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Modelling Dynamic Conditional Correlations in the Volatility of Spot and Forward Oil Price Returns

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Abstract: This paper estimates the dynamic conditional correlations in the returns on Tapis oil spot and one-month forward prices for the period 2 June 1992 to 16 January 2004, using recently developed multivariate conditional volatility models, namely the Constant Conditional Correlation Multivariate GARCH (CCC-MGARCH) model of Bollerslev [1990], Vector Autoregressive Moving Average – GARCH (VARMA-GARCH) model of Ling and McAleer [2003], VARMA – Asymmetric GARCH (VARMA-AGARCH) model of Chan et al. [2002], and the Dynamic Conditional Correlation (DCC) model of Engle [2002]. The multivariate estimates show that the ARCH and GARCH effects for spot (forward) returns are significant in the conditional volatility model for spot (forward) returns. Moreover, there are significant interdependences in the conditional volatilities between the spot and forward markets. The multivariate asymmetric effects are significant for both spot and forward returns. The calculated constant conditional correlations between the conditional volatilities of spot and forward returns using CCC-GARCH(1,1), VAR(1)-GARCH(1,1) and VAR(1)-AGARCH(1,1) are virtually identical. Finally, the estimates of the two DCC parameters are statistically significant, which makes it clear that the assumption of constant conditional correlation is not supported empirically.

Keywords: Asymmetric effects; Dynamic conditional correlations; Multivariate GARCH models; Forward prices and returns; Spot prices and returns.

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1. INTRODUCTION

Spot and forward prices of physical commodities, including oil, have been investigated over an extended period. Substantial research has been undertaken to analyze the relationship between spot and forward prices, and their associated returns. The efficient market hypothesis is crucial for understanding optimal decision making with regard to hedging and speculation, and also for making financial decisions about the optimal allocation of portfolios of assets with regard to their multivariate returns and associated risks.

To date, there has been little research regarding an analysis of the volatilities (or risks) associated with portfolios of returns for physical assets at the multivariate level. Such shocks to returns can be decomposed into predictable and unpredictable components. The most frequently analysed predictable component in shocks to returns is the volatility in the conditional variance.

When these conditional volatilities vary over time, GARCH models (see Engle [1982] and Bollerslev [1986]) may be used to capture dynamic clustering behaviour. In the last two decades, univariate and multivariate GARCH models have become widely established in theoretical and empirical financial economics and econometrics. The structural and statistical properties of these models have been fully developed, and the computational requirements are generally straightforward.

In modelling multivariate returns, such as on the spot and forward prices of oil, the shocks to returns not only have dynamic interdependence in risks, but also in the conditional correlations. This is an extension of the constant (or static) conditional correlation approach to analyzing multivariate risks associated with portfolios of assets.

There are several widely used oil markers, the most well known of which are Brent and WTI. However WTI spot prices are not available, so

that it is not possible to test the unbiasedness or efficient market hypothesis for this physical commodity. It follows that it is also not possible to determine optimal hedging strategies based on whether shocks to spot and forward returns are high and positively or negatively correlated.

One representative oil marker for light sweet crudes in the Asia and Pacific region, namely Tapis, has both spot and forward prices. Consequently, it is possible to determine whether to hedge or not, based on determining if the shocks to spot and forward returns are, in fact, high and either positively or negatively correlated.

The purpose of this paper is to estimate the dynamic conditional correlations in the returns on Tapis oil spot and one-month forward prices, using recently developed multivariate conditional volatility models. The dynamic correlations will enable a determination of whether the spot and forward returns are substitutes or complements, which can be used to hedge against contingencies.

The plan of the paper is as follows. Section 2 discusses briefly the univariate and multivariate GARCH models to be estimated. Section 3 describes the data and the empirical estimates of the univariate models, the multivariate models with constant conditional correlations, and the multivariate models with dynamic conditional correlations. Section 4 provides some concluding comments.

