Available online at www.sciencedirect.com
SCIENCE DIRECT®

Finance Research Letters 3 (2006) 114–132

Finance Research Letters

www.elsevier.com/locate/frl

Modeling dynamic conditional correlations in WTI oil forward and futures returns ☆

Alessandro Lanza [a,b], Matteo Manera [b,c,*], Michael McAleer [d]

[a] *Eni S.p.A., Rome, Italy*
[b] *Fondazione Eni Enrico Mattei, Milan, Italy*
[c] *Department of Statistics, University of Milan-Bicocca, Via Bicocca degli Arcimboldi 8, 20126 Milan, Italy*
[d] *School of Economics and Commerce, University of Western Australia, Australia*

Received 8 February 2005; accepted 31 January 2006

Available online 28 February 2006

Abstract

This paper estimates the dynamic conditional correlations in the daily returns on West Texas Intermediate (WTI) oil forward and futures prices from 3 January 1985 to 16 January 2004, using recently developed multivariate conditional volatility models. We find that the dynamic conditional correlations can vary dramatically, being negative in four of ten cases and being close to zero in another five cases. Only in the case of the dynamic volatilities of the three-month and six-month futures returns is the range of variation relatively narrow, namely (0.832, 0.996).

JEL classification: C32; G10; Q40

Keywords: Constant conditional correlations; Dynamic conditional correlations; Multivariate GARCH models; Forward prices and returns; Futures prices and returns; WTI oil prices

1. Introduction

Substantial research has been undertaken on spot, forward and futures markets of both physical and financial commodities. Much of the research on analyzing the connection between spot,

☆ An earlier version of this paper was presented at the 4th International Conference on Financial Engineering and Statistical Finance, Hitotsubashi University, Tokyo, Japan, March 2004.
* Corresponding author. Fax: +39 02 6473312.
E-mail address: matteo.manera@unimib.it (M. Manera).

1544-6123/$ – see front matter
doi:10.1016/j.frl.2006.01.005

forward and futures prices, and their associated returns, has concentrated on the unbiasedness or efficient market hypothesis and, when such prices are nonstationary, on cointegration among these variables. Hypotheses regarding efficient markets are important for understanding optimal decision making in terms of hedging and speculation. They are also crucial for making financial decisions about the optimal allocation of portfolios of assets in terms of their multivariate returns and associated risks.

The relationship between forward prices and futures prices is well documented in the literature. The seminal paper by Cox et al. (1981), for example, presents a number of testable propositions characterizing the differences between the two prices which show that equilibrium forward and futures prices are equal to the values of particular assets, even though they are not in themselves asset prices. Credit risk is one of the key differences between forward and futures markets. Weiner (1994) concentrates the analysis on the oil market and criticizes the empirical evidence which finds little difference between forwards and futures prices, since it generally originates form markets where credit risk is minimal. In contrast, this study concentrates on a market, for forward delivery of a type of crude oil from the North Sea, that experienced widespread and well-documented defaults when the spot price of the underlying commodity plunged from roughly \$30 to roughly \$10 per barrel in a short period of time in early 1986. The defaults were by relatively small, lightly capitalized trading companies, firms that neither produce nor consume the physical commodity. Although the market survived the default episode with market microstructure unaltered, patterns of change changed. The paper presents nonparametric tests for changing patterns of trade, in the direction of bank intermediation.

The problem of hedging long-term forwards with short-term futures in oil markets has been recently analyzed by Buhler et al. (2004) using the case study of Metallgesellschaft, an international trading, engineering and chemicals conglomerate. The authors critically revise the different hedging strategies which have been proposed in the literature. They attribute these differences to the underlying valuation approaches for oil futures and empirically compare five model-based hedging strategies. In particular, they consider a strategy which results from a two-regime pricing model. This model reflects the stylized fact that oil futures levels and volatility exhibit a very different behavior for low and high oil prices. The empirical application shows that time diversification is crucial for an effective hedging of long-term oil forwards with short-term futures.

Hedging strategies are also of extreme importance for oil stockpiling, that is the activity related to reserve a certain level of crude oil and/or oil products in designated areas to respond to supply disruptions or price hikes, and to make drawdown in occasional emergencies. Yun (2005) suggests that one of feasible options for improving the economics and the operational efficiency of oil stockpiling is to use the forwarding opportunities offered by various instruments of derivatives. This study proposes different selective hedging strategies with forward contracting, which are quantitatively analyzed and compared to the cases of no-hedge and traditional routine hedging strategies with minimum-variance hedge ratios. The main advantage of the proposed hedging strategies over the more traditional ones is not to predict future spot prices, but to use the sign and magnitude of the spread between spot and forward prices, which is easily available to the public. Using the weekly spot and forward prices of West Texas Intermediate (WTI) oil for the period October 1997–August 2002, this study shows that selective hedging strategies dominate the traditional routine hedging strategy, but do not improve upon the expected returns of no-hedge case.

On the contrary, little or no research has been undertaken on analyzing the volatilities (or risks) associated with these portfolios of returns at the multivariate level. Shocks to returns can be decomposed into predictable and unpredictable components. There are two predictable components in these shocks to returns, namely the serial correlation in shocks to the conditional mean and the volatility in the conditional variance. These volatilities can vary over time, either conditionally, as in GARCH-type models, or randomly, as in stochastic volatility (SV) models. SV models are typically computationally intensive, even at the univariate level. Extensions to multivariate SV models are presently at a relatively early stage of development. On the other hand, univariate and multivariate GARCH models have become widely established in theoretical and empirical finance and financial econometrics. The structural and statistical properties have been fully developed, and the computational requirements are not generally burdensome, except in special circumstances.

In the case of modeling multivariate returns, such as the returns on the forward and futures prices of different maturities in the market for WTI 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.

The purpose of this paper is to estimate the dynamic conditional correlations in the returns on WTI oil one-month forward prices, and one-, three-, six-, and twelve-month futures prices, using recently developed multivariate conditional volatility models. The dynamic correlations will enable a determination of whether the forward and various futures returns are substitutes or complements, which are crucial for deciding whether or not to hedge against unforeseen circumstances, as well as for pricing options and other derivatives. The models are estimated using daily data on WTI oil forward and futures prices, and their associated returns, from 3 January 1985 to 16 January 2004. At the univariate level, the estimates are statistically significant, with the occasional asymmetric effect in which negative shocks have a greater impact on volatility than positive shocks. There can be substantial differences among the estimated constant and dynamic conditional correlations. In contrast with the common vision that the volatilities of futures price returns at different maturities are perfectly positively correlated (see, among others, Alexander, 2001b), it is found that the dynamic volatilities in the returns in the WTI oil forward and future prices can be either independent or interdependent over time.

The plan of the paper is as follows. Section 2 analyses the relevant empirical literature on market efficiency and volatility of energy forward and futures markets. In Section 3 alternative multivariate volatility models are presented and discussed. Section 4 illustrates the relationship between multivariate volatilities and dynamic option pricing. The data used in the empirical analysis and the resulting estimates are presented in Section 5. Some concluding remarks are given in Section 6.

2. Market efficiency and volatility in energy markets

The literature on the relationships between spot and futures prices of petroleum products has examined issues such as market efficiency and price discovery, but far less attention has been paid to volatility, as well as correlations in the shocks to volatility, in the spot and futures markets. Given the importance of both aspects for the present paper, this section provides a comprehensive discussion of the relevant literature.

2.1. Market efficiency literature

A standard definition of market efficiency is that today's price of an item contains all the price information about that item. That is, today's price contains information about people's expectations about the future.

