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The hedging effectiveness of carbon futures market: an empirical analysis of European Union allowance (EUA)

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ABSTRACT

In recent years emissions allowances markets have become the most promising and quickly growing markets in the global commodities markets. The key issue of futures market is to determine hedge ratio properly and improve the hedging effect to averse the price risk of spot market. In this paper, we estimate the optimal hedge ratios and hedging effectiveness between spot and futures for European union allowance (EUA). It is concluded that the methods of Ordinary Least Square, Error Correction Model based on co-integrating relationship, and two kinds of Bivariate Generalized Autoregressive Conditional Heteroskedasticity models (Constant Conditional Correlation, CCC-BGARCH and Dynamic Conditional Correlation, DCC-BGARCH) can improve the hedging effectiveness strongly and more than 90% of the portfolio risk is avoided through hedging.

KEYWORDS Carbon Futures; Risk Hedging; Hedge Ratio; Multivariate GARCH

1 Introduction

The twenty-first session of the Conference of the Parties (COP) and the eleventh session of the Conference of the Parties serving as the meeting of the Parties to the Kyoto Protocol (CMP) takes place from 30 November to 11 December 2015, in Paris, France. UN negotiations are under way to develop a new international climate change agreement that will cover all countries. The new agreement will be adopted at the Paris climate conference in December 2015 and implemented from 2020. The European Commission has set out the EU's vision for a new agreement that will, through collective commitments based on scientific evidence, put the world on track to reduce global emissions by at least 60% below 2010 levels by 2050. Increasingly, emissions' trading is proving to be the preferred policy option in achieving emissions reductions. The rapid growth of the EU-ETS and the increasingly important position it occupies in the drift towards combating climate change has elicited the interest of industry experts and academics (see Frino et al. 2010; Montagnoli and de Vries, 2010; Zhang and Wei, 2010; Daskalakis et al. 2011). The European Union Emissions Trading System (EU ETS) is the main international carbon trading market, in which European Union allowances (EUAs) are traded with increasing intensity. One European Union Allowance (EUA) grants the holder the right to emit one ton of CO2.

Studies on hedging of carbon futures have been developed for recent years. Several empirical results show that spot and futures prices for emissions allowances contain a dynamic behavior. Benz and truck (2009) analyze the short-term spot price behavior of carbon emission allowances. Daskalakis and Psychoyios (2009) develop an empirical and theoretical valid framework for the hedging of futures and options for emissions allowances. Milunovich and Joyeux (2010) examine the issues of market efficiency and price discovery in emissions allowances futures markets under the EU ETS. Chevallier (2010) analyzes the modelling of risk premium in CO2 allowances spot and futures prices. Chang (2013) proposes time-varying hedge ratios and hedging effectiveness estimation using ECM-GARCH model. This paper is organized as follows. Section 2 provides the hedging theory and the models which are fitted to compute the optimal hedge ratio. Section 3 presents an empirical analysis of EUA. Section 4 concludes.

2 Methodology

2.1 Hedging theory

Ederington derives hedge ratios that minimize the variance of the hedged portfolio. Let $\triangle S_t$ and $\triangle F_t$ represent the log returns on spot and futures on the portfolio between period t and t-1. Define h as the ratio of futures holdings to a spot position that minimizes the

risk of the hedged portfolio. Then R_t is the return on the portfolio, which is given by

$$R_t = \Delta S_t - h\Delta F_t \quad (1)$$

$$\Delta S_t = \ln S_t - \ln S_{t-1}, \quad t = 1,...,T \quad (2)$$

$$\Delta F_t = \ln F_t - \ln F_{t-1}, \quad t = 1,...,T \quad (3)$$

The expected return E (R_t) and variance (R_t) of the portfolio are respectively as follows.

$$E(R_t) = E(\Delta S_t) - hE(\Delta F_t) \quad (4)$$

$$\begin{aligned} Var(R_t) &= Var(\Delta S_t) - 2hCov(\Delta S_t, \Delta F_t) + h^2 Var(\Delta F_t) \\ &= \sigma_{\Delta S}^2 - 2h\sigma_{\Delta S \Delta F} + h^2\sigma_{\Delta F}^2 \end{aligned} \quad (5)$$

Where $\sigma_{\triangle S}$ is the standard deviation of $\triangle S_t$, $\sigma_{\triangle F}$ is the standard deviation of $\triangle F_t$, $\sigma_{\triangle S \triangle F}$ is the covariance of $\triangle S_t$ and $\triangle F_t$. The optimal hedging ratio should be the optimal solution of the unconstrained optimization problems.

$$\min Var(R_t) = \sigma_{\Delta S}^2 - 2h\sigma_{\Delta S \Delta F} + h^2\sigma_{\Delta F}^2 \quad (6)$$

Solve the equation to get optimal solution as

$$h^* = \frac{\sigma_{\Delta S \Delta F}}{\sigma_{\Delta F}^2} = \frac{\rho\sigma_{\Delta S}\sigma_{\Delta F}}{\sigma_{\Delta F}^2} = \rho\frac{\sigma_{\Delta S}}{\sigma_{\Delta F}} \quad (7)$$

Where ρ is the correlation coefficient between $\triangle S_t$ and $\triangle F_t$.

