567	5.051	

Note: The two entries for each CCC are their respective estimates and asymptotic *t*-ratios

SPREAD are significantly correlated for RD and BP only. The variable INDEX is endogenous for oil companies ENI, RD and TFE. For these companies, shocks to volatilities in STOCK and INDEX are significantly correlated, and the corresponding CCC are the highest, varying between 0.481 (ENI) and 0.553 (TFE). The only company with three endogenous variables, i.e., STOCK, INDEX and SPREAD, is RD. The CCC in the shocks to the volatilities of SPREAD and INDEX for RD is low and statistically insignificant.

Panel b of Table 1 reports the constant conditional correlations ‘‘between’’ the volatilities of the STOCK equations of different companies. These correlations are the highest for the pairs BP-RD, BP-TFE and CVX-XOM, being 0.744, 0.680 and 0.632, respectively, whereas the CCC are the lowest for companies TFE-XOM, ENI-XOM and ENI-CVX, (i.e., 0.259, 0.262, 0.280, respectively), although they are all statistically significant.

Finally, the DCC-GARCH(1,1) estimates are given in Panel a and Panel b of Table 2. As the ‘‘within’’ estimates are concerned, at least one of the two DCC parameters is statistically significant for four of six companies, which makes it clear that the assumption of CCC is not, in general, empirically supported. For oil companies BP and CVX the parameters θ_1 and θ_2 are not statistically significant, which is not surprising since in both cases the CCC are low (−0.120 and 0.070, respectively) and insignificant. The parameters of the DCC-GARCH(1,1) model applied to the STOCK equation ‘‘between’’ companies show even stronger results against the assumption of constant conditional correlations. In this case, θ_2 is always highly significant, while θ_1 is not significant only for three pairs of eight.

The significant DCC of oil companies ENI and RD for the pair of equations STOCK-INDEX are plotted against time and presented in Figs. 1–2. The DCC with the highest range of variation are related to the pair STOCK-INDEX. The intervals of variation of the DCC are (0.028, 0.912) for ENI, (0.120, 0.792) for RD, and (0.323, 0.728) for TFE. Ranges of that amplitude indicate, within each oil company, low to high/extreme interdependence between the volatilities of the companies' stock returns and the relevant stock market indexes. Among the eight pairs of companies, the ‘‘between’’ DCC characterized by the larger range of variation are for the pairs BP-ENI (0.187, 0.800), CVX-XOM (0.258, 0.808), ENI-TFE (0.216, 0.840) and RD-TFE (0.337, 9.38). As in the case of the ‘‘within’’ DCC, the wide ranges of variation suggest that the volatilities associated with stock price returns of different oil companies go from low to high/extreme interdependence. As an example, Figs. 3–4 report the plots against time of the ‘‘between’’ DCC for the pairs of companies BP-CVX and BP-ENI.

The results presented above are particularly relevant for determining optimal hedging strategies. Following Brooks et al. (1999), we compare the mean returns and the mean variances of an optimally hedged portfolio (dynamic hedge portfolio) with: (i) the mean returns and the mean variances of a portfolio that comprises a long position in one oil stock only (unhedged portfolio); (ii) the mean returns and the mean variances of a portfolio constructed with one long position in the oil company stock and one short position in the other asset (naïve hedge portfolio). Panels a–d of Table 3 report the results for portfolios ENI-MIB30, RD-AEX, BP-CVX and BP-ENI. Although mean returns are never statistically significant, it clearly emerges that any hedging strategy generates a reduction in the variability relative to non-hedging. As for ‘‘within’’ portfolios composed by the company's stock and the corresponding market index, the näive hedge leads to a decrease in the volatility of the order of