In an efficient market speculators have a well-defined and important role in taking on risk and adding to market liquidity. According to the New York Mercantile Exchange (2004), hedge funds and commodity trading advisors have long been important participants in oil markets, on both long and short sides. At times, their activity can exacerbate volatility or strengthen a short-term trend in prices. Recent spikes in NYMEX heating oil crack spreads are a good example of this tendency. A newer development is the growth in passive, long only index investments, by institutional investors that are heavily weighted to energy futures.

Nonetheless, if we consider the net noncommercial positions in commodity and financial futures over the last decade, speculation in energy futures is small compared with other markets. In particular, speculative activity in oil is low relative to overall market size. NYMEX crude oil is the largest US commodity futures contract and net long positions have never exceeded one fifth of total open interest. Speculative activity in oil is also low relative to levels typically seen in other financial futures markets. Speculative flows in and out of oil during 2004 look very modest relative to the volumes that have traded in other futures markets (e.g., silver, dollar/sterling). There is currently around \$40 billions of institutional funds passively tracking long-only index products in the commodity sector. This has risen from less than \$10 billions three years ago. However it is still less than 4% of monthly average volume in major commodity futures markets.

The hypothesis that heating oil futures prices are good predictors of spot prices was tested by Bopp and Sitzer (1987), who found that, even when crude oil prices, inventory levels, weather, and other important variables were accounted for, futures prices still made a significant positive contribution to describing past price changes. Serletis and Banack (1990) used daily data for the spot and two-month futures crude oil prices, and for prices of gasoline and heating oil traded on the New York Stock Exchange (NYMEX), to test for market efficiency, and found evidence that was consistent with this hypothesis. Crowder and Hamid (1993) used cointegration analysis to test the simple efficiency hypothesis and the arbitrage condition for crude oil futures. In the price discovery literature, Quan (1992) examined the price discovery process for the crude oil market using monthly data, and found that the futures price did not play an important role in this process. Using daily data for NYMEX closing futures prices, Schwartz and Szakmary (1994) found that futures prices strongly dominated in the price discovery relative to the deliverable spots in all three petroleum markets. Gulen (1999) applied cointegration tests in a series of oil markets with pairwise comparisons on post-1990 data, and concluded that oil markets have grown more unified during the period 1994–1996 as compared with the period 1991–1994. Silvapulle and Moosa (1999) examined the daily spot and futures prices of WTI crude using both linear and nonlinear causality testing. They found that linear causality testing revealed that futures prices lead spot prices, whereas nonlinear causality testing revealed a bi-directional effect. Xiaowen and Tamvakis (2001) investigated information transmission between the NYMEX and London's International Petroleum Exchange, and found that NYMEX was a true leader in the crude oil market. Hammoudeh et al. (2003) and Hammoudeh and Li (2004) also investigated information transmission among NYMEX WTI crude prices, NYMEX gasoline prices, NYMEX heating oil prices, and among international gasoline spot markets, including the Rotterdam and Singapore markets, and found the NYMEX gasoline market to be the true leader.

The importance of accurate forecasts of energy prices for policy purposes has also been the subject of some very recent research. Wong-Parodi et al. (2005) compare the accuracy of forecasts for natural gas prices with the futures market, which provides an alternative forecast of natural gas prices determined by the interaction of numerous buyers and sellers in the natural gas market. Theoretically, futures market prices summarize privately available information about natural gas supply and demand. As a result, prices determined in the futures markets are considered as accurate price forecasts. Using Henry Hub prices over the period 1998–2004, the authors suggest that the futures market is slightly more accurate than the Energy Information Administration's short-term energy outlook (STEO) at predicting natural gas prices 2 years into the future. The results point out that futures market second year price forecasts are unbiased, while STEO second year forecasts are biased. Finally STEO uses more inputs and may have fewer statistical degrees of freedom than the futures market, which implies that STEO forecasts may be subject to additional sources of forecasting error and bias than the futures market.

Unlike natural gas-fired generation, generating electricity from renewable resources is, by its nature, largely immune to natural gas fuel price volatility and risk. Assuming that electricity consumers are rational (an therefore prefer the less risky of two otherwise identical expected cash flows), a policy maker interested in evaluating different resource options should compare the cost of fixed-price renewable generation to the hedged cost of natural gas-fired generation, rather than to projected costs based on uncertain gas price forecasts. Bolinger et al. (2006) compare natural gas prices that can be locked in through futures, swaps, and physical supply contracts to contemporaneous long-term forecasts of spot gas prices. They find that from 2000 to 2003, forward gas prices for terms of 2–10 years have been considerably higher than most contemporaneous long-term gas price forecasts. This difference is striking, and implies that comparisons between renewable and gas-fired generation based on these forecasts over this period have biased the judgment in favor of gas-fired generation.

2.2. Literature on volatility of energy forward and futures markets

Commodities are negatively or low correlated with other financial assets. This helps a portfolio manager to diversify exposure and raise the return for a given level of risk. Commodities and oil in particular are therefore a very attractive addition to a balanced portfolio. Volatility measurement and time-varying correlations among different volatilities are therefore extremely important to construct optimal portfolios.

The main features of the oil market, whose size, according to New York Mercantile Exchange (2004) is estimated about 82 million barrel per day (mb/d), or 30 billion barrel per year, can be summarized as follows: (i) term markets dominate volume of trade; (ii) a small percentage of trade is conducted on spot basis and serves to price a large share of the world's physical oil; (iii) physical trading in these spot markets is deeply connected to oil futures markets; (iv) oil futures have taken a growing role in price discovery due to the level of participation, their liquidity and their visibiliy; (v) futures markets attract a variety of players that are not necessarily directly related to the commercial side of the business and that have many different horizons and strategies.

In particular, futures trade corresponds to 277 mb/d (2003 average daily Brent and WTI futures volumes), whereas physical production is about 76.7 mb/d (2003 average daily global crude oil production), while the 2003 average BFO production (i.e., Brent, Forties and Oseberg crude oils) is close to 1.3 mb/d. Participation to the market NYMEX crude oil futures by occupation open interest includes institutional investors (8.4%), floor traders (7.2%), oil traders (33.5%), funds (13.5%), financial institutions (21%), end users (0.2%), marketers (3.9%), refiners (4.3%) and integrated companies (8.1%).

Commodity indices tend to be more volatile than indices of other financial assets. Industrial commodity markets can be less liquid than most financial asset markets and can be also subject to sharp swings in supply and disposition of physical products (New York Mercantile Exchange, 2004). Energy commodities are the most volatile, with natural gas and oil having significantly higher volatility than most others (copper, gold, etc.). Among petroleum-based commodities, gasoline and heating oil are most volatile. Seasonal variations and other short-term factors may affect relative volatility. Differences in volatility among crude oil, heating oil gasoline, gasoil and natural gas vary over time, while options prices generally reflect recent observed volatility. For instance, estimates of implied option volatility for WTI at November 2004 for the four quarters of 2005 are 39.7%, 35.9%, 32.2% and 30.1%, respectively.

Day and Lewis (1993) compared the forecasts of crude oil volatility using GARCH(1, 1), EGARCH(1, 1), implied volatility and historical volatility models, based on daily data from November 1986 to March 1991. Using OLS regressions of realized volatility on out-of-sample forecasts, they examined the unbiasedness of the forecasts. The accuracy of out-of-sample forecasts was compared using traditional criteria such as the mean forecast error, mean absolute error, and root mean squared error. They also analyzed the within-sample information content of implied volatility, by including it as predictor in the GARCH and EGARCH models. It was found that both implied volatilities, as well as the GARCH and EGARCH conditional volatilities, contributed incremental volatility information. The null hypothesis that implied volatilities subsumed all information contained in observed returns was rejected, as was the hypothesis that option prices had no additional information. This would indicate that a composite forecast based on implied volatility and GARCH estimates would yield superior results as each would contribute unique information that was not contained in the other. However, empirical evidence indicated that the GARCH forecasts and historical volatility did not add substantial explanatory power to forecasts that were based on implied volatilities.