2. ECONOMETRIC MODELS

This section presents models of the volatility in Tapis oil spot and forward prices returns, namely the Constant Conditional Correlation Multivariate GARCH (CCC-MGARCH) model of Bollerslev [1990], Vector Autoregressive Moving Average – GARCH (VARMA-GARCH) model of Ling and McAleer [2003], VARMA–Asymmetric GARCH (VARMA-AGARCH) model of Chan et al. [2002], and the Dynamic Conditional Correlation (DCC) model of Engle [2002]. The specification, and structural and statistical properties, of these models are discussed briefly in this section.

Consider the following specification:

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t$$

$$\varepsilon_t = D_t \eta_t, \quad (1)$$

where $y_t = (y_{1t}, \dots, y_{mt})'$, $\eta_t = (\eta_{1t}, \dots, \eta_{mt})'$ is a sequence of independently and identically distributed (iid) random vectors, F_t is information available to time t , $D_t = \text{diag}(h_{1t}^{1/2}, \dots, h_{mt}^{1/2})$, m

is the number of returns, and $t = 1, \dots, n$. Bollerslev [1990] assumed that the conditional variance for each return, h_{it} , $i = 1, \dots, m$, follows a univariate GARCH process, that is,

$$h_{it} = \omega_i + \sum_{j=1}^r \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^s \beta_{ij} h_{i,t-j} \quad (2)$$

where α_{ij} represents the ARCH effects (or the short-run persistence of shocks to return i) and β_{ij} represents the GARCH effects (or the contribution of shocks to return i to long-run persistence, namely $\sum_{j=1}^r \alpha_{ij} + \sum_{j=1}^s \beta_{ij}$). CCC-

MGARCH assumes independence of the conditional variances across returns and does not accommodate asymmetric behaviour.

In order to accommodate interdependence in the conditional variance, Ling and McAleer [2003] proposed and established the structural and statistical properties for:

$$H_t = W + \sum_{i=1}^r A_i \bar{\varepsilon}_{t-i} + \sum_{j=1}^s B_j H_{t-j} \quad (3)$$

where $H_t = (h_{1t}, \dots, h_{mt})'$, $\bar{\varepsilon} = (\varepsilon_{1t}^2, \dots, \varepsilon_{mt}^2)'$, and W , A_i ($i = 1, \dots, r$) and B_j ($j = 1, \dots, s$) are $m \times m$ matrices. VARMA-GARCH assumes that negative and positive shocks have identical impacts on the conditional variance. In order to accommodate asymmetric effects, Chan et al. [2002] proposed and established the structural and statistical properties for the VARMA-AGARCH specification:

$$H_t = W + \sum_{i=1}^r A_i \bar{\varepsilon}_{t-i} + \sum_{i=1}^r C_i I_{t-i} \bar{\varepsilon}_{t-i} + \sum_{j=1}^s B_j H_{t-j} \quad (4)$$

where C_i are $m \times m$ matrices for $i = 1, \dots, r$, and $I_t = \text{diag}(I_{1t}, \dots, I_{mt})$, where $I_{it} = 0$ when $\varepsilon_{it} > 0$ and $I_{it} = 1$ when $\varepsilon_{it} < 0$. If $m = 1$, equation (4) reduces to the asymmetric univariate GARCH, or GJR, model of Glosten et al. [1992]. Moreover, VARMA-AGARCH reduces to VARMA-GARCH when $C_i = 0$ for all i . If $C_i = 0$, with A_i and B_j being diagonal matrices for all i, j , then VARMA-AGARCH reduces to CCC-MGARCH. The parameters of models (1)-(4) are obtained by maximum likelihood estimation (MLE) using a joint normal density. When η_t does not follow a

joint multivariate normal distribution, the appropriate estimator is defined as the Quasi-MLE (QMLE).

The conditional correlation is assumed to be constant for all three models discussed above. From equation (1), it follows that $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_t' D_t$, so that $E(\varepsilon_t \varepsilon_t' | F_{t-1}) = \Omega_t = D_t \Gamma D_t$. The conditional correlation matrix is defined as $\Gamma = D_t^{-1} \Omega_t D_t^{-1}$, where Γ has typical constant element $\rho_{ij} = \rho_{ji}$ for $i, j = 1, \dots, m$ and $t = 1, \dots, n$.

