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BM(book-to-market ratio) factor: medium-term momentum and long-term reversal

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Abstract

To explain medium-term momentum and long-term reversal, we use the difference between the optional model and the CAPM model to construct a winner-loser portfolio. According to the CAPM model's zero explanatory ability with respect to stock market anomalies, we obtain an anomaly interpretative model. This study shows that this anomaly interpretative model can explain stock market perceptions and medium-term momentum. Most importantly, BM is a critical factor in the model's explanatory ability. We present a robustness test, which includes selecting new sample data, adding new auxiliary variables, changing sample years, and adding industry fixed effects. In general, the BM effect does have considerable explanatory power in medium-term momentum and long-term reversal.

Keywords: Stock market volatility, medium-term momentum, long-term reversal, holding period, formation period, book-to-market ratio, return on equity

Introduction

In a completely effective market, stock market volatility is random. However, through daily observations, we find that the stock market often shows regular fluctuations, which is counter intuitive. These cyclical fluctuations often occur during a certain period and are known as stock market visions. These phenomena have attracted academic attention because they can no longer be interpreted by traditional methods. The momentum and reversal effect, as two typical stock market visions, have caused heated discussion in the academic community. Retail investors and institutional investors believe that grasping momentum or reversal means that a stock's future returns can be predicted for profit. Some such cases do exist. Jegadeesh and Titman (1993) first discovered and proposed that the US securities market momentum effect exists for three to 12 months and provided a short-term profitability strategy. The authors also found that this strategy can obtain 1% of the excess return rate within a certain period. Wang Yonghong and Zhao Xuejun (2001) used one month for the smallest sort period and discovered that China's stock market has a clear reversal effect. The authors also proved that the inertial effect of China's stock market is not obvious. However, scholars have not given a definitive answer as to how to grasp these visions. Research is still advancing incrementally. This paper focuses on the interpretation of the above two visions, constructs a model, and identifies a new visions model that can be applied to the explanation of the two anomalies at the same time. First, we explain several important basic concepts and previous research results.

Momentum effect is also known as the inertial effect. It implies that the stock had a higher return in the past and will have a higher return in the future; lower stock yields in the past mean that the future return will be lower. Jegadeesh and Titman (1993) were the first academics to discover that the momentum effect existed in the US securities market in three to 12 months. Soon afterward, they offered a short-term profitability strategy and found that the strategy, within a certain period, obtained 1% excess return. Then, Kaul and Conrad (1993) used shares of the stock listed on the New York Stock Exchange and the US Stock Exchange during the period 1926 to 1989 to study the stock returns during eight different investment periods. The research found that four of the investment strategies achieved significant profits, two strategies belong to the momentum strategy, the other two are reverse strategy. Almost at the same time, Rouwenhorst analyzed the momentum effects of 12 European countries' stock markets and found that almost all of them showed short-term momentum effect and to a greater extent than the US market. While Rouwenhorst confirmed that applying momentum strategies to emerging markets could acquire significant profit, some scholars discovered that investors tended to adopt momentum strategy in their decision making. For example, Chen found that US investors have momentum tendency when they make medium-term investment decisions. Given this, we find that the stock market and the investors are affected by momentum effect within three to 12 months, which indicates the existence of the medium-term momentum effect. This effect brings tangible benefits for investors. Griffin (2003) used 40 countries to explain the momentum effect of macroeconomic cycle risk. He found that momentum gains were present and significant in these countries, and regardless of whether the economic cycle was in an upswing or a declining phase, the momentum gains were significantly positive. Thus, the momentum effect and the macroeconomic cycle do not have a significant relationship. Lee and Swaminathan (2000) first studied the relationship between the momentum effect and stock trading volume from the perspective of trading volume.

The author concluded that the trading volume of the stock can predict the income of the momentum strategy and the duration of the momentum effect. When using momentum strategies in high stock returns, the effect of the momentum effect will become less and will continue for a shorter time. In addition to the long-term reversal effects found in the US market, scholars found a reversal effect in other countries. This finding indicates that the effect is not the reason for data mining. Chan et al. (1996) and Chui et al. (2000) found short-term reversal effects in the Japanese market. Baytas and Cakici (1999) note long-term reversal effects in the other seven countries.

After understanding the mid-momentum effect, we find that the reversal effect becomes easier to interpret. In simple terms, the reversal effect is that the stock that performed poorly in the past period will show a better result in the future. De bondt and Thaler (1985) found that the portfolio of the worst performing 10% stocks paid 10% over the stocks that were winners after the three-year formation; the loser portfolio showed a higher than average market return at 19.6% while the winner portfolio was still lower than 5%. This study confirmed that the reversal effect exists over a long period, and reversal strategies can be used to achieve substantial returns over a longer period.

Much controversy surrounds the existence of the momentum effect and the reversal effect on developed countries' stock markets. Zhu (2003) is one of the representative scholars and has proved that China does not have a reversal effect through the study of the securities market. Chen Qiao and Wang Shi (2003) found that the inertial strategy based on the industry portfolio showed significant excess returns. Hameed and Ting (2000) found a significant price reversal effect in the Malaysian stock market indicating that there is a reversal effect in developed country stock markets. Gaunt's (2000) study found that the Australian market also shows a significant reversal effect. His sample interval was from 1974 to 1997, the formation period was five years and, after an 18-month holding period, the reversal effect appeared. From the theoretical results of these scholars, we conclude that there are divergent views on whether there are momentum and reversal trends in the Chinese market, and the conclusions are totally different. The focus of our study is to clarify medium-term momentum and long-term reversal effects rather than prove their existence. Based on the above literature, we know that the reversal effect is a ubiquitous phenomenon and is concentrated in the medium and long term. Thus, our decision will be more inclined to choose the mature US financial market so that the statement on the existence of medium-term momentum and long-term reversal will be unified. The US stock market has become a better option for our empirical analysis.

Typically, scholars are divided into two categories: behavioral finance and traditional finance. Behavioral finance scientists often use the theory of overreaction and underreaction to explain the reversal and momentum effects. The view of long-term overreaction was first introduced by De Bond and Thaler (1985, 1987). Additionally, there are several interpretative models in behavioral finance. The BSV model (Barberis, Shleifer, & Vishny, 1998) assumes that market investors have two deviations when they make personal decisions. One is a representative bias; because investors so easily overlook recent data, the result is over-reaction. The other is conservative bias; investors are insensitive to new information causing inadequate response to the information. The DHS model (Daniel, Hirshleifer, & Subramanyam, 1998) divides investors into information-based investors and non-information investors and considers whether investors are sensitive to new information. The HS model (Hong & Stein, 1999), based on assumptions concerning investors' sensitivity and type, interprets the under-reaction from different perspectives. Fama and French (1996), who are representatives of traditional finance schools, analyzed the reversal and momentum of stock returns and confirmed that the benefits of long-term reversal strategies can be explained by their three-factor model, but the model cannot explain the medium-term momentum effect. Fama and French (1996) also believed that the CAPM vision is due to the CAPM model, which lacks the consideration of other necessary risk factors. Considering the problem with the CAPM model, our analysis is established based on the traditional financial school, which uses a model similar to the factor model to explain the two visions.