2.2 Models for the estimation of hedge ratio

2.2.1 Ordinary Least Square

The OLS model for the estimation of hedge ratio is to establish the regression equation on the spot and futures returns data. The slope h is optimal hedging ratio.

$$\Delta S_t = \alpha + h\Delta F_t + e_t \quad (8)$$

2.2.2 Error Correction Model

$$\Delta S_t = \alpha + h\Delta F_t + \beta Z_{t-1} + e_t \quad (9)$$

$$\text{ECM: } Z_{t-1} = \ln S_{t-1} - \ln F_{t-1} \quad (10)$$

Where Z_{t-1} is the error correction term, h is the hedging ratio. α and β are the parameters.

2.2.3 Two kinds of GARCH models

An appropriate way to capture the time varying nature of volatility is the GARCH (p, q) process, which is given by

$$\begin{aligned} r_t &= u + e_t \\ e_t | \psi_{t-1} &\sim N(0, \sigma_t^2) \end{aligned} \quad (11)$$

$$\sigma_t^2 = c + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (12)$$

Where e_t denotes a real-valued discrete-time stochastic process, Ψ_{t-1} is the information set generated by the past values of e_t, σ_t^2 is known as the conditional variance.

The extension from a univariate GARCH model to a bivariate model requires allowing the conditional variance-covariance matrix of the m-dimensional zero mean random variables e_t, to depend on elements of the information set. Letting H_t, be measurable with respect to Ψ_{t-1}, the bivariate GARCH model can be written as

$$\begin{cases} r_{S,t} = u_S + e_{S,t} \\ r_{F,t} = u_F + e_{F,t} \end{cases}, \begin{pmatrix} e_{S,t} \\ e_{F,t} \end{pmatrix} | \psi_{t-1} \sim N(0, H_t) \quad (13)$$

$$H_t = \begin{bmatrix} \sigma_{S,t}^2 & \sigma_{SF,t} \\ \sigma_{SF,t} & \sigma_{F,t}^2 \end{bmatrix} = \begin{bmatrix} \sigma_{S,t} & 0 \\ 0 & \sigma_{F,t} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} \sigma_{S,t} & 0 \\ 0 & \sigma_{F,t} \end{bmatrix} \quad (14)$$

The conditional correlation coefficient between two random variables $\triangle S_t$ and $\triangle F_t$ that each have mean zero is defined

$$\rho_{ij,t} = h_{ij,t} / \sqrt{h_{ii,t} h_{jj,t}} \quad (15)$$

Where $h_{ij,t}$ is the row i and column j elements of conditional covariance matrix H_t. Then according to whether the correlation coefficient $\rho_{ij,t}$ is a constant, the multivariate GARCH model is divided into two categories:

A. CCC-BGARCH

The CCC-BGARCH model assumes that the $\rho_{ij,t}$ is a constant, and the relevant structure of the conditional covariance matrix representation of H_t is written by

$$H_t = D_t R D_t = (\rho_{ij} \sqrt{h_{iit} h_{jjt}}) \quad (16)$$

$$D_t = diag(\sqrt{h_{11,t}} \cdots \sqrt{h_{nn,t}}) \quad (17)$$

$$R = (\rho_{ij})_{N \times N} \quad (18)$$

$$h_{ii,t} = w_i + \sum_{p=1}^{P_i} \alpha_{i,p} e_{i,t-p}^2 + \sum_{q=1}^{Q_i} \beta_{i,q} h_{i,t-q} \quad (19)$$

B. DCC-BGARCH

The DCC-BGARCH model assumes that the $\rho_{ij,t}$ is time-varing, and the relevant structure

of the conditional covariance matrix representation of H_t is

$$H_t = D_t R_t D_t \quad (20)$$

$$\varepsilon_t = D_t^{-1} e_t \quad (21)$$

$$Q_t = \bar{Q} \circ (\upsilon' - A - B) + A \circ \varepsilon_{t-1} \varepsilon_{t-1}' + B \circ Q_{t-1} \quad (22)$$

