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Hedging with Futures: Does the Complex Model Beat the Simply Model When There is a Change in the Market Environment?

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Abstract:

This paper investigates the difference in hedging performance between complex models and simple models when there is a change in the market environment from the perspective of model misspecification and estimation error. Dynamic VAR-DCC-GARCH models are constructed to represent complex models and static OLS, VAR, EC-VAR models are selected to represent simple models. Our main findings suggest that there is no significant difference in hedging performance between the simple model and the complex model within the sample (the period before the market environment changes). There is a decline in the out-of-sample performance of the two types of models, and the hedging efficiency of the complex model falls more than the simple model, its out-of-sample performance is inferior to the simple model.

Keywords*: Stock index futures, Hedging, Stochastic process, Model selection, Model misleading risk, Model estimated risk.*

I. INTRODUCTION

Economic laws (if any) contained in complex economic phenomena must be objective, and there must be a most suitable econometric model that can be used to describe it. The model exists objectively, but it cannot be seen or touched, just like the “Black Cat in the Black Room”. The performance of the econometric model ultimately depends on two factors, one is the model misspecification. What an economist can do is rely on relevant theories, experience, and historical data to subjectively select models, and make statistical inferences based on the selected model, the idea behind it is to treat the model as a real model. However, the selected model is closely related to the historical background and macro policy. Once the background or policy changes, the relationship between economic variables will be destroyed. Continue to use the model to speculate about the future, which can easily lead to misleading risks [1]. The other is model estimation error. Assuming that we have chosen an effective model, but the true value of model parameters is unknown. The estimation of parameters depends on historical data containing noise information, then we use the estimated value for statistical inference, which may lead to the estimated risk.

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One of the core issues in futures research is to apply different models to estimate the optimal hedge ratio. A large number of studies have shown that the hedging effect of complex (or advanced) models is better than simple models [2-6]. Other studies have reached the opposite conclusion, they believe that the hedging performance of simple models is not necessarily inferior to complex (or advanced) models [7,8]. After combing and analyzing a large amount of literature, Moosa [9] found that although specification of a model is very important theoretically, the difference in efficiency brought by choosing a model does not seem to be significant. The futures hedging efficiency of seven dynamic and static models was compared by Poomimars et al. (2003) [10], and the results showed that there is no significant difference in hedging efficiency between the dynamic and the static model. Alexander and Barbosa [11] also reached similar conclusions. However, most of these studies stop at empirical results, and do not provide a more in-depth theoretical explanation for "Why the hedging efficiency of complex models is not necessarily higher than that of simple models". Although some scholars have begun to explain the principles. For example, Huang Ning et al. [12] used the sample stocks that are constituents of the CSI 800 earning announcement between 2010 to 2014, and make beta the point of penetration to research on the ineffectiveness of hedging resulting from the changing of news. The study involves the idea of "Information Changes Lead to Unreliable Estimation Results". Unfortunately, the author has not carried out further research on this idea. Fu Jianru and Zhang Zongcheng [7] used copper futures data from February 12, 2004 to January 9, 2009, to conduct an empirical test of model complexity and hedging effectiveness, and carried out a more in-depth theoretical explanation. However, the study of Fu Jianru and Zhang Zongcheng [7] still has some debatable points in the empirical test. One is that when judging whether the environment has changed, it has not undergone strict econometrics tests. The other is to use the random coefficient Markov Regime Switching (RCMRS) model as the complex model. The RCMRS model is not consistent with the modeling ideas of common models such as OLS, VAR, VECM, and GARCH, and it is difficult to define which model is more complex.

Because of this, we intend to further discuss the hedging performance of the model. According to the studies of Lucas [1], Lence and Hayes [13], Fu Jianru and Zhang Zongcheng [7], we believe that complex models have relatively less model-misspecification risk than simple models. However, more variables, parameters, and assumptions are likely to bring more noise, resulting in a relatively high risk of model estimation. Since the model setting, testing, and estimation are based on the economic environment within the sample, when the economic environment outside the sample changes, model (misset) risk and estimated risk of the complex model may be greater than that of the simple model, resulting in the performance of the complex model will be worse. Therefore, we propose a research hypothesis: when the market environment changes, the out-of-sample performance of the complex model is worse than that of the simple model. Compared with the in-sample hedging efficiency, the out-of-sample hedging efficiency of the complex model decreases more than the simple model.

