# Comprehensive Evaluation of Public Funds Based on Principal Component Analysis

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#### Question

- The following issues will be encountered jointly by securities rating agencies when conducting fund ratings and securities firms' wealth management departments when introducing funds.
- Problem 1: How to rate funds in terms of 8 market indicators
  - 1. timing ability of fund manager,
  - 2. stock selection ability of fund manager,
  - 3. percentile ranking of similar funds interval return in one year,
  - 4. Sharp index,
  - 5. Calmar ratio,
  - 6. Annualized volatility,
  - 7. Maximum drawdown rate,
  - 8. Percentile ranking of similar funds interval return in two years



#### Question

- Problem 2: How to test the proposed method for rating funds
  - i) To compare the excess return rate among rating (star) funds;
  - ii) To compare the abnormal yield among rating (star) funds, which is the difference between the cumulative yield of the fund and the yield of the CSI 300 index;
  - iii) To forecast future excess return with comprehensive score

#### Contents

- 1. Research background and significance
  - 1.1 background and significance
  - 1.2 Research status
  - 1.3 Innovative Points of Research
- 2. Analysis of performance evaluation indicators for public funds
  - 2.1 Traditional performance evaluation indicators
  - 2.2 Evaluation of Fund Risk Level
  - 2.3 Risk adjusted performance evaluation indicators
  - 2.4 Measurement of Fund Manager Capability
  - 2.5 Principal Component Analysis
- 3. Comprehensive Evaluation and Empirical Analysis of Public Funds
  - 3.1 Scoring Method of Public Funds
  - 3.2 Comprehensive scoring of public funds
  - 3.2 Verification of the evaluation result
  - 3.3 forecast future excess return with comprehensive score
- 4. Conclusions and suggestions
  - 4.1 Conclusions
  - 4.2 Suggestions



## 1.1 Research background and meaning

## Research background

- With the continuous development of the economy, people's demand for their own wealth management is also increasing. Public fund companies, as professional institutional investors in the Chinese market, are also mainstream institutions in wealth management.
- Public funds have attracted investors' attention due to their rich variety and low participation threshold. By September 26, 2019, the number of the top three most common funds reached a total of 5221. The number of hybrid funds was 2478, ranked first, the number of bond funds was 1745 in total, ranked second, and the number of stock funds was 998 in total, ranked third.
- Facing such a large number of funds in the market, the public investors often
  do not know how to choose excellent target products, so it is particularly
  important to build a reasonable fund performance evaluation system for
  providing investors with certain reference and guidance.

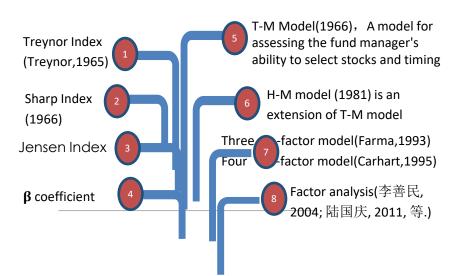
## 1.1 Research background and meaning

## Research meaning

- Theoretical significance:
  - Scientific weighting based on principal component analysis makes comprehensive evaluation more scientific
  - 2) The proposed method including fund rating and star rating is verified by comparing cumulative abnormal return rate and forecasting future excess return with comprehensive score
- Practical significance
  - Fund rating and star rating
  - 2) Screening high-quality funds and providing investors with certain reference significance
  - 3) Promote the diversified development of public fund ratings



## 1/2 Research status



## 1.2/Research status



#### 基金盈利能力的主要指标分析

胡安幸、戴亮(2017)主要分析夏普比率,运用上海交易所发行的开放式基金数据,使用夏普比率评选出最好基金,并进行实证分析,得出夏普比率可作为衡量基金业绩的重要辅助指标,建议与其他指标相结合来有效评估目标基金的业绩表现。



#### 基金风险指标分析

刘建(2018)提出随着证券市场衍生品工具不断增多,带来的市场波动也越大,投资者除关注收益之外,往往更青睐波动率低、收益适中的基金品种,文章根据近5年数据进行历史回测,选取了基金的年化收益波动率和最大回撤率2个指标作为评估基金的风险指标,并进行分析。

## 1.2/Research status



#### 因子分析法的应用

- 张帆 (2016)用因子分析法研究了中国基金的绩效;
- 王王文博和陈秀芝 (2006) 研究了因子分析和主成分分析 的比较问题;
- 李善民等(2004),采用主成分分析法和因子分析法研究上市公司的绩效。

## 1.3/Innovative Points of Research

#### Application and practical innovation:

- Using principal component analysis to extract principal components from market evaluation indicators, the interpretation of principal components is based on data analysis and is persuasive;
- The method of calculating indicator weights based on principal component analysis is data-driven and objective, therefore it is a scientific weighting method;
- Fund rating and star rating based on comprehensive evaluation are in line with market performance, and the comprehensive score proposed has a significant effect on the prediction of the excess return rate of funds.
- The R software package for calculating the comprehensive score and star rating of public funds can be used by fund sales agency practitioners and industry researchers for rating.

