International Journal of Control and Automation
Vol. 9, No. 8 (2016), pp.1-12
http//dx.doi.org/10.14257/ijca.2016.9.8.01

Behavioral Hedging Model based on the Dynamic Cumulative Prospect Value

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Abstract

This article studies the effects of investor dynamic psychological factors on the hedging model based on the cumulative prospect theory. This article selects the maximum dynamic cumulative prospect value as the hedging objective, and selects the Realized GARCH model to express the marginal distribution of assets, and selects the Clayton Copula function to express the nonlinear dependence between assets. Then this article sets up the Realized GARCH-Clayton Copula model to combine the risk of assets, selects the VaR function to express the hedging risk constraint with the investor behavioral characteristics, and gets the behavioral hedging model based on dynamic cumulative prospect value. Then the hedging model is used for the empirical study to compare with the hedging model based on the minimum variance, and the hedging model based on the minimum VaR. As the results, the hedging model based on the dynamic cumulative prospect value has better effects than the *hedging model based on the minimum variance and the hedging model based on the minimum VaR.*

Keywords*: Cumulative prospect theory, Dynamic reference points, Loss aversion coefficient, Clayton Copula function, Realized GARCH*

1. Introduction

With the development of the economy in China, numerous enterprises choose to buy commodity assets and short future assets to control the investment risk, most researches start the research of hedging model based on the minimum variance. Johnson L L (1960) put forward the hedging model based on the minimum variance first [1]. later on, Ederington L H (1979) raised the hedging model based on the ordinary least squares (OLS) method, in which the variation of future price and commodity price was linear fitted by OLS model, and the optimal hedging ratios was achieved by minimizing the variance model [2]. Chou W L, Denis K K F and Lee C F (1997) estimated the optimal hedging ratios of the Nikkei Stock Index with the Error Correction Model (ECM), and compared it with the hedging model based on the OLS model. The result shows that the Error Correction Model (ECM) is more effective than the OLS model [3]. Lien D and Tse Y K (2000) discussed the optimal hedging ratios from the perspective of lower partial moment risk restriction [4]. They got the hedging ratios based on the lower partial moment risk restriction and concluded the differences hedging results between the future contract and the option contract. Schweizer M (2010) studied the relationship between the return and the risk of hedging model, and established the hedging model based on mean variance model [5]. Cong J, Tan K S and Weng C (2014) further represented the lower partial moment hedging risk by the CVaR model, and accomplished the optimal hedging ratios under the lower partial moment risk restriction with the CVaR value [6]. Meanwhile, the effects of the time varying characteristics of asset prices on the hedging ratios were studied by multiple scholars, who use the econometric models to measure the volatility and the correlation of assets so as to improve the hedging

ISSN: 2005-4297 IJCA

effects. Lee H T and Yoder J K (2007) integrated the market regime switching into the hedging model with the conditional GARCH model and get the optimal hedging ratios between the commodity asset and the future asset in the market state transition process [7]. Considering the nonlinear correlation of assets, Hsu C C, Tseng C P and Wang Y H (2008) took advantage of the Copula function in describing the correlation, combined the GARCH model and the Copula function to solve the hedging ratios, and established the Copula GARCH model to determine the optimal hedging ratios [8]. By using the data of future market in Australia and the data of stock index in Korea, Moon G H, Yu W C and Hong C H (2009) discussed the advantages of the multivariate GARCH model in the estimation of the optimal hedging ratios [9]. In consideration of the hedging threshold, Lai Y H, Chen C W S and Gerlach R (2009) integrated the hedging threshold into the Copula-GARCH model and established a dynamic optimal hedging model with the hedging threshold restriction [10]. Basak S and Chabakauri G（2012）studied the hedging model in the incomplete market, and estimated the hedging model under the incomplete markets restriction [11].