To test the research hypothesis, we select samples that of suspected environmental changes, used relevant econometric theory to test the environmental changes of the samples, and explored the hedging performance of complex models and simple models based on environmental change samples. Compared with other related documents, this article solves two key issues of environmental change and model

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complexity definition: One is whether the selected samples have environmental changes is critical to the reliability of the research conclusions. This article adopts the test methods of Pfaff [14], Fu Jianru et al. [15] to examine the sample environment from multiple aspects. Check whether changes have occurred, making the research more rigorous. The other is Dynamic VAR-DCC-GARCH models are constructed to represent complex models and static OLS, VAR, EC-VAR models are selected to represent simple models. The two types of models have the same modeling ideas and are in the same line, which can ensure a clear definition of model complexity and simplicity.

The remainder of this paper is organized as follows. Section 2 describes the theory and method of judging the change of interval and explains the modeling idea of the complex model. Section 3 explains the data. Section 4 presents the main empirical results. Section 5 concludes the paper.

II. MATERIALS AND METHODS

The effectiveness of hypothesis testing in this article depends on two points: One is that there are significant environmental changes in the selected samples, and the other is that the hedging model used for comparison should ensure that the modeling ideas are consistent. Therefore, we first explain the theory and method of judging the interval mutation; then we explain the modeling idea of the selected complex model and simple model.

2.1 Judgment of Mutation Interval

To judge whether there are changes in the market environment in the selected sample interval, we try to test from two dimensions: One is to study the stationarity and stochastic process of the price series of a single market (the futures market and the spot market) respectively; The second is to explore the interaction between different markets and the information transmission mechanism.

2.1.1 Research on stationarity and stochastic process of futures and spots

The existing literature on the stability of futures and spot prices is mostly limited to simple unit root tests, and the stochastic process of futures and spot prices is rarely discussed. This article discusses the specific stochastic process followed by futures and spot prices. Firstly, it is necessary to determine whether the sequence of futures and spot logarithmic returns is stable; Secondly, if it is stable, we need to determine whether it is zero mean stationary? Or is the linear trend stable? If it is non-stationary, we need to check whether it has drift? According to the ADF three-stage inspection method [14], the specific model is set as follows:

$$\Delta y_t = \beta_1 + \beta_2 t + \pi y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-j} + \varepsilon_t \tag{1}$$

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$$\Delta y_t = \beta_1 + \pi y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-j} + \varepsilon_t \tag{2}$$

$$\Delta y_t = \pi y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-j} + \varepsilon_t \tag{3}$$

In the formula, y_{t-1} is the logarithm of the stock index spot and futures prices at the time $t-1$. Δy_t is the logarithmic return rate of stock index spot and futures at time t. ε_t represents the random error term a the time t, and k represents the lag order.

For the determination of the lag order k, this article adopts a general-to-specific method, using two information criterion indicators, namely AIC and BIC for judgment. The details are as follows: First, the lag stage k is initially selected through the two information criterion indicators of AIC and BIC; then, when the lag order is k, in the estimated result of the formula (1), whether the coefficient of Δy_{t-k} is significant and the residual error of ε_t estimates whether the sequence is uncorrelated. If the answer is yes, proceed to the next step, which is to judge whether the coefficient estimated by formula (1) is not significant when the lag order is $k-1$. When the lag order is $k-1$, the equation (1) estimates whether the residual sequence of ε_t is sequence correlation. If the answer is yes, determine $k-1$ as the lag order.

After determining the lag order k, follow the steps below to check. Step 1, estimate the formula (1), and use the t statistic τ_3 to test the authenticity of the null hypothesis "$\pi = 0$". The critical value in Fuller's study is used as the criterion (not the standard student t distribution). If τ_3 is greater than the Fuller critical value, the "$\pi = 0$" hypothesis cannot be accepted, and the logarithmic rate of return sequence is judged to be linear and stable, and the test ends; Step two, otherwise, proceed to step two test, which calculates the statistic ϕ_3 (F test), and use the critical value calculated by Dickey and Fuller to test the hypothesis "$\beta_2 = \pi = 0$". If ϕ_3 is significant, then use the standardized normal distribution statistics to re-test whether the hypothesis "$\pi = 0$" is true. If it is not true, the time series is linear and stable. If it is true, the time series contains unit roots with drift. Step 3, if ϕ_3 is not significant, estimate the formula (2), and then use the statistics τ_2 (t test) and statistics ϕ_1 (F test) to test the truth of the hypotheses "$\pi = 0$" and "$\beta_1 = \pi = 0$" as in the previous two steps. If the t-test is significant, the test ends, indicating that the non-zero mean of the time series is stable. Otherwise, the F test is continued. If it is significant, then use the standardized normal distribution statistics to re-test whether the hypothesis "$\pi = 0$" is true. If it is not true, the time series is stable with zero mean; if it is true, the time series contains unit roots with drift; Step 4, if the F test in step 3 is not significant, then estimate formula (3) and perform t-test on the hypothesis "$\pi = 0$". The significance indicates that the zero mean of the time series is stable, and the insignificance indicates that the time series is a pure random walk process. Which contains unit roots

