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Research on innovative stock value based on HP filtering and ARIMA model—Taking technology listed companies as an example

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Abstract: With the development of the world's securities markets, valuation researchers and securities investment experts from all over the world are conducting more and more research on financial market valuation analysis. However, most research and popular valuation methods in the financial market are still limited to traditional methods. Traditional valuation analysis mainly focuses on the following types: price-to-earnings ratio (P/E) valuation method, price-to-book ratio (P/B) valuation method Value method, enterprise value ratio (EV/EBITDA) valuation method. Traditional valuation methods are prone to differences in information uncertainty, which affects the difficulty of stock valuation (Wang Kunjing, 2022). Both the traditional price-earnings ratio method and the discounted cash flow method will be affected by future expectations (He Xianglin, 2021). The fatal flaw is that earnings before tax, depreciation and amortization will overestimate operating cash flow. Especially when financial markets fail, the fatal flaws of traditional valuation methods will be infinitely magnified, which will undoubtedly cause serious errors in judgment for securities investors, especially small and medium-sized investors. This article proposes to use an interdisciplinary analysis method ARIMA+HP filter analysis method to conduct valuation analysis on the securities market. The results show that the digital technology industry has a significant head effect. The opening price volatility shows a U-shaped relationship with company size and profitability. This method can make more comprehensive use of historical data and predict possible random fluctuations, provide securities investors with a more reliable valuation method, and at the same time open up new ideas for related research in the field of valuation analysis.

1. Introduction

Through research on interdisciplinary analysis methods, this article creatively proposes a valuation analysis method for securities investments based on ARIMA+HP filter analysis. Finally, the Tobit model is used to test the stability of the prediction results. This article aims to use this interdisciplinary valuation method to improve the limitations of traditional valuation strategies in the securities market, so that investors can avoid the financial risks brought by traditional valuation methods to the greatest extent.

The sections of this article are set up as follows: This article first selects three representative subdivisions of the digital technology industry (Beidou Navigation, Blockchain, Artificial Intelligence), and uses indicators such as company market value and price-earnings ratio to define the strength of individual stocks in each subdivision. Ranking, three representative categories of strong, medium and weak stocks are screened out. This article also uses the financial annual report data of listed companies as a supplement to the basis of classification to make up for the deviation caused by differences in the company's structure, accounting treatment and other differences. Secondly, the ARIMA+HP filter analysis method is used to analyze the trend of individual stock stock prices, and mathematical statistical methods are used for analysis. Data processing is used to analyze random fluctuations and long-term trends, so as to improve the model's ability to predict random events and make the model's prediction effect more effective. Finally, there is a summary and suggestions based on the important conclusions of the interdisciplinary valuation analysis method creatively proposed in this article. It is hoped that the universality of this interdisciplinary valuation analysis method can be improved and become a new breakthrough in research in the field of securities valuation [1-5].

2. Introduction and research data of sample stocks

2.1 Introduction to sample stocks

This article divides listed companies in the digital technology industry into three representative and important subdivisions, namely artificial intelligence, Beidou navigation, and blockchain. At the same time, based on individual stock market capitalization, price-to-book ratio, price-to-earnings ratio and other financial indicators, the most representative strong, medium and weak stocks in each segment are selected, and 2 stocks are selected from each category. Strong stocks are mainly characterized by larger market capitalization and higher price-to-earnings ratios; medium-trend stocks are mainly characterized by medium market capitalization and price-to-earnings ratios that fluctuate below high points; weak stocks are mainly characterized by small market capitalization, low price-to-earnings ratios or even losses.

This article selects Hundsun Electronics, UFIDA Network, Digital Certification, Digital Government Communication, Feitian Integrity, Zhuoyi Technology, China Coast Defense, Aerospace Electrical Appliances, Dahua Intelligent, Xingwang Yuda, Tianjian Technology, Broadcom Integration, Sugon, and Ecovacs, National Technology, Jiadu Technology, GQY Video, Lanying Equipment and other 18 listed companies in the digital technology industry. The opening price data of 730 trading days in 2019-2021, a total of 13140 sample data, based on the 2019-2021 year Stock market value, transaction price, individual stock earnings ratio and other related data are used as research samples.