The above research of hedging model is based on the hypothesis of rational investor. But, in fact, the investing decision of investor is influenced by the psychology factor. Since the 20th century, many researchers have started to research the psychology factor of investor during their investment decision-making process. The most important theory regarding psychology factor is the prospect theory proposed by Kahneman D and Tversky A (1979) which brought them the Nobel Economics Prize in 2002 [12]. The prospect theory corrected the decision-making model of rational investor and replaced the expected utility function with the value function. In the prospect theory, the value function is divided into two parts according to the risk attitude of investor. Lien D and Tse Y K (2002) discussed the effects of psychological factor on the hedging decisions [13]. Mattos F, Garcia P and Pennings J M E (2008) researched the hedging model based on the prospect theory [14]. They discussed the effects of the classic expected utility function and the prospect theory respectively on the hedging ratios, and determined the analytic formula of the optimal hedging ratios with the effects of the probability weight function and the loss aversion coefficient. Broll U, Egozcue M and Wong W K (2010) explored the differences between the expected utility function and the prospect theory, and discussed the effects of the different decision models on the optimal hedging ratios [15]. Conlon T, Cotter J and Gencay R (2013) studied the hedging model in commodity market, and explored the optimal hedging ratios and the hedging risk under the different risk aversion levels [16]. However, they failed to take the dynamic psychological factor of investors into consideration, especially the effects of the dynamic reference point and loss aversion coefficient on the hedging decision. Barberis N and Huang M (2001) pointed out that the assumption of static reference point in the prospect theory cannot well reflect the real of investor psychology factor [17]. Schmidt U, Starmer C and Sugden R (2008) proposed the third-generation cumulative prospect theory [18]，and pointed out that the reference point in the prospect theory should change upon the market condition. They proposed the new ideal of dynamic reference point and loss aversion coefficient and pointed out that the dynamic reference point and loss aversion coefficient would be influenced by the investment performance and wealth condition.

Relative to the past research, this article studies the dynamic psychological factors of investor on the hedging model based on the cumulative prospect theory. With the dynamic investment reference point and the loss aversion coefficient of investors considered, this article makes the establishment of dynamic reference points and loss aversion coefficient in the cumulative prospect theory, and takes the maximum dynamic cumulative prospect value as the investment goal of hedging model. In the meantime, the Realized GARCH model is selected to express the marginal distribution of assets, the Clayton Copula function is chosen to show the nonlinear dependence between the commodity asset and the future asset. Then this article sets up the Realized GARCH-Clayton Copula model to combine the risk of the commodity asset and the future asset, selects the VaR function to express the hedging risk constraint with the investor behavioral characteristics, and gets the behavioral hedging model based on the dynamic cumulative prospect value. Then this article presents the comparison of market investment effects between the behavioral hedging model based on the dynamic cumulative prospect value and the hedging model based on the minimum variance and the hedging model based on the minimum VaR.

The structures of this article are shown in the order as follows: Section 2 is research design, Section 3 is empirical methods, Section 4 is results and discussion, and Section 5 is conclusion.

2. Research Design

2.1. The Cumulative Prospect Theory

Based upon the hedging model, the investor holds the commodity asset and the future asset to hedge the investment risk of commodity asset. Suppose the return of commodity asset is $r_{s,t}$, the return of future asset is $r_{f,t}$, and the hedging ratio of future assets is β, then the return of the whole hedging portfolio can be expressed as $r_t = r_{s,t} - \beta r_{f,t}$.

In the previous researches, the assumption of rational investor was adopted in the study of hedging model research and the investment target function was expressed with the expected utility theory. However, many article showed that the investors are irrational and their investment decision will deviate from the expected utility function, therefore the hedging portfolio selected by the investors would be different. Kahneman and Tversky proposed the prospect theory to study the investor's different behavior on return and loss. The prospect theory is expressed as:

$$u(r_t) = \begin{cases} (r_t - c)^{\alpha} & , r_t \geq c \\ -\lambda (c - r_t)^{\beta} & , r_t < c \end{cases} \tag{1}$$

where, r_t is the return of investment portfolio, c is the reference point of investor to measure the return and loss. λ is the loss aversion coefficient, α and β are return curvature and loss curvature respectively.

Kahneman and Tversky didn't notice the investor's deviation on probability judgment of investment event at the early stage of research. Later they introduced the impact of the probability weighting function into the prospect theory and set up the cumulative prospect theory. Rieger M O and Wang M (2008) gave the prospect theory in the continuous time condition [19]. Let the function $F(r)$ as the probability distribution function of return in the continuous time condition, let p as the probability of investment event. In the region of investor profit, the probability weighting function $w^{+}(p)$ is $w^{+}(p) = p^{\gamma} / (p^{\gamma} + (1-p)^{\gamma})^{\frac{1}{\gamma}}$, and in the region of investor lost, the probability weighting function $w^{-}(p)$ is $w^{-}(p) = p^{\delta} / (p^{\delta} + (1-p)^{\delta})^{\frac{1}{\delta}}$.