When $m = r = s = 1$, the necessary and sufficient condition for the existence of the second moment of ε_t , that is $E(\varepsilon_t^2) < \infty$, is $\alpha_1 + \beta_1 < 1$. This condition is also sufficient for the QMLE to be consistent and asymptotically normal. Jeaneau [1998] showed that the log-moment condition, $E(\log(\alpha_1 \eta_t^2 + \beta_1)) < 0$, is sufficient for the QMLE to be consistent for GARCH(1,1), while Boussama [2000] showed that the QMLE is asymptotically normal for GARCH(1,1) under the same condition. McAleer et al. [2002] established the log-moment condition for GJR(1,1), namely, $E(\log((\alpha_1 + \gamma_1(\eta_t)) \eta_t^2 + \beta_1)) < 0$ and showed that it is sufficient for consistency and asymptotic normality of the QMLE. Hence, the second moment condition $\alpha_1 + \gamma_1/2 + \beta_1 < 1$ is also sufficient for consistency and asymptotic normality of the QMLE for GJR(1,1) (see Ling and McAleer [2002]). In empirical examples, the parameters are replaced by their respective QMLE, η_t is replaced by the estimated standardized residuals for $t = 1, \dots, n$, and expected values are replaced by their respective sample means.

Unless η_t is a sequence of iid random vectors, the assumption of constant conditional correlation is not valid. In order to capture the dynamics of time-varying conditional correlation, Γ_t , Engle [2002] and Tse and Tsui [2002] proposed the closely related Dynamic Conditional Correlation (DCC) and the Variable Conditional Correlation Multivariate GARCH models, respectively. The DCC model is given as

$$\Gamma_t = (1 - \theta_1 - \theta_2) \Gamma + \theta_1 \eta_{t-1} \eta_{t-1}' + \theta_2 \Gamma_{t-1}, \quad (5)$$

in which 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. Chan et al. [2003] proposed the Generalized Autoregressive Conditional Correlation (GARCC) model, which contains both DCC and VCC-MGARCH as special cases, and established the structural and statistical properties of GARCC. They showed that, if η_t follows an autoregressive process with stochastic coefficients rather than being a sequence of iid random vectors, model (1)-(2) is equivalent to Engle's [2002] DCC model in (5).

3. DATA AND EMPIRICAL ESTIMATES

The univariate and multivariate GARCH models are estimated using data on spot and forward returns for the period 2 June 1992 to 16 January 2004.

Figure 1 shows the returns to the spot and forward prices, for which the correlation coefficient is 0.944. It is clear from Figure 1 that there is substantial clustering of returns, and hence also in the volatilities.

The univariate estimates of the conditional volatilities based on the spot and forward returns are given in Tables 1 and 2. The three entries for each parameter are their respective estimates, asymptotic t-ratios and Bollerslev and Wooldridge [1992] robust t-ratios. The results in Table 1 are used to estimate the CCC model of Bollerslev [1990] and the DCC model of Engle [2002]. Both the ARCH and GARCH estimates are significant for spot and forward returns. Although the second moment condition is not satisfied, the log-moment condition is satisfied, so that the QMLE are consistent and asymptotically normal.

The univariate GJR estimates in Table 2 are reasonably similar to the corresponding estimates in Table 1. The estimates of the asymmetric effect at the univariate level are not statistically significant for either spot or forward returns. Moreover, the robust t-ratios exceed the asymptotic counterpart in 6 of 8 cases. As in Table 1, the second moment condition is not satisfied for either spot or forward returns, but the log-moment condition is satisfied, so that the QMLE are consistent and asymptotically normal.

Corresponding multivariate estimates for the VAR(1)-GARCH(1,1) and VAR(1)-AGARCH(1,1) models are given in Tables 3 and 4, respectively. The ARCH and GARCH effects for spot (forward) returns are significant in the conditional volatility model for spot (forward) returns. It is also clear from Table 3 that there are significant interdependences in the conditional volatilities between the spot and forward markets, specifically the forward GARCH effect is

significant for spot returns, while both the ARCH and GARCH spot effects are significant for forward returns.

