Research about stock market investment strategy based on dynamic factor model

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Abstract

The stock market is a highly complicated nonlinear dynamic system. Static stock selection model is difficult to reflect the change of market expectations. The same type or style of factors are combined in this study. The corresponding comprehensive stock selection factors be tested in the model. Finally, this study predicts the excess return of stock market based on comprehensive valuation factors.

Keywords

Dynamic Factor; Stock Market; Investment Strategies.

1. Introduction

The stock market is a highly complex and nonlinear dynamic system. Its change has inherent regularity and is influenced by many factors, such as market, economy and non-economy. One of the drawbacks of the static stock selection model is that it is difficult to reflect the many changes that market expectations have over time. The original intention of this study is to try to integrate the dynamic adjustment mechanism into the stock selection process so as to obtain more accurate forecast results. This study does not simply pile up a large number of factors in the model, but combines the same type or style of factors to obtain the corresponding comprehensive stock selection factor, and then put it into the model for testing. This study predicts the excess return of the stock relative to the industry by building a comprehensive valuation factor.

Quantified stock selection model can be divided into two categories according to the method of setting the weight of the sample window, that is, the dynamic stock selection model and the static stock selection model. The modeling mechanism of the static stock selection model uses only the samples in the fixed window period to fit in the stock selection model to estimate the factor weight (regression coefficient), and then uses the same factor weight to predict the next rate of return for all the sample data. Different from this, the modeling mechanism of dynamic stock selection model re-selects the sample interval after every forecasting of stock returns in the current period, repeats the model fitting process and then estimates the corresponding factor weights calculate the forecast value of the next rate of return. Compared with the static model, the stock picking mechanism of the dynamic model can respond to the complex and volatile stock market in time, so as to be more close to the latest changes in the market. Common window selection methods include extended window method and scroll window method. The extended window method selects all the data from the fixed initial period to the predicted period as a sample, and then fits the prediction model so that its window interval expands with time. The rolling window rule uses data from a fixed length of time before the forecasting period as a sample, so its window length is fixed and scrolls forward as time progresses.

This study first builds a dynamic multi-factor estimation model, then conducts an empirical analysis and tests the stability of each group. Finally, the test results are analyzed, and the shortcomings of this study and the direction of further research and improvement are proposed.

2. Modeling framework

This article predicts the excess return rate of the stock by constructing the valuation factor.

2.1 Sample source and range selection

The data used in this model are all from Juyuan financial database. The monthly data is from January 2006 to December 2012, a total of 84 sets of data, which are used as the sample data for model establishment, optimization and testing. The subjects were all stocks in the A-share market, excluding shares that were suspended at the end of each month. Select 2006 as the starting point for the data is considered consistent. The database is expected to be missing more data by 2006, so removed, only after 2006 data as a sample source.

2.2 Construction of Dynamic Multifactor Valuation Forecasting Model

The theoretical basis of this model is Fama-MacBeth's multi-factor model, which is currently a relatively mature and widely used prediction model. The specific model is constructed as follows:

Fama multi-factor model of the basic structure: For each time t, to meet the regression conditions I branch of the cross-sectional regression, the mathematical expression is:

$$r_{t+1,i} = a_t + b_{1,t}x_{1,t,i} + b_{2,t}x_{2,t,i} + \ldots + b_{K,t}x_{K,t,i} + e_i$$

Where $i = 1,\ldots,I$ traverses each stock, $t = 1,\ldots,T-1$ is the number of months, $r_{t+1,i}$ is the excess return rate of the industry relative to the weighted average return rate of the sector $t+1$, a_t is the intercept item, explanatory variable $x_{k,t,i}$ includes the aforementioned control variable and comprehensive factor score, $b_{k,t}$ is regression Coefficient, e_i is the residual term. The model uses $t+1$ stock excess returns to regress the t control variables and comprehensive factors during the regression. The choice of stock pool at the time of return ensures that both the return on stock $t+1$ and the t control variables must be non-null.