As mentioned, the BETA value in the CAPM model is not a reliable risk indicator. Some scholars found that if the new risk factor is added into the factor models, some excess returns can be explained. Some type of vision will disappear. But what variable should be added to the factor model to explain the medium-term momentum and long-term reversal? Scholars failed to reach a consensus on this point. Following the traditional financial idea, we consider the type of impact that occurs from adding BM and ROE into the model.

First, we validate the zero interpretation ability about the medium-term momentum and long-term reversal of the CAPM model. Then, we use the benefit forecast model obtained through the MC model (Lyle & Wang, 2015) to construct independent variables difference and obtain the vision interpretation model. This paper chooses the MC model as the basic model. We need to prove the following: First, this model has better ability than the CAPM model to forecast future stock earnings. Second, this model has the same ability as the three-factor model and the four factors in returning a prediction. The empirical test found that medium-term momentum was largely explained, and a small part of the long-term reversal was explained.

Additionally, through a series of studies, we discovered the BM as the most critical factor in explaining ability. Its value is totally different under the efficient market hypothesis. The long-term reversal explaining ability is far more than that of the medium-term momentum. We design a series of correlation experiments that are deemed significant to prove that the BM factor gradually becomes noticeable over time, which is also consistent with the traditional finance situation whereby the market tends to become an effective market, and the vision will gradually disappear.

For the BM effect, Fama and French (1992) studied all the stocks listed on NYSE, AMEX, and NASDAQ from 1963 to 1990 and found that the 1.53% combination of BM's highest value (the value combination) had the lowest monthly yield (the combination of charm). Xiao Jun and Xu Xinzhong (2004) used Shanghai and Shenzhen stock market shares from June 1993 to June 2001 as a sample and calculated holding shares' earnings in one year, two years, and three years to find that the BM effect does exist.

Finally, if we lack rigor in our research methods, we hope that other scholars in this area provide more in-depth study and more proof will emerge in the future.

The remainder of this paper is organized as follows: section2 presents the MC model and determines the parameters. Chapter 3 analyzes the BETA coefficients of the CAPM model based on the empirical analysis. In Chapter 4, the existence of the stock market, vision model, and empirical explanation are proposed. Chapter 5 analyzes the model's inherent explaining mechanism. Chapter 6 gives a robustness test, and Chapter 7 summarizes the full text.

Model

The specific formula of the MC model is shown in (Lyle & Wang, 2015), and other detailed derivation steps are given in the literature.

$$r_{i,t+1} = \underbrace{\mu_i\left(1-\omega_i\frac{\alpha_1}{\alpha_2}\right)}_{\beta 0} + \underbrace{\left(1-k_1\kappa_i\right)}_{\beta_1} bm_{i,t} + \underbrace{\left(\omega_i\frac{1-k_1\kappa_i}{1-k_1\omega_i}\right)}_{\beta_2} roe_{i,t} + \xi_{i,t+1} \quad (1)$$

$$\text{among } \beta_1 = \frac{1}{\alpha_2}, \beta_2 = \omega_i\frac{\alpha_1}{\alpha_2}, \xi_{i,t+1} = \frac{\alpha_1}{\alpha_2}\left(\varepsilon_{i,t}-\omega_i\nu_{i,t}\right) + \eta_{i,t+1}$$

We obtain the industry parameters from the estimated coefficients of (Chen & Wang, 2017):

$$\kappa = \left(1 - \beta_1\right) / k_1 \tag{2}$$

$$\mu = \beta_0 / \left(1 - \beta_2\right) \tag{3}$$

$$\omega = \frac{\beta_2/\beta_1}{1 + \left(\beta_2/\beta_1\right) k_1} \tag{4}$$

In developing the model, first, industry parameters must be determined. Over time, any company tends to become more like its peers. Any abnormal expected ROE (or excess expected return) will be gradually weakened due to the presence of industry competition. Equation (1) is also the core model for the anomaly interpretation.

Sample selection and data sources

After obtaining the prediction model, the coefficients and other implied parameters of this model must be confirmed. The sample is selected from the quarterly training data (the sunken data), which is made up of 100 quarterly data points. The period was from the first quarter of 1980 to the fourth quarter of 1994 for all the US financial markets in DataStream. We implement the out-of-sample prediction from the first quarter of 2010 to the fourth quarter of 2015. At this time, we no longer use a sample of all industries but select five, and these five industries will run through the anomaly interpretation and robustness test. The main reason we gather data in this way is that collecting whole industry involves extensive work and the probability of error is greater.

Empirical analysis

Sample regression analysis

First, the model is estimated through quarterly data by ordinary least squares (OLS). The model coefficients and model implicit parameters are calculated using Equ. (1). Panel B of Table 1 shows the time series mean for each industry. Panel A gives the summary result. The mean values (median) of log BM and log ROE are 0.045638 (0.0461) and 0.339625 (0.265), respectively. The constant coefficients corresponding to median and mean values are 0.032162 and 0.02985, respectively. By comparative analysis, we find that the first-order autoregressive persistence parameters of mean (median) values are 0.964003 and 0.962121, respectively, for a given industry; persistence values are high. The standard deviation of the industry persistence parameter is low, only 0.017613, while the ROE continuous parameter's standard deviation is 0.181218, which is larger than the log returns. Overall, the MC model has good persistence for expected returns.

Table 1 shows that the coefficient and implicit parameters between industries differ, which suggests that every industry's response to external change varies because of its unique characteristics. For most industries, the forecast returns are consistent with actual earnings; that is, the k value is large enough. Some industries, such as gas, water, and multiple utilities; life insurance; financial services; and equity investment instruments have slightly larger coefficients. Therefore, their returns are vulnerable to outside influences. Industries such as food and drug retail are different. ROE coefficient values are close to one implying returns are easily influenced.