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without drift.

2.1.2 The mutual influence and information transmission between the futures market and the spot market

Engle and Granger [16] proposed a "two-step" judgment method for the cointegration test. For the multivariate autoregressive process, Johansen[17][18], Johansen and Juselius [19] established two statistics, the maximum eigenvalue and the trace, to judge whether there are a cointegration relationship and cointegration rank among time series variables. This paper uses trace and maximum eigenvalue statistics to test the long-term stable relationship between futures and spots.

If there is a cointegration relationship between time series variables, it indicates that there is a long-term stable relationship between the futures market and the spot market. Therefore, the error-corrected vector autoregressive (EC-VAR) model is used to describe the futures spot logarithmic price series and its difference series.

$$\Delta S_t = c_1 + e_1 Z_{t-1} + \sum_{i=1}^{m} \alpha_{1i} \Delta S_{t-i} + \sum_{i=1}^{n} \beta_{1i} \Delta F_{t-i} + \varepsilon_{1t} \tag{4}$$

$$\Delta F_t = c_2 + e_2 Z_{t-1} + \sum_{i=1}^{m} \alpha_{2i} \Delta S_{t-i} + \sum_{i=1}^{n} \beta_{2i} \Delta F_{t-i} + \varepsilon_{2t} \tag{5}$$

$$Z_{t-1} = S_{t-1} - \left(a + bF_{t-1}\right) \tag{6}$$

In the above formulas, ΔS_t is the first-order difference of the spot logarithmic price at the time t, ΔF_t is the first-order difference of the futures logarithmic price at the time t, S_t is the spot logarithmic price at time t, and F_t is the logarithmic price of futures at the time t; ε_{1t} and ε_{2t} are white noise residuals; Z_{t-1} is the error correction term in the period $t-1$, indicating the deviation from the long-term equilibrium of the previous period. The model shows that the change of and is composed of two parts, one is the adjustment of the "short-term effect" caused by the previous a and b; the other is the adjustment of the "long-term effect" caused by the long-term equilibrium relationship between the two. If the coefficient e_1(e_2) of the error correction term of ΔS_t (ΔF_t) in equations (4) and (5) is smaller, the tendency of S_t (F_t) to be adjusted to correct the unbalanced state will be smaller; vice versa. Most adjustments will be done through F_t (S_t), which is spot a (futures) plays an important role in the price discovery function. At the same time, it can be seen from the definition of the error correction term of the above formula: when $Z_{t-1} > 0$, to return to the long-term equilibrium state, either F_t increases or S_t decreases, or both occur simultaneously. Therefore, theoretically judged, the error correction coefficient e_1 should be less than 0,

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and e_2 should be greater than 0.

When there is no co-integration relationship between futures and spots, the vector autoregressive (VAR) model is used to study the lead-lag relationship between the futures market and the spot market.

$$\Delta S_t = c_1 + \sum_{i=1}^{m} \alpha_{1i} \Delta S_{t-i} + \sum_{i=1}^{n} \beta_{1i} \Delta F_{t-i} + \varepsilon_{1t} \tag{7}$$

$$\Delta F_t = c_2 + \sum_{i=1}^{m} \alpha_{2i} \Delta S_{t-i} + \sum_{i=1}^{n} \beta_{2i} \Delta F_{t-i} + \varepsilon_{2t} \tag{8}$$

In equation (7), ΔS_t is the first-order difference of the spot logarithmic price at the time t, and in equation (8), ΔF_t is the first-order difference of the futures log price at the time t, ε_{1t} and ε_{2t} are white noise residuals. The structure and lag order of the model of formula (7), formula (8) and formula (4), formula (5), formula (6) are consistent, but do not include error correction term.