At the time of prediction, $a, b_1, b_2, \ldots, b_K$ is calculated from the historical value of the regression coefficient. The value of T period is $a_T, b_{1,T}, b_{2,T}, \ldots, b_{K,T}$. Use the following method to calculate:

1). The latest parameter method, that is, the direct use of the $T-1$ regression coefficient obtained as the T period of the regression coefficient;

2). In the method of parameter estimation, the historical regression coefficient adopts the method of assigning greater weight recently and the long-term assigning smaller weight, and the specific calculation method is as follows:

$$TimeWtdCoef = \frac{\sum_{m=1}^{N} MonthlyCoef_{T-m} / \sqrt{m}}{\sum_{m=1}^{N} 1/\sqrt{m}}$$

For the historical time span of the equal weight method and the time parameter method, the study was conducted by rolling 12 months, 24 months and 36 months respectively. Bring the valuation of the regression coefficient T into the formula:

$$\hat{r}_{T+1} = a_T + b_{1,T}x_{1,T} + b_{2,T}x_{2,T} + \ldots + b_{K,T}x_{K,T}$$

You can calculate the next period of the stock excess rate of return of the forecast value.

2.3 Dependent variable excess rate of return

In the preceding text, the variable $r_{t+1,i}$ indicates the excess return rate of the BB-only stock in the period t+1 (that is, rolling forward one month). First calculate the monthly returns of individual stocks, using the return of the logarithm of the return of the right to buy. Then calculate the weighted average rate of return (industry rate of return) of each stock in the industry and the excess return ratio of individual stocks relative to its industry rate of return, weighted by the market capitalization at the end of month t. Number of shares of the number of tradable shares was selected to ensure its real liquidity.

2.4 Control factor selection and calculation

In this model, two control variables are selected, which are the excess β and the market capitalization of the standardized logarithm company. β value calculation method:

$$\beta = \frac{\mathrm{cov}(R_i, R_M)}{\mathrm{var}(R_M)}$$

R_i represents the return rate of the ith stock, R_M represents the market rate of return, and this study replaces the gains of the CSI 300 index. The beta value is calculated using two-year yield data for 104 weeks and requiring a minimum of 26 weeks of non-null data to calculate the beta value, otherwise it is recorded as the default value. β= excess stocks β-industry weighted average β. The standardized log market capitalization factor is calculated as follows:

Capital stock Choose unlimited tradable share capital from which to calculate the end of the month stock market capitalization, and then take the logarithm of market value. Then the logarithmic market value in the 24 industries in the industry simple standardization process, the standard logarithm market value factor:

Standardization Logarithm Market Value Factor = (Market Share Logarithm - Industry Average Logarithm Market Value)/Standard Deviation of Market Share Logarithm

2.5 Selection and Treatment of Basic Valuation Factors

The nine basic valuation factors selected in this model are shown in the following table:

Table 1. Basic valuation factor definition

Basic valuation factor	Name	Definition
B/P	Net assets to market ratio	Net assets/total market capitalization
EBITDA/EV	EBITDA profit enterprise value ratio	Rollover 12 months EBITDA/enterprise value
FY1EP	The next year unanimously expected net profit to market ratio	Consistent with the expected forward one-year net profit/total market capitalization
S/P	Operating income to market value ratio	Rolling 12 months total operating income/total market capitalization
1/RV	Reset cost countdown	1/company replacement cost
FY2EP	The next two years, the expected net profit market value ratio	Consistent with expected forward two years of net profit/total market capitalization
C/P	Cash income market value ratio	Rolling 12 months net operating cash flow/total market capitalization
E/P	Net profit market value ratio	Scroll 12 months net profit/total market capitalization
FY3EP	The next three years, the expected net profit market capitalization ratio	Consistent with the expected forward three years net profit/total market value

First of all, according to the definition of nine basic valuation class factor. Then, in each industry, the valuation factors are normalized and weighted normalized to get the standardized valuation factors:

Standardized valuation factor = (basic stock valuation factor - the basic valuation factor industry weighted average)/industry-based stock valuation factor of the weighted standard deviation.

2.6 Outlier processing

The data acquired in the market will inevitably contain outliers. Different treatment of outliers will bring different results to the same model, so the handling of outliers is very crucial. In order to eliminate the influence of individual stock factor extreme value in stock pool, taking into account that all the factors have been standardized in the industry and the factors in the industry are normally distributed, so the conventional method is used to limit the range value to eliminate outliers: Limit the normalized logarithmic market value and the normalized valuation factor to values between -3 and 3, ie, -3 if the resulting value is less than -3, 3 if the value is greater than or equal to 3, -3 and -3 Between the same.

