Comparative Study of Hedging Models in US

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Abstract. This study focuses on the use of three dynamic hedging models in the American stock market, and it computes the dynamic correlation coefficient, dynamic hedging ratio, and hedging effectiveness of three common models (DCC, BEKK, CCC). This paper fills in the gaps in the application and comparison of three hedging models commonly used in the US stock market during the pandemic. The results showed that NASDAQ index and futures were highly correlated and had significant volatility spillover effect before and during the epidemic. The hedging efficiency of the three models before the epidemic was higher than 0.931, and the hedging efficiency of the three models during the epidemic was higher than 0.936. It is proved that futures hedging is a good way to avoid risk no matter before or during the epidemic, and the highest hedging efficiency is dcc-garch.

Keywords: Hedging; US; DCC; CCC.

1. Introduction

Both the China-Us trade war friction in 2018 and the epidemic in early 2020 have a relatively serious impact on the stock market. Therefore, people need to find a suitable way to avoid risk. Futures hedging spot is usually one of the important means for people to reduce risk losses, no matter before or after the epidemic. And it's very important to choose a more stable model for hedging in order to help people maximize their benefits. A few recent studies are available that are relevant, such as Yadav and Aggarwal et al.'s comparison of the VARMA- model with the diagonal-BEKK, and CCC models based on the Chinese equities market [1]. Lee, Huang, and others the price of G7 shares and the portfolio structure for oil (West Texas Intermediate crude) are used to compare the DCC CCC BEKK model [2]. Chen, Li, and others a comparison of the BEKK, DCC, and CCC models using data from the Chinese stock market and crude oil market [3]. Choudhry and Wu et al. carried out a comparison analysis of the four common GARCH models based on the daily stock of 20 UK enterprises [4]. Arouri and Lahiani et al. examined five dynamic hedging models to examine the earnings and volatility spillover effects link Chinese stock and global gold prices markets between 22/03/2004 nd 31/03/2011 [5]. Tansuchat and Chang et al. looked at how four multivariate volatility models (CCC, VARMA-GARCH, DCC, and BEKK) performed on the spot and futures returns of crude oil in the two international crude oil benchmark markets, Brent and WTI. They also calculated the appropriate hedging ratio and portfolio weight [6]. Toyoshima and Nakajima et al. looked at how three multivariate conditional volatility models—DCC, A-DCC, and diagonal-BEKK—affected the profitability of crude oil spot and futures contracts. [7]. Chang, Gonzalez-Serrano, also other Information on the three foreign currencies—the euro, the yen, and the two others—against the dollar on a daily basis for futures and the spot exchange rates. To choose the best monetary hedging approach, (CCC, VARMA-AGARCH, DCC and BEKK) model are used to obtain ideal portfolio weights and ideal hedging ratios. [8] Basher and Sadorsky et al. utilized GO-GARCH, DCC, and ADCC to simulate volatility and conditional correlations between the prices of EM shares, oil, gold, and bonds. In the study's conclusions. The GO-GARCH ratio is sometimes the best option for employing gold as a hedge against the cost of emerging market share [9]. Nawawi and Radzali et al. showed that hedging performed better as during global recession than it did that after crisis through their examination of the connection between Prices in the Asian and London markets for spot and futures. Compared to the lowest variance, CCC, and DCC models, the diagonal BEKK was found to perform better [10].

However, there are few studies on the comparison of ccc-garch, dcc-garch, bekk-garch based on futures hedging spot in the American market. This research tries to close that gap. By examining the dynamic correlation of the internal capital market in the context of the pandemic and contrasting three widely used dynamic hedging models, this research adds to the body of work on the effects of the global financial market. According to what we know, this paper adds the following to the body of literature. First, this paper applies three common models (DCC-garch Bekk-garch ccc-garch) to calculate their dynamic correlations. Through data collection, collation and analysis, it is concluded that futures and spot in the US capital market are closely related before and during the outbreak. Second, this paper calculates the hedging efficiency using the anticipated outcomes of DCC, BEKK, CCC models. According to the empirical analysis, the hedging efficiency of the three models is higher than 0.93 before and during the outbreak, and the highest one is dcc-garch. The pre-outbreak hedging efficiency was 0.939. The post-epidemic hedging efficiency was 0.956. Further confirms that futures hedging is a good hedge in the US market.

This article's subsequent sections are arranged as follows. The data statistics are shown in Section 2. The approach is explained in Section 3, the results are shown in Section 4, and the conclusions are discussed in Section 5.