Tests for the accuracy of forecasts based on traditional forecast error criteria also support the conclusion that the implied volatilities alone are sufficient for market professionals to predict short-run volatilities of up to two months. Duffie and Gray (1995) constructed in-sample and out-of-sample forecasts for volatility in the crude oil, heating oil, and natural gas markets over the period May 1988 to July 1992. Forecasts from GARCH(1, 1), EGARCH(1, 1), bivariate GARCH(1, 1), regime switching, implied volatility, and historical volatility predictors were compared with the realized volatility in terms of root mean-squared error. They found that implied volatility yielded the best in-sample and out-of-sample forecasts, and that historical volatility forecasts were superior to their GARCH counterparts in the out-of-sample forecasts.

The economic relevance of the oil market justifies the intense academic and policy debate over the contribution of futures contracts to oil price formation and oil spot price volatility. Historically, two main approaches have dominated the scene. According to the first, futures markets have an intrinsic information content which is captured by the lead-lag relationship between spot and futures returns. Conversely, the second approach emphasizes excess volatility and focuses on the change in the volatility level in the spot market after the introduction of the futures markets. Ng and Pirrong (1996) propose a more general approach which at the same time nests both types of regularities and offers a more comprehensive explanation of the dynamic relationship between spot and futures prices. Using a nonlinear, asymmetric error correction model with GARCH-type volatility applied to daily spot and futures price data for heating oil and gasoline, the authors find that 96% of the variation in volatility is explained by variations in the spread (basis) between spot and futures prices. Moreover, the effect of the basis is asymmetric: spot prices are more volatile when spot price exceeds the futures price than when the reverse is true. Both results are consistent with the theory of storage, according to which the level of inventories affects the volatility of spot and futures returns. The paper also finds that volatility shocks are more persistent in the futures market than the spot market, and that futures return shocks induce volatility in spot markets, while the reverse is not supported by the data. These last results are consistent with the view that futures markets facilitate the flow of information to the spot market. Finally, there is evidence of asymmetric adjustment of spot and futures heating oil prices to their long-run equilibrium levels, when the futures price exceeds the spot price and the greater the basis.

Nonlinear dynamics in futures contracts is the focus of Adrangi et al. (2001), who analyze futures prices of crude oil, heating oil and unleaded gasoline from the early 1980s. They find that ARCH-type processes, with controls for seasonal variation in prices, generally explain the nonlinearities in the data. Specifically, asymmetric GARCH models perform well for each contract, and the exponential GARCH model seems to satisfactorily fit the crude oil and unleaded gasoline series. The authors also find empirical evidence which supports the Samuelson hypothesis, according to which volatility in futures price changes increases as a contract's delivery date approaches.

Commodity markets in recent years have experienced dramatic growth in trading volume, the variety of contracts, and the range of underlying commodities. There also has been a great demand for derivative instruments utilizing operational contingencies embedded in delivery contracts. Routledge et al. (2000) present an equilibrium model of commodity spot and forward prices which incorporates the microeconomics of demand, supply and storage. This model is able to rationalize some fundamental differences between commodities and financial assets. In particular: (i) commodity futures prices are often "backwardated" (i.e., they decline with time-to-delivery); (ii) they exhibit time-varying volatility; (iii) the term structure of commodity forward price volatility typically declines with contract horizon (the Samuelson effect); (iv) many commodities have pronounced seasonalities in both price levels and volatilities. In equilibrium backwardation implies that immediate ownership of the physical commodity entails some benefit (convenience yield) which a long forward position does not. Convenience yield can be explained in terms of a timing option which is embedded in the spot commodity price, whereas it is absent in forward contracts (theory of storage). The authors find that: (i) the option's value changes over time due to both endogenous inventory and exogenous transitory shocks to demand and supply; (ii) forward price volatilities can initially increase with contract horizon (violation of the Samuelson effect) when inventory is sufficiently high; (iii) hedge ratios for long-dated forward positions using short-dated forwards are not constant, but are conditional on the current demand shock and the endogenous inventory level. Two versions of the model are calibrated to daily futures prices for the NYMEX light sweet crude oil contract, namely a one-factor specification and a two-factor extension, which allows for permanent as well as transitory shocks. The latter is more successful in matching both the high unconditional volatility of long-horizon crude oil futures prices and the conditional volatilities given contango and backwardation.

Kogan et al. (2005) extend Routledge et al.'s (2000) approach by noting that the models based on competitive storage ignore the production side of the economy. Inventory dynamics have little impact on the long-run properties of commodity prices, which in such model are typically driven by exogenously specified demand processes. As a consequence, prices in such models tend to mean revert too fast relative to what is observed in the data and the models are not able to properly describe the rich structure dynamics of return volatility. In particular, the relationship between the volatility of futures prices and the slope of the term structure of prices is nonmonotone and has a “V-shape.” Traditional models cannot capture this feature of the data, which instead can be generated by alternative mechanisms of futures price formation, such as equilibrium production models featuring constraints on investment. In the model proposed by Kogan et al. (2005) elasticity of commodity supply changes over time. Since demand shocks must be absorbed either by changes in prices, or by changes in supply, time-varying supply elasticity results in time-varying volatility of futures prices.

Managing and assessing risk is a key issue for financial institutions. Regarding market risk, the total capital requirement for a financial institution is defined as the sum of the requirements for positions in equities, interest rates, foreign exchange and commodities. Value-at-Risk (VaR) models are popular quantitative tools to assess the possible loss than can be incurred by a financial institution over a given time period and for a given portfolio of assets. Giot and Laurent (2003) address the computation of the VaR for long and short trading positions in commodity markets. In the first case, the risk comes from a drop in the price of the commodity, while the trader loses money when the price increases in the second case, since he would have to buy back the commodity at a higher price than the one he got when he sold it. The empirical application focuses on aluminum, copper, nickel, cocoa, Brent and WTI crude oils spot and futures prices. The authors investigate the empirical performance of alternative volatility models, such as skewed Student APARCH and skewed Student ARCH. While the former performs best in all cases, the latter delivers good results for several commodities and its estimation does not require nonlinear optimization procedures.

Information on the quantity of a commodity in storage and how this quantity changes over time is integral to the behavior of the commodity’s price. Linn and Zhu (2004) examine the short-term volatility of natural gas futures prices by studying the behavior of intraday prices for the nearby natural gas futures contract traded on the NYMEX and how price volatility is influenced by new information about the amount of gas in storage. Understanding natural gas volatility and its determinants is of practical importance given the level of trading activity in the spot and futures markets for this commodity. Specifically, the authors examine the impact on natural gas futures prices volatility of the Weekly American Gas Storage Survey report compiled and issued by the American Gas Association during the period 1 January 1999–3 May 2002 and the subsequent weekly report compiled and issued by the US Energy Information Administration after 6 May 2002. Results show that the weekly gas storage report announcement was responsible for considerable volatility at the time of its release and that volatility up to 30 min following the announcement was also higher than normal. Moreover, there is evidence of pronounced price volatility in this market at the beginning of the day and at the end of the day.

3. Modeling multivariate volatility

The purpose of the empirical section is to model the volatility in the returns of one-month WTI forward oil prices, and one-, three-, six-, and twelve-month oil futures prices. The estimated multivariate models are the constant conditional correlation (CCC) multivariate GARCH model of Bollerslev (1990) and the dynamic conditional correlation (DCC) model of Engle (2002). The specification, as well as the structural and statistical properties, of these models are discussed briefly in this section. McAleer (2005) provides a comprehensive comparison of univariate and multivariate conditional and stochastic volatility models.