This paper studies the short-term relationship between spots and futures using the Granger causality test method. The Granger causality between the two depends on the coefficients a and b in the EC-VAR model and the VAR model. Once some α_{2i} are significantly non-zero, then it can be considered that the spot Granger affects futures, specifically expressed as “There is a one-way relationship from spot to futures under the Granger causality test"; and once some β_{1i} is significantly non-zero, the futures Granger affects the spot, which is specifically expressed as "There is a one-way relationship from futures to spot under the Granger causality test".

2.2 Model Setting: VAR-DCC-GARCH Model

Ederington [20] first proposed the OLS model to estimate the optimal hedge ratio of futures. The researchers found that one of the reasons for the distortion of the OLS regression equation is its residual autocorrelation. To solve this problem, the B-VAR model is used to describe the changes in spot prices and futures prices. However, Lien [22], Lien and Luo [19] believed that the B-VAR model did not consider the co-integration relationship between spot prices and futures prices, and therefore used an error correction model to analyze the optimal hedging ratio. Empirical research shows that time-varying conditional moments are widely used in economic and financial time series. Because the positive semidefiniteness of the conditional variance-covariance matrix of the spot and futures returns can be guaranteed, Bollerslev [24] uses the often correlated GARCH model to describe the time-varying conditional moment, which is widely used. Decompose the covariance matrix of the mean equation into the following forms:

$$H_t = D_t R D_t = \rho_{ij} \sqrt{h_{iit} h_{jjt}} \tag{9}$$

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$$h_t = \omega + \sum_{i=1}^{p} A_i \varepsilon_{t-i} \circ \varepsilon_{t-i} + \sum_{i=1}^{q} B_i h_{t-i} \tag{10}$$

In the formula, $D_t = diag(\sqrt{h_{11,t}},\ldots,\sqrt{h_{nn,t}})$, ω is the n-dimensional column vector. R is a symmetric positive-definite matrix which elements are the (constant) conditional correlations $\rho_{ij}, i,j=1,\ldots,k$(with $\rho_{ij} = 1$, for $i = j$). A_i and B_i are $n \times n$ diagonal matrices, and $\circ$ is the matrix Hadamard operator. The elements of ω, A_i and B_i are positive numbers.

Engle [25] pointed out that, from a practical perspective, the assumption of the invariant conditional correlation coefficient is too strict. Therefore, the following time-varying correlation coefficient model is proposed:

$$H_t = D_t R_t D_t \tag{11}$$

Engle (2002) [20] constructed the following proxy process Q_t to ensure that the moment R_t is a positive definite matrix:

$$Q_t = \overline{Q} + a\left(z_{t-1}z'_{t-1} - \overline{Q}\right) + b\left(Q_{t-1} - \overline{Q}\right) = (1-a-b)\overline{Q} + az_{t-1}z'_{t-1} + bQ_{t-1} \tag{12}$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{13}$$

In the formula, $z_t = D_t^{-1}\varepsilon_t$, a and b are non-negative scalar quantities, and $a+b<0$ is to ensure the stability and positive definiteness of Q_t. $\overline{Q}$ is the unconditional covariance matrix of the standardized residual z_t.

III.DATA SELECTION

There are currently three types of stock index futures on the China Financial Futures Exchange: Shanghai and Shenzhen 300 Index Futures (IF), Shanghai 50 Index Futures (IH), and China Securities 500 Index Futures (IC). CSI 300 index futures were officially listed on April 16, 2010, and Shanghai 50 Index futures and China Securities 500 Index futures were both listed on April 16, 2015. This article discusses the selection of futures hedging models in the sample mutation interval and takes the Chinese A-share market in June 2015 to bid farewell to the bull market and begin to plummet as the mutation point of the sample mutation interval. The SSE 50 Index futures and CSI 500 Index futures have too few samples in the interval before the mutation point. Therefore, this paper only uses the CSI 300 Index and CSI 300 Index

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futures for empirical testing. Take the research sample from April 16, 2014 to September 2, 2015, a total of 342 trading days.

To test the proposed hypothesis, this paper selects a sample interval that contains a sudden change in the economic environment. The sample before the mutation is sample interval 1 (within the sample), and the sample after the mutation is sample interval 2 (outside the sample). The interval selection for sub-sample 1 is: April 16, 2014 to June 9, 2015, a total of 284 pairs of daily data; the interval selection for sub-sample 2 is: June 10, 2015, to September 2, 2015, a total of 61 To the data. Futures data adopts the continuous sequence of the current month (IF00). The data comes from Wonder.