The results in Table 4 mirror those in Table 3, but more significantly. In particular, the ARCH and GARCH effects for spot (forward) returns are significant in the conditional volatility model for spot (forward) returns. There are also significant interdependences in the conditional volatilities between the spot and forward markets, specifically the forward (spot) ARCH and GARCH effects are significant for spot (forward) returns. As compared with the insignificant asymmetric effect of the univariate estimates in Table 2, the multivariate asymmetric effects in Table 4 are significant for both spot and forward returns. Overall the multivariate VAR(1)-AGARCH(1,1) results in Table 4 dominate those in Tables 1-3.

Constant conditional correlations between the conditional volatilities of spot and forward returns using three multivariate GARCH models, namely CCC-GARCH(1,1), VAR(1)-GARCH(1,1) and VAR(1)-AGARCH(1,1), are given in Table 5. The two entries for each parameter are their respective estimates and asymptotic t-ratios. In spite of the estimates in Tables 1, 3 and 4 having different statistical implications, the constant conditional correlations for the three models in Table 5 are virtually identical at 0.93.

Finally, the DCC-GARCH(1,1) estimates are given in Table 6. As the three models in Table 5 yield very similar estimates of the constant conditional correlation, the DCC estimates in Table 6 are based only on the CCC model. The estimates of the two DCC parameters are statistically significant, which makes it clear that the assumption of constant conditional correlation is not supported empirically. This is highlighted by the dynamic conditional correlations between spot and forward returns in Figure 2, for which the mean, at 0.933, is virtually identical to the constant conditional correlation reported in Table 5. The dynamic conditional correlations are in the range (0.417, 0.993), signifying medium to extreme interdependence. Moreover, the skewness and kurtosis of the dynamic conditional correlation indicate a strong negatively skewed distribution.

In summary, the dynamic volatilities in the returns in Tapis oil spot and forward markets are generally interdependent over time, some times very strongly.

4. CONCLUSION

The purpose of this paper was to estimate the dynamic conditional correlations in the returns on

Tapis oil spot and one-month forward prices for the period 2 June 1992 to 16 January 2004, using recently developed multivariate conditional volatility models.

The multivariate estimates showed that the ARCH and GARCH effects for spot (forward) returns were significant in the conditional volatility model for spot (forward) returns. Moreover, there were significant interdependences in the conditional volatilities between the spot and forward markets. As compared with the insignificant asymmetric effect of the univariate estimates, the multivariate asymmetric effects were significant for both spot and forward returns. The calculated constant conditional correlations between the conditional volatilities of spot and forward returns using CCC-GARCH(1,1), VAR(1)-GARCH(1,1) and VAR(1)-AGARCH(1,1) are virtually identical. Finally, the estimates of the two DCC parameters were statistically significant, which makes it clear that the assumption of constant conditional correlation was not supported empirically.

The dynamic volatilities in the returns in Tapis oil spot and forward markets were generally interdependent over time. These findings suggest that a sensible hedging strategy would consider spot and forward markets as being characterized by different degrees of substitutability.

5. ACKNOWLEDGEMENTS

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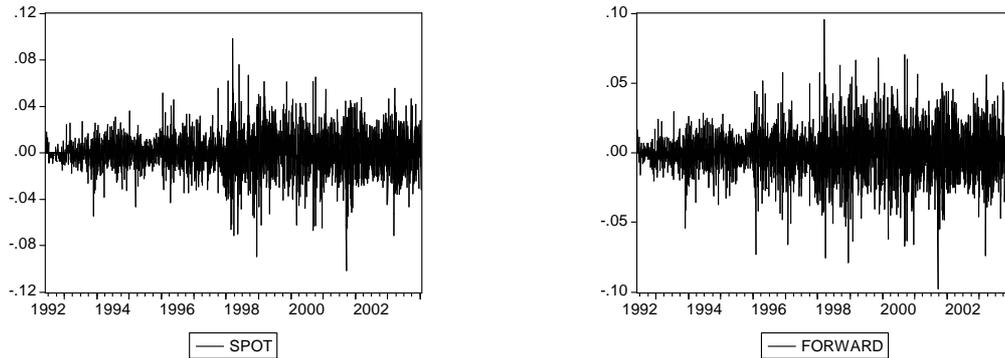
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Correlation Coefficient between Spot and Forward Returns = 0.944

