Valuation analysis of fund net unit value based on H-P filter and Tobit model -- Take a sample of 2430 from ten funds

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Abstract. As an investment product, the analysis of the historical net value of the fund is of great significance to the prediction of the fund. In this paper, the H-P filtering method, OLS regression analysis, and Tobit model are applied to analyze the historical net value, establish the model, and forecast. The results show that :(1) The risk level is positively correlated with the long-term trend fluctuation of the fund. (2) There are differences in the absolute and relative values of the long-term trend of funds with the same risk grade. The impact of the days change on the long-term trend may vary from individual to individual. (3) The selected fund industry allocation is mainly in the manufacturing industry, reflecting the steady and good development of China's manufacturing industry.

Keywords: Fund valuation; Net unit value of fund; H-P filtering method; Tobit model; Quantitative investment.

1. Introduction

Fund is an important part of China's portfolio investment trading market. Its low entry threshold, large transaction scale and flexible characteristics make it become the investment choice of many investors. With the development of fund theory and the evaluation of fund industry, fund net value is the most basic and critical factor, so it is of great significance to study the prediction of fund net value. By studying the historical net unit value of fund, investors can provide a reference for judging, which improve investment returns and reduce the risks. Forecasting fund net value is the most direct method to judge its trend.

In this paper, ten funds, 243 trading days in 2021, a total of 2430 data are chosen. Using the H-P filtering method to analyze the random fluctuations and long-term trends of the net unit value of funds, OLS prediction model and Tobit model for empirical test. The sections of this paper are as follows: The first part is the introduction, the second part is the literature review, the third part is the introduction and research data of sample funds, the fourth part is the change and forecast analysis of the net unit value of funds, and the fifth part is the conclusion.

2. Literature REVIEW

2.1 Fund net value and risk classification

The fund's net value is divided into unit net value and accumulated net value. This paper selects the former, and its calculation formula. Net value of fund units = (total fund assets - total fund liabilities)/ total fund share. AMAC conducts a comprehensive quantitative and qualitative assessment and classification of the risk levels of fund products based on the performance fluctuation, investment direction and scope, manager risk and other indicators. Specifically, there are five grades: R1, prudent low-risk products; R2, robust medium and low-risk products; R3, balanced medium risk grade product; R4, aggressive medium-high risk products; R5, aggressive high-risk grade product.

2.2 The valuation of net unit value of listed companies

2.2.1. A review of fund valuation theory of listed companies

Fund valuation refers to the process of calculating and evaluating the value of fund assets and liabilities according to fair prices to determine the net value of fund assets and fund shares. Its own has certain risk and uncertainty[1]. Valuation is not viewed statically as a number, but as a range. Valuation ability is the core competitiveness of asset management industry.

China's current funds are mostly based on Jensen and Carhart's model. Relevant literature shows a variety of valuation methods. There are many absolute valuation methods, such as absolute valuation, relative valuation, PE[2], PS, PB[3], etc. Quantification takes the form of net fund unit value, PCA-GA-BP neural network[4][5], Wavelet decomposition ARMA-GARCH model[6], GARCH-VAR model[7], POT[8][9]and other methods to carry out fund valuation and analysis.

2.2.2. Fund valuation methods of listed companies

Different models show different aspects of accuracy and optimization, but each model has its limitations. BP neural network has some problems in predicting the net value of fund, such as slow convergence speed, local minimum value and unstable learning effect. It is found that the GA-BP neural network model optimized by the genetic algorithm can predict the net value of fund in the life cycle more quickly and accurately. By establishing the wavelet decomposition ARMA-GARCH model and the empirical analysis of fund data, the prediction accuracy of wavelet decomposition ARMA-GARCH model is higher. Garch-var model, VAR model can measure the maximum loss of financial assets under a given holding period and confidence level. The POT method was used to determine the critical value, and then the parameter estimation and model test were carried out.

