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Hedging China's energy oil market risks

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Abstract   This paper is the first study to examine the effectiveness of the Shanghai
Fuel Oil Futures Contract (SHF) in risk reduction on the Chinese energy oil market.
We find that the SHF contract can help investors reduce risk by approximately
45 %, lower than empirical evidence in developed markets, when weekly data are
applied. In contrast, when using daily data, SHF contract can only help reduce risk
by approximately 9 %. However, the Tokyo Oil Futures Contract performs two
times better and reduces risk by about 17 %. The empirical results are robust when
variance complicated bivariate GARCH and bivariate distributions are used. Our
results imply that the energy oil futures market in China is not well-established and
more policies are needed to improve market efficiency.

Keywords   China energy oil market · Hedging risk performance · Bivariate
GARCH model · Shanghai fuel oil futures contract (SHF) · Tokyo oil futures
contract (TKF)

JEL Classifications   C32 · G32 · Q47

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1 Introduction

As oil prices continue soaring and fluctuating, hedging price risks in the energy commodity market are popular among both practitioners and academics. Oil futures contract is the most widely used instrument, through which investors can hedge risks by taking an opposite position in the futures market.

This paper provides evidence on how to hedge risks on the Chinese energy oil market. The principal purpose is to investigate the optimal hedging strategies for investors. China is the world's second largest energy oil importer, which makes it vulnerable to international energy market shocks. Thus, diversification risk exposures are essentially important to market practitioners.

There are many studies on optimal hedging strategies in empirical finance literature which try to provide the most accurate optimal hedging ratio (OHR, hereafter). Conventional studies estimate this by performing an ordinary least square (OLS) regression of the spot returns on the futures returns to obtain a constant OHR. However, the OLS regression misspecified the model because (1) the changes in the spot and futures price are not independent and correlated, (2) the unconditional distributions of spot and futures prices and returns are found to be asymmetric or skewed and fat-tailed, and (4) it is now well recognized that the spot and futures prices are cointegrated.

Recent works attempt to address the problems by utilizing various types of bivariate generalized autoregressive conditional heteroskedasticity models (BGARCH) to compute time-varying OHR. Under the convenient assumptions that the conditional density of the price changes is bivariate normal and the conditional variances follow a GARCH (1, 1) process, the so-called constant conditional correlation bivariate generalized autoregressive conditional heteroskedasticity (CCC-BGARCH) model is very simple to compute. A considerable number of researchers used this model to estimate time-varying hedge ratios and achieved high variance reductions as opposed to the use of the OLS hedge ratios (see e.g. Baillie and Myers 1991; Kroner and Sultan 1993; Chakraborty and Barkoulas 1999; Tse and Tsui 2002). However, the correlations and volatilities are changeable over time; this means that the OHR needs adjustment to account for the most recent information. This violates the constant conditional correlation assumption of the CCC-BGARCH model. Several other types of BGARCH models are recommended to capture the time-varying feature in conditional correlations of spot and futures prices (see e.g. Engle and Kroner 1995; Engle 2002). However, recent studies report that incorporating time-varying conditional cannot necessarily ensure better hedging performance.

In this paper, the OHR is based on both the CCC-BGARCH and dynamic conditional correlation bivariate generalized autoregressive conditional heteroskedasticity (DCC-BGARCH) models. Although the framework is standard, to the best of our knowledge, its application is unique to China's futures energy market. The rest of the paper follows the following format: the econometrics model is defined and data are described in Sects. 2, 3 contains the main results and Sect. 4 concludes the paper.

2 Econometric methodology and data

Assume the investor has a long fixed position of one unit in the spot market and a short position of $-h_{t-1}$ units in the futures market. The random return to a hedged portfolio at time t, R_t^p, is

$$R_t^p = R_t^s - h_{t-1}R_t^f, \tag{1}$$

where $R_t^s = P_t^s - P_{t-1}^s$ and $R_t^f = P_t^f - P_{t-1}^f$ are the changes in the spot and futures prices, respectively. R_t^s and R_t^f are the returns of spot and futures prices, where P_t^s and P_t^f are the logarithms of spot and futures prices. The standard mean–variance hedging model assumes the investor has a quadratic expected utility function

$$E[U(R_t^p)] = E(R_t^p) - \gamma Var(R_t^p), \tag{2}$$

where $\gamma > 0$ is the risk aversion coefficient. $E(R_t^p)$ is the expected value of the portfolio return and $Var(R_t^p)$ is the variance of the portfolio return. The investor solves the expected utility maximization problem (or the variance minimization problem) with respect to the hedge position h_{t-1}. By assuming the futures price P_t^f follows a martingale process (i.e., $E(P_t^f) = P_{t-1}^f$), the standard optimal hedging ratio (OHR) h_{t-1}^* for solving this problem is given by Eqs. 3 and 4:

$$h_{t-1}^* = \frac{\sigma_{sf,t}}{\sigma_{f,t}^2}. \tag{3}$$

$$h^* = \frac{\text{Cov}(\varDelta S_t, \varDelta F_t)}{\text{Var}(\varDelta F_t)} = \frac{\sigma_{sf}}{\sigma_f^2} = \rho \frac{\sigma_s}{\sigma_f} \tag{4}$$

where ρ is the correlation coefficient between $\varDelta S_t$ and $\varDelta F_t$, and σ_s and σ_f are standard deviations of $\varDelta S_t$ and $\varDelta F_t$, respectively.

2.1 Model specification

In the model below, let $R_t = (R_t^s, R_t^f)'$ denote the 2×1 time-series vector of the returns of spot and futures prices with time varying conditional covariance matrix H_t, the Bollerslev (1990) constant conditional correlation (CCC)-BGARCH model is

$$\begin{aligned} R_t &= \mu(\varsigma) + \varepsilon_t, \\ \varepsilon_t | \Omega_{t-1} &\sim F(0, H_t), \end{aligned} \tag{5}$$

where $\mu(\varsigma) = (\mu_s, \mu_f)'$ is the vector of conditional mean functions, $\varsigma = (\varsigma_s, \varsigma_f)'$ is a finite vector of parameters, $\varepsilon_t = (\varepsilon_{st}, \varepsilon_{ft})'$ is the vector of unexpected returns, Ω_{t-1} denotes the σ field generated by all the available information up through time $t-1$, F represents a certain form of bivariate distribution, and H_t is a 2×2 positive definite matrix, i.e.,

$$H_t = \begin{bmatrix} h_{ss,t} & h_{sf,t} \\ h_{sf,t} & h_{ff,t} \end{bmatrix} = \begin{bmatrix} \sqrt{h_{ss,t}} & 0 \\ 0 & \sqrt{h_{ff,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{sf} \\ \rho_{sf} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{ss,t}} & 0 \\ 0 & \sqrt{h_{ff,t}} \end{bmatrix}, \quad (6)$$

where ρ_{sf} is the constant conditional correlation coefficient, because the conditional correlations are assumed to be constant through time. Also, $h_{ss,t}$ and $h_{ff,t}$ denote the individual variances and are assumed to have a GARCH(p, q) structure, as,

$$
\begin{aligned}
h_{ss,t} &= c_s + \sum_{j=1}^{p} \alpha_{sj}\varepsilon_{st-j}^2 + \sum_{j=1}^{q} \beta_{sj}h_{ss,t-j}, \\
h_{ff,t} &= c_f + \sum_{j=1}^{p} \alpha_{fj}\varepsilon_{ft-j}^2 + \sum_{j=1}^{q} \beta_{fj}h_{ff,t-j},
\end{aligned}
\qquad (7)
$$

where p and q are lag orders, $j = 1, 2, \ldots, p$ (or q).

In order to deal with potential skewness, on the spot and futures returns in the process of estimation, we introduced a more flexible bivariate skewed-t distribution proposed by Bauwens and Laurent (2005). It is defined as

$$g(z|\xi, v) = \left(\frac{2}{\sqrt{\pi}}\right)^2 \left(\prod_{i=1}^{2} \frac{\xi_i s_i}{1 + \xi_i^2}\right) \frac{\Gamma((v+k)/2)}{\Gamma(v/2)[\pi(v-2)]^{k/2}} \left[1 + \frac{z^{*\prime}z^*}{v-2}\right]^{-(k+v)/2}, \quad (8)$$

where

$$
\begin{aligned}
z^* &= (z_1^*, z_2^*)', \\
z_i^* &= (s_i z_i + m_i)\xi_i^{I_i}, \\
m_i &= \frac{\Gamma((v-1)/2)\sqrt{v-2}}{\sqrt{\pi}\Gamma(v/2)}\left(\xi_i - \frac{1}{\xi_i}\right), \\
s_i^2 &= \left(\xi_i^2 + \frac{1}{\xi_i^2} - 1\right) - m_i^2,
\end{aligned}
\qquad (9)
$$

and

$$I_i = \begin{cases} -1 & \text{if } z_i \succ -\frac{m_i}{s_i} \\ 1 & \text{if } z_i \leq -\frac{m_i}{s_i}, \end{cases}, \quad i = 1, 2, \qquad (10)$$

where the scalar $m_i(\xi_i, v)$ and $s_i(\xi_i, v)$ represent the unconditional mean and the standard deviations of z. The bivariate skewed-t is denoted by $SKST(0, I_2, \xi, v)$. v is the degrees of freedom. ξ is a 2×1 vector of asymmetry parameters ξ_i. If $\xi_i = 1$, the $SKST$ $(0, I_2, \xi, v)$ becomes the symmetry student t density. If $\xi_i > 1$, the third-order moment is positive and the density is skewed to the right; if $\xi_i < 1$, the third-order moment is negative and the density is skewed to the left.