2.2 Research data sources and sample characteristics

The relevant data for the individual stocks selected in this article come from Guotai Junan database, Juchao Information Network, and annual reports on the official websites of listed companies. At the same time, the average opening price of 18 stocks in this sample is between 4.77-98.98. The six strong stocks are: Sugon (6003019), Ecovacs (603486), Hundsun Electronics (600570), UFIDA Network (600588), China Coast Defense (600764), Aerospace Electrical Appliances (002025). The six medium-level stocks are: National Technology (300077), Jiadu Technology (600728), Digital Certification (300579), Digital Zhengtong (300075), Dahua Intelligent (002512), Xingwang Yuda (002829), 6 weak stocks The horizontal stocks are: GQY Video (300076), Lanying Equipment

(300293), Zhuoyi Technology (002369), Feitian Integrity (300386), Tianjian Technology (002977), and Broadcom Integration (603068). The one with the largest standard deviation of the opening price is Cobos (61.32), indicating the largest overall fluctuation. The one with the smallest standard deviation of the opening price is QGY Video (0.70), indicating the smallest overall fluctuation. See Table 1 for details.

Table 1: Descriptive statistical analysis of sample opening price data

Stock code	minimum value	maximum value	average value	standard deviation	median
603019	25.00	65.55	36.87	8.14	35.56
603486	18.54	245.05	76.61	61.32	49.35
300077	5.78	41.50	11.26	7.82	7.80
600728	6.10	13.13	8.824	1.39	9.04
300076	3.97	7.70	5.367	0.70	5.32
300293	6.19	35.00	12.94	5.48	12.22
600570	49.50	120.00	82.30	16.53	84.93
600588	21.03	52.90	35.61	6.92	34.49
300579	21.60	66.00	40.30	8.30	40.51
300075	9.28	17.21	12.32	1.49	12.32
002369	4.03	12.35	7.77	1.73	7.92
300386	10.03	31.96	16.47	4.40	15.43
600764	22.950	46.900	29.856	4.159	28.550
002025	21.330	84.520	41.282	16.807	36.380
002512	2.880	7.720	4.774	1.099	5.060
002829	15.000	51.520	30.096	8.102	30.795
002977	35.980	160.980	98.975	21.003	92.000
603068	26.830	142.000	76.086	18.302	74.190

3. Empirical analysis of stock price prediction of individual stocks in digital technology industry economies

3.1 Long-term trend of individual stock opening prices

The HP filter analysis method was first proposed by Hodrick and Prescott when analyzing the post-war social economy of the United States, and has since been widely used in long-term macroeconomic trend analysis. HP filter analysis method decomposes Trend and Cycle by analyzing the slow changing trend of data variables and decomposing the trend in time series [6]. Think of it as a High-Pass Filter, which can use simple smoothing principles to move forward item by item, separate data of different frequencies in the time series, and obtain periodic fluctuation data and trend element data of different properties. This article first performs HP filter analysis on the original stock opening price data, and conducts further testing based on long-term trend data [7].

Suppose the time series is $Z = \{z1, z2, \ldots, zt\}$, the periodic data is $T = \{t1, t2, \ldots, tt\}$, and the trend element data is $G = \{g, g1, \ldots, gt\}$, then $Z = T + G$, $t = 1,2,3 \ldots n$. The trend is defined as the solution of the minimization problem of the following equation.

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

The natural number λ is called the smoothing parameter. When λ is larger, the predicted trend is smoother; when λ=0, Zn=Gn; when and only when λ approaches infinity, HP filtering degenerates into using the least squares method to estimate the trend. In the data analysis of this article, the value of λ is 14400, and the periodic fluctuation data and trend elements are obtained. The results are shown in Figure 1.