2. Data Statistics

The data statistics source is given from Investing Finance (https: // www.investing.com). In this paper, the NASDAQ spot and futures index from 2016/12/28-2019/12/28 and 2019/12/28-2022/12/28 were selected. To facilitate the study, 755 and 748 data were selected respectively in this paper. Because they can accurately depict the hedging connection between the US futures market and the US spot market before and during the outbreak, these two time periods were chosen. The basic data are as follows in Table 1 and 2.

Table 1. Descriptive data for the chosen date (from 2016/12/28-2019/12/28)

	spot	futures
mean	0.0008	0.0008
variance	0.0001	0.0001
max	0.0616	0.0648
min	-0.0463	-0.0564
Kurtosis	3.8244	4.9714
Skewness	-0.4144	-0.5422

Table 2. Descriptive data for the chosen date (from 2019/12/28-2022/12/28)

	spot	futures
mean	0.0005	0.0004
variance	0.0004	0.0003
max	0.1007	0.0971
min	-0.1219	-0.1084
Kurtosis	4.8299	4.2709
Skewness	-0.3004	-0.3037

Through data visualization, it can be found that mean and variance of futures and spot are roughly the same before and during the epidemic, the variance of spot is slightly larger, and the fluctuation range of spot data is also larger than futures.

3. Methodology

3.1. DCC-garch

Conventional models are frequently static for the fluctuation analysis of two sequences, but the dynamic correlation coefficient model may actually realize the dynamic correlation between them. The coefficient may change over time, and the difference across sequences varies. The model may be defined using the next.

$$D_t = diag(h_{11t}^{0.5}, \dots h_{ff}^{0.5}) \tag{1}$$

In equation (1), f is the number of variables and t is the current moment.

$$R_t = diag(q_{11t}^{-\frac{1}{2}}, \dots q_{ff\,t}^{-\frac{1}{2}}) Q_t diag(q_{11t}^{-\frac{1}{2}}, \dots q_{fft}^{-\frac{1}{2}}) \tag{2}$$

In equation (2), R_t is the dynamic conditional correlation coefficient matrix of $f \times f$. Residual equation:

$$H_t = D_t R_t D_t \tag{3}$$

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \xi_{t-1} \xi'_{t-1} + \theta_2 Q_{t-1} \tag{4}$$

In equation (3),H_t is the conditional covariance matrix $\mathrm{f} \times \mathrm{f}$. $\mathrm{D_t}$ is the $\mathrm{f} \times \mathrm{f}$ diagonal matrix formed by taking the diagonal elements of the conditional standard deviation over time obtained by the univariate garch model. The conditional covariance matrix H_t is the third equation's first term. $\mathrm{D_t}$ is the $\mathrm{f} \times \mathrm{f}$ diagonal matrix created by calculating the diagonal components of the conditional standard deviation over time that was derived using the univariate garch model. The conditional covariance matrix for $\mathrm{f} \times \mathrm{f}$ is called H_t. The conditional standard deviation over time given by the univariate garch model is taken to construct the diagonal elements of the $\mathrm{f} \times \mathrm{f}$ diagonal matrix, which is denoted by the symbol $\mathrm{D_t}$. In equation (4), $\xi_t$is the vector standardized residual is the vector standardized residual. The standardised residuals' unconditional correlation matrix is called Q. θ_1, θ_2 is non-negative number, and $\theta_1 + \theta_2 < 1$.

3.2. Bekk-garch

The BEKK model has the benefit of being able to simply implement restrictions to guarantee the variance covariance matrix is positive while lowering the precise number of estimated parameters. The following can be used to specify the model:

$$H_t = DD' + \sum_{i=1}^{p} E_i(\varepsilon_{t-i}\, \varepsilon'_{t-i})E' + \sum_{j=1}^{q} F_j\, H_{t-j} F_j{}' \tag{5}$$

In equation (5) The time series I is specified by the actual appropriate rate of return from time t-1 to time t. Within the above variance equation, the matrix of conditional variance-covariance is denoted by H_t. E and F are n order squares, while D is the lower triangular matrix.