As the research of Rieger and Wang, the investor's cumulative prospect function in the continuous time condition can be expressed as follows:

$$U(r_t)=\int_{c}^{\infty}-\frac{dw^{+}(1-F(r))}{dr}u(r)dr+\int_{\infty}^{c}\frac{dw^{-}(F(r))}{dr}u(r)dr \tag{2}$$

2.2. The Dynamic Cumulative Prospect Value of the Hedging

Barberis pointed out that the reference point and the loss aversion coefficient will change upon the early return and loss. In their opinion, $0 \le c \le r_t^f$, and r_t^f is risk-free rate at time t. $\lambda_t \ge \lambda_0 \ge 0$, and λ_0 is the initial loss aversion coefficient of the investor. Based upon Barberis' thoughts, Fortin I and Hlouskova J (2011) gave the dynamic form of the reference point and the loss aversion coefficient [20], which is

$$c_t=\begin{cases} r_t^f\,\dfrac{r_{t-1}}{r_t}, & r_t \ge r_{t-1} \\ r_t^f, & r_t < r_{t-1} \end{cases},\quad \lambda_t=\begin{cases} \lambda_0, & r_t \ge r_{t-1} \\ \lambda_0+\left(\dfrac{r_{t-1}}{r_t}-1\right), & r_t < r_{t-1} \end{cases} \tag{3}$$

where, r_t is the return of investment portfolio at time t. However, there are two problems in this formula: first, when $r_t > 0, r_{t-1} < 0$, and $(r_{t-1}/r_t) < 0$, then $c = r_t^f \cdot (r_{t-1}/r_t) < 0$, the required $0 \le c \le r_t^f$ in dynamic change cannot be met; Second, when $r_t < 0, r_{t-1} > 0$, and $(r_{t-1}/r_t) < 0$, then $\lambda_t = \lambda_0 + (r_{t-1} - r_t)/r_t < \lambda_0$, the required $\lambda_t \ge \lambda_0 \ge 0$ in dynamic change cannot be met. Therefore, this article tries to modify the dynamic form of reference point and loss aversion coefficient proposed by Fortin. The purpose of hedging is not only to avoid the risk of investing, but also to pursuit the return which is more than the average wealth of market, so this article lets the reference point c as the wealth of hedging portfolio to the average wealth of market. Let $r_{m,t}+1$ represent the average wealth of market, namely, $c_t = (r_t + 1)/(r_{m,t} + 1)$, and let dynamic loss aversion coefficient λ_t changes upon the reference point c_t. Therefore, the dynamic cumulative prospect function can be expressed as:

$$u(r_t)=\begin{cases} \left(r_t-c_t\right)^{\alpha}, & r_t \ge c_t \\ -\lambda_t\left(c_t-r_t\right)^{\beta}, & r_t < c_t \end{cases}$$

$$c_t=\frac{r_t+1}{r_{m,t}+1},\quad \lambda_t=\begin{cases} \lambda_0, & r_t \ge r_{m,t} \\ \lambda_0\left(\dfrac{r_t-r_{m,t}}{r_{m,t}}+1\right), & r_t < r_{m,t} \end{cases} \tag{4}$$

So, the objective of hedging portfolio with the dynamic cumulative prospect theory in the continuous time condition can be expressed as:

$$\max E(U(r_t,c_t))=\int_{c_t}^{\infty}-\frac{dw^{+}(1-F(r))}{dr}u(r)dr+\int_{\infty}^{c_t}\frac{dw^{-}(F(r))}{dr}u(r)dr$$

$$where,\ u(r_t)=\begin{cases} \left(r_t-c_t\right)^{\alpha}, & r_t \ge c_t \\ -\lambda_t\left(c_t-r_t\right)^{\beta}, & r_t < c_t \end{cases},\quad r_t=r_{s,t}-\beta r_{f,t} \tag{5}$$

$$c_t=\frac{r_t+1}{r_{m,t}+1},\quad \lambda_t=\begin{cases} \lambda_0, & r_t \ge r_{m,t} \\ \lambda_0\left(\dfrac{r_t-r_{m,t}}{r_{m,t}}+1\right), & r_t < r_{m,t} \end{cases}$$

Hence, the objective of hedging portfolio changes from expected utility function to the dynamic cumulative prospect value.