#### 2.1 Traditional Performance Evaluation Indexes

• The growth rate of fund unit net worth (unw, 基金单位净值):

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growth rate of unw= unw on the last day – unw on the first day unw on the f irst day
```

- ▶ This index is very easy to understand, and the data is very easy to obtain.
- However, this method ignores the impact of risks and is only effective for funds with low risk, such as monetary or bond funds

#### 2.2. Evaluation of Fund Risk Level(基金风险水平的评价)

Let  $R_i$  be the yield of the i-th security and  $\bar{R}$  be the average yield of N securities. Some risk assessment indicators are defined as follows

- ► Standard Deviation:  $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_i \bar{R})^2}$
- ▶  $\beta$  coefficient  $(T M \ model, H M \ model)$ :  $\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)},$

where  $R_m$  represents the market return,  $\beta_i$  reflects the volatility of fund i relative to the overall market. the higher the  $\beta$ , the greater the risk.

- Maximum Drawdown Rate (MDR): for a specified period,  $MDR = \frac{\text{the lowest net value-the highest net value}}{\text{the highest net value}},$  which is generally a negative number.
- Annualized Volatility (AV):
   AV = deviation of the yield over a specified period (by year)



#### 2.3 Risk Adjusted Return Evaluation(风险调整收益评价):

Let  $R_i$  be the average growth rate of of unit net worth of the fund i(££ i单位净值的平均增长率),  $\sigma_i$  represents the standard deviation of the fund i,  $R_f$  represents the risk-free rate of return.

▶ Sharpe Ratio (夏普指数): an index to reflect the comparison of return and risk,

$$S_i = (R_i - R_f)/\sigma_i \tag{1}$$

where the sharp ratio  $S_i$  denotes the excess return that the fund i can obtain for each unit of total risk. The higher the Sharpe ratio, the stronger the profitability of the fund.

▶ Calmar Ratio(卡玛比率): an index to describe the relationship between return in a statistical interval and maximum drawdown.

CalmarRatio = annualized rate of return/maximum drawdown rate. (2)

Calmar ratio is different from sharp index in the choice of risk measurement, which uses the maximum withdrawal as the risk measurement value, the larger the better.

#### 2.3 Risk Adjusted Return Evaluation(风险调整收益评价):

▶ Jenson Index(詹森指数): an index used to study the difference between the real return rate of the fund and the expected return rate calculated by the CAPM model.

$$J_i = R_i - [R_f + \beta_i (R_m - R_f)]$$
 (3)

where  $R_i$  is the historical average rate of return of fund i during the study period,  $R_m$  is the historical average rate of return for the market,  $\beta_i$  is the systematic risk that the fund i bears during the study period.

- ▶ Different from Sharpe index in (1) and Calmar ratio in (2), Jensen index in (3) measures the absolute performance, and only considers how much excess return can be obtained which is called as fund portfolio depth. Fund investment breadth is ignored in the definition of Jensen index.
- ➤ The Jenson index is widely used to evaluate the effectiveness of index enhanced funds(<a href="https://www.csai.cn/wenda/954218.html">https://www.csai.cn/wenda/954218.html</a>), which is currently a popular market for smart ETF funds
- ▶ Sharpe index, Calmar ratio and Jensen index have their own limitations.

#### 2.4 Evaluation of Fund Manager's Ability

1. T-M model

Treynor and Mazuy (1966) proposed to measure the ability of fund managers through stock selection ability and timing ability, and introduced the classical T-M model with quadratic term:

$$R_p - R_f = \alpha + \beta_1 (R_m - R_f) + \beta_2 (R_m - R_f)^2,$$
 (4)

- ▶  $R_p$ : the portfolio return,  $\alpha$ : the stock selection ability of fund managers, the larger its value, the higher the excess return of the fund;
- $\triangleright$   $\beta_1$ : the systematic risk that the fund bears,
- $\beta_2$ : the market timing ability of fund managers. if  $\beta_2 > 0$ , and the larger it is, the stronger the fund manager's market timing ability is,
- T-M model is the most basic model, which only uses one value of  $\beta$  to judge the timing ability of fund managers without distinguishing different market states.



#### 2.4 基金经理能力度量:

2. H-M model

Henriksson and Merton (1981) improved the T-M model to obtain the H-M model. They thought that the single  $\beta$  value in the T-M model (4) was not comprehensive enough, so they introduced double  $\beta$  values to measure the fund manager's timing ability:

$$R_p - R_f = \alpha + \beta_1 * (R_m - R_f) + \beta_2 * (R_m - R_f) * D$$

▶ D is a dummy variable, when  $R_m > R_f$ , D = 1, otherwise, D = 0. In other words, when the market economic cycle is in a rising state,  $\beta = \beta_1 + \beta_2$ ; when the market economic cycle is in a declining state,  $\beta = \beta_1$ . Since the samples we studied are hybrid funds, T-M model is used to evaluate the fund's stock selection and timing ability.

#### 2.5 Principal Component Analysis

(1) Introduction to Principal Component Analysis

Principal Component Analysis is a statistical dimension reduction method, and its basic idea is to use a few mutually independent components to reflect the vast majority of information of original variables. Suppose that  $\mathbf{x} = (x_1, x_2, ..., x_p)'$  is a p-dimensional random vector with mean  $\mu = (\mu_1, \mu_2, ..., \mu_p)'$  and covariance matrix  $\mathbf{\Sigma} = (\sigma_{ij})$ , let  $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p$  be the eigenvalues of  $\mathbf{\Sigma}$ , and  $\mathbf{t}_1, \mathbf{t}_2, \cdots, \mathbf{t}_p$  be the corresponding eigenvectors of  $\mathbf{\Sigma}$  (j = 1, 2, ..., p), then the j-th population principal components of  $\mathbf{x}$ , denoted by  $f_j$ , can be formulated as

$$f_j = \mathbf{t}'_j \mathbf{x}$$
,

where  $Var(f_j) = \lambda_j$  for  $j = 1, 2, \ldots, p$ . In the above definition, principal components  $f_j$ 's are mutually uncorrelated. It is common practice to use the cumulative contribution rate  $\sum_{j=1}^m \lambda_j / \sum_{j=1}^p \lambda_j$  to measure the degree to which the total variance is explained, where m represents the number of principal components. For a positive definite matrix, the size of its

#### 2.5 Principal Component Analysis

trace is often determined by a few large eigenvalues. Thus, only a few principal components are selected to make the cumulative contribution rate reach a relatively high level (e.g. 85%), so as to achieve the purpose of dimensionality reduction. Let  $\mathbf{f} = (f_1, f_2, \dots, f_p)'$  be the principal vector composed of all principal components. Then we can express it as

$$f = T'x$$
 (5)

in matrix form, where the coefficient matrix  $\mathbf{T} = (\mathbf{t}_1, \mathbf{t}_2, \dots, \mathbf{t}_p)$  is a positive definite matrix.

#### 2.5 Principal Component Analysis

#### (2) Data Processing

Suppose that there are n funds to be evaluated, each fund has p indexes, and the observed indexes of the i-th fund are  $x_0, x_2, \dots, x_{ip}, i = 1, 2, \dots, n$ , then the observation data matrix,  $\mathbf{X} = (x_{ij})_{p \times n}$ , is expressed as