2.2 Data description

Daily and weekly Chinese Yuan-based data on the SHF and TKF are used for the time period between 24 August, 2004 and 27 January, 2011; all data were obtained from the Bloomberg Terminal. The futures rates are closing prices based on the futures contracts underlying those currencies traded on the Shanghai Futures Exchange and the Tokyo Commodity Exchange. There are four outstanding futures contracts following the March–June–September–December cycle at any given time. The successive futures prices are collected based on the following procedures. Firstly, the futures rates of the nearest contract were collected until the contract reached the first week of the expiration month. Secondly, we rolled over to the next nearest contract. Thirdly, we repeated the two procedures. To keep tractability with literature, the weekly spot and futures prices are defined as the natural logarithms of Thursday's spot and futures prices.[1]

All the data for the spot and futures prices were obtained from the Bloomberg Terminal. Transformed data are to be used in the empirical specifications below the percent spot returns ($R_t^s = 100 \, (P_t^s - P_{t-1}^s)$), where P_t^s are the logarithms of the spot prices) and the percent futures returns ($R_t^f = 100 \, (P_t^f - P_{t-1}^f)$), where P_t^f are the logarithms of the futures prices). The starting point for each of the series is determined by the availability of its corresponding futures prices.

Table 1 reports summary statistics for the in-sample spot and futures returns of the spot and futures return series. The heteroskedastic and autocorrelation consistent standard errors for the mean, standard deviation, skewness, and excess kurtosis were also reported. They were computed as described by West and Cho (1995). The results in Table 1 show that the means of all spot and futures returns are very close to zero. For the Shanghai Futures Market, the standard deviation of the futures returns is larger than that of the spot returns. This is consistent with the conclusions in the well-established literature that the futures market is more volatile than the spot market (Chan et al. 1991; Brown-Hruska and Kuserk 1995; Faff and Mckenzie 2002; Illueca and Lafuente 2003). In addition, the results indicate that all returns exhibit a certain degree of skewness. In addition, the values in the column of excess kurtosis suggest that all returns have positive excess kurtosis (or leptokurtic). All the Jarque–Bera test statistics strongly reject the null hypothesis that the return series are normally distributed. The Ljung–Box test statistics at lags 20, $Q(20)$ show significant evidence of autocorrelation for the series. Furthermore, the non-normal distributional properties of the return series provide support for basing estimation and inference on more suitable distributions, like conditional symmetric t and skewed t distribution, than the multivariate normal distribution to avoid misspecification.

Table 2 presents the results for the Augmented Dickey–Fuller (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests of each oil return series. For all the price series, the ADF test rejects the null hypothesis of unit root and the KPSS test fails to reject the null hypothesis of non-stationary. This indicates that all return

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[1] Previous studies usually collect the data for the nearby futures contract until the contract reaches either the first day of the delivery month or its expiry date.

Table 1 Summary statistics of spot and futures returns

	Shanghai		Tokyo
	Spot	Futures	Futures
Mean	0.040	0.027	0.000
Standard deviation	1.011	1.875	1.020
Skewness	−1.092	−1.784	−0.859
Excess kurtosis	13.637	24.381	13.245
J-B	8,379.680 [0.000]	26,638.600 [0.000]	12,560.200 [0.000]
Q(20)	451.076 [0.000]	50.771 [0.000]	65.614 [0.000]

The spot and futures returns are defined as 100 times the log-difference of weekly spot and futures exchange rates. J-B is the Jarque–Bera test for the null hypothesis of normality. Q(20) is the Ljung–Box test of the null hypothesis that the first 20 autocorrelations are zero. P values are given in brackets

Table 2 Unit-root and stationary test

	Shanghai		Tokyo
	Spot	Futures	Futures
ADF	−8.427	−13.716	−11.772
KPSS	0.171	0.106	0.141
CERR	−12.62	−14.32	−12.42

ADF corresponds to statistic of Augmented Dickey–Fuller test of the null hypothesis that the return series has unit root. KPSS is Kwiatkowski–Phillips–Schmidt–Shin statistic for the null hypothesis that the return series has unit root. The critical values at 5 and 1 % for KPSS test are 0.739 and 0.463, respectively. The critical values for the ADF test are −3.435 and −2.864, respectively. In addition, we also conduct a nonlinear panel unit root test of Cerrato et al. (2011) for robustness check, as denoted by CERR

series are stationary which is consistent with literature (see Lien et al. 2002; Lien 2009; Park and Jie 2009). In general, the results of the unit root tests indicate that each return series is stationary. Other more powerful unit root tests can be used in future studies (See Lau et al. 2012 and Lau 2009 for details).