2.3 Further Review

Various valuation methods and models have different performance on the net value estimation and risk perception of funds. As time goes on, more accurate models are applied to estimate the net value of funds. Valuation is a dynamic range, and the rise and fall of the industry should be judged based on historical valuation and the overall development of the industry. This paper uses the H-P filtering method, OLS regression analysis and Tobit model to model valuation and analysis. Although such methods have been used in the relevant literature, most of them focus on the analyzing of a single fund, involving a relatively small area[10].

OLS pre-filtered the data before regression to eliminate short-term disturbances, and then tested it through the Tobit model to improve the accuracy. Model parameters with truncated data will bias OLS regression analysis, and the estimators are inconsistent. Therefore, the Tobit model is selected for inspection and analysis, because it fits the data characteristics studied in this paper and has a good interpretation of parameters. Its standard error is stable.

This paper selects a large number of samples and involves different risk levels, which makes the samples more comprehensive. Empirical analysis based on rich samples can make the analysis more accurate. At the same time, through a certain amount of sample size, we can understand the development of the relevant industry market, to obtain a broader level of results.

3. Fund profile and research data

3.1 Brief introduction of funds

While ensuring that the sampled funds cover different risk levels, different fund management companies and fund custodians are included as much as possible. The manufacturing industry is selected as the fund's industry allocation as the observation object. Ten different funds were chosen and analyzed. The paper analyzes the development of China’s manufacturing industry through the products with manufacturing as the main body of capital allocation. The manufacturing industry directly reflects the productivity level of a country. As the pillar industry of the country, China's manufacturing industry has maintained a good development trend.

Table 1. Fund basic information and manufacturing ratio statistics

Risk Level	Code	Shortcuts	Release date	Fund trustee	Fund Manager	Assets	Manufacturing
R1	001625	Currency type	2011.02.21	China CITIC Bank	Sujun LIAN	34.459 billion	/
	519510	Currency type	2015.07.17	BC	Zhuoran WANG	199 million	/
R2	007555	Bond - long bond	2020.03.26	Ping An Bank	Yongfeng MAO	2.421 billion	/
	004400	Bond - long bond	2017.02.24	CMB	Jie YANG	812 million	/
R3	000536	Bond type - convertible bonds	2014.03.03	ABC	Jianfei ZENG	856 million	17.48%
	009512	Bond - Hybrid debt	2010.11.25	ICBC	Guang DU	477 million	5.20%
R4	003961	Hybrid - Flexible	2016.12.12	SPDB	Sen LIN	2.694 billion	86.03%
	519918	Hybrid - partial strands	2014.06.03	CCB	Yan LI	3.429 billion	65.96%
R5	001126	Equity	2015.03.16	CCB	Dehui LI	2.318 billion	64.19%
	160634	Index - stocks	2015.06.01	CCB	Dong YAN	389 million	73.79%

3.2 Research data and descriptive statistics

In this paper, all five risk levels are selected, and the unit net value of 10 funds is taken as the research sample. The data relating to funding products come from the Tiantian Fund website, and the data involved include basic fund overview, historical net value, fund holdings and industry allocation. The sample data is the daily net fund unit value data of 10 funds during all trading days of 2021, with a total of 2430 samples.

In this sample, the average net unit value of the ten funds is between 0.7 and 3.4, which is in the middle of the overall fund market. The difference between the maximum value and minimum value of net unit value is the largest for Huaxia Xinghe Mixture. The maximum value was 4.678 on December 31st, 2021, and the minimum value was 2.445 on March 24th, 2021. Among them, the standard deviation of the net value of Huaxia Xing and Mixed units is 0.705, with the biggest fluctuation on the whole.