$$\mathbf{X} = \left[ \begin{array}{cccc} x_{11} & x_{21} & \cdots & x_{n1} \\ x_{12} & x_{22} & \cdots & x_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1p} & x_{2p} & \cdots & x_{np} \end{array} \right]$$

Let  $x_j = \frac{1}{n} \sum_{i=1}^{n} x_{ij}$ ,  $j = 1, \dots, p$  be the sample mean of the j-th index of these n funds,  $s_j^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_{ij} - x_j)^2$  be the sample variance. In order to ensure the unity of data magnitude, we standardize the original data by  $z_{ij} = (x_{ij} - x_j)/\sqrt{s_j}$ . It is obvious that the covariance matrix of the standardized sample is exactly the sample correlation matrix of original data:

$$\mathbf{R} = \left[ egin{array}{ccccc} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ dots & dots & \ddots & dots \\ r_{p1} & r_{p2} & \cdots & r_{pp} \end{array} 
ight],$$

where  $r_{kl} = \frac{1}{n-1} \sum_{i=1}^{n} (x_{ik} - \bar{x_k})(x_{il} - \bar{x_l})/s_k s_l$   $(k = 1, \dots, p, l = 1, \dots, p)$ represents the correlation between the k-th and l-th samples with  $r_{kk} = 1$ .



#### 2.5 Principal Component Analysis

(3) Estimation of Coefficient Matrix.

Starting from the correlation matrix  $\mathbf{R}$ , we solve the characteristic equation  $|\lambda \mathbf{I} - \mathbf{R}| = 0$  to obtain the eigenvalues and their corresponding eigenvectors, denoted as  $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \cdots \geq \hat{\lambda}_p, \hat{\mathbf{t}}_1, \hat{\mathbf{t}}_2, \cdots, \hat{\mathbf{t}}_p$  respectively. Then, the j-th sample principal components  $\hat{f}_j$  has the following expression

$$\hat{f}_j = \hat{\mathbf{t}}_j' \mathbf{z}$$

for  $j=1,2,\ldots,p$ , where  $\mathbf{z}$  is the normalized vector of each component. Similar to (5), the sample principal vector  $\hat{\mathbf{f}}=(\hat{f}_1,\hat{f}_2,\cdots,\hat{f}_p)'$  is expressed as

$$\hat{\mathbf{f}} = \hat{\mathbf{T}}'\mathbf{z},$$
 (6)

where  $\hat{\mathbf{T}} = (\hat{\mathbf{t}}_1, \hat{\mathbf{t}}_2, \cdots, \hat{\mathbf{t}}_p)$  is the estimated coefficient matrix.



#### 2.5 Principal Component Analysis

(4) Comprehensive Evaluation Strategy

Given the predefined threshold  $\alpha_0$ , when the cumulative contribution rate  $\sum_{j=1}^m \hat{\lambda}_j / \sum_{j=1}^p \hat{\lambda}_j \geq \alpha_0$ , m is selected as the number of principal components. Based on the first m sample principal components, we construct a comprehensive evaluation function as

$$F_z = \sum_{l=1}^{m} \left(\frac{\lambda_l}{\kappa}\right) \hat{f}_l = \omega_1 x_1 + \omega_2 x_2 + \dots + \omega_p x_p \tag{7}$$

with  $\kappa = \lambda_1 + \lambda_2 + \dots + \lambda_m$ , where  $\frac{\lambda_l}{\kappa}$  represents the contribution rate of the l-th principal component  $\hat{f}_l$  and  $\omega_j$  is the original weight of index  $x_j$ . Note we need to further normalize the weights to satisfy  $\sum_{j=1}^p \omega_j = 1$ . Finally, the comprehensive score (C-Score) of target fund is then calculated as

$$C-Score = \sum_{j=1}^{p} \omega_j y_j \tag{8}$$

where  $y_j$  is the score of the j-th evaluation index in the target fund according to scoring standards in Table A-1, whose value is between 0 and 5.



#### 3.1 Scoring Method of Public Funds

- Time period: Jan 1, 2017-Jan 1, 2019
- 500 Partial-share hybrid funds and flexible allocation funds established over 3 years from Wind database of China.
- Evaluation indicators: Timing ability (β), stock selection ability(α),
   percentile ranking of similar fund performance, Sharp index, Calmar ratio,
   annualized volatility, maximum drawdown rate and percentile ranking of