Table 1 Summary of model parameters

	Regression coefficients			Implied parameters		
	cons	bm	roe	k	w	μ
Panel A: Regression results summary						
5th percentile	-0.0119	0.013	0.1106	0.93523	0.707112	0.02003
25th percentile	0.02114	0.0322	0.179	0.950202	0.817889	0.031925
Mean	0.032162	0.045638	0.339625	0.964003	0.878349	0.056226
Median	0.02985	0.0461	0.265	0.962121	0.893978	0.041286
75th percentile	0.03772	0.0584	0.461	0.976566	0.938257	0.05825
95th percentile	0.05589	0.07149	0.61	0.995	0.98653	0.12964
Standard deviation	0.013273	0.017437	0.198346	0.017613	0.084486	0.181218
Panel B: Industry Coefficient						
Electricity	0.03705	0.0453	0.114	0.964343	0.731332	0.041817
Equity investment instrument	0.04606	0.0153	0.108	0.994646	0.89955	0.051637
Financial service	0.04952	0.0423	0.46	0.967374	0.941658	0.091704
Fixed line telecommunications	0.03535	0.0461	0.136	0.963535	0.763959	0.040914
Food and drug retail	0.03188	0.057	0.97	0.952525	0.972041	1.062667
food producers	0.05658	0.0288	0.51	0.98101	0.974212	0.115469
Forestry & paper	0.03507	0.0402	0.384	0.969495	0.930503	0.056932
Gas, water, & multiple utilities	0.06409	0.0225	0.59	0.987374	0.99193	0.156317
General industrial	0.03798	0.0436	0.262	0.966061	0.879962	0.051463
General retailers	-0.01148	0.0622	0.53	0.947273	0.91966	0.024426
Health care equipment & services	0.02878	0.0475	0.188	0.962121	0.817889	0.035443
Household goods & home construction	0.03397	0.0512	0.117	0.958384	0.710426	0.038471
Industrial engineering	0.02985	0.0554	0.277	0.954141	0.854701	0.041286
industrial metals & mining	0.03686	0.0332	0.259	0.976566	0.910593	0.049744
Industrial transportation	0.02691	0.0499	0.26	0.959697	0.860642	0.036365
Leisure goods	0.01774	0.0632	0.354	0.946263	0.870677	0.027461
Life insurance	0.04108	0.0187	0.461	0.991212	0.989546	0.076215
Media	0.01825	0.0584	0.233	0.951111	0.81924	0.023794
Mining	0.02114	0.0594	0.62	0.950101	0.938257	0.055632
Mobile telecommunications	0.01277	0.0709	0.6	0.938485	0.918977	0.031925
No life insurance	0.03772	0.0322	0.265	0.977576	0.916162	0.05132
Oil equipment & services	0.02799	0.0433	0.192	0.966364	0.836456	0.034641
Oil & gas producers	0.03311	0.0266	0.541	0.983232	0.981192	0.072135
Personal goods	0.0288	0.0545	0.179	0.955051	0.78464	0.035079
Pharmaceuticals & biotechnology	-0.01425	0.072	0.38	0.937374	0.86246	0.022984
Real estate investment & services	0.05535	0.0129	0.174	0.997071	0.957728	0.06701
Real estate investment trusts	0.04822	0.0132	0.269	0.996768	0.981286	0.065964
Software & computer services	0.02563	0.0593	0.56	0.950202	0.929461	0.05825
Sport services	-0.01356	0.0769	0.222	0.932424	0.75965	0.017429
Technology hardware & equipment	0.02293	0.0613	0.138	0.948182	0.707112	0.026601
Tobacco	0.02047	0.0529	0.356	0.956667	0.893978	0.031786
Travel & leisure	0.02875	0.0442	0.159	0.965455	0.80129	0.034185

Expected returns analysis

After determining the coefficient, we calculate the out-of-sample return. First, we need to predict in-sample return before interpreting vision. The reason is the following: first, the anomaly excess return is also a part of the actual benefit; second, predicting ability in 3, 12, 24, and 36 months is mainly possible because long-term reversal typically occurs between three to five years of holdings, and the medium-term momentum typically occurs between three to 12 months. Thus, if the model can predict returns within three years or less, it is likely that the MC model can explain the above two anomalies better.

By estimating the coefficients and the implicit parameters of the model, the expected returns of the holding period T are obtained:

$$\sum_{j=1}^{T} \mu_{t+j-1} = \hat{\mu} T + \frac{1-\hat{\kappa}^{T}}{1-\kappa} \left[\hat{\beta}_1 bm_t + \hat{\beta}_2 (roe_t - \mu) \right] \tag{5}$$

For the construction of the holding period under 1, 4, 8, and 12 quarterly periods according to (Chena et al., 2017) (see Table 2), we compare the average expected return and the average known earnings at different times. For example, the mean (median) expected return is 0.7808 (0.82983), 0.56554 (0.5757), 1.4438 (1.6883), and 1.3871 (0.78332), respectively. When the lead time is 1, 4, 8, and 12 quarters, the known returns were 0.74912 (1.07651), 0.9445 (1.87121), 1.4047 (2.4969), and 1.6952 (2.00348), respectively. Table 2 shows that most short-term gains can be predicted. This shows that the model reflects the actual value of future returns, particularly in one and four quarters.

Predictive ability regression tests

By expecting cross-sectional property, we need to verify the MC model's estimated reliability. We focus on companies' cross-sectional property in the three-year period.

Table 2 Summary of expected returns

	1Q ahead	4Q ahead	8Q ahead	12Q ahead	Long term	LT-1Q difference	12Q-1Q difference
Panel A: Expected log returns							
5th	-0.4794	-0.5047	-0.83602	0.79245	0.3987	-0.80482	-0.5963
25th	-0.2079	-0.3625	1.0216	0.9635	0.7758	-0.02842	-0.0692
Mean	0.7808	0.56554	1.4438	1.3871	1.3511	1.58205	0.721
Median	0.82983	0.5757	1.6883	0.78332	1.0587	1.4608	0.503
75th	0.89856	0.8399	1.7164	1.89945	2.0655	1.249	0.9803
95th	0.9563	1.56075	1.952	2.90988	2.7431	2.0729	1.5028
Standard deviation	0.633536	0.6896	1.0295	0.83071	0.868	0.7052	0.74976
Panel B: Realized log returns							
5th	-0.41356	-0.1694	-0.17981	-0.97937			0.3842
25th	-0.17805	-0.0497	-1.044	0.20461			1.0284
Mean	0.74912	1.3646	1.1662	1.6952			1.2974
Median	1.07651	0.9445	1.4047	2.00348			1.3002
75th	1.5181	1.87121	2.3969	3.2014			1.5355
95th	1.8595	2.1495	3.86763	3.5383			2.4085
Standard deviation	0.910017	0.967892	1.675042	1.7374			0.662228

We use the regression test method to estimate the mixed holding period log return within the limit time:

$$r_{i,t+T} = \delta_0 + \delta_1 E_t\left[r_{i,t+T}\right] + \omega_{i,t+T} \tag{6}$$

Under the condition of δ0 = 0,δ1 = 1, there will be an absolute true estimate of the expected return for any holding period. Thus, by meeting such a benchmark as much as possible, when δ1 is more important, the expected value is closer to the true value.