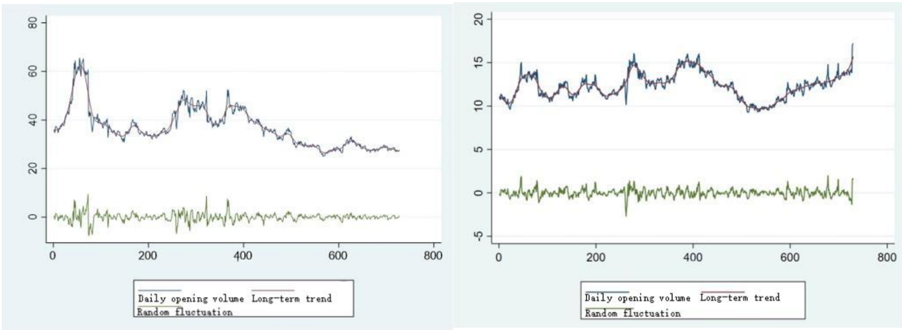

Figure 1: Long-term trend of net unit value of 600558 and 300386 stocks

It can be found from Figure 1 that after using the HP filtering method to decompose a trend that is smoother than the original net value trajectory, the ARIMA regression model is used to analyze that the stock price fluctuates strongly in cycles.

3.2 Forecast analysis of the net value of individual stocks

After performing HP filter analysis on individual stock opening price data, OLS regression was used to fit and predict the decomposed data (regression results are shown in Table 2). The explained variable is the opening price of individual stocks, and the explanatory variable is the number of securities trading days. It can be seen from Table 2 that each core coefficient has strong significance. The core coefficient indicates that for every additional trading day, the stock price of individual stocks increases (decreases) by a unit on average (a represents the core coefficient of each stock after regression analysis).

There are two problems in conducting OLS regression analysis on individual stock price data: First, after OLS regression, it is found that some stock data have a low fitting degree, but their core coefficients are still significant, indicating that the regression of some stock data is significant and meaningful. . But it may not be fully used to explain the model; secondly, the absolute value of the core coefficient is small, indicating that there is a possibility of chance in the core coefficient. In order to ensure the effectiveness of prediction, the Tobit model is used to conduct robustness testing when predicting individual stock stock prices [8][9]. Tobit models are roughly divided into 5 categories. This article chooses a truncated data model based on the characteristics of the data. The general form of the left truncated data structure is:

$$y_i = y^*, if y^* > L \tag{2}$$

The general form of the Tobit model is:

$$y^* = \beta x_i + u_i; y_i = y^*, if y^* > L \tag{3}$$

Among them, is the potential response variable, which can only be observed when the latent variable is greater than. The value is, is the independent variable vector, is the coefficient vector, and the error term obeys a specific distribution.

The results of the Tobit model robustness test are shown in Table 2. Through the robustness test, it can be found that the core coefficient obtained by the robustness test is consistent with the original core coefficient, indicating that its robustness is strong. There is no significant difference between the values of the Z test and the T test, indicating that their significance levels are basically the same, so we continue to choose the OLS method for regression analysis.

Table 2: Forecast analysis of the opening price of individual stocks in information technology industry economies