2.7 Comprehensive factor building

When synthesizing the basic valuation factors to synthesize the comprehensive valuation factors, the article is divided into two categories according to their own attributes: the intrinsic value of the market price-earnings ratio and the overall factor.

Table 2. Comprehensive valuation factor definition

Comprehensive factor	Name	Contains basic factors
Price to Intrinsic Value	The intrinsic value of the market price ratio	B/P, S/P, C/P, EBITDA/EV, 1/RV
Price to Earnings	Price-earnings ratio factor	E/P, FY1EP, FY2EP,FY3EP

When constructing comprehensive factors, all non-default basic factor standardized scores will be calculated and synthesized into comprehensive valuation factors according to the above table with equal weights. Finally, in all sectors of the comprehensive factor weighted standardization, you can get a comprehensive factor score. 0 if the final composite factor score is still the default.

2.8 Combination construction and weight distribution

First, the regression and forecast of the data during the sample period (January 2006 - December 2012) are carried out, and the forecast result of the excess return rate of individual stocks is obtained. In each of the 24 industries, we ranked the results of the excess returns rate from high to low, bought the stocks in the top 1/5 position and shorted the stocks in the last 1/5 position. If the current period The number of shares in the industry pool less than 5, then buy all the shares in the industry, of which the weight of shares of unlimited tradable shares of the market value of the stock market calculated as the weight of the investment portfolio in the industry between the industry pool stock market value of the total stock pool The ratio of market capitalization to construct the LS combination and calculate the LS yield of each period, and then further calculate the expectation of the LS yield, the monthly volatility, the probability of winning, the information ratio, the maximum Continuous retracement, order correlation coefficient, Top combination turnover rate, Bottom combination turnover rate and other indicators.

3. Empirical analysis

3.1 Comprehensive factor test

Mentioned earlier, we will be the basic valuation factors in accordance with their own properties of the synthesis of two types of integrated valuation factors. To test the performance of the synthetic factors in actual combat, this section conducts regression of control variables alone, control variables plus single composite factor regression, and control variables plus two-factor regression. The combination of the four factors, respectively, using the latest parameter method; equal-weight method by rolling 12,24,36 months; time-weighted method by reducing rolling 12,24,36 months for comparison. The regression results of the seven regression methods for each factor combination are shown in the following, and the prediction method for the optimal parameters of each combination is marked in red.