2.3. The Risk Constraint of the Hedging

According to the relevant theories of hedging, both the return and the risk restriction of hedging portfolio shall be considered. Das S, Markowitz H and Scheid J (2010) established the behavioral portfolio model with the risk restrictions [21]. In light of the ideas of Das, Markowitz and Scheid, the article considers the hedging method with the risk restriction and selects the VaR model to represent hedging risk constraint with the investor behavioral characteristics. Let r_t as the expected return of hedging portfolio, and let h as the maximum loss tolerance level of investor in the hedging portfolio. According to general the VaR method, the risk restriction is expressed as: let $\Delta r_t = h \cdot r_t$, the risk (VaR_a) of hedging portfolio at specified $1-a$ level is not more than h, and a refers to the significance level for calculation of VaR_a. So the VaR function of the hedging risk constraint can be written as:

$$P\{(\Delta r_t) < -VaR_a\} = \alpha \tag{6}$$

$F(r_s, r_f)$ refers to the joint distribution function of the commodity assets and future assets, and $f(r_s, r_f)$ is the density function for joint distribution function, so the VaR function can be represented as:

$$P\{r_{\Delta t} < -VaR_a\} = \iint_{r_{\Delta t} < -VaR_a} f(r_s, r_f) dr_s dr_f = \alpha \tag{7}$$

Then, the objective of hedging portfolio with the risk constraint can be expressed as:

$$\begin{gathered} \max E(U(r_t, c_t)) = \int_{c_t}^{\infty} -\frac{dw^{+}(1-F(r))}{dr} u(r) f(r_s, r_f) dr_s dr_f + \int_{\infty}^{c_t} \frac{dw\ (F(r))}{dr} u(r) f(r_s, r_f) dr_s dr_f \\ s.t\ P\{r_{\Delta t} < -VaR_a\} = \iint_{r_{\Delta t} < -VaR_a} f(r_s, r_f) dr_s dr_f = \alpha \end{gathered} \tag{8}$$

The optimal hedging ratios problem now is to find optimal weight to maximize the dynamic cumulative prospect utility function $E(U(r_t, c_t))$ under the risk restriction of the VaR function.

2.4. The Behavioral Hedging Model based on the Dynamic Cumulative Prospect Value

It is assumed in the previous hedging research that the assets are linearly dependent, but a lot of research shows that there is the nonlinear correlation between the assets. A. Sklar (1996) firstly established the copula theory [22]. The Copula function can effectively describe the nonlinear correlation between different assets. Sklar's theory is shown as follows: set F as $F(x_1, \cdots, x_n)$, to describe the joint distribution function of multi-dimensional distribution function $F_1(x_1), \cdots, F_n(x_n)$, $f(x_1, \cdots, x_n)$ is the density function of the joint distribution function $F(x_1, \cdots, x_n)$. Then there must exist a Copula function $C(\cdot)$ that fulfill $F(x_1, \cdots, x_n) = C(F_1(x_1), \cdots, F_n(x_n))$, and the probability density function of multivariate random variables $f(x_1, \cdots, x_N)$ can be expressed as:

$$f(x_1, \cdots, x_N) = c(F_1(x_1), F_2(x_2), \cdots, F_N(x_N)) \cdot \prod_{i=1}^{N} f_i(x_i), \quad -\infty \le x_1, \cdots, x_N \le +\infty \tag{9}$$

According to the theory of Copula function, the joint distribution function can be built with two-phase method: (1) confirm the marginal distribution; (2) select suitable Copula function to describe the correlation between different assets. The marginal distribution information of assets can be expressed as the volatility equation.

Engle R F and Bollerslev T (1986) proposed the GARCH model [23]. Nelson D B

(1991) established the EGARCH model to reflect the asymmetric effects in the volatility equation [24]. As the high frequency data is widely used, people start to research the volatility model with high frequency data. Andersen T G, Bollerslev T and Diebold F X (2003) set up the realized volatility model, and improved the accuracy of volatility model with the high frequency data [25]. Hansen P R, Huang Z and Shek H H (2012) integrated the high frequency data and low frequency data in the volatility model, and presented the Realized GARCH model [26]. It can effectively mitigate the volatility errors caused by market microstructure noise and non-trading time, and obtain better results than other models in volatility estimation. Such the Realized GARCH model is as follows:

$$
\begin{gathered}
r_t = \sqrt{h_t} z_t,\ \ z_t \sim N(0,1) \\
h_t = \omega + \beta h_{t-1} + \gamma x_{t-1} \\
x_t = \xi + \mu h_t + \tau_1 z_t + \tau_2 (z_t^2 - 1) + u_t,\ \ u_t \sim N(0, \sigma_u^2)
\end{gathered} \tag{10}
$$

where, x_t can be any one of realized volatility measure, and errors caused by market intraday microstructure noise and non-trading time are adjusted by coefficients ξ and μ. $\tau(z_t)$ is the lever function which is used to represent the asymmetric effects in the volatility equation, and parameters τ_1 and τ_2 are used to describe the different effects of the positive and negative returns to the volatility. But in Hansen's research, they adopted the normal distribution assumption, which is not accurate in describing the marginal distribution information of assets. Hence, this article selects the corrected t^* to describe the distribution of residual error h_t in Realized GARCH model. The density function of corrected t^* is

$$
f(h \mid t^*) = \left(\frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{(\nu-2)\pi}\,\Gamma(\frac{\nu}{2})} (1 + \frac{z^2}{\nu-2})^{-\frac{\nu+1}{2}} h \right) \sqrt{\frac{\nu-2}{\nu}} \tag{11}
$$

and, $\sqrt{\frac{\nu}{\nu-2}} h_t \sim t(\nu)$, $t(\nu)$ refers to normalized t distribution function which means the value is 0, the variance is 1 and the freedom parameter is ν. As a result, the Realized GARCH model is chosen in this article to represent the marginal distribution of assets.

The tail correlation of assets in the hedging portfolio is important. Among the plenty of Copula functions, because of the advantages of the Multiple Clayton Copula function in describing of the tail correlation, this article selects the Multiple Clayton Copula function to describe the joint distribution of assets. This article first selects the Realized GARCH model to describe the marginal distribution of assets, then selects the Multiple Clayton Copula function describe the joint distribution of assets, the last sets up the Realized GARCH-Clayton Copula model to describe the joint distribution of the commodity asset and the future asset. The equations are shown as follows:

$$
\begin{gathered}
r_{i,t} = \sqrt{h_{i,t}} z_{i,t},\ \ z_{i,t} \sim t^* \\
h_{i,t} = \omega_i + \beta_i h_{i,t-1} + \gamma_i x_{i,t-1} \\
x_{i,t} = \xi_i + \mu_i h_{i,t} + \tau_{i,1} z_{i,t} + \tau_{i,2} (z_{i,t}^2 - 1) + u_{i,t},\ \ \varepsilon_{i,t} \sim N(0, \sigma_{u_{i,t}}^2),\ \ i = s, f \\
(z_{s,t}, z_{f,t}) \sim c_{cl,t}(F_s(z_{s,t}), F_f(z_{f,t}))
\end{gathered} \tag{12}
$$

Among the equations above, the joint distribution function of the multiple Clayton Copula function is

$$C_{cl}(u_1,...,u_n)=[\sum_{i=1}^{n}u_i^{-\theta}-N+1]^{-\frac{1}{\theta}},\theta>0 \tag{13}$$

This article lets the Realized GARCH-Clayton Copula model to descript the risk of the hedging portfolio, and gets every asset risk into the VaR function in order to express the risk restriction of hedging portfolio. Then, the VaR function can be described as follows:

$$P\{\Delta r_t<VaR_a\}=\int\cdots\int_{\Delta r_t<VaR_a}C_{cl,t}(F(r_s),F(r_f))dr_s dr_f=\alpha \tag{14}$$

Consequently, it is possible to seek the hedging ratio with the risk restriction, so the behavioral hedging model based on the dynamic cumulative prospect value can be obtained as follows:

$$\max E\,U(r_t(c_t,\ ))=\int_{c_t}^{\infty}-\frac{dw^+(1-F(r))}{dr}u(r)f(r_s,r_f)dr+\int_{\infty}^{c_t}\frac{dw^-(F(r))}{dr}u(r)f(r_s,r_f)dr$$
$$s\,t\ P\{\Delta r_t<VaR_a\}=\int\cdots\int_{\Delta r_t<VaR_a}C_{cl,t}(F(r_s),F(r_f))dr_s dr_f=\alpha \tag{15}$$

Eventually, the hedging ratio problem is turned into the dynamic optimization problem for the determination of the optimal weight for the commodity assets and the future assets under the VaR function of risk restriction, so as to maximize the dynamic cumulative prospect value of hedging portfolio.