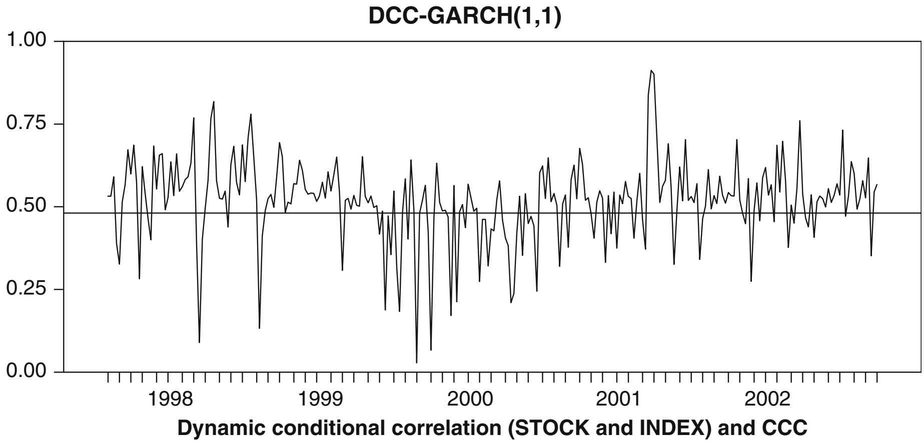
Table 2 DCC-GARCH(1,1) estimates

Oil companies	Standardized residuals of VECM equations:	θ_1	θ_2
Panel a. "Within" DCC estimates			
BP	STOCK, SPREAD	0.010	0.633
		0.217	0.643
CVX	STOCK, SPREAD	0.126	−0.069
		1.584	−0.211
ENI	STOCK, INDEX	0.198	0.106
		2.502	0.430
RD	STOCK, SPREAD	0.006	0.973
		0.491	18.721
	STOCK, INDEX	0.032	0.964
		2.620	57.423
	SPREAD, INDEX	0.033	0.758
		0.575	3.128
TFE	STOCK, INDEX	0.054	0.841
		0.695	2.314
XOM	STOCK, SPREAD	−0.008	0.976
		−1.247	49.480
Panel b. "Between" DCC estimates			
Std. res. of VECM eq. STOCK for oil companies	θ_1	θ_2	
BP, CVX	0.066	0.586	
	1.215	2.455	
BP, ENI	0.046	0.931	
	2.131	27.340	
BP, RD	0.032	0.963	
	2.444	47.977	
BP, TFE	0.028	0.951	
	1.406	27.021	
CVX, XOM	−0.026	0.993	
	−7.757	139.836	
ENI, RD	0.028	0.946	
	1.751	31.084	
ENI, TFE	0.042	0.948	
	2.965	49.447	
RD, TFE	0.065	0.925	
	2.827	33.890	

Notes: The estimated model is $\Gamma_t = (1-\theta_1-\theta_2)\Gamma + \theta_1\,\eta_{t-1}\,\eta'_{t-1} + \theta_2\,\Gamma_{t-1}$. The two entries for each parameter are their respective estimates and asymptotic *t*-ratios

16–19%, while a further reduction of 12% is obtained by allowing the hedge ratios to be time-varying. For hedging strategies involving BP and CVX, undertaking a short position in CVX for any long position in BP (naïve hedging) reduces risk by approximately 20%, while a minor improvement (around 5%) is achieved with time-varying hedge ratios. In contrast, for the pair BP-ENI, the naïve methodology leads to a risk decrease of 1% only, while a further 27% reduction is obtained by dynamic hedge ratios. If we compare the latter results with the corresponding DCC (see Figs. 3–4), gains in risk reduction due to time-varying hedges are likely to be larger when jumps in the level of correlations occur in the estimation period.

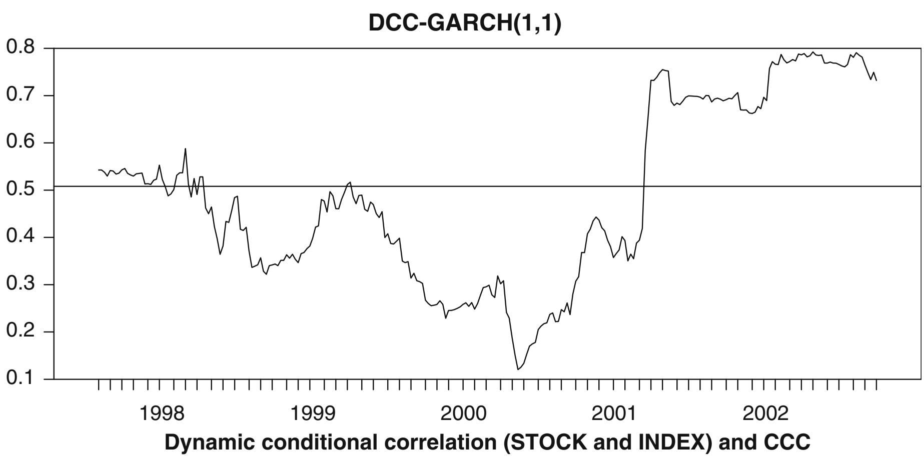
We have shown how multivariate GARCH models with DCC allow the researcher to calculate time-varying correlations between the volatility of two or more financial series. This possibility is of extreme importance for theoretical and empirical purposes. On the one hand, it helps to relate changes in the economic