Table 3. Control variables + two-factor combination of test results

Mode	Method	Time	ER	ERV	Hit	IR	MD	RankIC	topHW	bottomHW
Two factors	Latest parameters	1	-1.50%	1.99%	16.67%	-0.7534	-18.72%	-4.32%	91.20%	89.82%
		2	-0.66%	2.49%	41.67%	-0.2666	-22.71%	0.53%	84.27%	80.73%
		3	-0.07%	2.91%	47.22%	-0.0231	-22.71%	1.47%	82.32%	78.10%
		5	0.00%	3.30%	51.67%	0	-22.71%	1.89%	83.90%	74.29%
	The weight of 12 months	1	0.95%	1.92%	58.33%	0.4972	-2.86%	6.22%	36.08%	31.47%
		2	0.37%	2.42%	50.00%	0.1538	-8.33%	3.70%	37.90%	25.28%
		3	0.67%	2.50%	55.56%	0.2666	-8.33%	3.69%	38.46%	21.41%
		5	1.74%	3.30%	61.67%	0.526	-8.33%	6.74%	39.20%	21.97%
	The weight of 24 months	1	0.60%	3.13%	58.33%	0.1916	-7.85%	3.79%	33.90%	27.66%
		2	0.44%	2.82%	58.33%	0.157	-7.85%	4.45%	35.73%	18.47%
		3	0.76%	2.75%	63.89%	0.2755	-7.85%	4.36%	34.33%	16.69%
		5	1.60%	2.91%	74.58%	0.5481	-7.85%	6.93%	36.06%	19.59%
	The weight of 36 months	1	0.87%	3.24%	58.33%	0.2694	-6.66%	5.76%	31.81%	13.39%
		2	0.59%	2.87%	62.50%	0.2059	-7.55%	4.90%	31.38%	11.74%
		3	1.03%	2.66%	69.44%	0.3849	-7.55%	4.67%	32.43%	14.22%
		All	1.48%	2.68%	74.47%	0.5537	-7.55%	6.38%	34.15%	17.33%
	Time weight 12 months	1	-0.08%	1.96%	41.67%	-4.08%	-7.97%	2.38%	55.45%	49.05%
		2	-0.18%	2.33%	50.00%	-7.75%	-11.81%	2.65%	49.47%	36.53%
		3	0.16%	2.49%	52.78%	0.0625	-11.81%	2.36%	51.47%	32.71%
		5	1.35%	3.33%	63.33%	0.407	-11.81%	5.63%	48.22%	29.56%
	Time weight 24 months	1	-0.41%	2.43%	33.33%	-16.71%	-11.01%	1.77%	47.93%	44.28%
		2	-0.13%	2.56%	37.50%	-5.21%	-14.72%	3.34%	43.63%	29.23%
		3	0.38%	2.62%	47.22%	0.1469	-14.72%	3.37%	42.07%	24.31%
		5	1.30%	3.08%	61.02%	0.4234	-14.72%	6.10%	42.23%	24.69%
	Time weight 36 months	1	0.20%	2.58%	58.33%	7.63%	-9.02%	3.62%	44.51%	36.57%
		2	0.20%	2.53%	54.17%	8.02%	-9.41%	4.00%	39.75%	24.88%
		3	0.57%	2.55%	61.11%	0.2243	-9.41%	3.90%	38.02%	21.92%
		All	1.22%	2.76%	68.09%	0.443	-9.41%	5.82%	38.57%	23.61%

Table 4. Control variable combination test results only

Mode	Method	Time	ER	ERV	Hit	IR	MD	RankIC	topHW	bottomHW
Control only	Latest parameters	1	-1.98%	2.95%	33.33%	-0.6706	-23.11%	-6.95%	94.81%	90.03%
		2	-0.97%	3.03%	45.83%	-0.3203	-26.37%	-0.43%	83.74%	77.61%
		3	-0.49%	3.53%	50.00%	-0.1379	-30.18%	1.05%	77.25%	69.36%
		5	-0.35%	3.83%	48.33%	-0.0909	-30.18%	0.66%	79.20%	66.20%
	The weight of 12 months	1	-0.82%	4.94%	41.67%	-0.167	-15.91%	0.05%	54.94%	35.72%
		2	-0.77%	4.27%	45.83%	-0.1806	-21.26%	0.00%	43.16%	24.28%
		3	-0.20%	3.89%	50.00%	-0.0505	-21.26%	1.45%	38.06%	19.44%
		5	0.86%	4.20%	56.67%	0.2039	-21.26%	3.95%	34.64%	17.63%
	The weight of 24 months	1	0.30%	4.32%	50.00%	6.88%	-9.63%	-1.17%	32.49%	9.05%
		2	0.09%	4.04%	50.00%	2.19%	-13.21%	1.00%	30.17%	8.01%
		3	0.46%	3.78%	55.56%	0.1226	-13.21%	2.48%	26.88%	7.68%
		5	1.14%	4.00%	62.71%	0.2847	-13.21%	4.33%	26.91%	11.70%
	The weight of 36 months	1	0.87%	4.22%	58.33%	20.58%	-6.73%	2.28%	25.87%	6.08%
		2	0.29%	3.96%	54.17%	7.35%	-11.83%	2.06%	25.01%	6.52%
		3	0.65%	3.68%	58.33%	0.1766	-11.83%	3.11%	22.83%	6.51%

