Stock price valuation analysis of the digital technology industry based on the HP-ARIMA method - with 18 listed companies of different volume sizes in its 3 segments as an example

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Abstract. The world securities market has formed a more complete system since its origin in the 17th century, with a considerable number of small and medium-sized investors and institutional investors, and proposing innovative new methods for securities valuation models can assist investors in making more accurate investment decisions. This paper proposes for the first time to use an interdisciplinary analysis method, ARIMA + HP filter analysis, to analyze the valuation of the securities market, by taking the opening prices of individual stocks in digital technology industry segments: blockchain, artificial intelligence, and Beidou navigation as examples for valuation analysis, firstly, the initial data of the opening prices of individual stocks from 2019-2021 are analyzed by HP filter analysis, and secondly, the data are analyzed while doing Tobit model test. By analyzing the long-term trend of the digital technology industry after noise reduction, its corresponding valuation forecast and value judgment results show that the head effect of the digital technology industry is more significant, and the opening price volatility shows a U-shaped relationship with company size and profitability, and the opening price volatility of individual stocks is less, while the shorter the company's establishment time, the greater the stock price volatility. While the past literature focused on the traditional valuation of financial conditions and historical data analysis of a single variable, this paper analyzes the data of individual stocks in the digital technology industry through an interdisciplinary analysis method, which allows for a more comprehensive use of historical data and prediction of possible stochastic fluctuations, providing a more reliable valuation method for securities investors and opening up new ideas for research related to the field of valuation analysis.

Keywords: ARIMA, HP filtering analysis, Digital Technology, Securities Valuation.

1. Introduction

With the development of the world's securities markets, valuation research scholars and securities investment experts around the world have increasingly studied the valuation analysis of financial markets. However, most of the studies and their popular valuation methods in financial markets are still limited by traditional methods, and traditional valuation analysis mainly revolves around the following: price-to-earnings (P/E) valuation method [1], price-to-net ratio (P/B) valuation method [2], and enterprise value ratio (EV/EBITDA) valuation method [3]. Traditional valuation methods are prone to fatal flaws such as differences in information uncertainty affecting the difficulty of stock valuation [4], both traditional P/E and discounted cash flow methods can be affected by future expectations that affect their valuation [5], and EBITDA will overestimate operating cash flows. Especially in the case of financial market failure, the fatal flaws of the traditional valuation method will be infinitely magnified, which will undoubtedly cause serious errors in judgment for securities investors, especially small and medium-sized investors.

Therefore, this paper creatively proposes a valuation analysis of securities investment based on ARIMA+HP filtering [6] analysis through the study of interdisciplinary analysis methods. By selecting the most representative segment of the industry's individual stock opening prices for the study. The ARIMA+HP filter method is used to make corresponding valuation forecasts and value judgments on the long-term trend of the industry. The OLS regression method [7] was also used to test the significance of the decomposed data of opening prices and to ensure that the core coefficients are significant and the model is interpretable. Finally, the Tobit model is used to test the stability of the prediction results. The purpose of this paper is to improve the limitations of traditional valuation strategies in the securities market through this interdisciplinary valuation method, so that investors can avoid the financial risks associated with traditional valuation methods to the maximum extent.

This paper is set up as follows: firstly, this paper selects three representative segments of the digital technology industry (Beidou navigation, blockchain, and artificial intelligence), uses company market capitalization, P/E ratio and other indicators to define the strength ranking of individual stocks in each segment, and screens out representative strong, medium and weak stocks. this paper also uses listed company financial annual report data as a supplement to the division basis to compensate for company in deviations caused by differences in structuring methods, accounting treatments, etc. Secondly, by using ARIMA+HP filtering analysis to analyze the trend of individual stock prices [8], mathematical and statistical methods are used to analyze the stochastic fluctuations and long-term trends through data processing to enhance the model's prediction ability for stochastic events and make the model prediction more robust. Finally, we conclude with a summary and suggestions based on the important conclusions of the interdisciplinary valuation analysis method creatively proposed in this paper, hoping to enhance the universality of this interdisciplinary valuation analysis method and become a new breakthrough in the field of securities valuation research.