3. Empirical Method

3.1. Sample Selection

This article selects data from the CSMAR database. This article selects the daily trading data of the Yi Fang Da 300 ETF index fund as the commodity asset data, selects the daily data of the Hushen 300 index future as the future asset data. According to the research of Kahneman and Tversky, this article selects $\alpha=\beta=0.88$, $\lambda_0=2.25$, and $\gamma=0.61$, $\delta=0.69$ as the parameters of the cumulative prospect theory. The range of time is one year, from 01/01/2012 to 12/31/2012.

3.2. Estimation Method

(1) Estimation of the Marginal Density Function (Using Realized GARCH Model): This article selects the daily data which set the starting point from 01/01/2012. We use the estimation method of maximum likelihood value to estimate the parameters of Realized GARCH model in each day by rolling regression.

(2) Estimation of the Correlation Structure (Using Clayton Copula Function): This article selects the day return in the same selected sample. We use the estimation method of maximum likelihood value to estimate parameters of the Clayton Copula function by rolling regression.

(3) Simulation the return r_t^i of assets in the next day: Firstly, the multivariate random sequences u were generated in accordance with related structure estimated by (2), then, u was transformed as the random disturbance sequence $\eta_{i,t}=F^{-1}(u_i)$ via process (1). Here, F^{-1} is the distribution function, from which we can get r_t^i.

(4) Estimation the VaR model of the hedging portfolio in in the next day: According to (3), we can obtain the change of the hedging portfolio value at time t: $\Delta r_t=h\cdot r_t$ Here, r_t is the expected return of hedging portfolio. Under the given the α and h, we set Monte Carlo simulation method to repeat step (1) to (4) for 50000 times. Then 50000 Δr_t values can be obtained. Arranging the 50000 values from small to large, we choice the

optimal hedging weights solution set which is less than Δr_t in these 50000 values. In this set, we select the optimal hedging weight that can make $E(U(r_t, c_t))$ greatest. Then this group of weights is the optimal hedging ratios which can let the $E(U(r_t, c_t))$ greatest under the risk constrain. Therefore, this article can obtain the optimal hedging ratio which maximized the cumulative prospect value of hedging portfolio every day from 01/01/2012 to 12/31/2012.

4. Result Analysis

4.1. The Hedging Model Comparison

To get the effectiveness of the behavioral hedging model based on the dynamic cumulative prospect value, the article uses both classic hedging methods, namely the hedging model based on the minimum variance and the hedging model based on the minimum VaR, and compares their results with the behavioral hedging model based on the dynamic cumulative prospect value. In consideration of the actual situations of the hedging, the article also lets (0.05, 0.05), (0.05, 0.10) and (0.05, 0.15) as the different parameters of (α, h) to test the robustness of the behavioral hedging model based on the dynamic cumulative prospect value.

4.2. The Comparison among Different Hedging Models

4.2.1. Comparison of the Hedging Ratios among Different Hedging Models

Table 1 gives the results from the comparison of the optimal hedging ratios among the hedging model based on the minimum variance and the hedging model based on the minimum VaR and the behavioral hedging model based on the dynamic cumulative prospect value with three different parameters. As shown in the table, the average hedging ratios of the hedging model based on the minimum variance is the lowest, the average hedging ratios of the behavioral hedging model based on the dynamic cumulative prospect value with the parameter (0.05, 0.15) is the highest, and the average hedging ratios of the behavioral hedging model based on the dynamic cumulative prospect value with the parameter (0.05, 0.05) is in the middle. As to the variance of the hedge ratios, the hedging model based on the minimum variance is the lowest, the behavioral hedging model based on the dynamic cumulative prospect value with the parameter (0.05, 0.10) is in the middle, and the behavioral hedging model based on the dynamic cumulative prospect value with the parameter (0.05, 0.15) is the highest.