		All	1.20%	3.66%	63.83%	0.3286	-11.83%	4.38%	24.17%	9.46%
	Time weight 12 months	1	-2.52%	4.05%	33.33%	-0.6231	-27.10%	-8.45%	78.98%	66.92%
		2	-1.41%	4.07%	45.83%	-0.3455	-34.65%	-2.65%	59.25%	40.69%
		3	-0.84%	3.71%	44.44%	-0.2257	-34.85%	-0.84%	53.24%	32.88%
		5	0.37%	4.21%	56.67%	0.0887	-34.85%	2.37%	46.69%	26.40%
	Time weight 24 months	1	-0.59%	3.93%	41.67%	-14.97%	-9.66%	-5.33%	56.50%	32.78%
		2	-0.42%	3.85%	50.00%	-10.85%	-17.40%	-0.68%	43.83%	20.83%
		3	0.10%	3.63%	55.56%	0.0281	-17.40%	1.03%	38.63%	16.67%
		5	0.96%	4.00%	61.02%	0.2389	-17.40%	3.36%	36.77%	17.71%
	Time weight 36 months	1	0.07%	4.01%	50.00%	1.78%	-6.37%	-0.95%	44.69%	14.89%
		2	-0.11%	3.91%	50.00%	-2.85%	-13.61%	0.97%	35.90%	11.52%
		3	0.34%	3.64%	55.56%	0.0921	-13.61%	2.19%	31.74%	10.16%
		All	1.01%	3.74%	59.57%	0.2709	-13.61%	3.75%	32.57%	12.63%

Table 5. Control Variable + Intrinsic Value Market-to-Factor Factor Combination Test Results

Mode	Method	Time	ER	ERV	Hit	IR	MD	RankIC	topHW	bottomHW
PtoIV	Latest parameters	1	-1.77%	2.24%	16.67%	-0.787	-20.72%	-4.50%	91.94%	89.23%
		2	-1.00%	2.75%	37.50%	-0.3624	-25.78%	0.30%	85.75%	80.61%
		3	-0.39%	3.12%	44.44%	-0.1267	-27.45%	1.07%	82.72%	77.13%
		5	-0.21%	3.45%	46.67%	-0.06	-27.45%	1.65%	83.19%	71.83%
	The weight of 12 months	1	0.06%	2.49%	58.33%	2.58%	-8.75%	4.93%	37.61%	31.99%
		2	-0.13%	2.45%	50.00%	-5.37%	-13.68%	3.24%	38.34%	24.29%
		3	0.24%	2.54%	55.56%	0.0955	-13.68%	3.33%	38.81%	21.30%
		5	1.45%	3.27%	63.33%	0.442	-13.68%	6.50%	37.62%	20.71%
	The weight of 24 months	1	0.07%	2.93%	58.33%	2.22%	-9.15%	2.23%	30.23%	24.59%
		2	0.13%	2.75%	54.17%	4.88%	-10.88%	3.44%	30.19%	16.50%
		3	0.59%	2.78%	61.11%	0.2106	-10.88%	3.67%	29.89%	15.46%
		5	1.47%	2.91%	69.49%	0.506	-10.88%	6.50%	31.16%	18.21%
	The weight of 36 months	1	0.43%	3.27%	58.33%	13.01%	-8.05%	4.83%	27.71%	12.37%
		2	0.30%	2.82%	50.00%	10.71%	-8.05%	4.29%	28.02%	10.76%
		3	0.70%	2.80%	58.33%	25.06%	-8.05%	4.19%	28.23%	12.03%
		All	1.23%	2.85%	65.96%	43.27%	-8.05%	6.01%	29.85%	15.62%
	Time weight 12 months	1	-0.83%	2.46%	41.67%	-33.98%	-15.53%	0.73%	60.27%	52.46%
		2	-0.63%	2.53%	45.83%	-25.00%	-20.48%	1.69%	52.92%	38.56%
		3	-0.26%	2.59%	47.22%	-0.0994	-22.85%	1.57%	53.25%	33.82%
		5	1.10%	3.35%	58.33%	0.3268	-22.85%	5.18%	48.09%	29.75%
	Time weight 24 months	1	-0.85%	2.37%	41.67%	-35.66%	-12.87%	0.11%	54.69%	43.85%
		2	-0.32%	2.84%	45.83%	-11.21%	-20.07%	2.29%	45.62%	27.91%
		3	0.15%	2.82%	50.00%	0.052	-20.07%	2.58%	43.58%	23.28%
		5	1.22%	3.10%	62.71%	0.3932	-20.07%	5.66%	41.45%	24.00%
	Time weight 36 months	1	-0.01%	2.82%	58.33%	-0.40%	-7.07%	2.61%	43.21%	34.02%
		2	0.00%	2.78%	54.17%	0.08%	-11.55%	3.32%	37.63%	22.34%
		3	0.43%	2.76%	61.11%	0.1565	-11.55%	3.33%	36.04%	18.60%
		All	1.06%	2.95%	68.09%	0.3598	-11.55%	5.41%	36.73%	20.26%