OLS regression				Tobit returns		
ticker	Coef.	Robust Std. Err.	T	Coef.	Robust Std.Err.	T
603019	-2.46$\times 10^{-2}$	1.12$\times 10^{-3}$	-21.97	-2.46$\times 10^{-2}$	1.04$\times 10^{-3}$	-23.66
603486	2.31$\times 10^{-1}$	6.71$\times 10^{-3}$	34.48	-2.31$\times 10^{-1}$	6.43 $\times 10^{-3}$	35.98
300077	2.41$\times 10^{-2}$	1.24$\times 10^{-3}$	19.49	2.41$\times 10^{-2}$	1.03$\times 10^{-3}$	23.40
600728	-4.27 $\times 10^{-3}$	2.14 $\times 10^{-4}$	-19.93	-4.27 $\times 10^{-3}$	1.74 $\times 10^{-4}$	-24.50
300076	-1.51$\times 10^{-4}$	1.11$\times 10^{-4}$	-1.36	-1.51$\times 10^{-4}$	1.09$\times 10^{-4}$	-1.39
300293	1.31$\times 10^{-2}$	4.45 $\times 10^{-4}$	29.55	1.31$\times 10^{-2}$	7.98 $\times 10^{-4}$	16.47
600570	-2.74$\times 10^{-3}$	3.04$\times 10^{-3}$	-0.90	-2.74$\times 10^{-3}$	2.80$\times 10^{-3}$	-0.98
600588	1.21$\times 10^{-2}$	9.64$\times 10^{-4}$	12.55	1.21$\times 10^{-2}$	1.07 $\times 10^{-3}$	11.30
300579	1.47$\times 10^{-2}$	1.29 $\times 10^{-3}$	11.34	1.47$\times 10^{-2}$	1.26 $\times 10^{-3}$	11.65
300075	3.94$\times 10^{-4}$	2.18$\times 10^{-4}$	1.81	3.94$\times 10^{-4}$	2.43$\times 10^{-4}$	1.62
002369	4.88$\times 10^{-3}$	2.06 $\times 10^{-4}$	-23.73	-4.88$\times 10^{-3}$	2.34 $\times 10^{-4}$	-20.81
300386	7.53$\times 10^{-3}$	5.74 $\times 10^{-4}$	13.11	7.53$\times 10^{-3}$	7.03 $\times 10^{-4}$	10.71
600764	4.98$\times 10^{-3}$	*6.06*$\times 10^{-4}$	8.23	4.98$\times 10^{-3}$	6.63$\times 10^{-4}$	7.52
002025	7.11$\times 10^{-2}$	1.30$\times 10^{-3}$	54.56	7.11$\times 10^{-2}$	1.28$\times 10^{-3}$	55.46
002512	-3.50 $\times 10^{-3}$	1.20$\times 10^{-4}$	-29.29	-3.50 $\times 10^{-3}$	1.34 $\times 10^{-4}$	-26.18
002829	2.90$\times 10^{-2}$	6.36$\times 10^{-4}$	45.60	2.90$\times 10^{-2}$	8.89$\times 10^{-4}$	32.64
002977	-5.44$\times 10^{-2}$	7.50$\times 10^{-3}$	-7.25	-5.44$\times 10^{-2}$	6.92$\times 10^{-3}$	-7.87
603068	-3.02$\times 10^{-2}$	4.33$\times 10^{-3}$	-6.97	-3.02$\times 10^{-2}$	3.34$\times 10^{-3}$	-9.00

Based on the analysis results, OLS forecasts are performed on individual stock prices. The forecast time is from the first to the third year in the future (the 1st to 750th trading day), and the corresponding trading dates are from 2019 to 2021 fitting.

The first trading day in the future corresponds to the 750th day of the overall parameters. At this time, OLS is used to predict the unit stock prices of individual stocks as 0.492, 1.771, 0.558, 1.729, 1.558, 2.085, 1.695, 5.730, 1.026, 1.722, 2.260, 3.747, respectively. 1.939, 1.610, 1.435. The sixth trading day corresponds to the 250th day of the overall parameters. The predicted values are 0.491, 1.783, 0.554, 1.732, 1.566, 2.100, 1.700, 5.753, 1.025, 1.736, 2.266, 3.759, 1.950, respectively. 1.610, 1.434. The stock price obtained through the robustness test is the same as the result predicted by OLS. By comparing with the actual value, the maximum difference between the estimated value and the true value on the 245th day is 0.2522 (603068); the minimum predicted net value is 0.006795 (002977); the maximum difference between the estimated net value and the true value on the 250th day is 0.299 (00282); the minimum predicted net value is 0.006 (002512). It can be found that the predicted value is close to the actual value, and the ARIMA+HP filter analysis method is of great significance to the analysis of future stock price movement trends.

3.3 Heterogeneity analysis of stock unit net value

Looking at each value after regression analysis in Table 3 in turn, the core coefficients of security codes 603019, 603486, and 300077 are all negative, that is, the number of trading days of the stock has a negative correlation with the stock price. At the same time, the stock prices and standard error values of securities codes 002977, 002829, and 002512 were analyzed, and it was found that their values were generally less than 0.5, indicating that the OLS regression model had poor fitting effect and the relative error was also large. The number of trading days of the stock is related to The correlation between individual stock prices is weak. On the contrary, for the security code 002025, the core coefficients of the regression are all positive and the values are greater than 0.5, indicating that the regression fitting effect is good, and the standard error value is generally small. On the surface, there is a relationship between the number of trading days of individual stocks and the stock price. The correlation is strong and its change trend is positively correlated.