3 Empirical results

Here, the in-sample estimation and out-of-sample forecasting results of the CCC-GARCH models are reported. In addition, a check was done for the robustness of the results by changing model specification, data frequency, as well as futures contracts. The in-sample estimation results for the SHF and TKF are reported in Table 3. The estimates of the distribution parameters ξ_s, and ξ_f are significant for the skewed-t model at 5 percent significance level. The coefficient $\widehat{v}$, representing the degree of freedom coefficient is 5.183 which shows the dominant feature of the fourth-order moment in the Shanghai spot and futures series. The coefficients $\xi_s < 1$ and $\xi_f < 1$ indicate that the standardized residuals of the Shanghai spot and futures equations are relatively negative-skewed, respectively.

Table 3 CCC-BGARCH estimation results

	SHF			TKF		
	Normal	Student t	Skewed-t	Normal	Student t	Skewed-t
c_S	0.029 (0.029)	0.038 (3.607)	0.016	0.034 (0.031)	0.028 (4.138)	0.124 (0.077)
α_{s1}	0.097 (0.068)	0.083	0.051 (2.288)	0.111 (0.070)	0.105 (2.046)	0.344 (0.191)
β_{s1}	0.884 (0.077)	0.837 (1.182)	0.910 (1.198)	0.870 (0.078)	0.821 (1.044)	0.776 (0.076)
c_f	0.142 (0.071)	0.538 (1.611)	0.187 (1.545)	0.024 (0.018)	0.074 (1.689)	0.052 (0.041)
α_{f1}	0.068 (0.033)	0.193	0.078 (1.979)	0.026 (0.009)	0.031	0.065 (0.036)
β_{f1}	0.897 (0.034)	0.582 (1.149)	0.854 (1.114)	0.971 (0.005)	0.934 (1.166)	0.959 (0.021)
υ		5.325	5.183 (0.220)*		6.616	2.424 (0.210)*
ε_s			0.949 (1.088)*			1.023 (0.024)*
ε_f			0.835 (1.164)*			0.966 (0.034)*
Log-lik	−2,531.051	−2,381.846	−2,384.715	−2,373.767	−2,267.385	−2,118.036
AIC	6.739	6.345	6.358	6.732	6.434	6.017
BIC	6.775	6.388	6.413	6.771	6.479	6.075

The table reports the CCC-BGARCH results under flexible distributions for the SHF and TKF. The first six rows present the estimated coefficients for the BGARCH models. Log-lik, AIC, and BIC are the maximum loglikelihood value, Akaike information criteria and Schwarz information criteria of the models, respectively. The numbers in parentheses are the standard errors. *Denote the 5 % significance levels

In addition, the log-likelihood value of the bivariate normal model and the bivariate student-t model MC2 are $-2,373.767$ and $-2,267.385$, respectively. That is, the bivariate Student density increases the log-likelihood value by about 100 for incorporating an excess kurtosis parameter. The lower values of both *AIC* and *SIC* also support this argument. We can do a similar comparison between the CCC-BGARCH with bivariate student-t model and the bivariate skewed-t model. The increment in the log-likelihood value of the bivariate skewed-t density from that of the bivariate student-t density model is about 90. The increment in log-likelihood value can be attributed to adding the two asymmetric distribution parameters, i.e., the skewness parameters: ξ_s and ξ_f. To further evaluate the significance of the asymmetry in the bivariate distribution, we conducted the Likelihood Ratio (*LR*) test of the null hypothesis of symmetry, i.e. $H_0 : \xi_s = \xi_f = 0$. The computed test statistic is 48.6 which asymptotically follows the $X^2(2)$ distribution, rejects the symmetry assumption and favors the bivariate skewed-t distribution related CCC-BGARCH model. Both information based model selection criteria, *AIC* and *SIC* choose the bivariate skewed-t model which also provide support for the asymmetry distribution assumption. Further comparison among the three models shows that the CCC-BGARCH with bivariate skewed-t model have the lowest *AIC*, and *SIC* are more attractive than the CCC-BGARCH with bivariate normal and student-t models. However, for the SHF, the CCC-BGARCH with bivariate student t models is the best.