Descriptive statistics on DCC – Oil company ENI

MEAN	0.519
MINIMUM	0.028
MAXIMUM	0.912
STANDARD DEVIATION	0.124
SKEWNESS	-0.680
EXCESS KURTOSIS	2.628

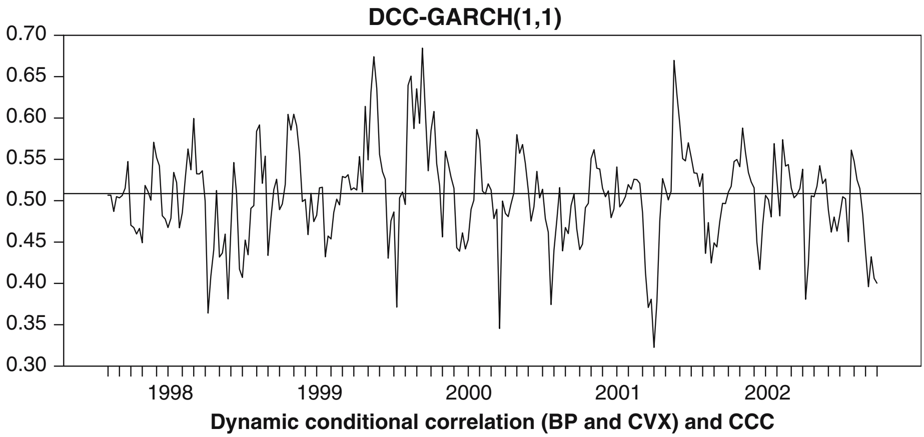
Fig. 1 Dynamic conditional correlation (DCC) between STOCK and INDEX—Oil Company ENI



Descriptive statistics on DCC – Oil company RD (STOCK and INDEX)

MEAN	0.486
MINIMUM	0.120
MAXIMUM	0.792
STANDARD DEVIATION	0.187
SKEWNESS	0.171
EXCESS KURTOSIS	-1.141

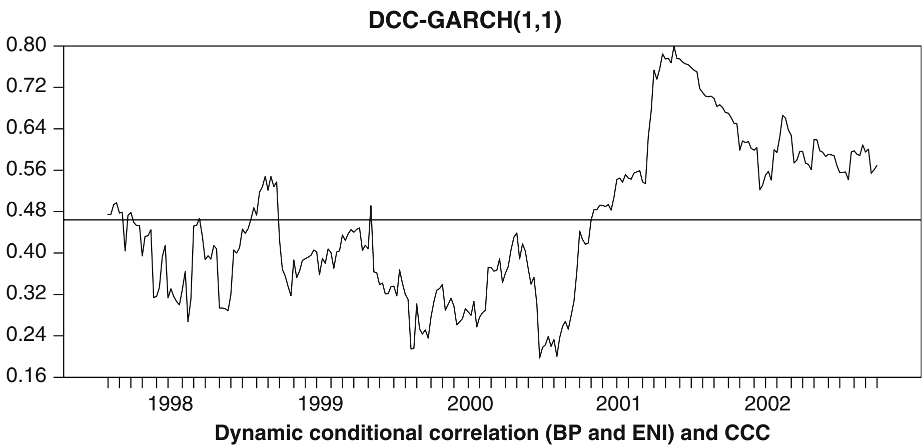
Fig. 2 Dynamic conditional correlation (DCC) between STOCK and INDEX—Oil Company RD



Descriptive statistics on DCC – Oil companies BP and CVX

MEAN	0.506
MINIMUM	0.323
MAXIMUM	0.684
STANDARD DEVIATION	0.057
SKEWNESS	0.017
EXCESS KURTOSIS	0.954

Fig. 3 Dynamic conditional correlation (DCC) between STOCK of oil companies BP and CVX



Descriptive statistics on DCC – Oil companies BP and ENI

MEAN	0.461
MINIMUM	0.187
MAXIMUM	0.800
STANDARD DEVIATION	0.146
SKEWNESS	0.386
EXCESS KURTOSIS	-0.681

Fig. 4 Dynamic conditional correlation (DCC) between STOCK of oil companies BP and ENI

Table 3 Hedging strategies

	Unhedged $\beta = 0$	Naïve hedge $\beta = 1$	Dynamic hedge $\beta = h_{ij,t}/h_{j,t}$
Panel a. Summary statistics for portfolio returns ENI-MIB30			
Return	0.007	0.016	0.013
	0.715	0.738	0.909
Variance	0.139	0.117	0. 101
Panel b. Summary statistics for portfolio returns RD-AEX			
Return	−0.009	0.009	0.004
	−1.721	0.276	0.167
Variance	0.178	0.145	0.124
Panel c. Summary statistics for portfolio returns BP-CVX			
Return	0.003	0.009	0.008
	0.671	0.896	1.046
Variance	0.163	0.130	0.121
Panel d. Summary statistics for portfolio returns BP-ENI			
Return	0.003	−0.004	−0.002
	0.671	−0.361	−0.306
Variance	0.163	0.161	0.125

Notes: The three entries for each column are: (i) the average portfolio return estimated as the OLS coefficient of the regression of returns on a constant term only; (ii) the corresponding *t*-ratio; (iii) the average variance of the portfolio over the sample period. $h_{ij,t}$ indicates the conditional covariance between returns i and j at time t; $h_{j,t}$ is the conditional variance of returns j at time t

environment (e.g., policy changes) to changes in the co-risk of the analyzed series; on the other hand, it allows practitioners to construct optimal hedging strategies.