   similar fund in recent two years (Table A-1).
- Principal component analysis is used to obtain the specific weights of each indicator after standardizing the raw data of the above 8 indicators.
- According to the scoring Standards in Tables A-1 and star rating standards in Table A-2 in the appendix, we rated the fund to determine its star rating.
- The scoring results were tested during April 1 to June 30, 2019.

#### 3.1 Scoring Method of Public Funds

**Table A-1 Fund Evaluation Scoring Standard Table** 

Index	Weight	Rules Description So	core
		$\beta\geqslant 2$	5
	$\omega_1$	$1.5 \leq \beta < 2$	4
timing ability $(\beta)$		$1 \leq \beta < 1.5$	3
timing ability $(\beta)$		$0.5 \leq \beta < 1$	2
		$0 \leq \beta < 0.5$	1
		$\beta < 0$	0
		$\alpha \geqslant 0.0005$	5
		$0.0004 \leq \alpha < 0.0005$	4
stock selection ability	(.1-	$0.0003 \leq \alpha < 0.0004$	3
$(\alpha)$	$\omega_2$	$0.0002 \leq \alpha < 0.0003$	2
		$0.0001 \leq \alpha < 0.0002$	1
		$\alpha < 0.0001$	0

## 3.1 Scoring Method of Public Funds

#### **Table A-1 Fund Evaluation Scoring Standard Table**

	$rank \le 0.1$	5
	$0.1 \leq rank < 0.2$	4
41-	$0.2 \leq rank < 0.3$	3
$\omega_3$	$0.3 \leq rank < 0.4$	2
	$0.4 \leq rank < 0.5$	1
	rank > 0.5	0
	$Sharp\ index\geqslant 3$	5
	$1 \leq Sharp \; index < 3$	
$\omega_4$	$0.5 \leq Sharp \; index < 1$	3
	$0 \leq Sharp \; index < 0.5$	2
	$Sharp\ index < 0$	0
	$Calmar\ ratio \geqslant 3$	5
	$1 \leq Calmar\ ratio < 3$	4
$\omega_5$	$0.5 \leq Calmar\ ratio < 1$	3
	$0 \leq Calmar \; ratio < 0.5$	2
	$Calmar\ ratio < 0$	0
		$0.1 \le rank < 0.2$ $0.2 \le rank < 0.3$ $0.3 \le rank < 0.4$ $0.4 \le rank < 0.5$ $rank > 0.5$ $Sharp \ index > 3$ $1 \le Sharp \ index < 1$ $0 \le Sharp \ index < 0.5$ $Sharp \ index < 0.5$

#### 3.1 Scoring Method of Public Funds

#### **Table A-1 Fund Evaluation Scoring Standard Table**

		4 🗆	<b>▶</b> ₹ 6	
		otherwise	0	
		stable in the top $80\%$ annually	1	
years	w8	stable in the top $60\%$ annually	2	
percentile ranking of similar fund in recent 2	ωs	stable in the top $50\%$ annually	3	
		stable in the top $40\%$ annually	4	
		stable in the top $30\%$ annually	5	
		$maximum \ drawdown < -0.4$	0	
	$\omega_7$	$-0.4 \leq maximum \; drawdown < -0.3$	1	
maximum drawdown		$-0.3 \leq maximum \; drawdown < -0.2$		
		$-0.2 \leq maximum \; drawdown < -0.1$	4	
		$-0.1 \leq maximum \; drawdown < 0$	5	
		$0.5 < annualized\ volatility$	0	
		$0.4 < annualized\ volatility \leq 0.5$	1	
difficultied voideling	ω6	$0.3 < annualized\ volatility \leq 0.4$	2	
annualized volatility	$\omega_6$	$0.2 < annualized \ volatility \leq 0.3$	3	
		$0.1 < annualized\ volatility \leq 0.2$	4	
		$0 < annualized\ volatility \leq 0.1$	5	

#### 3.1 Scoring Method of Public Funds

**Table A-2 Fund Star Rating Standards** 

	~
comprehensive score	star rating
[4, 5]	5-star
[3, 4)	4-star
[2, 3)	3-star
[1, 2)	2-star
[0, 1)	1-star

## 3.2 Comprehensive scoring of public funds

 We conducted principal component analysis, calculated the eigenvalues of the sample correlation matrix and the cumulative contribution rate of them.
 The results are as follows:

Table 3-1 Eigenvalues, contribution rates, and cumulative contribution rates of sample correlation matrix

No.	eigenvalue	contribution rate	cumulative contribution rate
1	4.1392	0.5174	0.5174
2	1.4319	0.1790	0.6964
3	0.9490	0.1186	0.8150
4	0.6800	0.0850	0.9000
5	0.3623	0.0453	0.9453
6	0.2207	0.0276	0.9729
7	0.1206	0.0151	0.9880
8	0.0961	0.0120	1.0000

The four principal components are selected for next analysis.