IV. EMPIRICAL ANALYSIS

4.1 Determination of Market Environment Change

4.1.1 Research on Stationarity and Stochastic Process

Firstly, estimate the formula (1), and the test results are shown in Table 1. It can be seen from Table I that the test statistics τ_3 and ϕ_3 of the futures and spot logarithmic price series of sub-sample 1 (within the sample) are both not significant at the 10% level, but the test statistics ϕ_2 are both significant at the 1% level, indicating For formula (1), the null hypothesis of "$\pi = 0$" and "$\beta_2 = \pi = 0$" is true, but the null hypothesis "$\beta_1 = \pi = 0$" is not true. But the test statistics of futures and spot logarithmic price series τ_3, ϕ_3 and ϕ_2 in sub-sample 2 (out of the sample) are all insignificant at the 10% level, indicating that “a”, “b” And the null hypothesis of "c" are both true.

TABLE I. ADF test with drift and trend terms: logarithmic price series

interval	variable	Lag	Test statistics		Significance
sub-sample 1 (within the sample)	lnxh	1	tau3	-2.2716	▲
			phi2	6.7559	***
			phi3	4.7396	▲
	lnqh00	1	tau3	-2.3553	▲
			phi2	6.6707	***
			phi3	4.8164	▲
sub-sample 2 (out of the sample)	lnxh	1	tau3	-2.9518	▲
			phi2	3.5467	▲
			phi3	4.4828	▲
	lnqh00	1	tau3	-2.9522	▲
			phi2	3.4984	▲
			phi3	4.3773	▲

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Note: *, ** and *** indicate significant at the 10%, 5%, and 1% level respectively; ▲ indicates not significant at the 10% level. The following table is the same.

Continue to test and estimate equation (2). The test results are shown in Table II. It can be seen from Table II, that the τ_2 statistic of the futures and spot logarithmic price series of sub-sample 1 (within the sample), is not significant at the 10% level, and the ϕ_1 statistic is significant at the 5% level. It shows that for equation (2), the null hypothesis "a" is true, but the null hypothesis "b" is rejected. In the sub-sample 2 (out of the sample), the statistics of the futures and spot logarithmic price series a and b are both in Not significant at the 10% level. So, the null hypotheses "A" and "a" are both accepted for equation (2). Combining the test results of equations (1) and (2), it can be determined that the futures and spot logarithmic price series of sub-sample 1 (within the sample) have unit roots and drift, while sub-sample 2 (out of the sample) futures and spot pairs The number price sequence also has unit roots, but without drift, it is a pure random walk process.

TABLE II. ADF test with drift: logarithmic price series

interval	variable	Lag	Test statistics		Significance
sub-sample 1 (within the sample)	lnxh	1	tau2	1.3328	▲
			phi1	6.1566	**
	lnqh00	1	tau2	1.2592	▲
			phi1	5.8553	**
sub-sample 2 (out of the sample)	lnxh	1	tau2	-1.992	▲
			phi1	2.7665	▲
	lnqh00	1	tau2	-1.7575	▲
			phi1	2.3478	▲

Next, test the first-order difference of the stock index futures spot logarithmic time series. The test results are shown in Table III. It is not difficult to find that the null hypothesis "$\pi = 0$" is rejected, indicating that the first-order difference series is stable and the test ends.

TABLE III. ADF test with drift and trend terms: first difference sequence of logarithmic price

interval	variable	Lag	Test statistics		Significance
sub-sample 1	D1_lnxh	1	tau3	-12.3756	***
	D1_lnqh00	1	tau3	-12.7871	***
sub-sample 2	D1_lnxh	1	tau3	-6.3849	***
	D1_lnqh00	1	tau3	-7.0134	***

4.1.2 The mutual influence and information transmission between the futures market and the spot market

Forest Chemicals Review
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A co-integration test is performed on stock index futures and spots to determine whether there is a long-term stable relationship between the two. The test results are shown in Table IV. It is not difficult to find that the two statistics of maximum eigenvalue and trace both show that: sub-sample 1 (within the sample), stock index futures and stock index spot logarithmic price series have a cointegration relationship at the 1% significance level; sub-sample 2 (out of the sample), there is no cointegration relationship between the two.