Consider the following specification:

$$y_t = E(y_t \mid F_{t-1}) + \varepsilon_t, \quad \varepsilon_t = D_t \eta_t, \tag{1}$$

where $y_t = (y_{1t}, \ldots, y_{mt})'$, $\eta_t = (\eta_{1t}, \ldots, \eta_{mt})'$ is a sequence of independently and identically distributed (iid) random vectors, F_t is the past information available up to time t, $D_t = \mathrm{diag}(h_{1t}^{1/2}, \ldots, h_{mt}^{1/2})$, m is the total number of oil price returns to be analyzed, and $t = 1, \ldots, n$. Bollerslev (1990) assumed that the conditional variance for each return, h_{it}, $i = 1, \ldots, m$, follows a univariate GARCH process, that is,

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

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 $\sum_{j=1}^{r} \alpha_{ij} + \sum_{j=1}^{s} \beta_{ij}$.

Although the CCC specification in (2) has a computational advantage over some other multivariate GARCH models, such as the BEKK model of Engle and Kroner (1995), which models conditional covariances, CCC nevertheless assumes independence of the conditional variances across returns and does not accommodate asymmetric behavior. In order to accommodate the asymmetric impacts of positive and negative shocks, Glosten et al. (1992) proposed the asymmetric GARCH, or GJR, specification for the conditional variance which, for $r = s = 1$, is given by

$$h_{it} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \gamma_i I_{i,t-1} \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \tag{3}$$

where

$$I_{it} = \begin{cases} 0, & \varepsilon_{it} \geqslant 0, \\ 1, & \varepsilon_{it} < 0, \end{cases}$$

is an indicator function to distinguish between positive and negative shocks on conditional volatility.

The parameters of models (1)–(3) are typically obtained by maximum likelihood estimation (MLE) using a joint normal density for η_t. When η_t does not follow a joint (multivariate) normal distribution, the solution to maximizing the likelihood function is defined as the Quasi-MLE (QMLE).

It is important to note that the conditional correlations are assumed to be constant for the CCC model. From Eq. (1), it follows that $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_t' D_t$, so that $E(\varepsilon_t \varepsilon_t' \mid F_{t-1}) = \Omega_t = D_t \Gamma D_t$. 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 $i, j = 1, \ldots, m$ and $t = 1, \ldots, n$.

When $m = r = s = 1$, such that a univariate model is specified, the necessary and sufficient condition for the existence of the second moment of ε_t in model (2), 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. For the GJR(1, 1) model (3) $\omega_1 > 0$, $\alpha_1 + \gamma_1 > 0$ and $\beta_1 > 0$ are sufficient conditions to ensure that the conditional variance $h_{1t} > 0$. The short-run persistence of positive (respectively, negative) shocks is given by α_1 (respectively, $\alpha_1 + \gamma_1$). Under the assumption that the conditional shocks η_{1t}, $t = 1, \ldots, n$, follow a symmetric distribution, the average short-run persistence is $\alpha_1 + \gamma_1/2$, and the average long-run persistence is $\alpha_1 + \gamma_1/2 + \beta_1$. Ling and McAleer (2002) showed that the necessary and sufficient condition for $E(\varepsilon_t^2) < \infty$ in the GJR(1, 1) model is $\alpha_1 + \gamma_1/2 + \beta_1 < 1$. McAleer et al. (2002) established the log-moment condition for GJR(1, 1), namely $E(\log((\alpha_1 + \gamma_1 I_{1t}(\eta_{1t}))\eta_{1t}^2 + \beta_1)) < 0$, and showed that it is sufficient for the consistency and asymptotic normality of the QMLE for GJR(1, 1). If the log-moment condition is satisfied, the second moment condition, namely $\alpha_1 + \gamma_1/2 + \beta_1 < 1$, is also sufficient for consistency and asymptotic normality of the QMLE for GJR(1, 1).

Unless η_t is a sequence of iid random vectors, the assumption of constant conditional correlation will not be 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 DCC model and the variable conditional correlation (VCC) multivariate GARCH model, respectively. The DCC model, which is a special case of the VCC model, is given as

$$\Gamma_t = (1 - \theta_1 - \theta_2)\Gamma + \theta_1 \eta_{t-1}\eta'_{t-1} + \theta_2 \Gamma_{t-1} \tag{4}$$

in which θ_1 and θ_2 are scalar parameters to capture the effects of previous shocks and previous dynamic conditional correlations on current dynamic conditional correlations.

The purpose of the empirical section is to investigate the asymmetric and interdependent effects of the conditional volatilities in the returns to the WTI oil forward and futures prices.

4. Multivariate volatility and dynamic option pricing

Risk in commodity markets can be managed via option instruments, which can be classified into two broad classes, standard exchange and over the counter (OTC). The former are standardized future exchanges, where prices are determined by buyers and sellers anonymously transacting via open outcry or electronic exchange. The latter are a series of forward contracts that typically exchange fixed priced exposure for floating price exposure. These transactions are directly negotiated between counterparties. Traditionally, standard exchange options are European-style options on underlying prices of WTI, natural gas, heating oil, gasoline, while recently there has been an increasing interest in options on differentials such as gasoline and heating oil cracks. Conversely, the typical OTC options are average-price options (Asian-style) on underlying prices, while recently European-style options have emerged on spreads, cracks and various inter-commodity differentials.

Commodity options can also be classified according to whether the user is a commercial or a noncommercial. Commercial users generally require: (i) average-price option structures that mirror the commercial risk-manager's physical exposures, typically ratable over an entire calendar month; (ii) combinations of calls and puts that provide a range of outcomes to offset physical exposures; (iii) options on differentials to hedge against basis, quality, or margin exposures. Noncommercial types of options include options on underlying prices or spreads that: (i) provide the noncommercial trader with maximum exposure to volatility; (ii) provide an asymmetric payout (limited downside and potentially unlimited upside); (iii) may be traded on hedged basis (with an offsetting delta position) in order to focus the trade on the volatility of the underlying asset. Noncommercials are interested in trading volatility as an asset class in itself. Volatility is traded as long or short straddles, it requires frequent hedging of the underlying to minimize delta and may be traded among different commodities (e.g., long crude oil volatility vs natural gas volatility).

A common approach for derivative pricing is based on modeling the entire forward price curve with multiple sources of uncertainty (Jamshidian, 1991; Cortazar and Schwartz, 1994; Clewlow and Strickland, 2000).

The simplest "single factor" model of the forward curve can be represented by the following stochastic equation:

$$\frac{\mathrm{d}F(t,n)}{F(t,n)} = \sigma(t,n)\,\mathrm{d}z(t), \tag{5}$$

where the elements of the model are the observed forward curve $F(t,n)$ which denotes the forward price at time t for maturity date n, and the volatility function $\sigma(t,n)$ associated with the source of uncertainty $\mathrm{d}z(t)$ (Brownian motion), that is the time t volatility of the n-maturity forward price return. The single volatility function is the "single factor" in the forward curve model (5).

A generalization of model (5) is represented by the "multi-factor" model:

$$\frac{\mathrm{d}F(t,n)}{F(t,n)} = \sum_{i=1}^{p} \sigma_i(t,n)\,\mathrm{d}z_i(t). \tag{6}$$

In this formulation there are p independent sources of uncertainty $\mathrm{d}z_i(t)$, $i = 1, \ldots, p$, which drive the evolution of the forward curve. Each source of uncertainty has associated with it a volatility function $\sigma_i(t,n)$ which determines by how much, and in which direction, the random shock $\mathrm{d}z_i(t)$ moves each point of the forward curve.