Furthermore, the way we have structured the empirical analysis into a "within" level and a "between" level has enabled us to deal with the additional issue of modelling the co-risk dynamics among companies and markets.

Two results of this paper require some additional comments. First, if one concentrates on the "between" analysis for companies operating in the Euro area, it is easy to notice a positive jump in 2001 and a subsequent adjustment to a level of correlation which is higher than in the period before the Monetary Union. This behaviour suggests that the sources of idiosyncratic risks affecting the oil industry in the Euro area have decreased or, in other words, that a major component of idiosyncratic risk has been the exchange rate between local currencies and the US dollar. Second, we have constructed optimal hedging strategies for each pair of assets on the basis of the estimated series of dynamic conditional correlations. As expected, hedge ratios which are determined taking into account the time-varying variances and correlations (dynamic hedge) are more effective in reducing risk exposure than hedge ratios calculated with simpler strategies (näive hedge). One possible interpretation of the better performance of time-varying strategies is that dynamic hedge ratios use additional information and, therefore, lead to gains in risk reduction when conditional correlations between returns vary from low to high levels.

Conclusion

In this paper we have measured the actual co-risk in stock returns and their determinants "within" and "between" different oil companies, using multivariate cointegration techniques in modelling the conditional mean, as well as multivariate GARCH models for the conditional variances and correlations in the system of conditional means. On the basis of multivariate GARCH estimates, optimal hedging strategies have been determined.

We have analyzed time series data on stock prices of six oil companies of different dimensions and from different countries, together with relevant stock market indexes, exchange rates and crude oil prices.

Relative to the previous literature, this paper is novel in several respects. First, we have investigated the determinants of the market value of the six oil companies (that is, Bp (BP), Chevron-Texaco (CVX), Eni (ENI), Exxon-Mobil (XOM), Royal Dutch (RD), and Total-Fina-Elf (TFE)) using the cointegrated VAR/VECM methodology. Then, we specified the conditional variances of VECM residuals with the Constant Conditional Correlation (CCC) model of Bollerslev (1990) and the Dynamic Conditional Correlation (DCC) model of Engle (2002). Finally, using the portfolio approach aiming at minimizing the variance of the portfolio, we calculated the optimal hedge ratios as the conditional correlation between two assets times the ratio of conditional standard deviations estimated by the DCC model.

The main findings of this paper can be summarized as follows.

Market index variables (INDEX) appear to be endogenous in the VECM for those companies whose capitalization is large compared with the size of the relevant stock market (namely, ENI, RD and TFE). The spread in oil prices is found to be endogenous for oil corporations BP, XOM, CVX and RD.

The constant conditional correlations have been initially calculated on pairs of standardized residuals for the VECM ‘‘within’’ each company. Results show that for cases where INDEX is endogenous, shocks to volatilities in STOCK and INDEX are significantly correlated for all companies, while the CCC corresponding to the pairs STOCK-SPREAD are significantly correlated for RD and BP only.

Subsequently, we have calculated the CCC ‘‘between’’ the STOCK equations of different companies. Our empirical findings suggest that the residual volatilities of the STOCK equations of different companies are all significantly positively correlated, the highest CCC occurring for the pairs BP–RD, BP–TFE and CVX–XOM.

As the estimates ‘‘within’’ companies are concerned, at least one of the two DCC-GARCH(1,1) parameters is statistically significant for four of six companies, which confirms that the assumption of CCC is not, in general, empirically supported. The parameters of the DCC-GARCH(1,1) model for the STOCK equation ‘‘between’’ companies show even stronger results against the assumption of constant conditional correlations.

If we look at the DCC plots against time, it can be remarked that, for companies in the Euro area, there is a positive jump in the DCC around the first half of 2001, followed by an adjustment to a higher level of correlation. Consequently, hedging strategies that take into account DCC have been found substantially more effective in reducing risk exposure than those which ignore any dynamics in conditional correlations. Indeed, the gain in risk reduction of time-varying hedging strategies is larger when the conditional correlations ‘‘jump’’ from low to high levels during the estimation period.

Further improvements in risk reduction may be achieved by capturing possible asymmetries in the volatility of oil stock returns and their determinants. Future research in this area should consider generalizations of the DCC model adopted in this paper, such as the VARMA-AGARCH with dynamic conditional correlations and the GARCC specifications illustrated in M. McAleer et al. (2003, unpublished paper) and in McAleer (2005), which are likely to offer the potential for more accurate hedging strategies.

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