Table 3 lists the estimated results about (7) for the 3, 12, 24, and 36-ahead months. In the presence of industry (not industry) fixed effect, the predicting coefficients are 0.717 (0.65284), 0.643 (0.5972), 0.5828 (0.50284), and 0.438 (0.4028), respectively, and the coefficient is significantly not zero at the 1% level. Because the holding period return proxies conditionally change according to the change in T and the holding period increases, the measurement error becomes large, and the coefficient is likely to gradually decrease. However, the correspondence between the expected return and the known return is better within two years, the predicted coefficient is greater than 0.5, and the slope coefficient under the three-year lead period has been significantly less than 0.5. This indicates that the MC model may lack the ability to explain long-term reversal, but we cannot exclude the human factor that could be influential and lead to such a result.

CAPM model parameters

After determining the basic coefficients of the MC model, we must determine the coefficients of the CAPM model. To ensure the consistency of the data, before predicting the CAPM model coefficients, we still use the historical quarterly data in DataStream as sample data although the calculation method will slightly differ. The stock returns

Table 3 Revenue return

Panel A: Regression parameter summary								
Data	Regression coefficients					Implied parameters		
	cons	bm	roe	F		k	w	μ
5th percentile	0.014	0.045	0.259	70.62		0.904	0.620	0.014
25th percentile	0.018	0.048	0.325	145.24		0.952	0.647	0.017
Mean	0.022	0.050	0.430	359.70		0.910	0.657	0.023
Median	0.025	0.058	0.539	879.02		0.948	0.800	0.041
75th percentile	0.029	0.065	0.872	1426.60		0.963	0.889	0.059
95th percentile	0.035	0.094	0.890	1552.22		0.976	0.913	0.064
standard deviation	0.027	0.054	0.205	819.93		0.015	0.090	0.036
	3M (1)	12M (2)	24M (3)	36M (4)	3M (5)	12M (6)	24M (7)	36M (8)
$E[r_{(i,t+1)}]$	0.717***	0.643***	0.5828***	0.438***	0.65284***	0.5972***	0.50284***	0.4028***
	(0.073)	(0.0615)	(0.0295)	(0.0103)	(0.0624)	(0.040)	(0.0105)	(0.004)
Cons	-0.0343	0.0368	0.0329***	0.0319**	0.0286	0.3058	0.2528**	0.2485**
	(0.063)	(0.0132)	(0.0202)	(0.2840)	(0.0468)	(0.008)	(0.0120)	(0.025)
Number of observations	2851	2212	2105	1776	2851	2212	2105	1776
Fixed effects	no	no	no	no	yes	yes	yes	yes
Adj.R^2	0.032	0.031	0.025	0.030	0.0193	0.0284	0.5020	0.1598

rate and the current stock price are directly substituted in the one-way linear regression model. When the company's stock is subjected to a linear regression model, we calculate the average value of all the companies in the industry to obtain the industry model coefficient.

Model

The CAPM model is as follows:

$$E(r_{i,t}) - r_{f,t} = \alpha_i + \beta_i \left(E(r_m) - r_{f,t}\right) + \varepsilon_i \tag{7}$$

where rf,t is the risk-free return rate. Typically, similar foreign research replaces the risk-free rate with the interbank interest rate or short-term treasury interest rates. In this section, we use short-term treasury interest rates. On the other hand, βi (BETA) is a systematic risk coefficient, and E(rm) represents the market portfolio rate of return. In practical application, we use the first-60-months average yield of one of the stock replacements E(rm). E(rm) − rf or the market risk premium is different from the market portfolio yield and risk-free rate of return. If α is 0, the CAPM model can explain the profit of the investment strategy. The investment strategy does not have excess returns. If α is significantly greater than zero, this indicates that the strategy has excess returns unexplained by the CAPM model.

Descriptive statistics

By collecting and sorting the sample data in the DataStream database, we use the reviews software to perform the regression analysis of the model. Table 4 shows the results of the constant, β, and residual.

Table 4 shows all the data of the estimated parameters (7). The predicted constants α are 0.0453, 0.0876, 0.4204, 0.4147, 0.6833, and 0.8456 respectively. Except for a few industries, the constant α in Table 4 is significantly not zero at the 1% level. This result is consistent with our daily observations that there is a large part of the returns that we cannot explain with conventional ideas. This proves that excess return does exist in the US stock market, and this excess return cannot be explained by the CAPM model. If we explain it from the perspective of behavioral finance, the excess returns are due to the existence of stock market anomalies. Therefore, this article becomes even more meaningful when interpreting the stock market vision.

Verification of existence in the stock market

Although many documents discuss excess returns caused by medium-term momentum and long-term reversal in the US market, we empirically test this conclusion using the method of Jegadeesh and Titman (1993). Before the empirical analysis, we made a simple graph of the collected sample data from 1980 to 2015, as shown in Figs. 1 and 2.

Through intuitive observation of Fig. 1, mid-term momentum is obvious from 1980 to 2010. In Fig. 2, only the two stages of 1992 to 1995 and 2007 to 2010 show an obvious long-term reversal phenomenon. This is consistent with the timing of two major events in US financial history. At other stages, it is difficult to find the presence of anomalies though intuitive observation. This shows on a cursory level that stock market visions do exist in the US market and have a more significant impact during the special period.

Table 4 Summary data for CAPM model parameters

	Regression coefficients		
	α_i	β_i	ε_i
Panel A: Model Coefficients Summary			
5th percentile	0.0453	0.8711	0.0377
25th percentile	0.0876	0.9875	0.0638
Mean	0.4204	1.2122	0.1329
Median	0.4147	1.1988	0.0943
75th percentile	0.6833	1.4300	0.1678
95th percentile	0.8456	1.5617	0.3370
Standard deviation	0.2954	0.2578	0.1137
Panel B: Industry parameters			
Electricity	0.8474	1.0670	0.0394
Equity investment instrument	0.7250	1.4428	0.1804
Financial service	0.0186	1.4257	0.2791
Fixed line telecommunications	0.8296	0.9953	0.2163
Food and drug retail	0.7390	0.9877	0.2578
Food producers	0.4911	0.8347	0.0356
Forestry & paper	0.6136	1.5032	0.0896
Gas, water, & multiple utilities	0.5107	1.4082	0.0933
General industrial	0.0622	1.5265	0.0476
General retailers	0.6694	0.9696	0.0485
Health care equipment & services	0.3203	1.3564	0.1079
Household goods & home construction	0.1835	0.8694	0.0759
Industrial engineering	0.0832	1.4800	0.0654
Industrial metals & mining	0.3524	0.9059	0.0953
Industrial transportation	0.0986	1.3895	0.2684
Leisure good	0.0888	1.3269	0.1080
Life insurance	0.8441	1.7830	0.1584
Media	0.4231	1.2069	0.0705
Mining	0.0614	1.0754	0.0959
Mobile telecommunications	0.2658	1.4790	0.0896
No life insurance	0.4000	0.8725	0.0479
Oil equipment & services	0.0257	1.5329	0.0759
Oil & gas producers	0.0671	1.0304	0.1860
Personal goods	0.4062	1.1343	0.0695
Pharmaceuticals & biotechnology	0.7483	0.9581	0.0499
Real estate investment &services	0.0838	1.5968	0.5369
Real estate investment trusts	0.0671	1.0343	0.1636
Software & computer services	0.8521	1.3055	0.0968
Sport services	0.7386	1.1907	0.0590
Technology hardware & equipment	0.6631	0.9056	0.1074
Tobacco	0.5633	0.9867	0.0284
Travel & leisure	0.6084	1.2080	0.4078

