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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%. The Tokyo Oil Futures Contract (TKF), however, performs two times better, reducing risk by around 17%. The empirical results are robust when variance complicated bivariate GARCH (BGARCH) and bivariate distributions are used. Our results imply the energy oil futures market in China is not well-established and further policy is needed to improve market efficiency.

Keywords: China Energy Oil Market, Hedging Risk Performance, Bivariate GARCH model.

JEL classification: C32; G32; Q47

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1. Introduction

As the cash 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 (i) the changes in the spot and futures price are not independent and correlated, (ii) the unconditional distributions of spot and futures prices and returns are found to be asymmetric or skewed and fat-tailed, and (iii) it is now well recognized, however, that the spot and futures prices are cointegrated.

Recent work attempts 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 amount of research uses this model to estimate time-varying hedge ratios and achieves 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 the OHR needs adjustment to account for the most recent information; however, 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 energy futures market. The results are singular in several aspects.

The rest of the paper follows the following format: the econometrics model is defined and data are described in section2, section 3 contains the main results and section 4 concludes the paper.

2. Econometric Methodology and Data

Assume the investor has a fixed long 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

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

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

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

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}^* solving this problem is given by the

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

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

where ρ is the correlation coefficient between ΔS_t and ΔF_t, and σ_s and σ_f are standard deviations of ΔS_t and ΔF_t, respectively.

2.1. Model Specification

In the model below, let $R_t = (R_t^s, \quad R_t^f)'$ 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

$$R_t = \mu(\varsigma) + \varepsilon_t,$$
$$\varepsilon_t \mid \Omega_{t-1} \sim F(0, H_t),$$

where $\mu(\varsigma) = (\mu_s\ ,\ \ \mu_f)'$ is the vector of conditional mean functions, $\varsigma = (\varsigma_s, \quad \varsigma_f)'$ is a finite vector of parameters, $\varepsilon_t = (\varepsilon_{st}, \quad \varepsilon_{ft})'$ 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 distributions, and H_t is a 2×2 positive definite matrix, i.e.,

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

where ρ_{sf} 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,

$$h_{ss,t} = c_s + \sum_{j=1}^{p} \alpha_{sj} \varepsilon_{st-j}^2 + \sum_{j=1}^{q} \beta_{sj} h_{ss,t-j},$$
$$h_{ff,t} = c_f + \sum_{j=1}^{p} \alpha_{fj} \varepsilon_{ft-j}^2 + \sum_{j=1}^{q} \beta_{fj} h_{ff,t-j},$$

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

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

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

where

$$z^* = (z_1^*, z_2^*)',$$
$$z_i^* = (s_i z_i + m_i)\xi_i^{I_i},$$
$$m_i = \frac{\Gamma((v-1)/2)\sqrt{v-2}}{\sqrt{\pi}\Gamma(v/2)}(\xi_i - \frac{1}{\xi_i}),$$
$$s_i^2 = (\xi_i^2 + \frac{1}{\xi_i^2} - 1) - m_i^2,$$

and

$$I_i = \begin{cases} -1 & \text{if } z_i \succ -\frac{m_i}{s_i} \\ 1 & \text{if } z_i \le -\frac{m_i}{s_i}, \end{cases}, \; i = 1,\ 2,$$

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 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, TKF are used. The futures rates are closing prices based on the futures contracts underlying these 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. First, the futures rates of the nearest contract are collected until the contract reaches the first week of the expiration month. Second, we roll over to the next nearest contract. Third, we repeat the two procedures. To keep the 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 are obtained from the Bloomberg Termina. 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.

[Insert Table 1 Here]

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, the standard deviation, the skewness, the excess kurtosis are also reported. They are computed in the same way as 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, Chan, and Karolyi (1991), Sharown and Gregary (1995), Faff and Mckenzie (2002), Ellueca 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

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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.

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 multivariate normal distribution to avoid misspecification.

[Insert Table 2 Here]

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 series are stationary which is consistent with the literature. In general, the results of the unit root tests indicate that each return series is stationary.

3. Empirical Results

[Insert Table 3 Here]

In this section, the in-sample estimation and out-of-sample forecasting results of the CCC-GARCH models are reported. In addition, a check is 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 $\hat{v}$, representing the degree of freedom coefficients are 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 $\xi_f < 1$ which indicates that the standardized residuals of the Shanghai spot and futures equations are relatively negative-skewed, respectively.

In addition, the log-likelihood value of the bivariate normal model and the bivariate student- t

model MC2 are -2373.767 and -2267.385, respectively. That is, the bivariate Student density increases the log-likelihood value by around 100 for incorporating an excess kurtosis parameter. The lower values of both AIC and SIC also supports 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 in 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 conduct the Likelihood Ratio (LR) test of the null hypothesis of symmetry, i.e. H0 : $\xi_s = \xi_f = 0$. 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 criterias, 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. For the SHF, however, the CCC-BGARCH with bivariate student t models are 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 construct a hedged portfolio based on the two types of OHRs estimated under various distributions. The hedged portfolio at time t is defined in equation (1). We compute and compare the reduction in variance of each portfolio return (VR) relative to the no hedging position.

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

[Insert Table 4 Here]

Table 4 reports the in-sample and out-of-sample performances of the optimal hedge ratios from the CCC-BGARCH models and OLS and naïve hedging strategies. For hedging with the SHF contract in Panel A, all the CCC-BGARCH models produce higher variance reductions than the OLS and naïve hedging strategies. The CCC-BGARCH models with multivariate student t distributions outperform those with normal and skewed-t distributions in terms of variance reductions.