3.3. CCC-garch

Bollerslev developed the CCC (Constant Conditional Correlational) model (1990). It is predicated on the notion that the conditional correlation coefficient may not change over time in some situations. This simplifies the model and facilitates CCC-MGARCH model estimation by assuming that the correlation coefficient matrix is constant. The following is how the time-varying covariance matrix is presented:

$$\mathrm{H_t} = \mathrm{D_t R_t D_t} \tag{6}$$

$$D_t = diag(h_{11t}^{\frac{1}{2}}, h_{22t}^{\frac{1}{2}} \dots h_{nnt}^{\frac{1}{2}}) \tag{7}$$

$$R = \rho_{it}\sqrt{w_i w_t} \tag{8}$$

In equation (9), It is a diagonal array composed of the condition standard deviation of each asset. In equation (10), R is the invariant matrix of conditional correlation coefficients

3.4. hedging Effectiveness

This paper also calculates the value of hedging effectiveness to compare which model has higher hedging efficiency. The formula for calculating HE is as follows.

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \quad (9)$$

In equation (11), $var_{unhedged}$is Unhedged risk variance.$var_{hedged}$is Hedge risk variance.

4. Results

The statistical examination of the data indicates that it is found that the dynamic correlation coefficient within the US capital market is always fluctuating, and the dynamic correlation coefficient of futures and spot is always above 0.93, indicating that NASDAQ futures and spot are highly correlated before and during the epidemic. It can be seen from fig 1 that the dynamic correlation coefficient fluctuates between 0.98 and 0.93 during 2016-2019. In 2018/ 12 / 10, the dynamic correlation coefficient decreased to 0.93. The reasons for this phenomenon can be summarized as the beginning of trade friction between China and the United States, the monetary policy from easing to tightening, the economic growth and slowdown, and the expectation of the Federal Reserve to raise interest rates (The estimation results are from DCC model).

As can be seen from fig 2, the correlation coefficient of dcc from 6 March 2020 to 6 May 2020 also decreased below 0.95. This phenomenon can be summarized in the following reasons. As the epidemic worsened in the United States, tougher quarantine measures were implemented across the country. And March 16,2020 is known as Black Week, the biggest drop since Black Monday, 1987 (The estimation results are from DCC model).

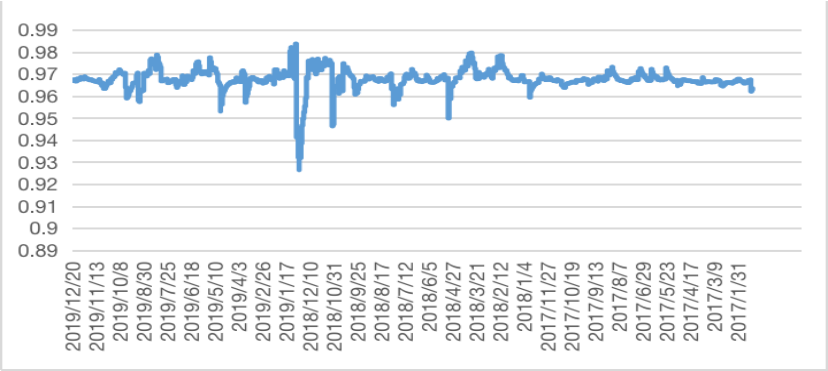


Fig 1. Dynamic Correlation Coefficient 2016-2019

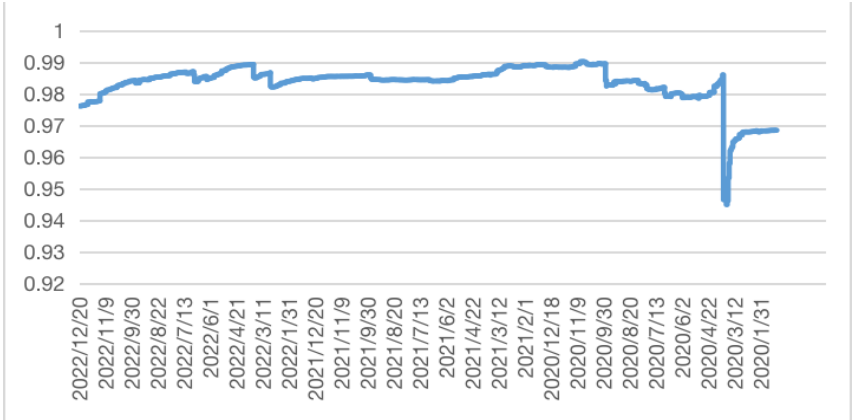


Fig 2. Dynamic Correlation Coefficient 2019-2022

The fig3-fig5 data respectively visualized the hedge ratio of 2016-2019available by empirical analysis in 2016-2019, Through empirical analysis, it can be found that the dynamic hedge ratio of dcc model and ccc model fluctuates less from 2016 to 2019. The dynamic volatility ratio of bekk is larger than other.