Figure 1. Returns to Spot and Forward Prices for Tapis, 2 June 1992 – 16 January 2004

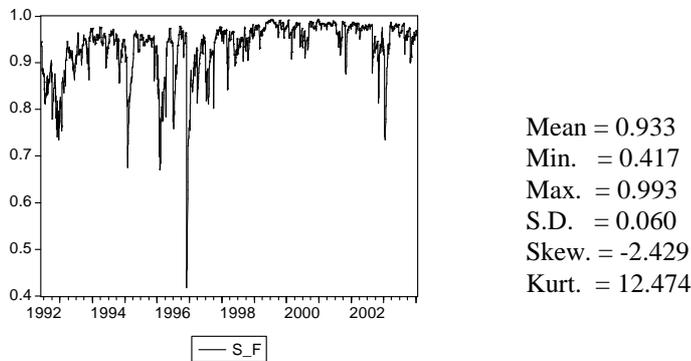


Figure 2. Dynamic Conditional Correlations Between Spot and Forward Returns

Table 1. Univariate AR(1)-GARCH(1,1) Estimates

Returns	ω	α	β	Log-moment	Second moment
Spot	3.25E-07	0.064	0.940	-0.002	1.003
	7.605	7.126	126.424		
	2.994	13.068	218.232		
Forward	3.72E-07	0.057	0.945	-0.002	1.002
	9.161	5.960	116.032		
	2.773	12.831	232.221		

Note: The three entries for each parameter are their respective estimates, asymptotic t-ratios and Bollerslev-Wooldridge (1992) robust t-ratios.

Table 2. Univariate AR(1)-GJR(1,1) Estimates

Returns	ω	α	γ	β	$\alpha+\gamma/2$	Log moment	Second moment
Spot	2.95E-07	0.057	0.011	0.941	0.063	-0.002	1.004
	8.674	4.654	0.702	124.426			
	2.720	10.263	1.502	222.523			
Forward	3.47E-07	0.052	0.009	0.946	0.057	-0.002	1.002
	10.950	4.029	0.590	116.078			
	2.630	8.939	1.276	234.327			

Note: The three entries for each parameter are their respective estimates, asymptotic t-ratios and Bollerslev-Wooldridge (1992) robust t-ratios.

Table 3. VAR(1) – GARCH(1,1) Estimates

Returns	ω	α_s	β_s	α_f	β_f
Spot	4.67E-06	0.051	0.877	0.0005	0.045
	7.571	7.841	60.877	0.073	3.968
Forward	5.64E-06	0.045	-0.113	0.015	1.023
	8.605	7.048	-7.076	2.186	75.280

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

Table 4. VAR(1) – AGARCH(1,1) Estimates

Returns	ω	α_s	γ_s	β_s	α_f	γ_f	β_f
Spot	3.37E-06	0.023	0.035	0.868	0.005		0.064
	8.338	8.525	32.050	399.235	3.437		22.220
Forward	3.55E-0.6	0.040		-0.125	-0.006	0.030	1.056
	8.322	20.804		-48.267	-3.917	31.917	227.514

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

Table 5. Constant Conditional Correlations between Spot and Forward Returns

Model	ρ_{12}
CCC-GARCH(1,1)	0.9317 364.493
VAR(1)-GARCH(1,1)	0.9323 392.793
VAR(1)-AGARCH(1,1)	0.9346 460.848

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

Table 6. DCC-GARCH(1,1) Estimates

Model	θ_1	θ_2
$\Gamma_t = (1 - \theta_1 - \theta_2)\Gamma + \theta_1\eta_{t-1}\eta_{t-1}' + \theta_2\Gamma_{t-1}$	0.059 10.301	0.928 118.98

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