2. Review of Literature

2.1. Research Industry

Emerging technologies represented by big data, artificial intelligence, and blockchain technologies have triggered a new round of investment boom, as traditional stock valuation methods and data analysis methods have limited, and in some cases potentially erroneous, estimates of the benefits of new technologies. Meanwhile, the digital technology economy today accounts for 5% of global GDP as well as enough to address 3% of global employment demand. Therefore, it is important to conduct investment strategy studies and innovative stock valuation methods in the digital technology industry as an example.

2.2. Quantitative Investment Approach

Quantitative investment refers to the analysis of trading through computer programs as an alternative to the traditional human brain analysis and judgment. With the development of statistical methods and computer technology, algorithms such as neural networks [9], plain Bayesian, and random forest [10] have been gradually incorporated into stock valuation analysis and investment strategy design. Nowadays, quantitative investment methods and trading strategies can be greatly expanded.

2.3. Quantitative Investment Data

The first feature in quantitative investment data selection is the gradual trend of three-dimensional and comprehensive with the development of technology to achieve a more efficient use of information and data to cover the overall market. It also helps to build a more stable portfolio. The second feature is the objective rationalization, relying on computer analysis can greatly reduce the impact of investor sentiment in data selection. The third feature is the equal importance of return and risk, quantitative models pay more attention to risk management, making data analysis more robust.

2.4. Summarize

Nowadays, quantitative investment strategies are becoming more and more mature, which greatly make up for the shortcomings of traditional investment methods, but the utilization of historical data and the elimination of stochastic fluctuations also need to be improved. In this paper, we use ARIMA+HP filtering analysis based on interdisciplinary analysis to analyze the stock valuation of digital technology industry to fill the gap in this research area.

3. Sample Stock Profile and Research Data

3.1. Sample Stocks Profile

Table 1. Descriptive statistical analysis of sample opening price data

Stock Code	Min	Max	Mean	Std Dev	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	22.95	46.90	29.86	4.159	28.55
002025	21.33	84.52	41.28	16.81	36.38
002512	2.88	7.72	4.77	1.10	5.06
002829	15.00	51.52	30.10	8.10	30.80
002977	35.98	160.98	98.98	21.00	92.00
603068	26.83	142.00	76.09	18.30	74.19

In this paper, listed companies in the digital technology industry are divided into three representative and important segments, namely, artificial intelligence, Beidou navigation, and blockchain. The sample data is shown in Table 1. The most representative strong, medium and weak stocks in each segment are also selected based on financial indicators such as market capitalization size, P/N ratio and P/E ratio of individual stocks, and two stocks are selected in each category. Strong stocks are mainly characterized by larger market capitalization and higher P/E ratios; medium stocks are mainly realized as medium market capitalization and P/E ratios that fluctuate below the high point; weak stocks are mainly characterized by smaller market capitalization and lower P/E ratios or even losses.

In this paper, we select stocks from 18 listed companies in the digital technology industry, including Hundsun Electronics, UFIDA Network, Digital Certification, Digital Government, Feitian Integrity, ZhuoYi Technology, China Haiphong, Aerospace Electric, Dahua Intelligence, StarNet Yuda, Sky Arrow Technology, Broadcom Integration, CK Shuguang, Coors, Nationz Technologies, Jiadu Technology, GQY Vision, and Blue Ying Equipment, for a total of 730 trading days in 2019-2021. The opening price data of the trading days, a total of 13,140 sample data, are used as the research sample for the 2019-2021 year, including stock market capitalization, trading price, individual stock P/E ratio and other related data. The data comes from CSAMR.

3.2. Study data sources and sample characteristics

The relevant data of selected stocks in this paper are obtained from Guotaian database, Juchao information website and the annual reports of each listed company's official website. Meanwhile, the average opening price of 18 stocks in this sample is between 4.77-98.98. 6 stocks with strong level are: CK Shuguang, Coors, Hang Seng Electronics, UFIDA, China Haifeng and Aero-space Electric, 6 stocks with medium level are: Nationz Technologies, Jiadu Technology, Digital Certification, Digital Government, Dahua Intelligence and StarNet, 6 stocks with weak level are. GQY Vision, Lan Ying Equipment, Zhuo Yi Technology, Feitian Integrity, Sky Arrow Technology, and Broadcom Integration. The largest standard deviation of the opening price is Coors 61.32 The largest overall volatility, the smallest value of the standard deviation of the opening price is QGY Vision 0.70, the smallest overall volatility.