The standard method to determine the set of common factors that drive the dynamics of the forward curve is the eigenvector decomposition of the covariance matrix of the forward price returns. The p eigenvectors υ_i, $i = 1, \ldots, p$, of the covariance matrix yield estimates of the factors driving the evolution of the forward curve, whereas the eigenvalues λ_i represent the variances of the independent sources of uncertainty which drive the forward points in proportions determined by the eigenvectors. The p (discretized) volatility functions can be obtained as $\sigma_i(t, t+\tau_j) = \nu_{ji}\sqrt{\lambda_i}$, where τ_j, $j = 1, \ldots, m$, is the relative maturity of the forward prices and ν_{ji} is the jth element of the ith eigenvector.

The forward curve plays a crucial role in pricing different types of energy derivatives. For instance, consider an European option, with maturity n, on a portfolio of forward prices with maturities on a set of dates s_k, $k = 1, \ldots, m$ $(T \leqslant s_1 \leqslant \cdots \leqslant s_m)$ with face values c_k. The payoff at the maturity n is defined to be $C(T, \{c_k, F(T, s_k)\})$, with the price at time t given by the expectation:

$$C\big(t, \{c_k, F(t,s_k)\}\big) = E_t\big[P(t,n)C\big(n, \{c_k, F(n,s_k)\}\big)\big]. \tag{7}$$

The expectation operator $E_t[\cdot]$ can be evaluated via Monte Carlo simulation simply as the average of the simulated payoff values. Specifically, the observed forward price curve $F(t,s_k)$ is simulated until time n to obtain $F(n,s_k)$ for all k. Expectation in Eq. (7) is taken over the m-dimensional (normal) distribution of the correlated natural logarithms of the forward prices, $\ln(F(n,sk))$.

The Monte Carlo simulation is based on the $m \times m$ covariance matrix W of the forward prices at the maturity of the option. An efficient sampling technique requires the decomposition of the covariance matrix of the forward prices into p eigenvectors w_i and p eigenvalues μ_i.

If we indicate with R the number of replications in the Monte Carlo simulation and with η_i, $i = 1, \ldots, p$, vectors of standard normally distributed pseudo-random numbers, Clewlow and Strickland (2000, p. 154) represent Eq. (6) as:

$$C\big(t, \{c_k, F(t,s_k)\}\big) = P(t,n)\frac{1}{R}\sum_{j=1}^{R}\big[C\big(n, \{c_k, F(t,s_k)Y_j(t,n,s_k);\ k = 1, \ldots, m\}\big)\big], \tag{8}$$

where

$$Y_j(t,n,s_k) = \exp\left[-\frac{1}{2}\sum_{i=1}^{n}\big\{w_{ki}^2\mu_i\big\} + \sum_{i=1}^{n}\big\{w_{ki}\sqrt{\mu_i}\eta_i\big\}\right]. \tag{9}$$

Notice that the p volatility functions enter the simulated option price (8) through (9), since $\sigma_i(t, t+\tau_k) = w_{ki}\sqrt{\mu_i}$. Moreover, the size of eigenvalues μ_i indicate the relative importance of the corresponding eigenvector w_i in reproducing the $m \times m$ covariance matrix of forward prices.

The accuracy of the Monte Carlo simulation can be increased by combining the decomposition of the covariance matrix Ω with the estimation of the DCC matrix Γ_t in model (8), according to the following two-step procedure. First, estimate univariate GARCH models on each of the m forward price returns to obtain $D_t = \mathrm{diag}(h_{1t}^{1/2}, \ldots, h_{mt}^{1/2})$. Second, obtain the typical element ρ_{ijt} of the Γ_t matrix as $\rho_{ijt} = Q_{ijt}/(Q_{iit}^{1/2} Q_{jjt}^{1/2})$, where $Q_t = W\Lambda_t W' \cdot W$ is the $m \times m$ matrix of eigenvectors of $\sum_t \varepsilon_t \varepsilon_t'/n$, while Λ_t is a $m \times m$ diagonal matrix whose first p elements are modeled by univariate GARCH, while the remaining m–k elements are kept constant (Alexander, 2001a). The first p eigenvalues and the first p elements of Λ_t are inputs to Eq. (5), which is averaged over the R Monte Carlo replications to determine the option price at time t.

5. Data and empirical results

The univariate and multivariate GARCH models are estimated using daily data on WTI oil one-month forward price (WFORW) and one- (WFUT1), three- (WFUT3), six- (WFUT6), and twelve-month (WFUT12) futures prices, and their associated returns, for the period 3 January 1985 to 16 January 2004.

The univariate estimates of the conditional volatilities based on the forward and futures returns are given in Table 1. The three entries for each parameter are their respective estimates, asymptotic t-ratios and Bollerslev–Wooldridge (1992) robust t-ratios. The results in Table 1 (Panel a) are used to estimate the CCC model of Bollerslev (1990) and the DCC model of Engle (2002). Both the short- and long-run persistence of shocks are significant for forward and futures returns. The ARCH (GARCH) effect is the largest (smallest) for the twelve-month futures returns. Although the second moment condition is not satisfied for the twelve-month futures price returns, the log-moment condition is always satisfied, so that the QMLE are consistent and asymptotically normal.

The univariate GJR estimates in Table 1 (Panel b) are reasonably similar to the corresponding estimates in Table 1 (Panel a). At the univariate level, the estimates of the asymmetric effect in which negative shocks have a greater impact on volatility than positive shocks are significant only when the asymptotic t-ratios are used. The second moment condition is not satisfied for the forward and twelve-month futures returns, but the log-moment condition is always satisfied, so that the QMLE are consistent and asymptotically normal.

Constant conditional correlations between the volatilities of forward and futures returns using the CCC model based on estimating univariate GARCH(1, 1) models for each returns are given in Table 2 (Panel a). For the five returns, there are ten conditional correlations, with the highest estimated constant conditional correlation being 0.975 between the standardized shocks to the volatilities in the three-month and six-month futures returns, and the lowest being 0.656 between the standardized shocks to the volatilities in the forward and twelve-month futures returns. The calculated constant conditional correlations would seem to be consistent with a reasonable expectation that the correlation decreases as the length of the forward contract increases.

Finally, the DCC estimates of the conditional correlations between the volatilities of forward and futures returns based on estimating univariate GARCH(1, 1) models for each returns are given in Table 2 (Panel b). Based on the asymptotic standard errors, the estimates of the

Table 1
Univariate volatilities

Panel a. Univariate AR(1)–GARCH(1, 1) estimates

Returns	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\beta}$	Log-moment	Second moment
WFORW	4.29E–06	0.114	0.890	−0.009	0.994
	6.259	24.619	180.481		
	3.898	6.235	67.277		
WFUT1	5.04E–06	0.102	0.897	−0.016	0.999
	7.406	22.959	185.918		
	3.978	6.726	76.461		
WFUT3	2.52E–06	0.078	0.919	−0.012	0.997
	7.291	17.066	206.711		
	2.685	7.871	103.907		
WFUT6	3.13E–06	0.090	0.901	−0.020	0.992
	8.693	19.994	177.192		
	3.858	6.699	75.440		
WFUT12	4.82E–08	0.197	0.853	−0.004	1.050
	16.291	55.153	631.711		
	17.763	6.814	50.820		

Panel b. Univariate AR(1)–GJR(1, 1) estimates

Returns	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\beta}$	$\hat{\alpha}+\hat{\gamma}/2$	Log-moment	Second moment
WFORW	4.24E–06	0.134	−0.042	0.892	0.113	−0.014	1.005
	6.246	23.651	−6.211	187.561			
	3.836	3.992	−1.194	65.007			
WFUT1	5.11E–06	0.111	−0.016	0.896	0.103	−0.016	0.999
	7.390	20.421	−2.462	184.325			
	4.010	4.191	−0.524	73.317			
WFUT3	2.26E–06	0.066	0.016	0.924	0.073	−0.011	0.997
	6.694	10.917	2.271	214.241			
	2.435	4.550	0.819	110.516			
WFUT6	2.76E–06	0.075	0.019	0.908	0.084	−0.018	0.993
	7.965	12.748	2.691	182.992			
	3.631	4.188	0.830	82.079			
WFUT12	4.36E–08	0.177	0.025	0.857	0.189	−0.003	1.046
	14.717	32.343	3.534	610.328			
	10.824	3.902	0.352	53.780			