Table 3: Heterogeneity analysis of unit stock prices of digital technology industry economies in different regions

ticker	Coef.	OPG Std. Err.	Z	P>|z|	[95% Conf. Interval]	
603019	-2.46$\times 10^{-2}$	1.39$\times 10^{-3}$	-17.60	0.000	2.74$\times 10^{-2}$	2.19$\times 10^{-2}$
603486	-2.31$\times 10^{-1}$	6.26$\times 10^{-3}$	36.98	0.000	2.19$\times 10^{-1}$	2.44$\times 10^{-1}$
300077	-2.41$\times 10^{-2}$	1.21$\times 10^{-3}$	19.98	0.000	2.17$\times 10^{-2}$	2.65$\times 10^{-2}$
600728	-4.27$\times 10^{-3}$	1.57$\times 10^{-4}$	-27.21	0.000	-4.57$\times 10^{-3}$	-3.96$\times 10^{-3}$
300076	1.51$\times 10^{-4}$	1.06$\times 10^{-4}$	-1.42	0.157	-3.59$\times 10^{-4}$	5.78$\times 10^{-5}$
300293	1.31$\times 10^{-2}$	1.61$\times 10^{-3}$	8.18	0.000	9.99 $\times 10^{-3}$	1.63$\times 10^{-2}$
600570	-2.74$\times 10^{-3}$	2.71$\times 10^{-3}$	-1.01	0.311	-8.07$\times 10^{-3}$	2.57$\times 10^{-3}$
600588	-1.21$\times 10^{-2}$	1.20$\times 10^{-3}$	10.10	0.000	9.75$\times 10^{-1}$	1.45$\times 10^{-2}$
300579	1.47$\times 10^{-2}$	1.41$\times 10^{-3}$	10.39	0.000	1.11$\times 10^{-2}$	`1.74$\times 10^{-2}$
300075	3.94$\times 10^{-4}$	2.89$\times 10^{-4}$	1.36	0.174	-1.73$\times 10^{-4}$	9.61$\times 10^{-4}$
002369	-4.88$\times 10^{-3}$	2.86$\times 10^{-4}$	-17.07	0.000	-5.43$\times 10^{-3}$	`4.31$\times 10^{-3}$
300386	7.53$\times 10^{-3}$	1.01$\times 10^{-3}$	7.46	0.000	5.53 $\times 10^{-3}$	9.51$\times 10^{-3}$
600764	4.98$\times 10^{-3}$	7.61$\times 10^{-4}$	6.55	0.000	3.49$\times 10^{-3}$	6.48$\times 10^{-3}$
002025	7.11$\times 10^{-2}$	1.31$\times 10^{-3}$	54.11	0.000	6.85$\times 10^{-2}$	7.37$\times 10^{-2}$
002512	-3.50$\times 10^{-3}$	1.76$\times 10^{-4}$	-19.96	0.000	3.85$\times 10^{-3}$	3.16$\times 10^{-3}$
002829	2.90$\times 10^{-2}$	1.50$\times 10^{-3}$	19.32	0.000	2.61$\times 10^{-2}$	3.20$\times 10^{-2}$
002977	-5.44$\times 10^{-2}$	1.17$\times 10^{-2}$	-4.63	0.000	-7.74$\times 10^{-2}$	-3.14$\times 10^{-2}$
603068	-3.02$\times 10^{-2}$	4.01$\times 10^{-3}$	-7.51	0.000	-3.80$\times 10^{-2}$	-2.23$\times 10^{-2}$

4. Research conclusions and implications

The prosperity and development of the securities market is inseparable from the development of various securities valuation methods and valuation models. This article proposes an interdisciplinary analysis method, selects three subdivisions: artificial intelligence, blockchain, and Beidou navigation, and uses three years of stock opening price data of individual stocks to study stock price fluctuations and predict them. After using the HP filtering method to reduce noise, ARIMA was used to obtain the short-term trend and long-term trend random fluctuations, and the long-term trend data was used as the explained variable. After conducting OLS regression and Tobit model robustness testing, the following important conclusions were drawn:

1) Judging from the analysis results of the three subdivisions, it is shown that the head effect of the digital technology industry is significant. There is not much difference in the asset size between the leading companies and the mid-level companies in the three subdivisions. However, the profit margin exceeds that of the mid-level companies and the weak companies. The stock price is several times or even dozens of times.

