Analysis of fund net unit changes and forecasts based on the Tobit model and H-P filter method

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Abstract. In order to forecast the net unit value of funds in the new energy industry, this paper selects the net unit fund value as a sample, each15 fund in the front-end, middle-end, and back-end of the new energy industry, uses the H-P filter method for data denoising, then uses OLS and Tobit models for modeling regression analysis. Conclusion: front-end industry funds in the new energy industry perform uncommonly well; middle-end investment risk is low; back-end investment risk is high. The heterogeneity analysis partly indicates a positive reinforcing relationship between the size of the fund and its long-term trend.

Keywords: fund valuation; fund net unit value; H-P filtering method; Tobit model.

1. Introduction

With the development of China's capital market, stocks, funds, and other financial products have increasingly become the most popular financial investment commodities for investors in China, "enter at low prices and sell at high prices" has become the basic tenet of every investor in the transaction, where the trading price of funds is closely related to the net value of the fund. Forecasting the net value of fund units is one of the most important topics for investors and economists alike. Domestic financial development is relatively slow, so few studies are related to funding NAV forecasting in China. The sample size of the study is also small and not universal. Based on this, this paper selects unit fund NAV as a sample, each15 fund in the new energy industry's front-end, middle-end, and back-end, using the H-P filter method to analyze the long-term trend of fund unit NAV, conducts an empirical test of Tobit model modeling.

The paper is structured as follows: Part I is an introduction, Part II is a literature review, Part III is an overview of the new energy industry and research data, Part IV is an empirical analysis of fund net unit forecasts for the new energy industry, Part V is a research conclusion and recommendations.

2. Review of the literature

2.1 Net Unit Value, Risk Classification, and Valuation Methodology

2.1.1 Net unit value and risk classification of the fund

The net-net unit value is the net asset value represented by each fund unit, which is inextricably linked to both the macro environment and investor psychology. For the macro environment, Patrick (2011) uses multivariate cointegration analysis and finds that any movement in selected macroeconomic variables can be used to predict the movement in NAV[2]. The relationship between fund net unit value and fund risk has also been a hot topic of research as investor psychological factors are manifested in the fact that investors tend to desire an increase in fund NAV but at the same time fear the presence of fund risk.

Fund risk refers to a fund's risks in its operations. The fund's risk level ranges from r1 to r5, corresponding to Cautious, Stable, Balanced, Aggressive. The risk level also increases progressively. Ding Chunxia et al. (2018) study the relationship between fund illiquidity risk and fund NAV find that fund risk, and fund NAV are inversely related, with the greater fund risk, the more likely the fund NAV will fall[1].

2.1.2 Valuation methods for financial derivatives

Foreign financial markets have developed earlier and better systems, so in the valuation of financial derivatives, foreign research is mainly, W. C (1995) used artificial neural networks to predict the year-end net asset value (NAV) of mutual funds then compared the results of the neural networks with regression results[4]. Wojciech (2019) et al. found that various variables in the money market change rapidly and dramatically. Therefore extended their algorithm for non-stationary variables using Tobit regression then determined their critical values.[8]

Domestic research started late, the valuation of PE private equity funds in China is commonly used by Liu Kun (2012) comparable company law and discounted cash flow method, but these methods cannot make reliable predictions of fund net worth[1]. Han et al. (2018) optimized generalized regression neural networks using an artificial fish swarm algorithm to forecast investment in mutual funds in Taiwan[7]. Lu et al. (2020) established a dynamic quantitative investment strategy based on moment component absorption rate to forecast stock market ups and downs[2].

2.2 Net Unit Value Time Series Processing

In order to smooth out complex financial data for subsequent empirical testing, Peng Zhou (2015) uses an ARIMA model to remove nonlinear features from the time series and increase the forecasting accuracy[9]. In contrast, Peter C.B (2020) uses the HP filter method, which is typically used to generate new time series. Advantages of HP filters in that, depending on the choice of the smoothing parameter (λ), it can include long-term behavior, from deterministic linear trends to smooth Gaussian processes to stochastic trends, combinations of stochastic and deterministic trends. [10]

2.2.1 H-P filtering method

The data used in this study, which are time-series data, contain only stochastic fluctuations and long-term trends, i.e.

$$ATt=Tt+Ct \tag{1}$$

Where t=1, 2, 3, ..., n. The H-P filtering method separates the long-term trend T_t from the fund net unit time series AT_t. This method is based on nonlinear regression using the symmetric data moving average principle, forming an HP filter that filters out a smoothed series, T_t, from inside the time series AT_t. The objective function of the decomposition is to minimize the following equation.

$$\min\{\sum_{i=1}^{n}(AT_t - T_t)^2 + \lambda\sum_{i=2}^{n-1}[(T_{t+1} - T_t) - (T_t - T_{t-1})]\}^2 \tag{2}$$

where the smoothing factor λ of the above equation takes the value of 14400 in this paper.