Table 2. Descriptive statistical analysis of sample net worth data

Fund Rating	Code	Min	Max	Average	Standard Deviation	Median
R1(1)	001625	0.55	1.679	0.726	0.203	0.644
R1(2)	519510	0.501	1.346	0.705	0.122	0.685
R2(1)	007555	1.019	1.636	1.451	0.242	1.515
R2(2)	004400	1.034	1.695	1.172	0.241	1.041
R3(1)	000536	0.998	1.577	1.236	0.177	1.19
R3(2)	009512	0.94	1.469	1.164	0.15	1.118
R4(1)	003961	3.034	4.088	3.464	0.266	3.393
R4(2)	519918	2.445	4.678	3.524	0.705	3.51
R5(1)	001126	1.565	2.023	1.824	0.12	1.857
R5(2)	160634	1.06	1.876	1.463	0.274	1.456

4. Empirical analysis On the prediction of net fund Share of listed companies

4.1 Long-term trends in net unit value of the fund

Based on the characteristics of relevant data, H-P filtering was used for analysis to eliminate impurities in the short-term trend and select the long-term trend. This method is widely used in macroeconomic analysis of long-term trends. Using simple and symmetrical moving average method and H-P filter, the smooth sequence with certain trend change is separated from the variable time series data. So, time series data is divided into two parts: periodic data and trend factor data. In this paper, the historical net value data of the original fund is analyzed by H-P filtering, and the follow-up processing is based on long-term trend data.

$$\min\{\sum_{t=1}^{n}(z_t - g_t)^2 + \lambda \sum_{t=3}^{n}[(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2\} \quad (1)$$

Where λ is a natural number and is called a smoothing parameter. When λ=0, Z_n=G_n, and when λ approaches infinity, HP filtering degenerates into least square trend estimation. In this paper, the value of λ is 14400. The original net value data selected are decomposed to obtain periodic fluctuation data and trend elements. The software used for data processing and analysis in this paper is Stata16, and the results are shown in Figure 1.

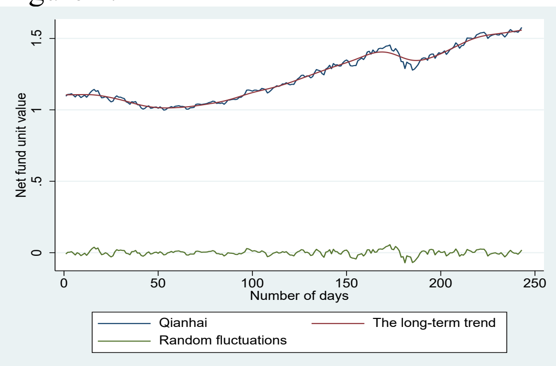

Figure 1. Long-term trend of net value of sample funds (choose one from 10, R3(1)Qianhai)

It can be seen from Figure 1 that a relatively smooth long-term trend curve can be obtained through H-P filtering analysis, namely the red curve in the figure. The green curve is the periodic fluctuation trend below the set, the red curve represents the trend element sequence G, and the green curve represents the periodic element sequence C. By analyzing the trend of H-P filtering, it can be seen that R1 funds have extremely strong periodic fluctuations, followed by R2, R3, R4 and R5, with increasing degree of net trajectory and long-term trend fluctuations. Although the cyclical fluctuation of R5 is weaker than that of R1, the historical net unit fluctuation is large, which increases the difficulty for the subsequent model prediction.

4.2 Prediction analysis of net value of fund shares

After H-P filtering analysis of the historical net value data related to the sample funds, OLS regression was used to fit and forecast the decomposed data. Table 3 lists the results of the correlation regression analysis, where the explained variable is the net value of the fund unit and the explained variable is the number of trading days of the fund. Each core coefficient is at its significance level. The core coefficient represents the expected increase or decrease in the net unit value of the average fund for each additional trading day, with a long-term upward or downward trend.

In OLS analysis, there are two problems: First, after using OLS regression, it is found that the data fitting degree of some funds is not high, but it is significant in the significance test of their core coefficients. This only shows that part of the data regression is significant and can not necessarily be used to explain the whole model; Second, the absolute value of the core coefficient is small, varying in the thousandth or even ten-thousandth of the net value, which indicates that the core coefficient may be accidental. Therefore, to ensure the forecast's effectiveness, the Tobit model was used to test the robustness of the forecast. Tobit models can be roughly divided into five categories. Truncated data models are selected according to the characteristics of the data selected in this paper. The left truncated data structure is generally $y_i = y^*$, if $y^* > L$.