#### 3.2 Comprehensive scoring of public funds

Table 3-2 The first four feature vectors and explanation of principal components

Original index	1	2	3	4
Timing ability( $\beta$ )	-0.0589	-0.6212	0.7619	0.0617
Stock selection ability $(\alpha)$	0.8212	-0.1020	-0.3886	0.1380
ranking in last year	0.8871	-0.2624	-0.0196	0.0784
Sharpe index	0.8585	-0.1420	0.0251	-0.4223
Calmar ratio	0.8642	0.0366	0.1142	-0.4182
Annualized volatility	0.2550	0.8218	0.3459	-0.0926
Maximum drawdown	0.6316	0.4895	0.2893	0.3567
Ranking in recent 2 years	0.8524	-0.1743	-0.0115	-0.4025
Interpretation	Profitability	Risk Control	Management	Performance
		Ability	Ability	Stability

## 3.2 Comprehensive scoring of public funds Explanation of principal components.

- the first principal component has a large loading (in absolute value) on stock selection ability(α), ranking percentile of similar funds in last year, Sharp index, Calmar ratio, maximum drawdown and ranking in recent two years. According to the meaning of these indexes, we interpret the first principal component as 'profitability'.
- ▶ The second principal component has a large loading on timing ability( $\beta$ ), annualized volatility and maximum drawdown, which are then interpreted as 'risk control ability'.
- ▶ The third principal component has a great loading on timing ability  $(\beta)$ , stock selection ability $(\alpha)$  and annualized volatility, which mainly reflects the management ability of fund managers. Therefore, the third principal component is interpreted as 'management ability'.
- ➤ The fourth principal component has a considerable loading on the Sharp index, Calmar ratio, maximum drawdown and ranking in recent two years. Therefore, the fourth principal component is intepreted as "performance stability".

#### 3.2 Comprehensive scoring of public funds

➤ Through the comprehensive evaluation strategy (7)-(8), we can obtain the weight of individual evaluation indicator for calculating the comprehensive score in (8).

Table 3-3 the weight of individual indicator for the comprehensive score of the Fund

Original index	Final Weight
Timing ability( $\beta$ )	-0.0060
Stock selection ability $(\alpha)$	0.1104
ranking in last year	0.1321
Sharpe index	0.1078
Calmar ratio	0.1349
Annualized volatility	0.1516
Maximum drawdown	0.2104
Ranking in recent 2 years	0.1588
Sum	1.0000

#### 3.2 Comprehensive scoring of public funds

• In order to test the significance of the obtained weight coefficients, we calculate the above weights 500 times through resampling and calculate the *t* value of each weight according to the sample mean and standard error, the results are reported in Table 3-5:

Table 3-4 t-test for the weight of individual evaluation

	$\omega_1$	$\omega_2$	$\omega_3$	$\omega_4$	$\omega_5$	$\omega_6$	$\omega_7$	$\omega_8$
t-value	-3.6667	21.1718	8.2501	18.8066	97.4963	1.9642	3.6895	10.1714

▶ The t-values in Tables 3-5 reject the assumption that the weight coefficient is zero with probability tending to 1 almost. Therefore, the weights of all evaluation indicators are statistically significant.

#### 3.2 Comprehensive scoring of public funds

5-star

4-star

The comprehensive score of each fund based on the evaluation index can be calculated by the following formula::

$$CScore_i = \sum_{i=1}^8 \omega_i x_i^*$$

where  $\varpi_j$ 's values are given in Table 3-4 and  $x_i^*$  is the score of the fund's *i*-th evaluation index, whose value is between 0 and 5. Then, based on the comprehensive scoring and star rating criteria (see Table A-2), we get the star rating distribution of 500 funds (see Figure 1).



3-star

2-star

1-star

Figure 1: star rating distribution of 500 funds