3. New Energy Industry and Research Data

3.1 New Energy Industry Overview

Based on the breakdown of the industry, the new energy industry can be broadly divided into three parts: upstream, midstream, and downstream.

New energy upstream industry chain is mainly rare mineral resources, including mineral resources lithium, cobalt, nickel, etc. Therefore, this article extracts fifteen funds from the major fund holdings of the above companies, such as the Western Leeds Quantitative Growth Mix.

The new energy midstream industry is mainly responsible for producing and recycling components, including batteries, structures, other components, semi-finished products, etc. The target of this study is specifically the funds such15 as Cinda Australia Bank New Energy Industry Equity.

Downstream is the industry that processes raw materials and components to manufacture finished products or engage in production services, which is at the end of the entire new energy industry chain. The target of this study is specifically the Shenwan Xinjiang New Energy Vehicle and other15 funds.

3.2 Research data and descriptive statistics

The data required for the empirical part of the fund's daily net unit value in this paper is obtained from the official databases of Daily Fund. The data is collected through Python crawler technology. The data mainly includes the daily net unit value of the front, middle, and back-end 45 funds from the issue date to 2022-1-21. The total amount of data is in the form of 52373 articles. The following table provides a descriptive analysis of each fund's daily net unit value.

Table 1 Descriptive Analysis of the Fund Net Unit Value

Name	Average	Median	Name	Average	Median	Name	Average	Median
R1	2.137	1.940	R16	1.556	1.565	R31	1.307	0.966
R2	1.346	1.335	R17	1.107	1.109	R32	1.458	1.062
R3	0.814	0.705	R18	0.990	0.852	R33	1.645	1.200
R4	1.202	1.099	R19	1.006	0.901	R34	2.002	1.910
R5	1.670	1.103	R20	1.286	1.279	R35	1.336	1.400
R6	1.620	1.188	R21	1.472	1.573	R36	1.412	1.471
R7	1.917	1.327	R22	1.473	1.336	R37	0.989	1.000
R8	2.279	2.269	R23	1.519	1.567	R38	1.001	1.005
R9	2.435	2.313	R24	0.642	0.613	R39	1.311	1.400
R10	0.987	0.943	R25	2.067	1.838	R40	1.031	1.031
R11	1.040	1.059	R26	2.308	1.808	R41	0.900	0.890
R12	1.692	1.738	R27	2.177	1.935	R42	1.531	1.090
R13	1.406	1.232	R28	1.959	1.706	R43	1.633	1.530
R14	1.121	1.136	R29	2.131	1.507	R44	1.743	1.390
R15	1.942	1.868	R30	2.435	2.528	R45	1.312	1.409

As can be seen from the chart above, the fund NAV average is are1.573,1.609,1.374, which shows that the middle-end of the fund has a higher average fund NAV; the median of the funds is are1.417, 1.474,1.250, which shows that the front end of the fund has a faster fund NAV growth rate in the latter part.

4. Empirical analysis of fund net unit forecasts for the new energy industry

4.1 Long-term trends in the net unit value of the New Energy Industry Fund

Financial markets are a financial system with psychological, policy, macroeconomic, and other influencing factors. Therefore, in the collected data, multiple problems may accompany the occurrence of extreme values incomplete data. To address the above various problems that may lead to unstable experimental data, this paper performs denoising pre-processing on the fund day net values since the issue date to improve the random wandering and unit root situation. The experimental environment is Eviews10, and the method is HP filtering. The following graph shows the long-term trend result of 1 representative fund net unit value. The horizontal axis is time, and the vertical axis is the fund's net value.

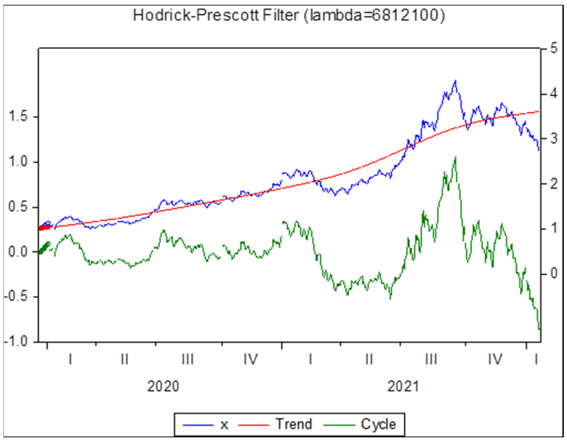

Figure 1 Represents the long-term trend chart of the fund

As can be seen from the chart above, the net value of the New Energy Industry Fund shows a stable to positive trend for the most part from a long-term trend, with the net value of fund units rising, where the ups and downs are cyclical with changes in policy and the macroeconomy seriously.