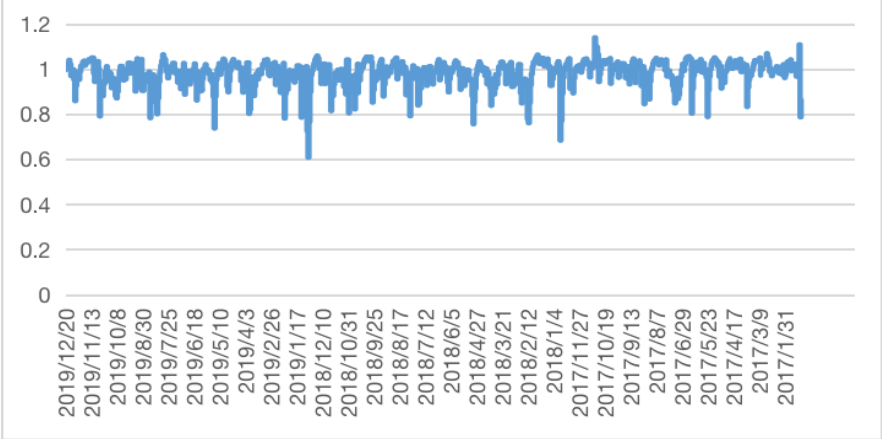


Fig 3. Bekk-garch hedge ratio 2016-2019

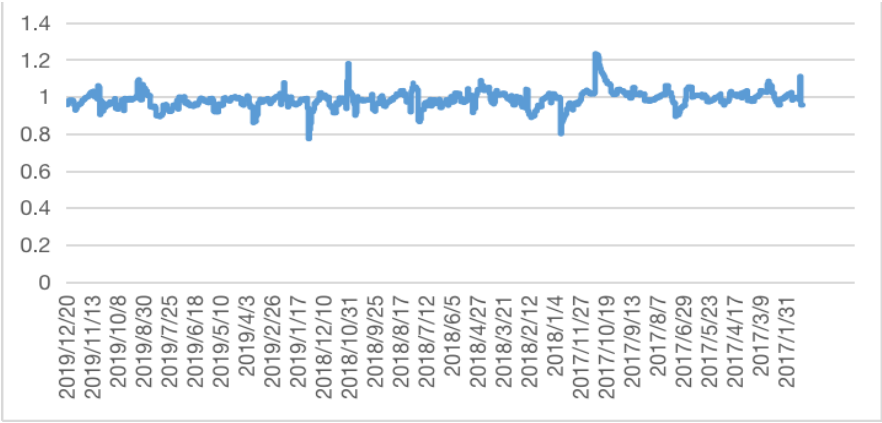


Fig 4. Ccc-garch hedge ratio 2016-2019

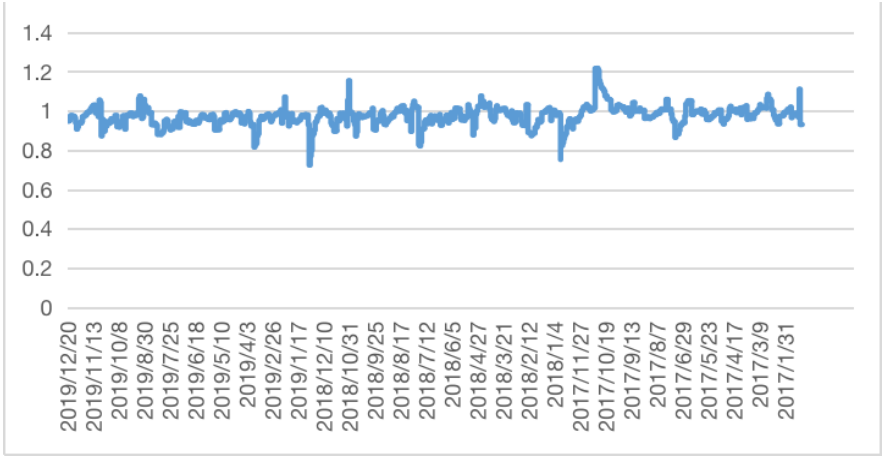


Fig 5. Dcc-garch hedge ratio 2016-2019

The fig 6-fig 8 data visualized the dynamic hedge ratio of 2019-2022. Through empirical analysis, it can be found that from 2016 to 2019, the dynamic hedge ratio of dcc model and ccc model fluctuates less, and the fluctuation range is basically between 0.8 and 1.2, while the dynamic volatility ratio of bekk is larger, and the fluctuation range is roughly between −0.2 and 1.