3.1 Hedging performance of the daily shanghai fuel oil contracts

In order to evaluate the hedging performance of various hedging strategies, we constructed a hedged portfolio based on the two types of OHRs estimated under various distributions. The hedged portfolio at time t is defined in Eq. (1). We computed and compared the reduction in variance of each portfolio return (VR) relative to the no hedging position.

$$VR = 1 - \frac{Var(R_t^p)}{Var(R_t^S)}, \tag{11}$$

Tables 4 and 5 report the in-sample and out-of-sample performances of the optimal hedge ratios. Both tables report results for daily results only to save space. Data used in the estimation procedure are from 24 August, 2004 to 27 January, 2011. For out-of sample performance, the results are based on last year's data: the last 252 days of data for the daily sample, and the last 52 weeks of data for the weekly samples. Table 4 reports the in-sample and out-of-sample performances of the optimal hedge ratios from the CCC-BGARCH models, OLS and naïve hedging strategies. For hedging with the SHF contract in Panel A, all the CCC-BGARCH models produced higher variance reductions than the OLS and naïve hedging strategies. However, the magnitude of risk reductions of the models is very small, ranging from 5.6 to 8.7 %; indicative of poor performance of the models. This can be attributed to numerous factors, for instance, data frequency and model misspecifications.

Table 4 Hedge performance of SHF with CCC-BGARCH model

	OLS	Naïve	Normal	Student	Skewed-t
Panel A					
In-sample	−1.888	−2.095	0.0740	0.0865	0.0851
Panel B					
Out-of-sample	−2.989	−3.288	0.0568	0.0637	0.0673

The table reports the magnitude of variance reduction (VR) of each model

Table 5 Hedge performance of SHF with DCC-BGARCH model

	OLS	Naïve	Normal	Student	Skewed-t
Panel A					
In-sample	−1.888	−2.095	0.1102	0.0996	0.1244
Panel B					
Out-of-sample	−2.989	−3.288	0.0501	0.0609	0.05837

The table reports the magnitude of variance reduction (VR) of each model

The CCC-BGARCH model with multivariate student t distributions outperformed those with normal and skewed-t distributions in terms of variance reductions. Here, a full sample data set (24 August, 2004 to 27 January, 2011) was used for the estimation and calculation of reduction in variance of each portfolio return (VR) relative to the no hedging position.

Panel B presents the results for the out-of-sample hedging performance in terms of variance reduction for the SHF contracts. Among the three distribution specifications, the CCC-BGARCH models with multivariate skewed-t distribution produced the largest variance reduction, while the model with a normal distribution had the lowest. The three CCC-BGARCH models outperformed the OLS and naïve strategies.

In general, the OHR under the CCC-BGARCH models outperformed the OLS and naïve strategies in all cases. However, the magnitude of risk reduction of the models was very small, ranging from 5.6 to 8.7 %; indicative of poor performance of the models. This can be attributed to numerous factors such as data frequency, model misspecifications and so on. In the following subsections, the possible factors will be analyzed.

3.2 Time-varying conditional correlations

The correlations and volatilities are changeable over time, thus the OHR should be adjusted to account for the most recent information. However, the CCC-BGARCH model assumes the constant conditional correlation between spot and futures returns. This is a possible factor resulting in the poor performance of the CCC-BGARCH models. To capture the time-varying feature in conditional correlations of spot and futures prices, we improved on the simple version of Engle's (2002)

dynamic conditional correlation (DCC)-BGARCH model, which proves to outperform other peer models in estimating the dynamic OHR.

The DCC-BGARCH model differs from Bollerslev's CCC-GARCH model in the structure of conditional variance matrix H_t and is formulated as the following specification:

$$
\begin{aligned}
H_t &= D_t \Gamma_t D_t, \\
D_t &= \text{diag}\left\{\sqrt{h_{ss,t}}, \ \sqrt{h_{ss,t}}\right\}, \\
u_t &= D_t^{-1}\varepsilon_t, \\
Q_t &= (1 - \varphi_1 - \varphi_2)\overline{Q} + \varphi_1 u_{t-1} u_{t-1}' + \varphi_2 Q_{t-1}, \\
\Gamma_t &= \text{diag}\{Q_t\}^{-\frac{1}{2}} Q_t \ \text{diag}\{Q_t\}^{-\frac{1}{2}},
\end{aligned}
\tag{12}
$$

where ε_t is the unexpected return and has the same definition as in Eq. (5). u_t represents the vector of standardized ε_t. Q_t is the 2×2 positive definite covariance matrix with the parameters $\varphi_1 \geq 0$, $\varphi_2 \geq 0$ and $\varphi_1 + \varphi_2 < 1$. $\overline{Q}$ is the unconditional covariance matrix of u_t.