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

4.1. Long-term trend of the opening price of an individual stock

HP filter analysis was first proposed by Hodrick and Prescott in their analysis of the post-war U.S. society and economy, and has since been widely used in the analysis of long-term macroeconomic trends. hp filter analysis analyzes the trend of slow-moving data variables and decomposes the trend under the time series, decomposing the Trend and Cycle. Filter, which can apply the simple smoothing principle for item-by-item nudging, separating data with different frequencies in the time series to obtain cyclical fluctuation data and trend element data of different nature. In this paper, we first do the HP filter analysis on the original stock opening price data and further test it based on the long-term trend data.

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

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

where the natural number, λ is referred to as the smoothing parameter. When λ is larger, the predicted trend is smoother; when $\lambda = 0$, $Zn = Gn$; when and only when λ tends to infinity, the HP filter degenerates to estimating the trend by the least squares method. In the data analysis of this paper, λ is taken as 14400, and the periodic fluctuation data and trend elements are obtained, The obtained results are shown in Figure 1. Among Line introduction and XY Introduction: Blueline:Daily opening price, Redline:Long-term trends, Greenline:Random fluctuations, X:Stock trading day, Y:stock price

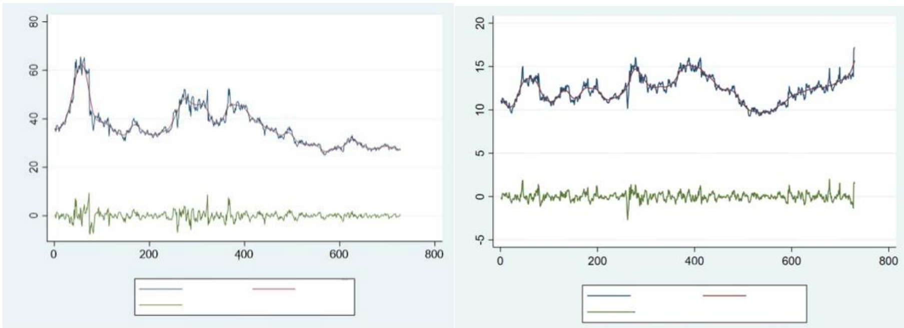

Figure 1. Long-term trend of net unit value of individual stock in digital technology industry economies

From Figure 1, it can be found that the HP filter method is used to decompose a smoother trend compared to the original net value trajectory and then the ARIMA regression model is used to analyze the strong fluctuation of the stock price cycle.

4.2. Predictive analysis of individual stock unit net worth

After doing HP filtering analysis on individual stock opening price data, OLS regression is used to fit and predict the decomposed data (regression results are shown in Table 2). The explanatory variable is the opening price of individual stocks and the explanatory variable is the number of trading days of securities. From Table 2, the core coefficients are highly significant, and the core coefficients indicate that for each additional day of trading, the unit stock price of individual stocks increases (decreases) by an average of a units (a indicates the core coefficient of each stock after regression analysis).

The OLS regression analysis of individual stock price data has two problems: first, after the OLS regression, it is found that some of the stock data have a low fit, but their core coefficients still show significance, indicating that some of the stock data regressions are significant and meaningful. However, it may not be fully used to explain the model; second, the absolute value of the core coefficients is small, indicating that there is a possibility of chance in their core coefficients. In order to ensure the predictive validity, the Tobit model was used for robustness testing while predicting individual stock prices. tobit models are broadly classified into five categories, and this paper selects truncated data models according to 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:

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

Where $y^*$is the latent strain variable, which can be observed only when the latent variable is greater than L and takes the value of y_i, y_x is the vector of independent variables, β is the vector of coefficients, and the error term u_i obeys a specific distribution.

The results of the Tobit model robustness test are shown in Table 2. the core coefficients obtained from the robustness test are consistent with the original core coefficients, which indicates its robustness. And the values of Z-test and T-test are not significantly different, indicating that their significance levels are basically the same, so the OLS method is continued to be selected for regression analysis.