TABLE IV. Cointegration test

Internal	variable	Maximum eigenvalue statistics			Trace statistics	
		Rank	Test Statistic	Significance	Test Statistic	Significance
sub-sample 1 (within the sample)	I30300 & IF00	r <= 1	1.454872	▲	1.454872	▲
		r = 0	35.19191	***	36.64678	***
sub-sample 2 (out of the sample)	I30300 & IF00	r <= 1	0.116776	▲	0.116776	▲
		r = 0	9.294685	▲	9.411461	▲

To better explore the interaction between stock index futures and spot and the direction of information transmission, according to the previous test results, for the sub-sample 2 (out-of-sample) futures spot log price time series, a vector autoregressive (VAR) model (formula (7) and (8)). For sub-sample 1 (in-sample) futures spot logarithmic price series, the error-corrected vector autoregressive (EC-VAR) model (Equations (4), (5) and (6)) is used to explore the long-term relationship between the two. In the error correction vector autoregressive model, the coefficients and cointegration vectors of the error correction terms are shown in Table V. It is not difficult to find that at the 1% level, the error correction term coefficient of the spot logarithmic price series equation is significant and the sign is negative (under the theoretical judgment), while the error correction term coefficient of the futures logarithmic price series equation is not significant and the sign It is negative (does not meet the theoretical presumption). This shows that when the stock index futures spot price deviates from the long-term equilibrium state, the spot price is generally adjusted to return to the equilibrium state, and the adjustment speed is 43.24%.

TABLE V. Cointegration equation and error correction term coefficients: EC-VAR model

Internal	variable	Cointegration equation coefficient			Error correction factor
		Constant term	Spot	futures	
sub-sample 1	I30300 IF00	0	1	-1.000123***	-0.43242*** -0.177851

To examine the relationship between futures and spots in the short term, Granger (Grange) causality test is used for the VAR model and the EC-VAR model. The test results are shown in Table VI. The

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GRANGE causality test shows that in the interval of sub-sample 1 (within the sample), there is a two-way GRANGE causality between the futures spot price series, but in the second sub-sample (out of the sample), there is no relationship between the futures spot logarithmic price series. GRANGE causality in one direction.

According to the above empirical test results, it can be found whether it is the random process followed by the futures and spot logarithmic price series, or the mutual influence and information transmission mechanism between the futures market and the spot market, whether it is a long-term or short-term relationship, there are obvious differences between sub-sample one and sub-sample two. From this, we judged that there is a significant environmental change between the first sub-sample interval and the second sub-sample interval.

TABLE VI. GRANGE Causality Test of Spot Futures

Sub-sample 1 (within the sample): VEC model			Sub-sample 2 (out of the sample): VAR model		
Dependent variable: D(I30300)			Dependent variable: D(I30300)		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
D(IF00)	9.01	0.029	D(IF00)	2.03	0.363
Dependent variable:D(IF00)			Dependent variable:D(IF00)		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
D(I30300)	16.73	0.001	D(I30300)	1.06	0.588

4.2 Optimal hedging ratio and hedging efficiency

After confirming that the sample has environmental changes, to verify the proposed hypothesis, we plan to use the dynamic VAR-DCC-GARCH model as the main research model, and at the same time use the static OLS, VAR, and EC-VAR models that are in the same line of modeling ideas as the basic model. Test and compare the hedging performance of the two types of models before and after the two stages. Firstly, estimate the VAR model and the EC-VAR model, obtain the estimated residuals of the two types of models, and then perform the bivariate ARCH effect test on the residuals. The test results are shown in Table VII: the chi-square statistics all show high significance, so it shows that there is an ARCH effect.

TABLE VII. Multivariate ARCH effect test

VAR Model			EC-VAR Model		
Chi-sq	df	Prob.	Chi-sq	df	Prob.
144.87	45	2.01E-12	159.03	45	1.21E-14

According to the above empirical test results, considering the single-period model, the VAR-DCC-GARCH model is used to estimate the optimal hedging ratio, and the in-sample and

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out-of-sample hedging efficiencies are calculated separately (using the Ederington [20] measurement method). To compare the hedging efficiency of the complex model and the simple model, we also estimated and calculated the in-sample and out-of-sample hedging efficiency of the three static models of OLS, VAR, and EC-VAR. The specific results are shown in Table VIII.