The general form of Tobit model is: $Y^* = \beta x_i + u_i$; $Y_i = y^*$, if $y^* > L$. Among them, Y^* is the potential strain variable, which can be observed only when the potential variable is greater than L. Its value is Y_i, x_i is the independent variable vector, β is the coefficient vector, and the error term u_i obeys a specific distribution. Through the robustness test, it can be concluded that the core coefficients are consistent, indicating good robustness. Moreover, there is no significant difference between the two values' t-value, indicating basically the same significance level. Therefore, the OLS method is continued to be selected for regression analysis.

Table 3. Forecast analysis of net Unit Value of Fund (1)

	OLS			Tobit		
Variables	Coef.	Std. Err.	T-value	Coef.	Std. Err.	T-value
R1(1)	-0.000335	3.13E-05	-10.7	-3.35E-04	3.12E-05	-10.75
R1(2)	-0.00026	3.90E-05	-6.67	-2.60E-04	3.88E-05	-6.7
R2(1)	0.0018591	1.77E-04	10.51	1.86E-03	1.76E-04	10.55
R2(2)	0.0021472	1.54E-04	13.93	2.15E-03	1.54E-04	13.99
R3(1)	0.0023275	5.75E-05	40.51	2.33E-03	5.72E-05	40.68
R3(2)	0.0020695	2.92E-05	70.98	2.07E-03	2.90E-05	71.27
R4(1)	0.003067	1.27E-04	24.07	3.07E-03	1.27E-04	24.17
R4(2)	0.0092812	2.22E-04	41.81	9.28E-03	2.21E-04	41.98
R5(1)	-0.00109	7.49E-05	-14.55	-1.09E-03	7.46E-05	-14.61
R5(2)	0.0035572	9.93E-05	35.82	3.56E-03	9.89E-05	35.97

Based on the above analysis results, an empirical prediction was made on the net unit value of the fund on the 1st and 6th trading days in the future, namely the 245^{th} and 250^{th} trading days, corresponding to the trading dates of January 4^{th}, 2022 and January 11^{th}, 2022 respectively. The prediction was made using the results obtained by OLS regression analysis. At the same time, the Tobit model was used to test the robustness. The first trading day in the future corresponds to the 245^{th} day of the overall parameter, and the net unit value of each fund predicted by OLS is 0.779, 0.770, 1.418, 1.212, 1.579, 1.409, 4.035, 4.687, 1.757, 1.759 respectively. Compared with the actual value, the maximum difference between the estimated value and the true value on day 245 is 0.1403, which is R1(1) net forecast value, and the minimum is 0.00028, which is R4(2) net forecast value.

After six trading days which corresponds to the 250^{th} day of the total parameter, and the predicted values are 0.778, 0.7691, 1.425, 1.221, 1.589, 1.417, 4.047, 4.724, 1.753, 1.773. Compared with the actual net unit value, the maximum difference between the estimated value and the real value of 250^{th} day is 0.191, which is R1(1) net forecast value, and the minimum is 0.008, which is R2(1) net forecast value. It can be found that the predicted value is close to the actual value, and the funds with relatively higher prediction accuracy are the eastern region types. It is proved that the model's prediction accuracy is higher for the funds with the largest holdings in the east, and the model is of great significance for predicting the trend change of the net value of the fund in the short term in the future.

4.3 Heterogeneity analysis of net fund unit value

Table 4. Forecast analysis of net Unit Value of Fund (2)

Variables	Coef.	R2	Adjusted R2
R1(1)	-3.35E-04	0.3222	0.3193
R1(2)	-2.60E-04	0.1558	0.1523
R2(1)	1.86E-03	0.3141	0.3113
R2(2)	2.15E-03	0.446	0.4437
R3(1)	2.33E-03	0.872	0.8714
R3(2)	2.07E-03	0.9543	0.9542
R4(1)	3.07E-03	0.7063	0.7051