4.2 Forecast analysis of the Net Unit Value of the New Energy Industry Fund

Since the fund issue date, the initial issue of the fund has been priced at one yuan. The fund net value below zero dollars is not required for the empirical evidence of this paper. The explanatory variables are restricted in value for such characteristics, so the text uses the Tobit model. The regression model is tested for clad results, the Tobit model was selected for causal inference, and the regression results are shown below.

Table 2 Tobit Regression

Tobit model					
Core variables	Core factors	Core variables	Core factors	Core variables	Core factors
R1	.0057***	R16	0.0015***	R31	.0011***
R2	.0030 ***	R17	0.0003**	R32	.0021***
R3	-5.84e-06**	R18	0.0005***	R33	.0030***
R4	.0015***	R19	0.0006**	R34	.0050***
R5	.0026***	R20	0.0007***	R35	.0030***
R6	.0021***	R21	0.0015***	R36	.0026***
R7	.0030***	R22	-0.0001**	R37	-.0007***
R8	.0012***	R23	0.0002***	R38	-.000***8
R9	.0049***	R24	-0.0000**	R39	.0031***
R10	.0002***	R25	0.0039***	R40	-.0002***
R11	.0005***	R26	0.0017***	R41	.0002***
R12	.0025***	R27	0.0012***	R42	.0029***
R13	.0007***	R28	0.0009***	R43	.0044***
R14	.0003***	R29	0.0026***	R44	.0044***
R15	.0055***	R30	0.0011***	R45	.0034***

The core coefficients are selected as issue dates. As can be seen from the table above, most of the coefficients are positive, and most of them are significant at the 99% level, which shows that the issue dates of the funds in the New Energy Industry sample are mostly positively associated with the fund NAV. It also confirms the result in the previous section, that is, as the fund issue dates increase, the fund NAV also increases in the same direction. The mean core coefficients for the front and back ends are 0.00225, 0.00111, and 00.00223.00111, showing that the front end is the fastest growing on average, followed by the back end and the bottom end. In the OLS regression results, the coefficient results of the core coefficients are highly consistent with the Tobit regression results, in which the majority of the regressions' R^2 are greater than 0.7, indicating that the model fit is also better.

4.3 Empirical forecasts of the fund net unit value

This section presents the empirical forecasts of the NAV of some of the fund units for the 3rd, 6th, 17th, and future trading days, which correspond to January 24, January 27, and February 7. January 24 is the 502nd day of the total number of days. At this time, the net unit value of the fund is 0.006×502+0.722=3.734. Similarly, the OLS predicted values for the 6th and 17th trading days are 3.752 and 3.818. The robustness test of the Tobit model shows that the predicted results are the same and highly consistent with the long-term trend of the fund's actual value, which indicates that the model has empirical evidence. The model is empirically robust.

4.4 Heterogeneity analysis of the net unit value of new energy industry funds

In order to test whether there is heterogeneity in the growth of fund NAV per unit due to fund asset value, this paper divides all funds into three sub-samples in descending order of asset value and performs regression analysis separately. Table 3 illustrates that fund asset value size significantly contributes to fund net unit value growth for funds with higher, average, and lower asset values.

Table 3 Tobit regression by total asset value

Larger total asset value		Medium total assets		Smaller total asset value	
Name	Core factors	Name	Core factors	Name	Core factors
R5	.0026***	R3	-5.84e-06**	R10	.0002***
R13	.0007***	R33	.0030***	R35	.0030***
R29	.0026***	R9	.0049***	R45	.0034***
R6	.0020***	R22	-.0001*	R18	.0005**
R41	.0003***	R12	.0025***	R34	.0050***
R42	.0029***	R19	.0006**	R39	.0031***
R32	.0021***	R14	.0003***	R28	.0009***
R43	.0043***	R26	.0017***	R24	-.0000*
R7	.0030***	R40	-.0002***	R38	-.000***8
R44	.0044***	R25	.0039***	R37	-.0007***
R8	.0012***	R30	.0011***	R36	.0026***
R15	.0055***	R2	.0030***	R4	.0015***
R31	.0011***	R21	.0015***	R16	.0015***
R1	.0057***	R27	.0012***	R17	.0003*
R30	.0011***	R23	.0016***	R20	0.0007***