Table 5 shows the results for the DCC-BGARCH models. For the in-sample estimation, the DCC-BGARCH with skewed-t distribution produced the largest variance reduction. The DCC-BGARCH with student t distribution performed best, in terms of variance reduction for the out-of-sample forecasting. All the DCC-BGARCH models performed better than the OLS and naïve strategies. The out-of-sample hedging performance of the DCC-BGARCH models is not sufficient, although the in-sample performance is better than the CCC-BGARCH models, by about 10–12.4 %. SHF contract, at least in daily data, cannot provide satisfactory protection from risk exposure.

When the hedging performance between the CCC-BGARCH and DCC-BGARCH models were compared, results show that the CCC-BGARH models perform better for in-sample estimation, while the DCC-BGARCH is better for out-of-sample forecasting.

3.3 Cross-hedging with the TKF contract

The out-of-sample hedging performance of the DCC-BGARCH models is not sufficient, although the in-sample performance is better than the CCC-BGARCH models, by about 10–12.4 %. Thus, the results in Sects. 3.1 and 3.2 imply that the SHF contract, at least in the daily data, cannot provide satisfactory protection from risk exposure. In this subsection, we proposed another futures contract, the TKF contract, which can provide a better hedge against variance risk. The results are presented in Table 6. Panels A and B display the results for CCC-BGARCH and DCC-BGARCH models, respectively.

For the in-sample estimation, all the BGARCH specifications using the TKF contract produced higher variance reductions than those using the SHF contract. To be specific, the CCC-BGARCH models using the TKF data can achieve variance reduction of 17–18 %, while those using the SHF achieved only about 5.6–8.7 %.

Table 6 Cross-Hedge performance of TKF

	OLS	Naïve	CCC-BGARCH			DCC-BGARCH		
			Normal	Student	Skewed-t	Normal	Student	Skewed-t
Panel A								
In-sample	−1.538	−1.734	0.1768	0.1768	0.1698	0.1768	0.1062	0.1698
Panel B								
Out-of-sample	−6.127	−6.73	0.1593	0.1593	0.1547	0.1593	0.1024	0.1431

The table reports the magnitude of variance reduction (VR) of each model

Similarly, the DCC-BGARCH models using the TKF data produced variance reduction of about 10.6–17.7 %, compared with 10–12.4 % when using the SHF contract. In conclusion, the daily TKF contract is more favorable in terms of risk reduction in comparison to the domestic SHF contract. We also ran the model using other futures contracts, for example, Light Sweet Crude Oil (WTI) futures contracts from NYEMEX, as well as heating and crude oil contracts from India futures exchange were not able to hedge against fuel oil spot market in Shanghai; unfortunately, and results can be provided upon request. This robustness checking once confirmed that futures contracts, for example WTI from NYEMEX, as well as heating and crude oil contracts from India futures exchange cannot be used as an instrument to replace TKF contract, for improving the hedging performance in China's energy market. As indicated by Tanai and Lin (2013) time span maybe relevant to the degree of financial market integration. They find no evidence of significant contagion among Shanghai Cooperation Organization (SCO) countries in the first half of sample periods. However, market integrations among SCO countries are evident after 2005, which is the sample period of our contracts data under investigation. Recently Lau et al. (2013) present an empirical finding that financial asset price volatility maybe affected by the institutional factor of corruption. Therefore one reason why the future oil contracts are not efficient in China may be due to its informal institutional arrangement, under the influence of bribery.

3.4 Hedging with weekly data

Estimating hedging performance using daily data is fairly adopted for speculators in futures market; however, it is too frequent for measuring behaviors of hedgers, such as commodity holders, who aim to hedge risk exposure, instead of speculating in the market. This argument is consistent with the findings of Moon et al. (2010). The authors employed daily, weekly and monthly crude oil and gold futures traded at the New York Mercantile Exchange (NYMEX) from March 1983 to November 2007. Using various GARCH models, it became evident that there is more variance reduction as the sample frequency declined from daily to weekly to monthly. This result implies that a less frequent hedge trading would be more beneficial.