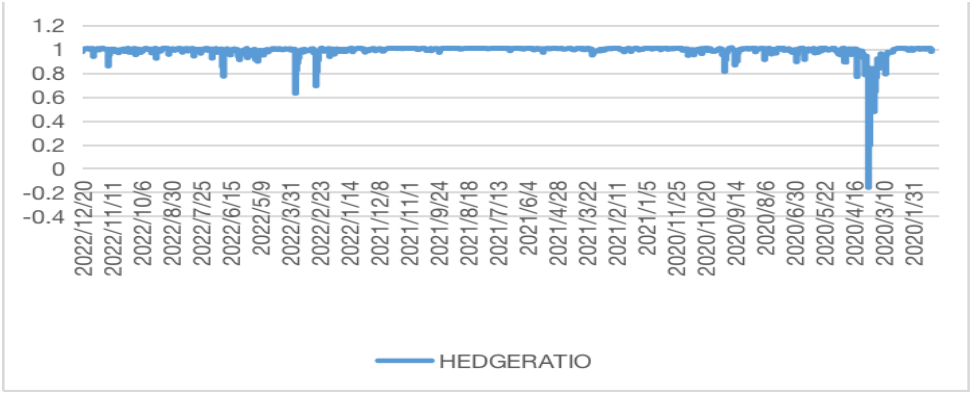


Fig 6. Bekk-garch hedge ratio 2019-2022

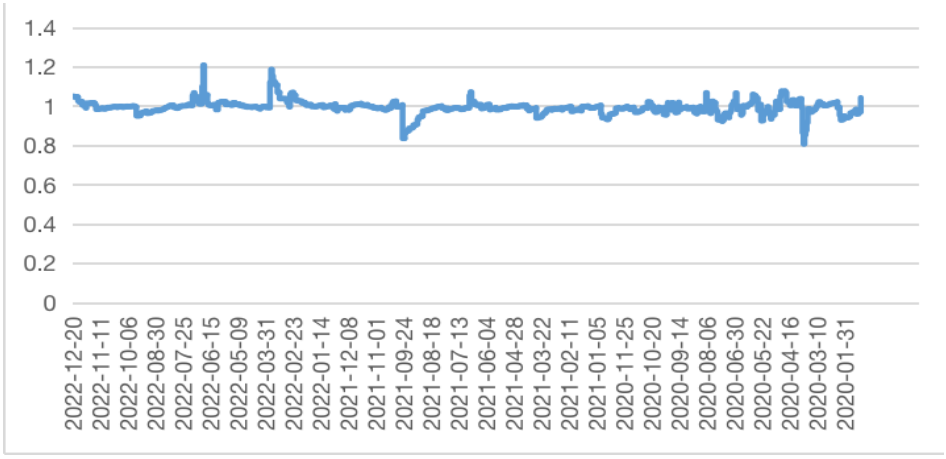


Fig 7. Ccc-garch hedge ratio 2019-2022

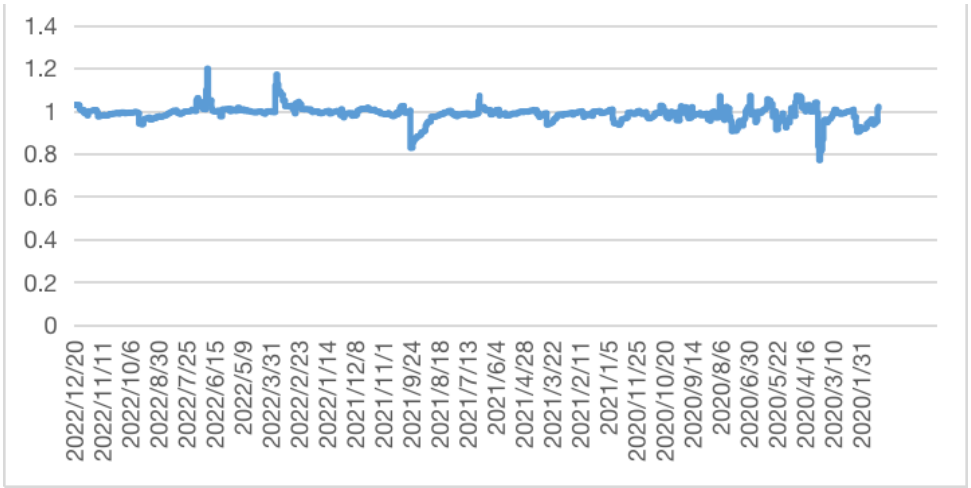


Fig 8. Dcc-garch hedge ratio 2019-2022

The following tables 3-4 calculate the mean, variance, maximum, minimum, kurtosis, and skewness of 2016-2019 and 2019-2022 Dynamic Correlation Coefficient.