As can be seen from the table above, the core coefficients in the first tier, which consists of the funds with the largest asset size, mostly remain above 0.002the level of the maximum value 0.0056, with the average value 0.0026 being approximately the largest of the three groups (the remaining two groups are 0.0018, 0.0014). The ratio of the core coefficients of the three sub-samples is 1.1438: 1:0.6738. The coefficients in the first group are all positive, which shows that the issue date and the net unit value of the fund are positively correlated. i.e., the reason for that is the larger size of the funds may reflect the public's recognition of the funds or their managers, as well as less concern about the risk of fund liquidation; this is a virtuous circle, i.e., The more favorable the fund's indicators are, the more the public recognizes and invests in the fund, the mutual reinforcement of the two drives the net unit value of the larger funds compared to the medium and small-sized funds The net value of larger funds is increasing at a more stable and greater rate than that of medium and smaller funds.

It is reflected in the fact that as the size of the fund decreases, each additional day of issue date brings a smaller and smaller percentage increase in the net value per unit of the fund. Some funds even have a negative core coefficient, i.e., the number of issue dates is inversely proportional to the net value per unit, which is reflected in the fund returns, i.e., a state of loss.

5. Conclusion

5.1 Research findings

This paper takes the popular new energy industry fund as the research object selects the series data of the net unit value of each15 front-end, middle-end, and back-end fund to guide quantitative investment with the following conclusions.

Heterogeneity exists between funds. By total asset value, the larger the total asset value, the faster the rise in NAV per unit of the fund: by sector, the front-end rose fastest on average, and the middle-end rose the slowest on average. The back end is rising fast, but many funds have abnormal long-term trend fluctuations, or even declines, which can be seen in the back end of the performance of each fund is more differentiated and higher risk.

5.2 Recommendations

The predictions in this article are convincing. Therefore, funds with more considerable total assets or funds in the front-end and mid-industry of the new energy sector are up better and smoother, which should be the main investment target.

Meanwhile, this study has two shortcomings: firstly, there is a single explanatory variable. Secondly, the modeling method used in the study lacks comparison with the results of other methods. These two aspects are breakthroughs and key points for further research to facilitate more accurate forecasting of the fund's net unit value.

References

[1] Lu Wanbo,Huang Guanglin,Kris Boudt. Stock market up and down forecasting and quantitative investment strategies:based on time-varying moment component analysis[J]. China Management Science,2020,28(02):1-12.

[2] Patrick Kuok-Kun Chu, Relationship between macroeconomic variables and net asset values (NAV) of equity funds: Cointegration evidence and vector error correction model of the Hong Kong Mandatory Provident Funds (MPFs),Journal of International Financial Markets, Institutions and Money,Volume 21, Issue 5,2011,Pages 792-810,ISSN 1042-4431,

[3] Ho-Yong Kim, Okyu Kwon, Gabjin Oh,A causality between fund performance and stock market,Physica A: Statistical Mechanics and its Applications,Volume 443,2016,Pages 439-450,ISSN 0378-4371,

[4] W.-C. Chiang, T.L. Urban, G.W. Baldridge,A neural network approach to mutual fund net asset value forecasting,Omega,Volume 24, Issue 2,1996,Pages 205 -215, ISSN 0305-0483,

[5] King, Michael R. and Dan Segal. "The Long-Term Effects of Cross-Listing , Investor Recognition , and Ownership Structure on Valuation. " (2000).

[6] Pan, W., Shao, Y., Yang, T., Luo, S., & Li, X. (2017). Prediction of mutual fund net value using Backpropagation Neural Network. 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA), 198-201 .

[7] Bae, Kee-Hong et al. "Relative industry valuation and cross-border listing." Journal of Banking and Finance 119 (2020): 105899.

[8] Wojciech Grabowski, Aleksander Welfe,The Tobit cointegrated vector autoregressive model: application to the currency market,Economic Modelling, Volume 89,2020,Pages 88-100,ISSN 0264-9993

[9] Phillips, Peter C. B. and Sainan Jin. "BUSINESS CYCLES, TREND ELIMINATION, AND THE HP FILTER." International Economic Review (2021): n. pag.

[10] Zhou, Pengxiao and Fang-Tao Li. "Prediction of Fund Net Value Based on ARIMA-LSTM Hybrid Model." (2021).