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 produce the largest variance reduction, while the model with normal has the lowest. All the three CCC-BGARCH models outperform the OLS and naïve strategies.

In general, the OHR under the CCC-BGARCH models outperforms the OLS and naïve strategy in any cases. However, the magnitude of risk reductions of the models is very small, ranging from 5.6% to 8.7%; i.e., the models perform poorly. This can be attributed to numerous factors, for instance, data frequency, model misspecifications and so on. In the following subsections, we will try to analyze possible factors.

3.2. Time-varying Conditional Correlations

The correlations and volatilities are changeable over time, which means the OHR should be adjusted to account for the most recent information. The CCC-BGARCH model, however, assumes the constant conditional correlation between spot and futures return. 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 improves 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:

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

where ε_t is the unexpected returns and has the same definition as in equation (11). $h_{ss,t}$ and $h_{ff,t}$ follow the same process as in equations (14) and (15). u_t represents the vector of standardized ε_t . Q_t is the 2×2 positive definite covariance matrix with the parameters $\varphi_1 \geq 0,\quad \varphi_2 \geq 0$ and $\varphi_1 + \varphi_2 < 1$. $\overline{Q}$ is the unconditional covariance matrix of u_t .

[Insert Table 5 Here]

Table 5 shows the results for the DCC-BGARCH models. For the in-sample estimation, the DCC-BGARCH with skewed-t distribution produces the largest variance reduction. The DCC-BGARCH with student t distribution performs the best in terms of variance reduction for the out-of-sample forecasting. All the DCC-BGARCH models perform better than the OLS and naïve strategies.

When compare the hedging performance between the CCC-BGARCH and DCC-BGARCH models, we can see 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, around 10% to12.4%. Thus, both the results in subsection 3.1 and 3.2 imply that the SHF contract, at least in daily data, cannot provide satisfactory protection to risk exposure. In this subsection, we propose another futures contract, the TKF contract, which can provide better hedge against variance risk. The results are presented in Table 6. Panel A and B display the results for CCC-BGARCH and DCC-BGARCH models, respectively.

[Insert Table 6 Here]

For the in-sample estimation, all the BGARCH specifications using the TKF contract produce higher variance reductions than those using the SHF contract. To be specific, the CCC-BGARCH models using the TKF data can achieve variance reduction by 17% to 18%, while those using the SHF are only around 5.6% to 8.7%. Similarly, the DCC-BGARCH models using the TKF data produce variance reduction by around 10.6% to 17.7%, compared with 10% to 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 run the model using other futures contracts, for example, WTI from NYEMEX, and heating and crude oil contracts from India futures exchange; unfortunately, expected results were not obtained, and results are provided upon request.

3.4. Hedging with Weekly Data

[Insert Table 7 Here]

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 to speculate in the market. This argument is consistent with the findings of Moon el al. (2010). The authors employ daily, weekly and monthly crude oil futures and gold futures traded at the New York Mercantile Exchange (NYMEX) from March 1983 to November 2007. Using various GARCH models evidence is found that there is more variance reduction as the sample frequency declines from daily to weekly to monthly. This result implies less frequent hedging trading would be more beneficial.

In this subsection, weekly data are used to analyze the hedging performance of various models and results are presented in Table 7. Panel A reports results for the SHF contract and Panel B for the TKF. For both the in-sample estimation and out-of-sample forecasting, all the BGARCH models produce higher variance reduction than the OLS and naïve strategies. The SHF contract reduces risk in terms of out-of-sample variance reduction by around 40% to 49%, and the TKF contract reduces risk by around 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 empirical results for developed countries.

4. Conclusions

Hedging using futures contract is a popular short-term risk-minimizing strategy for investors. Successful hedging strategy gives investors protection against currency exchange rate changes. In this paper, the authors examine the hedging performances of the domestic SHF and the TKF futures contracts. The results reveal 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 return and avoid misspecification of the models, we estimate 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 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, (2002, 2009), and Park and Jie, (2009)).

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 the Chinese energy fuel oil market is not well-established and more market and regulation efforts are needed to help investors diversify risk exposure.

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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	8379.680[0.000]	26638.600[0.000]	12560.200[0.000]
Q(20)	451.076[0.000]	50.771[0.000]	65.614[0.000]

Notes: 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

Notes: ADF corresponds to statistic of Augmented Dicky-Fuller test of the null hypothesis that t 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

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	-2531.051	-2381.846	-2384.715	-2373.767	-2267.385	-2118.036
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

Notes: The table reports the CCC-BGARCH results under flexible distributions for the SHF and TKF. The first six rows presents the estimated coefficients for the BGARCH models. Loglik, AIC, BIC are the maximum loglikelyhood value, Akaike information criteria and Schwarz information criteria of the models. The numbers in parentheses are the standard errors. * denote the 5% significance levels.

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

Notes: The table reports the magnitude of variance reduction (VR) of each models.

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

Notes: The table reports the magnitude of variance reduction (VR) of each models.

Table 6. Cross-Hedge Performance of TKF

			CCC-BGARCH			**DCC-BGARCH**		
	OLS	Naïve	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

Notes: The table reports the magnitude of variance reduction (VR) of each models.

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

Notes: This table reports the magnitude of variance reduction (VR) of each models using weekly data.