In terms of the choice of hedging model in the market, in sub-sample 1 (within the sample), the static model and the dynamic model did not show significant differences in hedging efficiency. On the contrary, the hedging efficiency of the static model is slightly higher than that of the dynamic model. It is consistent with the research conclusion of Moosa [9]: Although "model setting is very important" is widely accepted in theory, a large number of studies have shown that the differences in hedging generated by different model settings seem to be disregarded. For sub-sample 2 (out of sample), regardless of static model or dynamic model, the hedging efficiency of sub-sample 1 (within-sample) is inferior to that of hedging. It is particularly worth noting that, compared with the in-sample interval, the dynamic model has the worst out-of-period hedging efficiency, and the degree of decline ((87.33%-63.88%)/87.33%=28.34%) is much higher than that of the static model (OLS Model: (88.63%-81.50%)/88.63%=8%; VAR Model: (88.63%-80.86%)/88.63%=8.77%; EC-VAR Model: (88.58%-80.44%)/88.58%=9.19%)). And it is found that the more complex the model, the greater the drop in the hedging efficiency of the sample period. These conclusions are consistent with our hypotheses.

TABLE VIII. Comparison of Optimal Hedging Ratio and Hedging Efficiency of Spot Futures

Model		Term	Empirical Result
Static	OLS	Hedge ratio	0.883
		Efficiency (Subsample 1)	88.63%
		Efficiency (Subsample 2)	81.50%
	VAR	Hedge ratio	0.900
		Efficiency (Subsample 1)	88.63%
		Efficiency (Subsample 2)	80.86%
	EC-VAR	Hedge ratio	0.909
		Efficiency (Subsample 1)	88.58%
		Efficiency (Subsample 2)	80.44%
dynamic	VAR-DCCGARCH	Hedge ratio (Subsample 1)	0.545
		Hedge ratio (Subsample 2)	0.927
		Efficiency (Subsample 1)	87.33%
		Efficiency (Subsample 2)	63.88%

V. CONCLUSION

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The performance of the econometric model depends on the model (misset) risk and the estimated risk of the model. When the corresponding econometric test is passed, a complex (or advanced) model has a smaller model (misset) risk than a simple model, but because it contains more variables and parameters, the estimated risk of the model is relatively larger. Therefore, the overall performance of the model is not certain to be better than the simple model. When the market environment changes, use the sample to select the model before the change and estimate the model, and then use the selected and estimated model to perform out-of-sample testing on the changed sample, then the model of the complex (or advanced) model (misset) The risk will be greater, considering that the estimated risk of complex (or advanced) models is higher than that of simple models, the performance of complex (or advanced) models should be inferior to simple models in terms of out-of-sample.

This article selects the daily settlement price sequence of the Shanghai and Shenzhen 300 stock indexes and their corresponding futures from April 16, 2014, to September 2, 2015, as the sample, and uses June 10, 2015, as the demarcation point to determine the inside and outside samples period. First, using the methods of Pfaff [14] and Fu Jianru et al. [15], the stationarity and random process characteristics of logarithmic price series within and outside the sample are studied. At the same time, the co-integration test and GRANGE causality test are used to explore the long-term and short-term relationship between the futures spot in the sample and the out-of-sample period, to determine whether the market environment changes in and out of the sample. Then, select the dynamic VAR-DCC-GARCH model with the same modeling ideas as the main research model, and the static OLS, VAR, and EC-VAR models as the basic models to empirically test and compare the hedging performance of the two types of models before and after the two stages. To verify the proposed hypothesis.

The empirical results show that within the sample, the futures spot logarithmic price sequence is a unit root random process with drift, while outside the sample is a pure random walk process. In the sample, there is a long-term co-integration relationship between the futures spot logarithmic price series, and the spot is driven by futures. In the short term, there is a two-way GRANGE causality. Outside of the sample, there is not only any long-term co-integration relationship, but no short-term GARANGE causality in any direction. Therefore, it can be determined that the market environment has changed significantly within and outside the sample. As for hedging efficiency, there is no obvious difference between the static model and the dynamic model in the sample. Outside the sample, the hedging efficiency of all models is inferior to the in-sample efficiency. And, the more complex, the greater the decline in hedging efficiency. The out-of-sample efficiency of the dynamic VAR-DCC-GARCH model decreased by 28.34%, which was the worst performance among all models. The empirical results are consistent with the hypothesis proposed in the article.

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