Notes. Model AR(1)–GARCH(1, 1) is: $y_{it} = \mu_i + \phi_i y_{i,t-1} + \varepsilon_{it}$; $\varepsilon_{it} = h_{it}^{1/2}\eta_{it}$; $h_{it} = \omega + \alpha\varepsilon_{i,t-1}^2 + \beta h_{i,t-1}$, where y_{it} indicates the ith return, $i = 1, \ldots, m$ (see Eqs. (1) and (2)). The log-moment and second moment conditions for the AR(1)–GARCH(1, 1) model are $\frac{1}{n}\sum_{t=1}^{n}(\log(\hat{\alpha}_{i1}\hat{\eta}_{it}^2 + \hat{\beta}_{i1})) < 0$ and $\hat{\alpha}_{i1} + \hat{\beta}_{i1} < 1$, respectively. Model AR(1)–GJR(1, 1) is: $y_{it} = \mu_i + \phi_i y_{i,t-1} + \varepsilon_{it}$; $\varepsilon_{it} = h_{it}^{1/2}\eta_{it}$; $h_{it} = \omega_i + \alpha_i\varepsilon_{i,t-1}^2 + \gamma_i I_{i,t-1}\varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}$ (see Eqs. (1) and (3)). The log-moment and second moment conditions for the AR(1)–GJR(1, 1) model are $\frac{1}{n}\sum_{t=1}^{n}(\log(\hat{\alpha}_{i1} + \hat{\gamma}_{i1} I_{it}(\hat{\eta}_{it}^2)\hat{\eta}_{it}^2 + \hat{\beta}_{i1})) < 0$ and $\hat{\alpha}_{i1} + \hat{\gamma}_{i1}/2 + \hat{\beta}_{i1} < 1$, respectively. The three entries for each parameter are their respective estimates, asymptotic t-ratios and Bollerslev–Wooldridge (1992) robust t-ratios.

Table 2
Constant conditional correlations (CCC), dynamic conditional correlations (DCC) and descriptive statistics

Panel a. CCC estimates based on GARCH(1, 1) model

Returns	WFORW	WFUT1	WFUT3	WFUT6	WFUT12
WFORW	1.000				
WFUT1	0.884	1.000			
WFUT3	0.855	0.921	1.000		
WFUT6	0.818	0.871	0.975	1.000	
WFUT12	0.656	0.686	0.787	0.839	1.000

Panel b. DCC estimates based on GARCH(1, 1) model

Returns	$\hat{\theta}_1$	$\hat{\theta}_2$
WFORW, WFUT1	0.218	0.506
	17.157	27.882
WFORW, WFUT3	0.188	0.746
	5.671	12.972
WFORW, WFUT6	0.097	0.869
	9.277	56.258
WFORW, WFUT12	0.059	0.934
	7.103	94.473
WFUT1, WFUT3	0.078	0.911
	11.160	112.651
WFUT1, WFUT6	0.070	0.916
	11.671	124.294
WFUT1, WFUT12	0.046	0.953
	9.175	179.445
WFUT3, WFUT6	0.049	0.945
	9.505	151.155
WFUT3, WFUT12	0.051	0.948
	91.826	4222.739
WFUT6, WFUT12	0.055	0.944
	13.340	226.657

Panel c. Descriptive statistics for DCC

Returns	Mean	Min	Max	S.D.	Skewness	Kurtosis
WFORW, WFUT1	0.894	−0.291	0.998	0.085	−5.181	40.842
WFORW, WFUT3	0.857	−0.155	0.994	0.112	−3.015	15.776
WFORW, WFUT6	0.818	0.111	0.985	0.107	−1.954	8.281
WFORW, WFUT12	0.689	−0.013	0.960	0.177	−0.971	3.277
WFUT1, WFUT3	0.922	0.403	0.994	0.062	−2.924	16.126
WFUT1, WFUT6	0.869	0.324	0.988	0.088	−2.274	10.046
WFUT1, WFUT12	0.715	−0.133	0.969	0.213	−1.472	4.560
WFUT3, WFUT6	0.974	0.832	0.996	0.019	−2.411	10.800
WFUT3, WFUT12	0.817	0.016	0.980	0.199	−2.183	7.012
WFUT6, WFUT12	0.873	0.051	0.993	0.212	−2.421	7.626

Notes. CCC is the typical constant element $\hat{\rho}_{ij} = \hat{\rho}_{ji}$ for $i, j = 1, \ldots, m$ and $t = 1, \ldots, n$, of the estimated conditional correlation matrix defined as $\hat{\Gamma} = \hat{D}_t^{-1}\hat{\Omega}_t\hat{D}_t^{-1}$, where $\hat{D}_t = \mathrm{diag}(\hat{h}_{1t}^{1/2}, \ldots, \hat{h}_{mt}^{1/2})$ and $\hat{\Omega}_t = \frac{1}{n}\sum_{t=1}^{n} \hat{\varepsilon}_t\hat{\varepsilon}_t'$. DCC is the typical time-varying element $\hat{\rho}_{ij,t} = \hat{\rho}_{ji,t}$ of the estimated conditional correlation matrix defined as $\hat{\Gamma}_t = (1 - \hat{\theta}_1 - \hat{\theta}_2)\hat{\Gamma} + \hat{\theta}_1\hat{\eta}_{t-1}\hat{\eta}_{t-1}' + \hat{\theta}_2\hat{\Gamma}_{t-1}$ (see Eq. (4)). The two entries for each estimated parameter $\hat{\theta}_1$ and $\hat{\theta}_2$ are their respective estimates and asymptotic t-ratios. Min = minimum value. Max = maximum value. S.D. = standard deviation.