In this subsection, weekly data are used to analyze the hedging performance of various models and the results are presented in Table 7. Panels A and B report

Table 7 Hedge performance with weekly data

		OLS	Naïve	CCC			DCC		
				Normal	Student	Skewed-t	Normal	Student	Skewed-t
SHF	In-sample	−0.027	−0.1079	0.4608	0.4618	0.4597	0.4327	0.3967	0.4874
	Out-of-sample	−0.0853	−0.1724	0.4313	0.4285	0.4314	0.4314	0.491	0.43
TKF	In-sample	−0.4496	−0.559	0.3469	0.3566	0.3563	0.3469	0.3564	0.3567
	Out-of-sample	−2.1442	−2.4147	0.283	0.2952	0.2955	0.2624	0.255	0.2883

This table reports the magnitude of variance reduction (VR) of each model using weekly data

results for the SHF and TKF contracts, respectively. For both the in-sample estimation and out-of-sample forecasting, all the BGARCH models produced higher variance reduction than the OLS and naïve strategies. The SHF contract reduces risk in terms of out-of-sample variance reduction by about 40–49 %, and the TKF contract reduces risk by about 36 %. In general, the SHF performs better in variance reduction than the TKF contract, for the weekly data. However, the magnitude of variance reduction is still less than the empirical results for developed countries. The empirical results imply that the Chinese energy fuel oil market is not well-established and more market and regulation efforts are needed to help investors diversify risk exposure. Among other factors, financial constraints, corruption and legal institutions may play an important role in improving the effectiveness of the financial market (Gur 2012) and eventually enhance the hedging effectiveness of the futures market. Other more advanced time series models can be used for risk management. Puigvert-Gutierrez and de Vincent-Humphreys (2012) propose models of probability density functions for EURIBOR, which was estimated from the prices of options on EURIBOR futures. And the option-implied probability density functions can be used to measure the degree of uncertainty for monetary policy and financial stability in a country.

4 Conclusions

Hedging using futures contracts is a popular short-term risk-minimizing strategy for investors. Successful hedging strategy gives investors protection against changes in currency exchange rate. In this paper, the authors examined the hedging performances of the domestic SHF and the TKF futures contracts. The results revealed that the SHF contract provides little risk reduction in daily hedging while the TKF provides two-times higher risk reduction. Both contracts provide better hedging performance when weekly data are applied.

The OHRs are estimated with the CCC-BGARCH and DCC-BGARCH models. To capture the fat-tails and asymmetry properties of the spot and futures returns and avoid misspecification of the models, we estimated the BGARCH model with flexible distributions such as bivariate symmetric student-t and bivariate skewed-t density functions. The use of asymmetry distributions improves the goodness-of-fit. However, it also confirms additional evidence that there is no guarantee that the

models of the goodness-of-fit have higher variance reduction and lower variances in returns. In addition, the results show that simple OLS hedge ratios fail to outperform the complicated BGARCH models in terms of variance reduction. This contradicts many previous studies on developed futures markets (Collins 2000; Lien et al. 2002; Lien 2009; Park and Jie 2009). Because data from different markets were used, we found this contradiction in general, that the performance of hedging strategies depends on market liquidity and time series characteristics. Zanotti et al. (2010) used different models including naïve, ordinary least squares, and GARCH to evaluate the hedging effectiveness of the European electricity markets. The authors found evidence that hedging strategies cannot reduce portfolio's variance in a market where it is very illiquid. More importantly, time varying GARCH model outperformed the naïve, ordinary least squares and traditional GARCH models. Some models outperform others because of Market liquidity and time series characteristics of the sample. Salvador and Arago (2013) incorporated nonlinearity to the model by using a Markov Switching GARCH model. They compared different models of the hedging performance in the European stock indexes and concluded from the in-sample and out-sample performance that the nonlinear model outperforms the linear models. Lau and Bilgin (2013) investigated the hedging performance of the Shanghai futures market, with the London futures market acting as the channel for volatility spillover. The authors incorporated structural changes, basis effects, and return and volatility spillover effects, and found that the estimated hedging performance was not improved. As mentioned by Moosa (2003), only high correlation between prices of the un-hedged position and the hedging instrument can produce a good hedging performance. Therefore, government can improve market efficiency in Shanghai Futures Exchange Markets (not only the fuel oil contracts) as a whole, and attention should be given to the transaction cost involved in financial constraints, corruption and legal institutions, in particular for using hedging instrument in an emerging market like China.

Energy commodity futures prices have soared and deviated from cash prices in the past few years, when institution investors are increasingly interested in commodities. However, the phenomenon does not show up in the Chinese energy futures market, because the SHF contract provides little hedging benefits to investors. The results presented in this paper provide evidence that the Chinese energy fuel oil market is not well-established and more market and regulation efforts are needed to help investors diversify risk exposure.