Table 2. Forecast analysis of the opening price of individual stock units in IT industry economies

	OLS Reggession			Tobit Reggession		
Stock code	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 results of the analysis, OLS forecasts of individual stock share prices are made for the future years 1 - 3 (1st - 750 trading days), corresponding to a three-year time fit of the trading dates 2019 - 2021, respectively. The 1st trading day in the future corresponds to the 750th day of the overall parameter, at which point the predicted unit share prices of individual stocks using OLS are 0.492, 1.771, 0.558, 1.729, 1.558, 2.085, 1.695, 5.730, 1.026, 1.722, 2.260, 3.747, 1.939, 1.610, 1.435 1.435, the 6th trading day corresponds to the 250th day of the overall parameter, and its 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, 1.610, 1.434, respectively, which pass the robustness test The obtained individual stock unit share prices are the same as those predicted by OLS. By comparing with the actual value, the maximum difference between the estimated and true value on day 245 is 0.2522 (stock code 603068); the smallest predicted net value is 0.006795 (stock code 002977); the maximum difference between the estimated and true value on day 250 of the predicted net value is 0.299 (stock code 00282); the smallest predicted net value is 0.006 (stock code 002512). code 002512). It can be found that the predicted value is similar to the actual value, and the ARIMA+HP filtering analysis is important for the analysis of future stock price movement trend.

4.3. Heterogeneity analysis of the net value of stock units

Looking at each value after regression analysis in Table 3 in turn, the core coefficients of securities codes 603019, 603486, and 300077 are negative, i.e., the number of days of stock trading days obtained is negatively correlated with the stock unit share price. At the same time, the analysis of the stock price and the standard error values of stock codes 002977, 002829, 002512 can be generally less than 0.5, indicating that the OLS regression model for its poor fit, and the relative error is also larger the correlation between the number of trading days of the stock and the stock price of the individual stock is weak. On the contrary, for stock code 002025, the core coefficients of the regression are all positive and the values are greater than 0.5, indicating that the regression fits better and the standard error values are generally smaller, and the correlation between the number of trading days and the stock price of the surface stock is stronger and the trend of its change is positive.

Table 3. Heterogeneity analysis of stock unit share price in digital technology industry economies under different geographic regions

Stock Code	Coef.	OPG Std. Err.	Z	P>|z|	[95% Conf. Interval]	
603019	-2.46× 10^{-2}	1.39× 10^{-3}	-17.60	0.00	2.74× 10^{-2}	2.19× 10^{-2}
603486	-2.31× 10^{-1}	6.26× 10^{-3}	36.98	0.00	2.19× 10^{-1}	2.44× 10^{-1}
300077	-2.41× 10^{-2}	1.21× 10^{-3}	19.98	0.00	2.17× 10^{-2}	2.65× 10^{-2}
600728	-4.27× 10^{-3}	1.57× 10^{-4}	-27.21	0.00	-4.57× 10^{-3}	-3.96× 10^{-3}
300076	1.51× 10^{-4}	1.06× 10^{-4}	-1.42	0.16	-3.59× 10^{-4}	5.78× 10^{-5}
300293	1.31× 10^{-2}	1.61× 10^{-3}	8.18	0.00	9.99 × 10^{-3}	1.63× 10^{-2}
600570	-2.74× 10^{-3}	2.71× 10^{-3}	-1.01	0.31	-8.07× 10^{-3}	2.57× 10^{-3}
600588	-1.21× 10^{-2}	1.20× 10^{-3}	10.10	0.00	9.75× 10^{-1}	1.45× 10^{-2}
300579	1.47× 10^{-2}	1.41× 10^{-3}	10.39	0.00	1.11× 10^{-2}	`1.74× 10^{-2}
300075	3.94× 10^{-4}	2.89× 10^{-4}	1.36	0.17	-1.73× 10^{-4}	9.61× 10^{-4}
002369	-4.88× 10^{-3}	2.86× 10^{-4}	-17.07	0.00	-5.43× 10^{-3}	`4.31× 10^{-3}
300386	7.53× 10^{-3}	1.01× 10^{-3}	7.46	0.00	5.53 × 10^{-3}	9.51× 10^{-3}
600764	4.98× 10^{-3}	7.61× 10^{-4}	6.55	0.00	3.49× 10^{-3}	6.48× 10^{-3}
002025	7.11× 10^{-2}	1.31× 10^{-3}	54.11	0.00	6.85× 10^{-2}	7.37× 10^{-2}
002512	-3.50× 10^{-3}	1.76× 10^{-4}	-19.96	0.00	3.85× 10^{-3}	3.16× 10^{-3}
002829	2.90× 10^{-2}	1.50× 10^{-3}	19.32	0.00	2.61× 10^{-2}	3.20× 10^{-2}
002977	-5.44× 10^{-2}	1.17× 10^{-2}	-4.63	0.00	-7.74× 10^{-2}	-3.14× 10^{-2}
603068	-3.02× 10^{-2}	4.01× 10^{-3}	-7.51	0.00	-3.80× 10^{-2}	-2.23× 10^{-2}