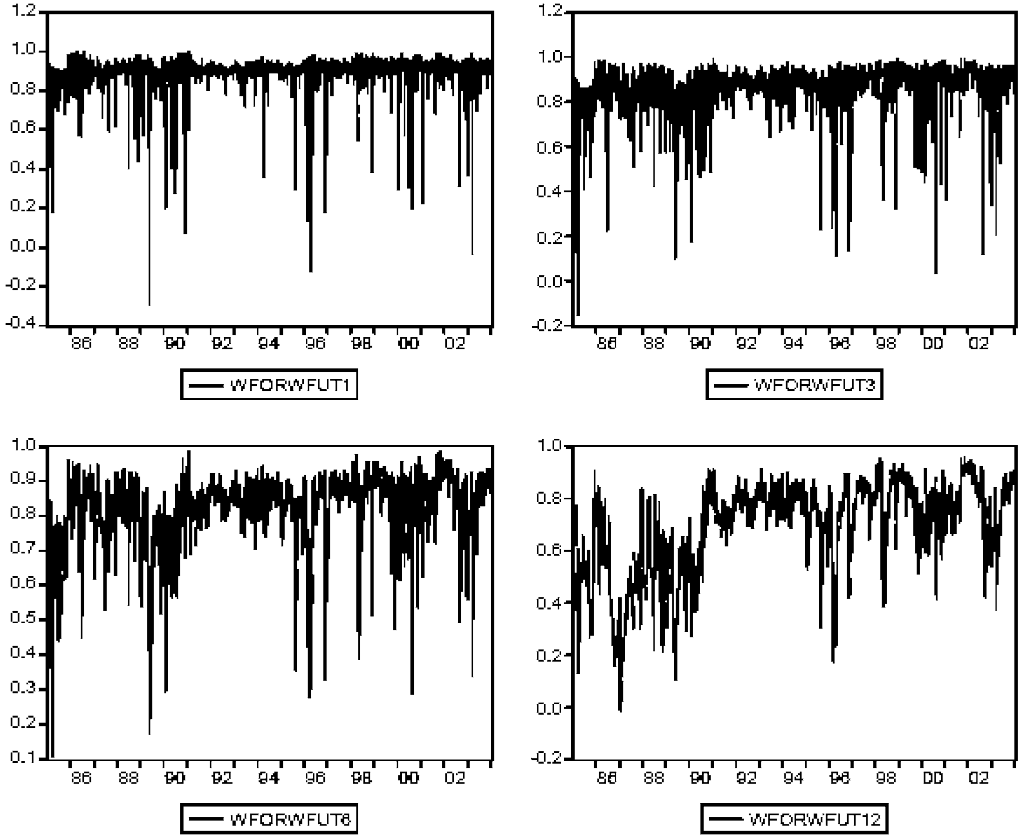

Fig. 1. Dynamic conditional correlations (DCC) between WTI forward and futures returns. *Notes*. The sample period spans from 3 January 1985 to 16 January 2004. Returns are calculated as $(P_t - P_{t-1})/P_{t-1}$, where P_t is the WTI oil price at time t, $t = 1, \dots, n$. WFORWFUT1 is the DCC between WTI one-month forward and one-month futures returns. WFORWFUT3 is the DCC between WTI one-month forward and three-month futures returns. WFORWFUT6 is the DCC between WTI one-month forward and six-month futures returns. WFORWFUT12 is the DCC between WTI one-month forward and twelve-month futures returns.

two DCC parameters are always statistically significant, which makes it clear that the assumption of constant conditional correlation is not supported empirically. The short-run persistence of shocks on the dynamic correlations is greatest between the forward returns and the one-month futures returns, followed closely by the forward returns and the three-month futures returns.

One would expect correlations between commodity futures to be more or less perfect most of the time, since in the crude oil futures markets price decoupling only occurs over very short time spans, so that correlations may deviate below 1 but only for a short time (see, among others, Alexander, 2001b).

The time-varying nature of the conditional correlations is highlighted by the dynamic conditional correlations between the standardized shocks to the forward and futures returns in Figs. 1 and 2. These dynamic correlations vary dramatically, being negative in four of ten cases, close to zero in another three cases, and in the middle range for two other cases. Only in the case of the dynamic correlations between the three-month and six-month futures returns is the range of

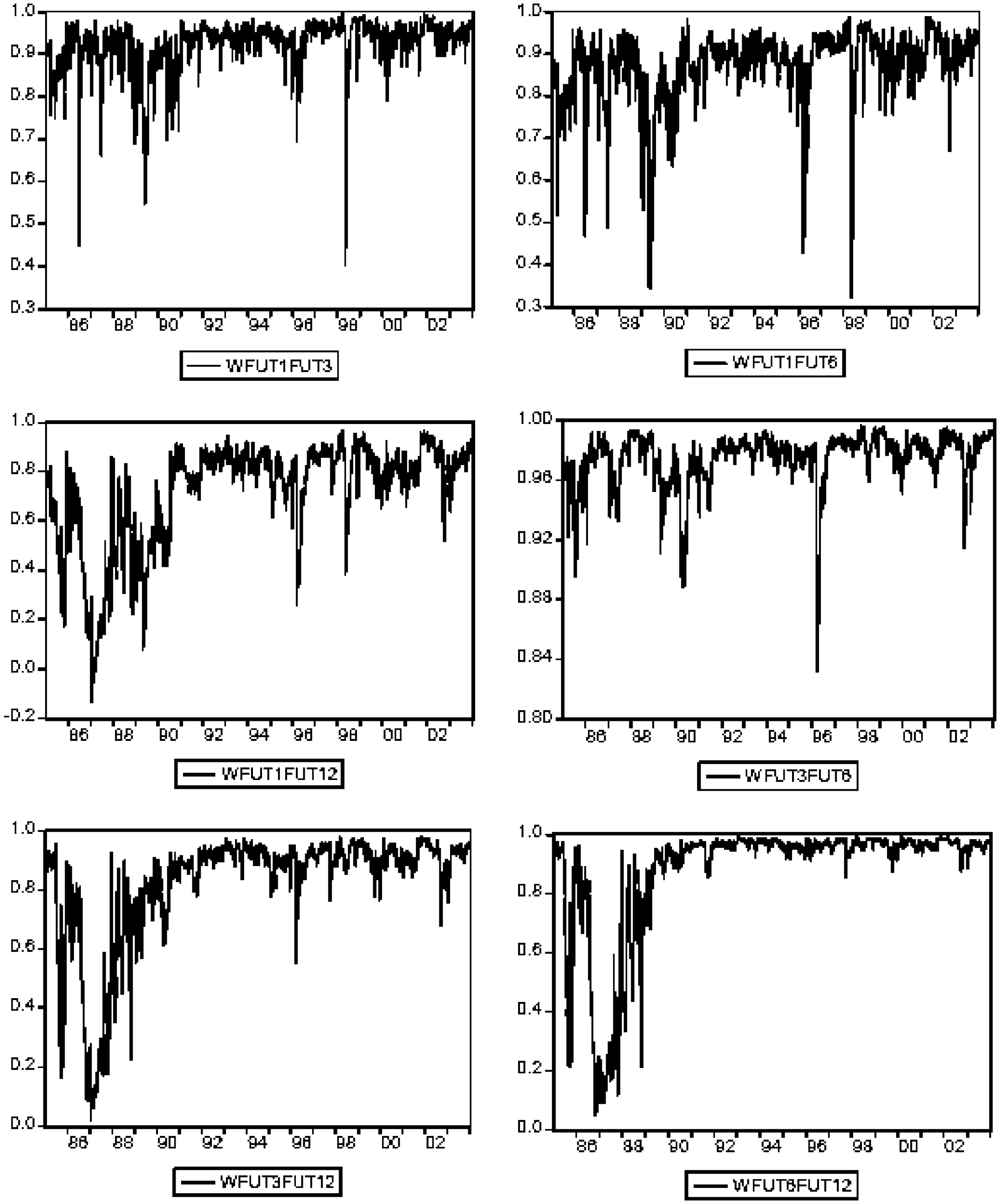

Fig. 2. Dynamic conditional correlations (DCC) between WTI futures returns. *Notes*. WFUT1FUT3 is the DCC between WTI one-month and three-month futures returns. WFUT1FUT6 is the DCC between WTI one-month and six-month futures returns. WFUT1FUT12 is the DCC between WTI one-month and twelve-month futures returns. WFUT3FUT6 is the DCC between WTI three-month and six-month futures returns. WFUT3FUT12 is the DCC between three-month and twelve month futures returns. WFUT6FUT12 is the DCC between six-month and twelve-month futures returns.

variation relatively narrow, namely (0.832, 0.996) (see Table 2, Panel c). Therefore, while the dynamic conditional correlations vary considerably, it is only in one of ten cases that the variations do not lead to an economically meaningful range of variation.

The skewness and kurtosis of the dynamic conditional correlations indicate a strong negatively skewed distribution. As an example, we may consider the first graph in Fig. 1, which gives the DCC estimates between the forward and one-month futures returns. The mean correlation from Table 2 (Panel c) is 0.894, which is very close, but not identical to, the CCC estimate of 0.884. The informational value of the DCC estimate can be evaluated by examining the time series behavior of the time-varying conditional correlations in Fig. 1, as well as the maximum and minimum dynamic levels, as reported in Table 2 (Panel c). The maximum value of 0.998 means that, on the corresponding day, forward and one-month futures returns would have the same risk, so that taking a position in the forward or futures market would be equally risky for a one-month horizon. However, if we consider the minimum dynamic conditional correlation of -0.291, we could conclude that shocks to the conditional volatilities would not be perfect substitutes in terms of risk. In general, the dynamic volatilities in the returns to the WTI oil forward and future prices can be either independent or interdependent over time.