Table 6. Control variable + P/E multiple factor combination test results

Mode	Method	Time	ER	ERV	Hit	IR	MD	RankIC	topHW	bottomHW
PtoE	Latest parameters	1	-1.67%	1.83%	16.67%	-0.911	-19.93%	-4.99%	93.19%	89.74%
		2	-0.67%	2.23%	41.67%	-0.302	-22.31%	0.65%	84.20%	81.70%
		3	-0.12%	2.76%	47.22%	-0.042	-22.31%	1.81%	81.40%	75.17%
		5	-0.10%	3.41%	45.00%	-0.029	-27.27%	1.47%	84.55%	71.85%
	The weight of 12 months	1	1.20%	2.05%	58.33%	58.42%	-1.13%	6.06%	39.34%	36.45%
		2	0.45%	2.52%	54.17%	17.69%	-8.93%	3.79%	38.14%	28.03%
		3	0.72%	2.53%	58.33%	0.2859	-8.93%	3.99%	38.38%	22.88%
		5	1.45%	3.30%	61.67%	0.4378	-8.93%	5.94%	39.25%	22.25%
	The weight of 24 months	1	0.64%	3.79%	58.33%	17.01%	-11.26%	3.58%	39.18%	24.91%
		2	0.48%	3.31%	58.33%	14.41%	-11.26%	4.08%	36.05%	16.82%
		3	0.86%	3.18%	61.11%	0.2714	-11.26%	4.48%	34.83%	14.63%
		5	1.61%	3.40%	69.49%	0.4749	-11.26%	6.04%	36.38%	17.47%
	The weight of 36 months	1	1.02%	3.99%	50.00%	25.60%	-8.99%	5.42%	31.29%	10.81%
		2	0.56%	3.49%	45.83%	16.06%	-8.99%	4.32%	31.56%	9.56%
		3	0.95%	3.20%	52.78%	0.2971	-8.99%	4.75%	31.95%	10.89%
		All	1.37%	3.20%	59.57%	0.4281	-8.99%	5.85%	34.26%	14.20%
	Time weight 12 months	1	0.08%	1.79%	41.67%	4.74%	-6.94%	2.12%	58.32%	54.92%
		2	-0.09%	2.31%	41.67%	-4.01%	-11.71%	2.92%	49.37%	39.22%
		3	0.06%	2.41%	47.22%	0.0267	-12.99%	2.76%	49.17%	32.91%
		5	1.01%	3.30%	55.00%	0.3052	-12.99%	4.87%	47.80%	28.49%
	Time weight 24 months	1	0.02%	3.18%	50.00%	0.56%	-12.41%	1.64%	52.62%	45.73%
		2	0.10%	3.11%	45.83%	0.0324	-13.75%	3.26%	45.45%	28.32%
		3	0.50%	2.97%	55.56%	0.1695	-13.75%	3.59%	43.09%	23.38%
		5	1.26%	3.34%	61.02%	0.3776	-13.75%	5.28%	43.30%	23.60%
	Time weight 36 months	1	0.45%	3.44%	50.00%	0.1311	-11.83%	3.39%	45.81%	30.16%
		2	0.29%	3.25%	45.83%	0.09	-11.83%	3.69%	38.61%	19.96%
		3	0.69%	2.99%	55.56%	0.2303	-11.83%	4.05%	36.73%	17.46%
		All	1.16%	3.06%	61.70%	0.3808	-11.83%	5.37%	38.20%	19.51%