4.4. Research Findings and olicy Implications

The prosperity of the securities market cannot be achieved without the development of various securities valuation methods and valuation models. In this paper, by proposing an interdisciplinary analysis method, three segments of artificial intelligence, blockchain, and Beidou navigation are selected to study stock price fluctuations and forecast them using three-year stock opening price data of individual stocks. After using HP filtering method to reduce noise, ARIMA is used to derive the short-term trend and long-term trend stochastic fluctuations, and OLS regression and Tobit model robustness test are conducted using long-term trend data as the explanatory variables. The following important conclusions were drawn:

1. The results of the analysis of the three segments show a significant head effect in the digital technology industry, with little difference in asset size between leading companies and mid-cap stocks in the three segments, yet profitability outperforms mid-cap and weak stocks by several times or even tens of times.

2. Compared to leading stocks weak stocks, mid-cap stocks have less volatility and strong stability in their opening prices.

3. The opening price volatility of BeiDou Navigation stocks is significantly stronger than that of Blockchain and AI stocks.

4. Artificial intelligence and blockchain stocks have relatively high decidability coefficients and better model fits, and their long-term trend stability is stronger. The stock price volatility of BeiDou Navigation stocks may lead to a decrease in the robustness of OLS regression, resulting in a decrease in forecast accuracy.

This paper offers corresponding policy insights based on the findings obtained, and aims to use this thinking as a breakthrough for subsequent research. while allowing investors to better solve valuation challenges:

1. There are many emerging segments in the digital technology industry, and at the same time digital technology as the embodiment of the core competitiveness of countries around the world, small and medium-sized enterprises need to comply with the development of the times and policy guidance to improve their core competitiveness, while giving way to the market more in digital technology services to promote the flourishing development of the digital technology industry.

2. For the convergence selection of stock positions, as the volatility of individual stock prices can have a significant impact on investors' investment decisions, holding a position in mid-potential stocks can take advantage of their relatively high stability to reduce capital risk when investing in the digital technology sector.

3. For the selection of the three segments of the investment industry, the strong volatility of the opening price of BeiDou Navigation stocks is more suitable for gaming investors with strong risk appetite, while the other two industries are more suitable for risk-averse investors.

4. ARIMA + HP filter analysis method of valuation needs to be combined with individual stocks can be determined by the coefficient of analysis, the degree of fit of the model varies from industry to industry stocks, and requires constant attention to market dynamics, specific analysis of specific issues.

5. Conclusions

Refer This paper uses the ARIMA+HP filter analysis method to give a forecast statistical analysis of the stock opening price based on an interdisciplinary perspective, and makes some improvements to the traditional stock valuation method. First, perform HP filtering on the initial data of the opening price of individual stocks in 2019-2021 Analyze, and do Tobit model test while analyzing the data. After analyzing the long-term trend of the digital technology industry after noise reduction, the main conclusions are as follows:

(1) The profitability distribution of the digital technology industry has a significant head effect.

(2) The opening price of stocks with a moderate scale has less volatility and greater stability.

(3) The opening price of the Beidou navigation stock chapter is the most volatile, and the prediction accuracy may decrease.curate due to volatility.

Based on the above research conclusions, this paper gives the following policy recommendations.

(1) The government needs to strengthen subsidies for small and micro enterprises, and at the same time give way to the market in terms of digital technology services, so as to promote the vigorous development of the digital technology industry.

(2) For the potential stocks in the position, the relatively high stability can be used to reduce the capital risk.

(3) For investors with risk appetite, Beidou Navigation can be used as a reference with its own high profitability. ences

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