#### 3.3 Verification of the evaluation result

In order to test the effectiveness of the comprehensive scoring and star rating method we proposed, we selected the average performance of various star level funds from April 1 to June 30, 2019 to compare with the average performance of the Shanghai and Shenzhen 300 Index and similar funds.

Table 3-5 comparison among various star level funds

	5-star	4-star	3-star	2-star	1-star	CSI300 Mea	n of similar funds
Yield rate	1.63%	0.63%	-0.72%	-2.20%	-2.87%	-1.21%	-1.23%
Risk free rate	0.38%	0.38%	0.38%	0.38%	0.38%	0.38%	0.38%
Excess return rate	1.25%	0.25%	-1.10%	-2.58%	-3.25%	-1.58%	-1.60%
Sharp index	0.15	-0.03	-0.08	-0.26%	-0.24%		-0.13%
Maximum drawdown	ı-4.34%	-10.47%	-11.78%	-14.63%	-14.26%	-13.49%	-9.51%

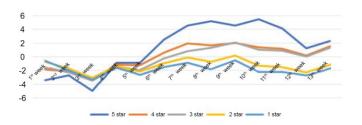
#### Summary:

- 1) The performance of CSI 300 index and the average of similar funds are between 3-star and 2-star funds;
- 2) Sharp index acts similar as excess return rate and maximum drawdown rate;
- 3) Five stars perform best, four stars perform second, and one star performs worst.

#### 3.3 Verification of the evaluation result

- ▶ The time interval: April 1 2019- June 30, 2019
- ▶ The abnormal yield is the difference between the cumulative yield of the fund and the yield of the CSI 300 index.

Figure 2: comparison on cumulative abnormal return rate



#### 3.4 forecast future excess return with comprehensive score

- ▶ Aim: to test whether the comprehensive score proposed in this project has a significant effect on the prediction of the excess return rate of funds.
- ▶ Dependent variable : the excess return rate of funds.
- ▶ Independent variables: the comprehensive score of the fund, eight evaluation indicators.
- ▶ Validation data is selected from January 3 to April 4, 2019, involving 60 cross-sectional data in the first quarter of 2019.

The following fixed effect model is used for fitting:

$$y_{it} = \beta_0 + \beta_1 x_{1,i,t-1} + \dots + \beta_{10} x_{10,i,t-1} + \gamma_1 F S_2 + \dots + \gamma_4 F S_5 + \varepsilon_{it}$$
, (9) where  $x_1$  to  $x_{10}$  represent timing ability, stock selection ability, percentile ranking of similar funds, Sharp index, Calmar ratio, annualized volatility, maximum drawdown and percentile ranking of similar fund in 2017 and 2018, fund comprehensive score  $(x_{10})$ ,  $FS_2$  to  $FS_5$  respectively represent 2 to 5 star fund.

- 3.4 forecast future excess return with comprehensive score
- ▶ Using R programming, the fitting results of the model are in Table 3-7

Table 3-6 Fitting results of fixed effect models

Coefficient	Estimate	Stand error	t-value	p-value(Pr>t)
$\beta_0$	-3.589	1.912	-1.878	0.061
$\beta_9$	0.060	0.019	3.170	0.002
$\beta_{10}$	1.447	0.631	2.295	0.022
$\gamma_1$	1.376	1.373	1.002	0.317
$\gamma_2$	4.424	1.925	2.299	0.022
$\gamma_3$	0.018	2.393	0.007	0.994
$\gamma_4$	-2.914	2.895	-1.007	0.315

#### 3.4 forecast future excess return with comprehensive score

► Using R programming, the fitting results of the model are in Table 3-7

Table 3-7 Fitting results of fixed effect models

	Coefficient	Estimate	Stand error	t-value	p-value(Pr>t)
	$eta_0$	-3.589	1.912	-1.878	0.061
•	$eta_{10}$	1.447	0.631	2.295	0.022

#### ▶ Summary:

- i) From Table 3-7, the estimated coefficient  $\beta_{10}$  of the comprehensive score is 1.447 and its p-value 0.022 is less than 0.05, indicating that the comprehensive score has a significant effect on the prediction of the future excess return rate of the fund.