Table 1. The Hedging Ratios among Different Hedging Models

	minimum variance	minimum VaR	(α, h) (0.05, 0.05)	(α, h) (0.05, 0.10)	(α, h) (0.05, 0.15)
Mean	1.0053	1.0652	1.1794	1.2425	1.4081
Maximum	1.8056	2.2577	2.1129	3.0249	4.9201
Minimum	0.3658	0.4531	0.1755	0.2717	0.3105
Std	0.9004	0.9335	1.184	1.0176	1.2045

4.2.2. Comparison of the Hedging Effects among Different Hedging Models

Table 2 gives the results of the day return among the hedging model based on the minimum variance and the hedging model based on the minimum VaR and the behavioral hedging model based on the dynamic cumulative prospect value with three different parameters.

Table 2. The Day Return among Different Hedging Models

	minimum variance	minimum VaR	(α, h) (0.05, 0.05)	(α, h) (0.05, 0.10)	(α, h) (0.05, 0.15)
Mean	0.0012	0.0017	-0.0004	0.0019	0.0026
Maximum	0.0028	0.0032	0.0039	0.0041	0.0053
Minimum	0.0007	0.0013	-0.0017	-0.0011	-0.0027
Std	0.0108	0.0135	0.0327	0.0234	0.0482

As shown in Table 2, the average day return of the behavioral hedging model based on the dynamic cumulative prospect value with the parameter (0.05, 0.15) is the highest, the average day return of the behavioral hedging model based on the dynamic cumulative prospect value with the parameter (0.05, 0.05) is the lowest; and the average day return of the hedging model based on the minimum VaR is the middle.

Table 3 gives the Sharpe ratios among the hedging model based on the minimum variance and the hedging model based on the minimum VaR and the behavioral hedging model based on the dynamic cumulative prospect value with three different parameters.

Table 3. The Sharpe Ratios among Different Hedging Models

	minimum variance	minimum VaR	(α, h) (0.05, 0.05)	(α, h) (0.05, 0.10)	(α, h) (0.05, 0.15)
Sharpe ratio	0.2653	0.4652	0.4794	0.5173	0.6271

As shown in Table 3, the Sharpe ratio of the hedging model based on the dynamic cumulative prospect value is the highest, the Sharpe ratio of the hedging model based on the minimum variance is the lowest and the Sharpe ratio of the hedging model based on the minimum VaR is in the middle, it can be seen that under the circumstance of three different parameter set, this article obtains the robustness result of the behavioral hedging model based on the dynamic cumulative prospect value, which is better than the other hedging models. These results successfully confirm the effectiveness of the behavioral hedging model based on the dynamic cumulative prospect value. To sum up, the behavioral hedging model based on the dynamic cumulative prospect value not only increases the return of the hedging portfolio, but also lowers the risk of hedging portfolio. It obtains better investment effects in the market than the other hedging models, and is more functional in the hedging effects. The empirical results verify the strength and the stability of the behavioral hedging model based on the dynamic cumulative prospect value, which are very instructive for investors.

5. Conclusion

The article studies the effects of investors dynamic psychological factors on the hedging model based on the cumulative prospect theory. We make the establishment of dynamic reference points and loss aversion coefficient in the cumulative prospect theory, and take the maximum dynamic cumulative prospect value as the investment goal of hedging model. In the meantime, the Realized GARCH model is selected to express the marginal distribution of assets, the Clayton Copula function is chosen to show the nonlinear dependence between the cumulative prospect theory assets, the Realized GARCH-Clayton Copula model is set up to combine the risks of assets. This article selects the VaR function to express the hedging risk constraint with the investor behavioral characteristics, and gets the behavioral hedging model based on the dynamic cumulative prospect value, then presents the comparison of market investment effects between the behavioral hedging model based on the dynamic cumulative prospect value and the hedging model based on the minimum variance and the hedging model based on the minimum VaR in the market. According to the empirical results, the investor psychological factors have an important influence on the hedging portfolio. The behavioral hedging model based on the dynamic cumulative prospect value has better effects than the hedging model based on the minimum variance and the hedging model based on the minimum VaR. When the hedging model is used for Yi Fang Da 300 ETF index fund and the Hushen 300 index, it not only increases the returns, but also lowers the risk of hedging significantly. In conclusion, if investors plan to use the future assets for the dynamic hedging their assets, it is recommended to use the hedging model based on the dynamic cumulative prospect value. The research in the article provide new theories of the hedging article, further we will focus on the different psychological reactions of investors on the hedging and the design of hedging strategies based on dynamic activities market.

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