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1} \quad (23)$$

2.2 Performance Evaluation

The residual risk of the portfolio after hedging strategy and the hedging effectiveness are calculated as follows:

$$Var(R(h^*)) = Var(\Delta S - h^* \Delta F) = \sigma_{\Delta S}^2 - 2h^* \rho \sigma_{\Delta S} \sigma_{\Delta F} + h^{*2} \sigma_{\Delta F}^2 \quad (24)$$

$$H_E = \frac{\sigma_{\Delta S}^2 - Var(R(h^*))}{\sigma_{\Delta S}^2} = 1 - \frac{Var(R(h^*))}{\sigma_{\Delta S}^2} \quad (25)$$

3 Data and empirical results

3.1Data

Daily settlement price from the spot and the futures markets of European Union allowances (EUAs) are used in the empirical tests. The sample data of 118 trading days are from July 1st to December 11th in 2015. Some descriptive statistics are presented in Table 1. As previously found in other studies, returns exhibit excess kurtosis and skewness.

Table 1 Statistics of CSI 300 index futures and spot return series

Series	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
△S	0.000689	0.033209	-0.035305	0.010546	0.119427	3.912596
△F	0.000655	0.033040	-0.035305	0.010490	0.108014	3.906965

3.2 The estimation of hedging ratio

3.2.1 Hedging ratio estimated by OLS

$$\Delta S_t = 0.00004 + 0.9881 \Delta F_t + e_t \quad (26)$$

regression equation indicate that the coefficient of the explanatory variables $\triangle F_t$ is significant. The regression results show that investors need to purchase 0.9881 units futures positions for each unit of the spot position in the opposite direction to hedge.

$$\Delta S_t = 0.00003 + 0.9842 \Delta F_t - 0.4482 ECM_{t-1} + e_t \quad (27)$$

The optimal hedge ratio is 0.9842 which is smaller than the estimation value of the OLS model.

3.2.3 Hedging ratio estimated by two kinds of GARCH models

The optimal hedge ratios estimated by CCC-BGARCH and DCC-BGARCH model are dynamic time series, illustrated in Figure 1.

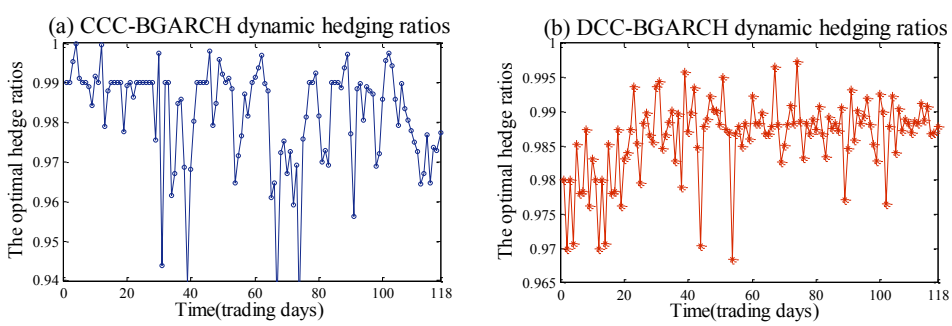


Figure 1 Dynamic hedging ratios estimated by CCC-BGARCH and DCC-BGARCH model

3.2.4 Comparison of hedging effectiveness

According to the performance evaluation index of the optimal hedging models, the hedging performance of the different model (OLS, ECM, CCC-BGARCH and DCC-BGARCH) is shown in table 2. It is concluded that the methods can improve the hedging effectiveness strongly and more than 90% of the portfolio risk is avoided through hedging.

Table 2 Hedging efficiency of OLS、ECM、CCC-BGARCH and DCC-BGARCH model

Models	Standard deviation of returns before hedging	Standard deviation of returns after hedging	Hedging performance
OLS	1.055%	0.194%	96.602%
ECM	1.055%	0.194%	96.600%
CCC-BGARCH	1.055%	0.195%	96.597%
DCC-BGARCH	1.055%	0.195%	96.586%

4 Conclusions

In this paper, we apply some models for the estimation of the optimal hedge ratio and their effectiveness of the hedging models, including Ordinary Least Square, Error Correction Model based on co-integrating relationship, and two kinds of Bivariate Generalized Autoregressive Conditional Heteroskedasticity models (CCC-BGARCH and DCC-BGARCH). Our findings suggest that all of the methods can improve the hedging effectiveness strongly and more than 90% of the portfolio risk is avoided through hedging.

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