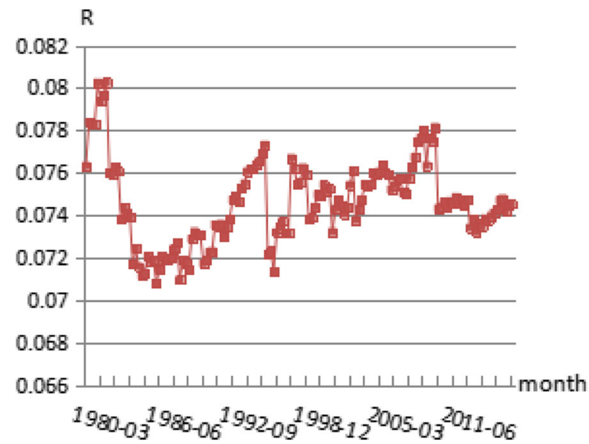

Fig. 1 Monthly change chart

Verification method and sample data

Verification method

Medium-term momentum and long-term reversal will generate excess returns, which are contrary to the effective market hypothesis. According to De bondt and Thaler (1985) research methods and conclusions, we use the collected historical data to build the portfolio. Samples are arranged in ascending or descending order (ascending or descending order does not affect the result) and then the data are divided into 10 samples; each has the same number of shares. We define the combination with the lowest returns as L and the highest returns as the winner portfolio called W. The momentum strategy involves buying the winner portfolio at the same time as selling the loser portfolio to obtain profit, which can be expressed as W-L. The contrarian effect is the opposite. According to the effective market hypothesis, the W-L portfolio profit should be zero; that is, following the principle of no arbitrage. However, if the stock price fluctuation truly has momentum or reverse effect, these portfolios will generate profit or loss within a certain period. This phenomenon has been called stock market anomalies.

The constructs are arranged according to the return rate in the forming period (denoted by F). We then calculate the returns of the respective combinations in

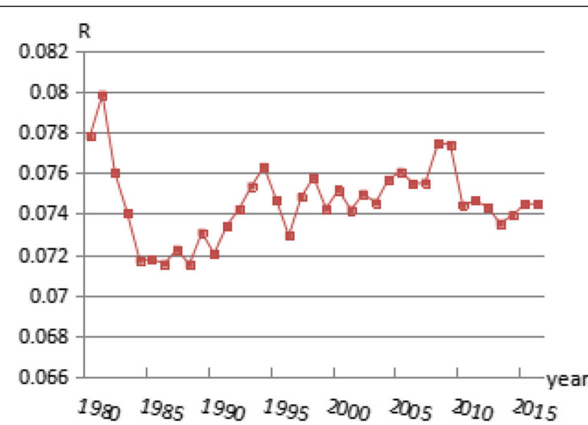

Fig. 2 Annual average change

different holding periods (denoted by H). Under the profitability of the FH investment strategy, within t time, investors first sell the former F-stage loser portfolio and then buy the equal amount of the winner portfolio holding the W-L portfolio for H period. Due to the medium-term momentum and long-term reversal's particularity, the time is limited to three to 12 months of the medium-term momentum and three to five years of long-term reversal. Considering that previous studies often use 3, 6, 9, 12, 18, 24, 30, and 36 months, we choose the formation and duration period as follows: 3, 6, 9, 12, 18, 24, 30, 36, and 48. Ultimately, we produce 100 trading strategies. The specific methods and research processes are as follows:

1) After the screening method described above, we obtain each stock's monthly closing price by backing to the right. This price can easily be used to calculate the next month's return rate. The above data in chronological order are divided into 60 months to calculate the monthly return rate of each stock in k months:

$$r_{n,k} = LnP_{n,k} - LnP_{n,k-1} \tag{8}$$

where rn,k is the monthly yield rate of the nth stock on the k month, and Pn,k is the closing price of the nth stock for the k month.

2) Using excel to calculate the monthly yield of all the stocks in (8) and plotting them in tables, we obtain the stock's cumulative yield:

$$R_n = \prod\nolimits_{k=1}^{m} \left(1 + r_{n,k}\right) - 1 \tag{9}$$

where Rn represents the cumulative yield of the nth stock, and m is the number of months of formation. Otherwise, n = 1,m = 3, and R1 = (r1,1 + 1) * (r1,2 + 1) * (r1,3 + 1) − 1 represent the case of the (3) combination of the first stock. Respectively, r1,1, r1,2,, and r1,3 represent the monthly return rate of the first to the third in the first month. Then, we use excel to obtain the cumulative yield of all stocks in the first three months.

3) We sum the cumulative yield of all stock Rn in ascending or descending order. We then take the first 10% and 10% stock. Because our sample is just 100 stocks, that is the top 10 and the last 10 stocks. After sorting, the top 10 stocks are defined as the winner portfolio (wp), and the last 10 stocks are defined as the loser (loser portfolio, referred to as lp). Here we identify the stocks that have been sorted by 100 stocks according to their stock code, return to the monthly yield rate table, find the corresponding monthly rate of return, for example: (3) combination, to find the 10 stocks in the fourth, fifth, and sixth-month yields. After finding and summarizing the stocks, we can calculate (3) the first group of wp and lp. The formula is:

$$wp = \prod\nolimits_{1}^{J} \left(r_{n,k} + 1\right) - 1 \tag{10}$$

$$lp = \prod\nolimits_{1}^{j} \left(r_{n,k} + 1\right) - 1 \tag{11}$$

To distinguish between the top 10 and the bottom 10,we define J as the number of months of the top 10 stock holdings and j as the number of months of the holding period of the last 10 stocks, and the values are equal. For example, wp = (r1,4 + 1) * (r1,5 + 1) * (r1,6 + 1) − 1 in the (3, 3) combination of the first stock. Therefore, we obtain a (3, 3) combination of the first group of wp and the same for lp. Followed by April, May, and

June for the formation of the period, we first find the first July, August, and September of the wp and lp. We return to step (2), and so on, until we calculate all combinations of wp and lp in the (3, 3) combination and, finally, calculate a total of 100 combinations.