From the test results point of view, the control variable plus two-factor combination of the best forecasting ability. In contrast, the use of only control variables and the control variable + intrinsic value of the market value of the composite factor combination was significantly lower than the two-factor combination in predictive efficiency; at the same time, the expected return, hit rate, information rate, the maximum retracement, etc. are not as good Two-factor combination. The control variable + P/E composite factor combination returns higher than the two-factor combination in a few time periods, but in the long run, the average return falls back below the two-factor combination. In addition, in the long term, the volatility of the P/E composite factor combination is higher than that of the two-factor combination and the hit ratio is lower than the two-factor combination, and the maximum withdrawal is also inferior to the two-factor combination. Therefore, the outstanding performance in a short period of time can be explained as the composite factor of price-earnings ratio plays a leading role in the market in the short term, and its role in the two-factor model may be impaired by the intrinsic value of the market price than the comprehensive factor, but in the long-Predictors of P/E multiple factors are less stable and prone to sharp fluctuations. It is not advisable here to use only the P/E multiplier as the only predictor. From the actual test point of view, two-factor combination is the best choice. From the point of view of regression model, we statistically compare and test the four factor combination models. To test the role of the two types of synthetic factors in the prediction model, the effects of the synthetic factors were determined using adjusted R-measures and F-tests. The adjustment of R square can determine whether the new factor of the model contributes to the explanation of the dependent variable of the model. The average R-square of the regression of the four factors in the sample is as follows:

Table 7. Each factor combination model adjusts the R-square result

Factor combinations	Control only	PtoIV	PtoE	Two factors
Adjust R side	0.0404	0.0502	0.0498	0.0573

It can be seen that after adding the comprehensive factor into the model, the adjustment of the R-factor is more improved than before. Therefore, adding the comprehensive factor into the model can improve the explanation of the dependent variable (ie, the excess return rate). F test is used to determine whether there is a significant difference between the two models. We test the control variables + two-factor model and the control-only model for F-test. The p value corresponding to the F value changes with time as shown in the following figure:

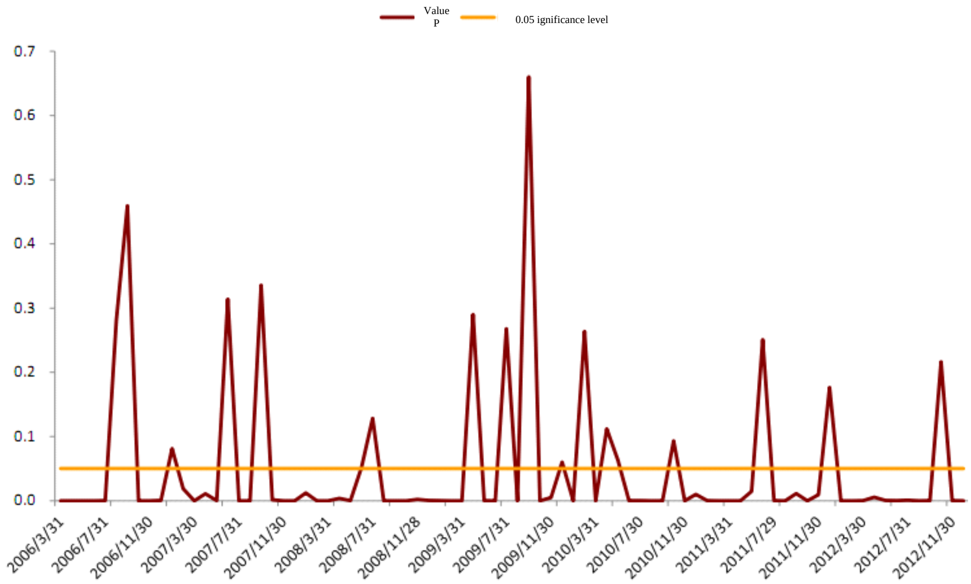

Figure 1 . F test for each period significance level

According to the statistics, the p value corresponding to the F value was 0.0514 in each period; at the 5% significance level, the number of months with significant difference between the two models was about 78% of the total months, and there was no significant difference in the number of months 22 %. In summary, from the perspective of the model's own statistical point of view, the two types of synthetic factors contribute to the explanation and modeling of excess returns.

3.2 Factor Weight Stability Analysis

The stability test of the weight of the four factors was carried out. The results are shown in Table 8 and Table 9.