References

Baillie, R., & Myers, R. J. (1991). Bivariate GARCH estimation of the optimal commodity futures hedge. *Journal of Applied Econometrics, 6*(2), 109–124.

Bauwens, L., & Laurent, S. (2005). A new class of multivariate skew densities with application to GARCH models. *Journal of Business and Economic Statistics, 23*(3), 346–354.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *Review of Economics and Statistics, 72*(3), 498–505.

Brown-Hruska, S., & Kuserk, G. (1995). Volatility, volume and the notion of balance in the S&P 500 cash and futures market. *Journal of Futures Markets, 15*(6), 677–689.

Cerrato, M., Peretti, C., Larsson, R., & Sarantis, N. (2011). A nonlinear panel unit root test under cross section dependence. *University of Glasgow Business School-Economics Working Paper*, 2011/08.

Chakraborty, A., & Barkoulas, T. J. (1999). Dynamic futures hedging in currency markets. *European Journal of Finance, 5*(4), 299–314.

Chan, K., Chan, K. C., & Karolyi, G. (1991). Intraday volatility in the stock index and stock index futures markets. *Review of Financial Studies, 4*(4), 652–684.

Collins, R. A. (2000). The risk management effectiveness of multivariate hedging models in the Soy complex. *Journal of Futures Markets, 20*(2), 189–204.

Engle, R. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics, 20*(3), 339–360.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory, 11*(01), 122–150.

Faff, R. W., & McKenzie, M. D. (2002). The impact of stock index futures trading on daily returns seasonality: a multicountry study. *The Journal of Business, 75*(1), 95–125.

Gur, N. (2012). Financial constraints, quality of institutions and firm size: what do perceptions tell us? *Eurasian Economics Review, 2*(2), 17–36.

Illueca, M., & Lafuente, J. (2003). The effect of spot and futures trading on stock index market volatility: a nonparametric approach. *Journal of Futures Markets, 23*(9), 841–858.

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

Lau, C. K. M. (2009). A more powerful panel unit root test with an application to PPP. *Applied Economics Letters, 16*(1), 75–80.

Lau, C. K. M., & Bilgin, M. H. (2013). Hedging with Chinese aluminum futures: international evidence with return and volatility spillover indices under structural breaks. *Emerging Markets Finance and Trade, 49*(S1), 37–48.

Lau, C. K. M., Demir, E., & Bilgin, M. H. (2013). Experience-based corporate corruption and stock market volatility: evidence from emerging markets. *Emerging Markets Review, 17*, 1–13.

Lau, C. K. M., Suvankulov, F., Su, Y., & Chau, F. (2012). Some cautions on the use of nonlinear panel unit root tests: evidence from a modified series-specific non-linear panel unit-root test. *Economic Modelling, 29*(3), 810–816.

Lien, D. (2009). A note on the hedging effectiveness of GARCH models. *International Review of Economics and Finance, 18*(1), 110–112.

Lien, D., Tse, Y. K., & Tsui, A. K. (2002). Evaluating the hedging performance of constant-correlation GARCH model. *Applied Financial Economics, 12*(11), 791–798.

Moon, G. H., Yu, W. C., Hong, C. H., & Chen, Y. C. (2010). Risk management of commodities with hedging strategies. *Winona State University Working Paper*.

Moosa, I. A. (2003). The sensitivity of the optimal hedge ratio to model specification. *Finance Letters, 1*(1), 15–20.

Park, S. Y., & Jie, S. Y. (2009). Estimation and hedging effectiveness of time-varying hedge ratio: flexible bivariate GARCH approaches. *Journal of Futures Markets, 30*(1), 71–99.

Puigvert-Gutierrez, J. M., & de Vincent-Humphreys, R. (2012). A quantitative mirror on the EURIBOR market using implied probability density functions. *Eurasian Economic Review, 2*(1), 1–31.

Salvador, E., & Arago, V. (2013). Measuring hedging effectiveness of index futures contracts: do dynamic models outperform static models? A regime-switching approach. *Journal of Futures Markets, 34*(4), 299–398.

Tanai, Y., & Lin, K. P. (2013). Mongolian and world equity markets: volatilities and correlations. *Eurasian Economic Review, 3*(2), 139–167.

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*(3), 351–362.

West, K. D., & Cho, D. (1995). The predictive ability of several models of exchange rate volatility. *Journal of Econometrics, 69*(2), 367–391.

Zanotti, G., Gabbi, G., & Geranio, M. (2010). Hedging with futures: efficacy of GARCH correlation models to European electricity markets. *Journal of International Financial Markets, Institutions and Money, 20*(2), 135–148.