4) When we obtain all the (3, 3) combinations of wp and lp, we obtain the average winner combination (recorded as wp) and the average loser combination (recorded as lp). The formula is:

$$\overline{wp} = \frac{1}{x}\sum_{x=1}^{x} wp_x \tag{12}$$

$$\overline{lp} = \frac{1}{x}\sum_{x=1}^{x} lp_x \tag{13}$$

5) We begin to buy a combination of winners with a certain market value at the holding period p and, at the same time, sell the loser portfolio with the same market value. If we do not consider the cost, we form a zero-cost portfolio (wl):

$$wl = \overline{wp} - \overline{lp} \tag{14}$$

6) t test to the data:

$$t = \frac{\overline{x}}{\left(\frac{s}{\sqrt{n}}\right)} \tag{15}$$

where x is the mean of wp − lp, s is the standard deviation of wp − lp, and the number of samples n is the number of wp − lp.

Then, we perform the significant test of the data obtained to meet the significance of the test requirements of the wl analysis. If wl > 0, that means there is a significant momentum in the period. If wl < 0, there is a clear reversal effect in the financial market.

Sample data

Because the explanations and the recommendations are based on industry, we still select five industry historical data from the 32 industries, protecting the number of observations and laying the foundation for follow-up work. The inspection time was set at the beginning of 1996, and 100 stocks were selected from listed companies at the beginning of 1996 (20 listed companies in each industry). In this way, we construct a loser and winner portfolio with only 10 deals. We take all the sample monthly closing prices from 1996 January to 2015 December.

Empirical results

By screening and processing the above sample data, we obtain the final 100 sets of data in Table 5 (Fig. 3).

Table 5 shows a clear reversal effect of the loser stock portfolio, particularly in the formation of 3, 6, and 18 months. The loser portfolio in the holding period of three to five years will have a significant positive return, which is a different conclusion than that obtained from the intuitive observations of Figs. 1 and 2. In Table 5, the wl are 0.063969, 0.0623610, 0.059098, 0.057092, 0.111089, 0.10444, 0.093842, 0.0292616, -0.04673042, and -0.1975691, respectively, at the forming period of three months, and all the results were significant. At the forming period of 48 months, the wl are 0.12959, 0.1136495, 0.0613, 0.0284981, 0.0868, 0.0740122, 0.0965, 0.0778, 0.319,2 and 0.2169.

Table 5 One hundred groups of wp, lp, wl, t value summary table

Hold period q	Forming period p	3 months	6 months	9 months	12 months	18 months
3 months	wp	0.0385	0.0392	0.0370	0.0356	0.0665
	lp	-0.0255	-0.0232	-0.0221	-0.0215	-0.0446
	wl	0.063969※	0.0623610※	0.059098※	0.057092※	0.111089※
	t	6.9500	6.1090	5.7480	5.5560	5.4110
6 months	wp	0.0486	0.0407	0.0352	0.3688	-0.2683
	lp	-0.0285	-0.0182	-0.0222	0.7132	-0.7778
	wl	0.0770677※	0.058856※	0.057340※	-0.344455※	0.509538※
	t	4.3075	2.6328	3.1859	4.8540	4.1248
9 months	wp	0.0238	0.0319	0.0247	0.0381	0.0580
	lp	-0.0169	-0.0155	-0.0185	-0.0262	-0.0562
	wl	0.0406283※	0.0474118※	0.0431439※	0.0642729※	0.1142328※
	t	5.1079	3.1171	-4.0875	5.8650	7.1266
12 months	wp	0.0387	0.0507	0.0332	0.0313	0.0625
	lp	-0.0105	-0.0129	-0.0164	-0.0146	-0.0479
	wl	0.04915※	0.063644※	0.049570※	0.045913※	0.1104
	t	4.6594	0.9907	2.8650	6.8660	1.1066
18 months	wp	0.0390	0.0563	0.1897	-0.1742	0.0485
	lp	-0.0103	-0.0106	-0.0258	-0.0255	-0.0418
	wl	0.049247※	0.066929※	0.202296※	-0.151084※	0.0903
	t	12.1355	3.8790	2.7135	-4.8593	1.1042
24 months	wp	0.0498	0.0521	0.0542	0.0354	0.0289
	lp	-0.0134	-0.1464	0.0097	0.0005	-0.0462
	wl	0.063209※	0.1984872※	0.0444647※	0.0348749※	0.0751517※
	t	3.3684	3.4058	2.2480	2.8288	6.1173
30 months	wp	0.0408	0.0319	0.0126	0.0097	0.0119
	lp	-0.0491	-0.0314	-0.0302	-0.0183	-0.0187
	wl	0.089843※	0.0633350※	0.0428105※	0.0280763※	0.0306
	t	3.8345	2.8411	1.9135	3.8645	1.1342
36 months	wp	0.0909	0.0098	-0.0043	-0.0116	-0.0280
	lp	0.0503	0.0410	0.0216	0.0148	0.0321
	wl	0.0405775※	-0.031161※	-0.025845※	-0.026374※	-0.0601
	t	2.7015	2.3710	4.7250	6.2186	-1.1700
48 months	wp	0.1087	0.0964	0.0495	0.0211	0.0569
	lp	-0.0208	-0.0172	-0.0118	-0.0074	-0.0299
	wl	0.12959※	0.1136495※	0.0613	0.0284981※	0.0868
	t	2.3094	2.0923	1.6293	2.2380	-1.1901
60 months	wp	0.0103	0.0139	0.0153	0.0162	0.0171
	lp	-0.0204	-0.0167	-0.0101	-0.0090	-0.0032
	wl	0.0307244※	0.0306	0.0254	0.0252	0.0204
	t	-3.5518	-1.8998	-1.6082	1.2573	-0.0508
Hold period q	Forming period p	24 months	30 months	36 months	48 months	60 months
3 months	wp	0.0591	0.0497	-0.0286	-0.0246	-0.0612
	lp	-0.0453	-0.0441	-0.0579	0.0221	0.1364
	wl	0.10444※	0.093842※	0.0292616※	-0.04673042※	-0.1975691※