R4(2)	9.28E-03	0.8788	0.8783
R5(1)	-1.09E-03	0.4677	0.4655
R5(2)	3.56E-03	0.8419	0.8412

4.3.1 Heterogeneity analysis of core coefficients

Based on the analysis of the relevant core coefficients in Table 4, the impact of the change of days on the long-term trend may vary from individuals. There are differences between the long-term trends of funds of different risk levels, reflecting the different risk levels' return characteristics. By comparing the absolute correlation coefficients of the ten funds in the sample, it can be found that R1 funds are generally less than 0.001. With the improvement of risk level, R2 and R3 funds' core coefficients are greater than 0.001 and less than 0.003; R4 and R5 medium-high risk funds' average correlation coefficients are greater than 0.003.

Funds of different sizes and sizes may have different economies of scale. The asset sizes of the selected sample funds are not the same, which may also affect the rise and fall trend of the obtained core coefficient. Similarly, different fund allocation is also the reason for the difference between products with the same risk level. In general, the smaller the risk level, the smaller the parameters of the long-term trend of the fund, that is, the smaller the volatility.

4.3.2 Analysis of model interpretation ability

$$R^2 = 1-(RSS/TSS) \tag{2}$$

$$\text{Adjusted } R^2 = 1- (1-R2)(n-1)/(n-k-1) \tag{3}$$

By observing R^2 and adjusted R^2 in Table 4, it can be seen that R2 values of R1 and R2 are relatively small, showing weak or moderate correlation, and the fitting effect is relatively weak. The R2 values of R3, R4 and R5 regression are all close to or over 0.5, and the two variables are moderately correlated, which indicates that the regression fits effect well, and the standard error value is generally small. There is a large positive correlation between the number of trading days and the net unit value of the fund. Among them, the fitting effect of R3 and R4 is better than that of R5, both exceeding 0.7, showing a strong correlation. This is because R5 itself fluctuates more and has more uncertainties.

5. Conclusion

This paper selects the 2021 net unit value data of 10 funds, covering all risk levels, and a total of 2430 samples, to analyze the fluctuations of net unit value and make predictions. In the analysis process, short-term fluctuations were decomposed by the H-P filtering method, and long-term trend data were used as explained variables. OLS regression analysis was performed, and Tobit model robustness test was used. Therefore, the following research results and implications are drawn.

5.1 Research Results

(1) R3 has a relatively higher fitting degree with the R4 type fund model. R1 and R2 are mainly money and bond-related funds, and their holdings are mainly Treasury bonds and some corporate bonds, with a stable long-term trend. For R5 funds, due to the high-risk degree, the fluctuation of net value leads to the decline of OLS prediction accuracy.

(2) There are differences in the absolute value and relative value of the long-term trend of funds with different risk levels, and the impact of the change of days on the long-term trend may vary from individual to individual. Risk level and fund long-term trend fluctuations are positively correlated. There are also coefficient differences between funds with the same degree of risk, which reflects the influence of other factors on the net value change trend of funds.

(3) Most of the funds in the selected samples are mainly allocated to the manufacturing industry. From the change of the historical net value of funds, we can observe the development of manufacturing industry in China. The trend of R3-R5 fund in 2021 reflects the overall steady trend of China's manufacturing industry, which is stable and good.

5.2 Policy Implications

(1) It can be found that China's fund market does not fully reflect the matching of risk and return. Better investment methods should be carried out and the manager should understand the macro market in order to smooth out volatility as much as possible and improve the risk-return ratio of financial products.

(2) Based on the heterogeneity of funds with different risk levels and long-term trends, the prediction of funds should consider the risk levels of funds and implement different investment strategies for funds with varying levels of risk.

(3) In response to the demand for environmental protection, China's manufacturing industry and the other related industries are undergoing various changes. The government should provide necessary assistance to manufacturing enterprises in transformation.

There is still room for further research. More samples can be selected for research to obtain broader or more accurate conclusions. At the same time, some factors other than time can be considered for more diversified analysis, or combined with the change of related industries.

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