Table 3. Dynamic Correlation Coefficient from (2016/12/28-2019/12/28)

	ccc-garch	dccgarch	bekk-garch
mean	0.9789	0.9676	0.9772
variance	0.0000	0.0000	0.0006
max	0.9789	0.9837	0.9989
min	0.9789	0.9264	0.6877
Kurtosis	-2.0054	18.1161	61.3411
Skewness	-1.0020	-2.6253	-6.4559

Table 4. Dynamic Correlation Coefficient from (2019/12/28-2022/12/28)

	ccc-g arch	dcc-garch	bekk-garch
mean	0.9872	0.9833	0.9755
variance	0.0000	0.0000	0.0052
max	0.9872	0.9901	0.9992
min	0.9872	0.9450	-0.1167
Kurtosis	-2.0054	9.0420	104.2465
Skewness	-1.0020	-2.5991	-8.8882

The following tables 5-6 calculate the mean, variance, maximum, minimum, kurtosis, and skewness for 2016-2019 and 2019-2022 Hedging Ratio.

Table 5. Hedging Ratio from (2016/12/28-2019/12/28)

	ccc-garch	dcc-garch	bekk-garch
mean	0.9859	0.9735	0.9792
variance	0.0021	0.0025	0.0036
max	1.2317	1.2167	1.1382
min	0.7725	0.7238	0.6089
Kurtosis	5.2577	4.8285	4.3518
Skewness	0.5847	0.1097	-1.6317

Table 6. Hedging Ratio from(2019/12/28-2022/12/28)

	ccc-garch	dcc-garch	bekk-garch
mean	0.9931	0.9876	0.9839
variance	0.0012	0.0013	0.0046
max	1.2081	1.1981	1.0122
min	0.8068	0.7694	-0.1600
Kurtosis	7.4595	8.1408	140.2237
Skewness	-0.0030	-0.7389	-10.1527

By comparing the dynamic hedge ratio, it can be seen that no matter in 2016-2019 or 2019-2022, dcc and ccc models have no significant fluctuations. However, the bekk model showed a large degree of fluctuation before and during the epidemic. It can be seen that the dcc model and ccc model are more stable. There will be no large fluctuations due to emergencies. Furthermore, this paper calculate the hedging efficiency in Table 7.

Table 7. Hedging efficiency

HE	2016-2019	HE	2019-2022
dcc-garch	0.9387	dcc-garch	0.9556
ccc-garch	0.9381	ccc-garch	0.9550
bekk-garch	0.9307	bekk-garch	0.9364

By comparing the above table, it can be learned that the hedging efficiency of dcc model is the highest whatever before and during the epidemic, which further demonstrates the dynamic hedging ratio results of fig 3-8. Moreover, through the horizontal comparison of the above table, it can be found that the hedging efficiency during the epidemic is significantly higher than before the epidemic.

5. Conclusion

In this paper, 755 and 748 data sets of US stock indexes and futures from 2016/12/28 to 2019/12/28 and 2019/12/28-2022/12/28 were collected to analyze the dynamic correlation and hedging ratios of

the two markets. The novelty of this paper is to fill the blank during the outbreak of stock spot and futures hedge risk research and compared before and during the outbreak which kind of hedge model effect is better, through the empirical analysis, dcc model and ccc model compared to dynamic hedge before the outbreak efficiency increased 0.02, bekk model also has a slightly increase. Therefore, it can be found that hedging is a very effective hedge, especially during the outbreak. This paper only makes the relationship between three common Dynamic hedging models (DCC-garch Bekk-garch ccc-garch) for spot and futures, and some of the above alternatives will be carefully evaluated and used in the subsequent studies of this paper. In addition, this paper will only use futures and equity assets for hedging in this part of hedging. In the following studies, this paper will try more models like alpha-g arch or try more hedging portfolios such as gold futures to hedge NASDAQ spot.

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