Table 5 One hundred groups of wp, lp, wl, t value summary table *(Continued)*

	t	5.5660	5.7970	4.0500	-6.3380	-6.9130
6 months	wp	0.0690	0.0364	-0.0425	0.0217	0.0292
	lp	-0.0335	-0.0551	-0.0407	-0.1476	0.1022
	wl	0.102505※	0.091487※	-0.001725※	0.1693044※	-0.0730656※
	t	4.1339	8.3676	-3.3159	6.4333	2.4222
9 months	wp	0.0597	0.0467	-0.0421	0.0054	-0.0460
	lp	-0.0442	-0.0427	0.0397	0.1088	-0.0912
	wl	0.103965※	0.089413※	-0.0818328※	-0.1034639※	0.0452
	t	6.1218	10.2500	-3.3015	-2.3915	-1.9165
12 months	wp	0.0503	0.0450	-0.0387	-0.0693	-0.0594
	lp	-0.0404	0.0478	0.0383	0.0731	-0.0612
	wl	0.090685※	-0.0028797※	-0.076932※	-0.1423882※	0.0018128※
	t	5.1261	-6.2303	-3.9858	-4.9017	2.1925
18 months	wp	0.0487	0.0393	0.0322	-0.0609	0.0515
	lp	-0.0437	-0.0439	-0.0396	-0.0672	0.0517
	wl	0.092433※	0.0832855※	0.0719	0.0063171※	-0.00022※
	t	2.3860	4.2167	1.2674	3.3433	-2.0865
24 months	wp	0.0477	0.0446	0.0385	-0.0723	-0.0552
	lp	-0.0200	-0.0398	-0.0326	0.0418	0.0564
	wl	0.0676301※	0.0844540※	0.071153※	-0.1141	-0.1116
	t	3.0767	10.1525	7.2020	-1.2751	-1.9976
30 months	wp	0.0291	0.0330	0.0318	0.0527	-0.0463
	lp	-0.0245	-0.0399	-0.0343	0.0604	-0.0495
	wl	0.0536	0.0729	0.0661	-0.0077	0.0032618※
	t	1.0736	1.0897	1.1173	0.8520	5.9153
36 months	wp	-0.0217	-0.0325	-0.0293	-0.0590	0.0477
	lp	0.0241	0.0175	0.0158	0.0647	0.0484
	wl	-0.0457920※	-0.0500914※	-0.045144※	-0.1237	-0.000688※
	t	-5.0737	-8.0590	-5.0440	-1.1230	-4.5070
48 months	wp	0.0445	0.0504	0.0401	0.2460	0.1566
	lp	-0.0295	-0.0460	-0.0378	-0.0732	-0.0604
	wl	0.0740122※	0.0965	0.0778	0.3192	0.2169
	t	-3.0458	1.0312	0.9965	1.0826	-0.6063
60 months	wp	0.0255	0.0267	0.0211	0.0041	0.0044
	lp	-0.0027	-0.0024	0.0264	0.0600	0.0465
	wl	0.0282	0.0291	-0.0053	-0.0558800※	-0.0421593※
	t	1.0402	1.0100	-0.9474	-4.0311	-3.6525

Note: * is a significant result after the bilateral t-test with = “wp” corresponding to the winner portfolio. “lp” corresponds to the average return of the strategy portfolio. We conduct the t-test about the “wl” value

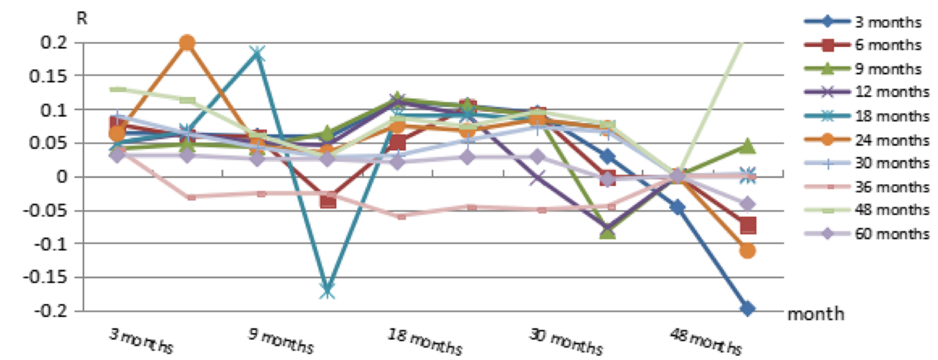

Fig. 3 Shows the different rates of W-L combinations in different holding periods

Among them, the results were significant for 3, 6, and 24 months. The loser and winner portfolios shown in Table 5 have obvious performance in the momentum effect. Through observation, we find that the momentum effect has significant performance through the three to nine months' holding period. During the same period, the wl portfolio showed an increasing trend with an increase in the formation period. Therefore, we conclude that when the combination period and holding period become longer, the effect of the reversal and the momentum become less significant.

CAPM model zero interpretation ability

Chan (1988) argued that the risk of winners and losers is changing over time and, when the risk factor is controlled, the reversal strategy can only produce minimal returns. In accordance with the method of Chan (1988), the CAPM model can be used to analyze whether the risk was controlled in the process of momentum or reversal of the strategy's profitability:

$$r_{pt} - r_{\mathcal{A}} = \alpha + \beta(r_{mt} - r_{\mathcal{A}}) + \varepsilon_t \quad p \in (\omega, \iota) \tag{16}$$

$$r_{\iota t} - r_{\omega t} = \alpha^c + \beta^c(r_{mt} - r_{ft}) + \varepsilon_t \tag{17}$$

The time interval t is one month, rmt is the return of the equal market index, and the return of the loser and winner portfolio is checked by (16). (17) is used to test the W-L portfolio (the same as L-W). The test results show that the BETA value can explain most of the change in the winner and loser portfolio earnings (above 75%). However, the W-L (or L-W) portfolio cannot be explained by this BETA. In the case of strategy 3-36, which brings out momentum returns, there is a positive return on the winner portfolio, a negative return on the loser portfolio, and this W-L portfolio's BETA value is not significant at all. Therefore, the BETA, as a risk measure value, has no ability to explain the momentum and reverse profitability. This is theoretically affirmed by the CAPM model having zero interpretation on the medium-term momentum and long-term reversal.

Vision interpretation

We determined all the coefficients required for the MC model and the CAPM model, and we also used the MC model to make a revenue forecast test for all data from

January 2010 to December 2015. Then, following the development of the paper, we focus on the interpretation of medium-term momentum and long-term reversal.

Building an explanatory model

First, we compare the CAPM model with the MC model, see (1) and (7). To facilitate understanding, we summarize two models that remove the constant term as follows:

MC model $r_{i,\ t+1} = \beta_1 bm_{i,\ t} + \beta_2 roe_{i,\ t} + \xi_{i,\ t+1}$ (1)

CAPM model $E(r_{i,\ t}) - r_{f,\ t} = \beta_i(E(r_m) - r_{f,\ t}) + \varepsilon_i$ (7)

E(ri,t) is the expected return, and ri,t+1is the expected log return. The coefficient of ROE reflects the profitability of different firms in the same industry, and the βi in the CAPM model is also an indicator of profitability.