2) Compared with leading stocks and weak stocks, the opening price of Chinese stocks has less volatility and strong stability.

3) The opening price volatility of Beidou Navigation stocks is significantly stronger than that of blockchain and artificial intelligence stocks.

4) Artificial intelligence and blockchain stocks have relatively high determination coefficients, better model fitting, and strong long-term trend stability. The stock price fluctuations of Beidou Navigation stocks may cause the robustness of OLS regression to decrease, leading to a decrease in forecast accuracy.

Based on the research conclusions obtained, this article gives corresponding enlightenment and is committed to using this idea as a breakthrough for subsequent research, while allowing investors to better solve valuation problems:

1) There are many emerging subdivisions in the digital technology industry. At the same time, digital technology is the embodiment of the core competitiveness of countries around the world. Small, medium and micro enterprises need to adapt to the development of the times and policy guidance, improve their core competitiveness, and at the same time give way to more digital technology services. market to promote the vigorous development of the digital technology industry.

2) Regarding the profit-seeking choice of stock positions, since the volatility of individual stock prices will have a significant impact on investors' investment decisions, when investing in the digital technology industry, holding positions in trend stocks can use their relatively high stability to reduce funds risk.

3) Regarding the choice of investment industries in the three subdivisions, the strong volatility of the opening price of Beidou Navigation stocks is more suitable for gaming investors with strong risk preferences, while the other two industries are more suitable for risk-averse investors.

4) The valuation of ARIMA+HP filter analysis method needs to be analyzed and judged based on the determination coefficient of individual stocks. Stocks in different industries have different degrees of model fitting. It is necessary to always pay attention to market dynamics and analyze specific issues in detail.

5. Conclusions

This article creatively use the database or Python to crawl the time series data of securities opening prices, separate short-term fluctuations and long-term trends, and then use Hodrick-Prescott noise reduction technology to remove short-term fluctuations and retain the long-term trend. Select variables related to time series in long-term trends and use the ARIMA machine learning algorithm to conduct quantitative forecasts. It aims to improve the limitations of traditional valuation strategies in the securities market through the promotion and application of information technology in the field of valuation, so as to maximize the benefits for investors.

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References

[1] Liao Dongsheng. Research on digital asset valuation issues [J]. Friends of Accounting, 2022(13):2-9.

[2] Li Dan, Yuan Yuan. Analysis of the causal relationship between government health expenditure and economic growth in my country - based on HP filtering method and Granger causality test [J]. China Primary Health Care, 2022, 36(06): 12-14.

[3] Lin Xuefei, Wang Baohai. Analysis and prediction of beef prices in my country based on HP filter decomposition ARIMA-GARCH model [J]. Heilongjiang Animal Husbandry and Veterinary Medicine, 2020(12): 30-34.

[4] Yang Ruyi, Cao Shanshan, Sun Wei. Data set for research on price fluctuations of solanaceous vegetables in Beijing Xinfadi Market from 2012 to 2018 based on HP filtering method [J]. Chinese Scientific Data, 2023, 8(01):253-263.
[5] Wang Zhi, Li Xinlan. Comparative study on Internet enterprise value evaluation models [J]. Financial Theory and Practice, 2021, 42(05): 75-82.
[6] Zhang Qianqian, Lin Tianhua, Qi Xuyang, Zhao Xia. A review of research on stock forecasting based on machine learning [J]. Journal of Hebei Academy of Sciences, 2020, 37(04): 15-21.
[7] Yang Xiaoyun. Thoughts on macro analysis of stock investment [J]. The Economist, 2019(03):76-78.
[8] Moraux Franck. On Bankruptcy Procedures and the Valuation of Corporate Securities [J]. Finance, 2019, 40(3).
[9] Sung S. Kwon. The value-relevance of fundamental signals and the impact of financial regulations on security valuation and earnings management [J]. Corporate Ownership & Control, 2019, 16(3).