6. Conclusion

In this paper we estimated the dynamic conditional correlations in the returns on WTI oil forward and futures prices from 3 January 1985 to 16 January 2004, using recently developed multivariate conditional volatility and conditional correlation models. The dynamic correlations enabled a determination of whether the shocks to the volatilities in the forward and futures returns of various maturities were substitutes or complements. Such empirical estimates are crucial for deciding whether or not to hedge against unforeseen circumstances, as well as for dynamic option pricing.

In contrast with the common view that the volatility of futures price returns at different maturities are perfectly correlated, our empirical evidence suggests that the DCC can vary dramatically.

Based on the asymptotic standard errors, the DCC estimates of the conditional correlations between the volatilities of forward and futures returns were always statistically significant. This result made it clear that the assumption of constant conditional correlation was not supported empirically. This was highlighted by the dynamic conditional correlations between the forward and futures returns, which varied dramatically. Only in the case of the dynamic volatilities of the three-month and six-month futures returns was the range of variation relatively narrow, namely (0.832, 0.996). In general, the dynamic volatilities in the returns in the WTI oil forward and future prices could be either independent or interdependent over time.

Future research includes a more detailed examination of the design of an optimal hedging strategy based on estimating a wider range of models yielding dynamic conditional correlations.

Acknowledgments

The authors wish to thank Damiano Brigo, Felix Chan, Umberto Cherubini, Alessandro Cologni, Giliola Frey, Marzio Galeotti, Toshiki Honda, Kazuhiko Ohashi and Peter Thomson for insightful discussion, seminar participants at the Fondazione Eni Enrico Mattei, Catholic University of Milan and University of Milan-Bicocca, the Editor and two anonymous referees for useful comments and suggestions, and Margherita Grasso for efficient research assistance. The third author is most grateful for the hospitality of the Fondazione Eni Enrico Mattei, and the financial support of the Australian Research Council.

References

Adrangi, B., Chatrath, A., Dhanda, K.K., Raffiee, K., 2001. Chaos in oil prices? Evidence from futures markets. Energy Economics 23, 405–425.

Alexander, C.O., 2001a. Orthogonal GARCH. In: Alexander, C.O. (Ed.), Mastering Risk. Financial Times/Prentice Hall, London, pp. 21–38.

Alexander, C.O., 2001b. Market Models: A Guide to Financial Data Analysis. Wiley, Chichester.

Bolinger, M., Wiser, R., Golove, W., 2006. Accounting for fuel price risk when comparing renewable to gas-fired generation: The role of forward natural gas prices. Energy Policy 34, 706–720.

Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH approach. Review of Economics and Statistics 72, 498–505.

Bollerslev, T., Wooldridge, J.M., 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. Econometric Reviews 11, 143–172.

Bopp, A.E., Sitzer, S., 1987. Are petroleum futures prices good predictors of cash value? Journal of Futures Markets 7, 705–719.

Buhler, W., Korn, O., Schobel, R., 2004. Hedging long-term forwards with short-term futures: A two-regime approach. Review of Derivatives Research 7, 185–212.

Clewlow, L., Strickland, C., 2000. Energy Derivatives: Pricing and Risk Management. Lacima Publications, London. Chapter 8, pp. 134–162.

Cortazar, G., Schwartz, E., 1994. The valuation of commodity contingent claims. The Journal of Derivatives 1, 27–39.

Cox, J.C., Ingersoll Jr., J.E., Ross, S.A., 1981. The relation between forward prices and futures prices. Journal of Financial Economics 9, 321–346.

Crowder, W.J., Hamid, A., 1993. A co-integration test for oil futures market efficiency. Journal of Futures Markets 13, 933–941.

Day, T.E., Lewis, C.M., 1993. Forecasting futures markets volatility. Journal of Derivatives Winter 1, 33–50.

Duffie, D., Gray, S., 1995. Volatility in energy prices. In: Managing Energy Price Risk. Risk Publications, London, pp. 39–55.

Engle, R.F., 2002. Dynamic conditional correlation: A new simple class of multivariate GARCH models. Journal of Business and Economic Statistics 20, 339–350.

Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. Econometric Theory 11, 122–150.

Giot, P., Laurent, S., 2003. Market risk in commodity markets: A VaR approach. Energy Economics 25, 435–457.

Glosten, L., Jagannathan, R., Runkle, D., 1992. On the relation between the expected value and volatility of nominal excess return on stock. Journal of Finance 46, 1779–1801.

Gulen, S.G., 1999. Regionalization in world crude oil markets: Further evidence. Energy Journal 20, 125–139.

Hammoudeh, S., Li, H., 2004. The impact of the Asian crisis on the behaviour of US and international petroleum prices. Energy Economics 26, 135–160.

Hammoudeh, S., Li, H., Jeon, B., 2003. Causality and volatility spillovers among petroleum prices of WTI, gasoline and heating oil in different locations. North American Journal of Economics and Finance 14, 89–114.

Jamshidian, F., 1991. Commodity option valuation in the Gaussian futures term structure model. Review of Futures Markets 10, 324–346.

Kogan, L., Livdan, D., Yaron, A., 2005. Futures prices in a production economy with investment constraints. NBER Working Paper No. 11509.

Ling, S., McAleer, M., 2002. Stationarity and the existence of moments of a family of GARCH processes. Journal of Econometrics 106, 109–117.

Linn, S.C., Zhu, Z., 2004. Natural gas prices and the gas storage report: Public news and volatility in energy futures markets. The Journal of Futures Markets 24, 283–313.

McAleer, M., 2005. Automated inference and learning in modeling financial volatility. Econometric Theory 21, 232–261.

McAleer, M., Chan, F., Marinova, D., 2002. An econometric analysis of asymmetric volatility: Theory and application to patents. Journal of Econometrics. In press.

New York Mercantile Exchange, 2004. Proceedings of the New York Mercantile Exchange Conference 'Oil Price Formation and Speculative Activity'. New York, 22–23 November 2004.

Ng, V.K., Pirrong, S.C., 1996. Price dynamics in refined petroleum spot and futures markets. Journal of Empirical Finance 2, 359–388.

Quan, J., 1992. Two step testing procedure for price discovery role of futures prices. Journal of Futures Markets 12, 139–149.

Routledge, B.R., Seppi, D.J., Spatt, C.S., 2000. Equilibrium forward curves for commodities. The Journal of Finance 55, 1297–1338.

Schwartz, T.V., Szakmary, A.C., 1994. Price discovery in petroleum markets: Arbitrage, co-integration and the time interval of analysis. Journal of Futures Markets 14, 147–167.

Serletis, A., Banack, D., 1990. Market efficiency and co-integration: An application to petroleum markets. Review of Futures Markets 9, 372–385.

Silvapulle, P., Moosa, I., 1999. The relationship between spot and futures prices: Evidence from the crude oil market. Journal of Futures Markets 19, 175–193.

Tse, Y.K., Tsui, A.K.C., 2002. A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. Journal of Business and Economic Statistics 20, 351–362.

Xiaowen, S.L., Tamvakis, M.N., 2001. Spillover effects in energy, futures markets. Energy Economics 23, 43–56.

Yun, W.-C., 2005. Selective hedging strategies for oil stockpiling. Energy Policy. In press.

Weiner, R.J., 1994. Default, market microstructure, and changing trade patterns in forward markets: A case study of North-Sea oil. Journal of Banking & Finance 18, 955–977.

Wong-Parodi, G., Dale, L., Lekov, A., 2005. Comparing price forecast accuracy of natural gas models and futures markets. Energy Policy. In press.