- ii) The higher the comprehensive score of the fund, the higher the expectation of the future excess return rate, which further indicating the effectiveness of the proposed evaluation method.
- iii) The goodness of fit  $R^2$  of model (8) is 50.11%.

#### 3.4 forecast future excess return with comprehensive score

- ▶ It should be noticed that the estimated weights vary in different periods. With the rolling of the time (by day), the calculated weights of the evaluation indicators also have a trend of changing. However, the calculation method of weights is the same.
- ▶ The starting and ending date of the data selected in this project is from January 1, 2017 to January 1, 2019.
- ▶ We can also roll the deadline from January 1 to May 31, 2019 to get the time series of the weights, and then calculate the comprehensive score and rating of the fund in this interval, which would be a dynamic process.
  - It can be predicted that the star rating of each fund will not change significantly in a short rolling time, but it will fluctuate in the long run, which also explains the scarcity of five-star funds with excellent performance in the market.

#### 4.1 Conclusions

对本文所述随机选取的500只偏股混合型和灵活配置型开放式基金在2017年1月1日和2019年1月1日的表现进行评分和评星。具体结论如下:

(1) 500只灵活配置型基金和偏股混合型基金中,能够评为5星级的基金占比2%,4星级的占比14.4%,3星级的占比23.2%,2星级占比49.6%,1星级的占比10.8%,评价结果表明最优和最差的数量较少,中间评级的占比最多,符合目前公募基金市场的整体现状(即二八现象)。此评价结果具有较强的客观性和参考意义,通过验证可以看出,3-5星级基金的超额收益率和夏普比率都优于同期指数表现和同类基金平均表现,所以建议投资者在筛选的时候,最好选择评星在3星级及以上的基金。

#### 4.1 Conclusions

(2) 在对这500只基金的8大指标进行数据整理和打分评级过程中发现, 盈利能力、风险控制、择时和选股能力这三个指标,单项分数高的基金 很多,但是80%以上的基金在业绩稳定性这一单项上得分较低,造成这 种现象的原因有中途更换基金经理、市场风格轮动、基金的策略和主题 没有随着证券行情的转换而转换、证券市场的热点转换较快等原因。 2017年是成长股占优,2018年是医疗板块、科技板块走势较好,而到了 2019年又是医药板块、消费板块、5G板块涨势较好,所以,市场多数公 募基金会出现2018年业绩排名较好,而2019年业绩排名又不尽人意,反 之亦然。如何保持好业绩的稳定是十分重要的,考察了投资经理的宏观 预判和对政策的灵敏度。当然也有少数业绩稳定性优秀的基金,如,张 清华的易方达新收益混合A(代码:001216)连续两年业绩排名前30%, 胡昕炜的汇添富消费行业混合(代码:000083)连续两年业绩排名前1/4, 以上2只基金,通过本文的评价体系得分都在3分以上,分别评星为5颗星 和4颗星。

#### 4.1 Conclusions

(3)本文提出的基于主成分分析法对基金进行综合打分和评星,先对所选基金的8大评价指标进行主成分分析,然后基于主成分的贡献率来计算综合评分,间接得到每个评价指标在计算综合评分时所占的权重,该权重即为综合评价对每个因子所需要赋予的权。

由于基于主成分分析计算指标权重的方法是依赖数据的,所以本文提出的计算指标权重的方法是客观的,具有科学性。实证分析的结果表明,本文提出的基于综合评分及评星的结果与公募基金的市场表现情况相符,筛选的五星级基金在盈利能力、回撤控制和稳定性上的表现确实优于其他星级基金及同时期的沪深300指数和同类型基金的平均。此外,我们还构造了固定效应模型检验出基金的综合评分对预测未来超额收益率具有显著作用,从而进一步说明本文提出的基于主成分分析法的基金综合评分方法是有效的,筛选出的星级基金对于投资者购买目标基金具有一定的参考价值。

## 4 Conclusions and Suggestions

#### 4.2 Suggestions

本文主要基于主成分分析法对公募基金进行评价,主要目标是将市场现有的基金进行评级,打上标签,基于本文实证研究结果,下面我们站在基金销售机构、投资者和基金管理人的角度上来分别提供建议。

#### i) 对于基金销售机构而言:

在市场上寻找并引进目标公募基金时,不可盲目或仅做形式审查,首先应该了解基金管理人的资质、内部控制、投资流程、投研团队实力、内部考核制度等信息,对基金管理人进行审慎性调查,这也是监管对基金销售机构提出的要求,其次应该对拟引进的公募基金产品进行尽职调查,不能仅看基金经理的名气或得奖情况,应该按照盈利稳定性、风险控制能力、业绩稳定性和基金择时、选股能力这4个方面,对公募基金进行评分评星,并对基金业绩进行归因分析,找出取得业绩的原因是配置能力或选股择时能力。最后,将目标基金销售给投资者之前,需要充分了解投资者的风险承受能力、投资预期等要素,还需要为投资者充分揭示产品的风险。

#### 4.2 Suggestions

ii) 对于基金投资者而言:

首先,要明确自己的风险偏好,其次,需要了解自己对于流动性的要求,最后根据自身对行业投资的偏好来确定符合自身需求的公募基金。投资者在关注基金评价和评星结果的同时,也需要查看目标产品的风险等级是否与自己的风险承受能力相匹配,建议在相匹配的产品里,选择评价和评星级别高的产品。其次,投资者在选定拟投资的公募基金后,还应该仔细查看该基金的合同和招募说明书,了解其投资范围、各种费率、流动性等重要信息。最后,投资者在购买公募基金后,还需要按时关注产品重点信息,如基金经理变更、重仓股风险、业绩大幅波动、持仓股黑天鹅等突发非预期事件,并对所持有的产品进行评估,做出继续持有、赎回或者换仓的操作。

#### 4.2 Suggestions

iii) 对公募基金管理人而言:

要充分承担"受人之托、代人理财"的责任,首先,要建立完善的内部控制机制和风控体系,制定合理的投资决策和投资流程,建立以长期业绩为导向的考核激励机制,避免因为追求短期的规模,而使得基金经理不遵循自己的投资理念和投资风格,发生风格漂移事件,给投资者带来损失。其次,管理人在挑选基金销售机构为其销售金融产品时,需要充分考虑销售机构的资质、公司内控、反洗钱制度等信息,对其进行审慎性评估,最后基金管理人作为市场重要的机构参与者,有义务责任维护证券市场稳定。

## Further research prospects

- ▶本文的评价体系比较偏微观,并**没有考虑宏观政策等因素**,而这类因素 往往其着很大的作用,希望在未来的基金绩效评价研究中,能够加入宏 观经济、货币政策、财政政策预期等因素,将其纳入到基金评价过程中 去,给予基金未来走势一种合理的评估。
- ▶本文较为重视投资者的需求,基金的评价绝对不能脱离投资者匹配这一环节,所以后续的基金绩效评价研究中,希望能够根据投资者风险偏好、投资者行为分析、投资目标等要素对其进行分类,再根据投资者分类,细化基金的绩效评价标准,并进行动态调整。

# Thanks!