Table 8. Factor Stability Checklist

Mode	Time	Intercept		Beta	
		Mean	Value t	Mean	Value t
Two factors	1	0.0009	0.16	-0.0051	-0.35
	2	0.0027	0.89	-0.0005	-0.06
	3	0.0047	1.96	-0.0017	-0.23
	5	0.0069	3.11	0.0018	0.27
	All	0.0055	2.28	-0.0023	-0.43
Only control variables	1	-0.0028	-0.38	-0.0042	-0.28

	2	0.0001	0.02	0.0001	0.01
	3	0.0027	0.89	-0.0013	-0.18
	5	0.0055	2.2	0.0031	0.45
	All	0.0048	1.71	-0.0014	-0.24
PtoIV	1	-0.0003	-0.05	-0.0062	-0.42
	2	0.0018	0.54	-0.0015	-0.16
	3	0.0039	1.52	-0.0024	-0.33
	5	0.0062	2.69	0.0015	0.22
	All	0.005	1.89	-0.0026	-0.49
PtoE	1	0.0002	0.04	-0.0035	-0.24
	2	0.0024	0.73	0.0009	0.1
	3	0.0045	1.79	-0.0008	-0.1
	5	0.0069	3.08	0.0031	0.44
	All	0.0059	2.35	-0.0012	-0.22

Table 9. Factor Stability Checklist (Continued)

Mode	Time	CompanySize		PtoIV		PtoE	
		Mean	Value t	Mean	Value t	Mean	Value t
Two factors	1	-0.0022	-0.58	0.0045	1.49	0.0043	1.64
	2	-0.0039	-1.94	0.0032	1.59	0.0031	2.13
	3	-0.0045	-2.7	0.0022	1.42	0.0026	2.17
	5	-0.0066	-4.25	0.0038	3.43	0.0025	2.81
	All	-0.0058	-3.09	0.0042	4.26	0.002	1.73
Only control variables	1	0	0.01				
	2	-0.0022	-0.92				
	3	-0.0032	-1.7				
	5	-0.0054	-3.2				
	All	-0.005	-2.3				
PtoIV	1	-0.0015	-0.36	0.0065	1.8		
	2	-0.0033	-1.56	0.0047	2.12		
	3	-0.004	-2.32	0.0035	2.04		
	5	-0.0061	-3.79	0.005	4.19		
	All	-0.0055	-2.59	0.0051	5.26		
PtoE	1	-0.0018	-0.46			0.0065	1.87
	2	-0.0037	-1.76			0.0048	2.51
	3	-0.0043	-2.56			0.0037	2.38
	5	-0.0065	-4.14			0.0039	3.75
	All	-0.0059	-3.08			0.0036	3.06

The unilateral test is used to determine the criterion of significance, and the critical value of t under 95% confidences is 1.65. Table 8 and Table 9 show that, in the long run, except the weight of Beta value is not significant, the market value and the weight of the two types of comprehensive valuation factors are significant. The market capitalization weight is significantly negative and the comprehensive valuation factor weight is significantly positive. This also shows that the integrated valuation factor contributes to the prediction of excess return. To sum up, the optimal model we choose is the control variable + two-factor model, and the weighting method of the factors uses equal weight to scroll the 12-month method.

4. Summary

Stock rate of return can be broken down into the average rate of return of the industry and stocks relative to the industry excess return rate in two parts. Arguments include the stock market value, Beta value and the comprehensive valuation factor, the market value, Beta value as a control variable. This article seeks to show that stock excess returns are the result of their independent variables relative to the industry's excess. This paper tries to use the latest parameter method in parameter estimation, equal weight method and time weight method. Through the comparison within the sample, the method of equal weight rolling for 12 months is the best method to estimate the parameters. In this method, the statistic phase of the return on investment, winning ratio, information ratio, maximum withdrawal, turnover ratio and other statistics Than the rest of the methods are more prominent. At the same time, the L/S combination achieved good positive returns both in the sample and in the sample, with a smaller maximum retracement. In addition, there is certain volatility in the valuation factors. In 2011, the valuation factors performed poorly, with a sharp correction in 2012 and 2013, especially the 2013 valuation models.

Future directions for improvement and experimentation: Modeling the relative industry excess returns for individual stocks. Returns on individual stocks are derived from industry average returns and excess returns, so they can be used in combination with other industry selection models or better. In addition, the integrated valuation factor in this article is constructed by using human-like classification and other weighting methods. In the future, different valuation factor classification methods and different weight assignment methods may be tried to achieve optimization. At the same time, you can try to model other types of factors other than the valuation model into the model.

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