Since the two models are not of the same magnitude, the expected log returns in the MC model need to be transformed to the same magnitude as those in the CAPM model:

$$nr_{i,t+1} = Ae^{\beta_0+\beta_1 bm_{i,t}} + \beta_2 roe_{i,t} - 1 + \eta^{nr}_{i,t+1} \tag{18}$$

The above formula relates the expected net return (ηi,t+1 nr), the expected log returns (Aeβ0+β1bmi,t+β2roei,t −1), and known net returns (nri,t+1). The expected log returns are transformed into the above function form so that we can obtain expected net return. In this case, the expected return is multiplied by the expected logistic return index (by the conditional logistic variance). Parameter A represents this multiplication. Parameter A can be estimated using two non-linear irrelevant regression condition equations, including (1) and (19):

$$bm_{i,t} = \sum\nolimits_{j=1}^{\infty} k_1^{j-1}\left(E_t\left[r_{i,t+j}\right] - E_t\left[roe_{i,t+j}\right]\right) \tag{19}$$

After obtaining the value of parameter A, the expected net return can be expressed as:

$$r_i' = Ae^{r_i} - 1 \tag{20}$$

After that, we introduce a new parameter γ:

$$\gamma = r_i' - E(r_i) \tag{21}$$

The meaning of γ is easy to understand. It is the difference between the two models' predictions of future returns. Logically, if the model has a certain ability to explain the medium-term momentum and long-term reversal, this part of the interpretation is also fully included in the γ parameter. Then, we place the actual returns sample data directly from the database into formula (22), which is:

$$R' = R - \gamma \tag{22}$$

Finally, according to the series of R′ data calculated by (22), we construct a new winner and loser portfolio and use the same method to verify the existence of the anomalies in the previous chapter to obtain the new returns value. Examining whether the mid-momentum and the long-term reversal are weakened, if γ contains these two return anomalies, then, through the new empirical analysis, the two anomalies will be well addressed. We offer an empirical test theory as follows. The sample data are expanded from December 2015 to June 2016.

By comparing the sunken sample data in the DataStream database with the data calculated using the MC model and the CAPM model into (20), (21), and (22), we obtain the returns of Fig. 4 in Fig. 5, which corresponds to the change in Fig. 1.

Both the mid-momentum and the long-term reversal have weakened in the graphical trend in Figs. 1, 2, and 4, and the change in the monthly return is more obvious than the previous change. We show powerful graphical evidence in Figs. 5 and 6 and provide a more convincing empirical test.

Empirical test

In addition to the processing of the sample, the interpretation process is consistent with the anomalies existence test. That is, the winner and loser portfolios are constructed based on the new return data.

Table 6 shows that the winners' portfolio at different stages of formation is explained to a large extent by the three to nine-month holding period's mid-momentum and the three to five-year holding period's reversal effect (Fig. 6). Additionally, the different formation periods of the loser portfolio in the three to nine-months holding period of the momentum effect and the three to five-year holding period of the reversal effect are also interpreted to a certain degree. For example, the (3, 3) winners (losers) portfolios in Tables 5 and 6 are 0.0385 (-0.0255) and -0.1384 (0.0631), respectively. The (3, 48) winners (losers) portfolios in Tables 5 and 6 are -0.0246 (0.0221) and 0.13942 (-0.0246), respectively. The values in Table 6 satisfy the stochastic fluctuations in the effective market returns. Thus, the model can explain the mid-momentum and long-term reversal of the two anomalies to some extent, and the mid-momentum explaining capability is greater than the long-term reversal. We present the three-dimensional line graph corresponding to Table 6, which is more intuitive reflecting the change after the change.

From the described empirical study, we draw two conclusions: first, the MC model has a certain ability to predict income, which is excellent news for the future of the US stock market. Second, based on the CAPM model, we obtain a new model with explanatory ability for medium-term momentum and long-term reversal. According to the empirical results, this model can explain the medium-term momentum and shows weak ability, but not completely zero, for long-term reversal. In the existing study of

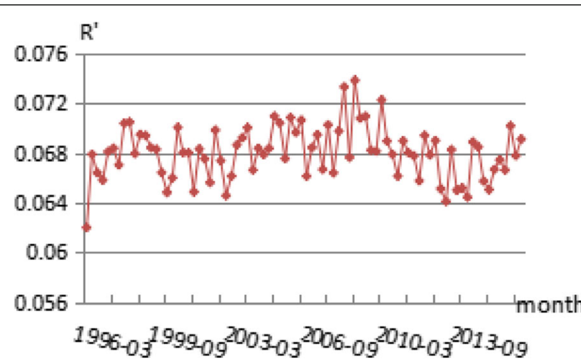

Fig. 4 Monthly change chart (adjusted)

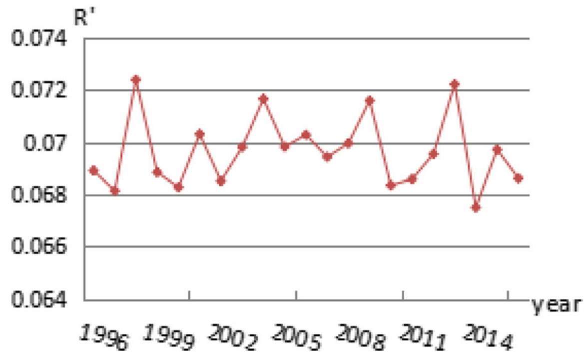

Fig. 5 Annual average earnings graph (adjusted)

the US market, there are few models that can explain both mid-term momentum and long-term reversal.

Correlation analysis

Since we have verified that the MC model does exhibit some explanatory power for mid-momentum and long-term reversal, an ensuing problem arises: whether the BM or ROE is a factor in the interpretation of the model? Given this question, we conducted the following tests.

First, we remove the BM factor and ROE factor. Second, we repeat the same process as described above. The reconstructed model with only the BM factor or ROE factor can explain the two stock market anomalies, but the ability of the ROE factor is weaker than the model with only the BM factor.

As the two company basic indicators have some explanatory power concerning the vision, we need to determine whether there is a correlation between them and between ROE, BM and BETA.

Richard and Jeong (1997) proposed such a model:

$$\frac{P_t}{B_t} = 1 + \sum\nolimits_{\tau=1}^{\infty} (1+r)^{-\tau} E_r \left[\frac{(ROE_{t+\tau} - r) B_{t+\tau-1}}{B_r} \right] \tag{23}$$

It has been proven that there is a correlation between the current book value (the reciprocal of the book market ratio) and the current ROE, and the current book value also contains more information on the future ROE compared to the current ROE, which will cause change in the ROE. Additionally, Richard and Jeong (1997) tested the correlation between the ROE and BETA values and found that the coefficients were negative. This indicates that there is no correlation between the two values. Next, we must verify the relevance of the BM factor and the BETA and the hybrid correlation between the three.

We use the mixed regression method proposed by Newey and West (1987) to regress Eqs. (24) and (25), in order to weaken heteroscedasticity and sequence dependency that mixed regression may cause.

$$BM = r_0' + r_1' BETA_t \tag{24}$$

$$BE = r_0 + r_1 BETA_r + r_2 ROE_r \tag{25}$$

Table 6 Existential verification results

Hold period q	Forming period p	3 months	6 months	9 months	12 months	18 months
3 months	wp	-0.1384	-0.0843	-0.2944	0.2095	-0.0283
	lp	0.0631	0.0295	-0.0298	-0.3943	0.3943
	wl	-0.2015※	-0.1138※	-0.2646※	0.6038※	-0.4226※
	t	-7.5469	-9.5765	-2.3137	-6.5177	-2.1533
6 months	wp	-0.0103	-0.0384	0.0483	0.2048	0.1948
	lp	0.0384	0.2940	-0.9387	0.2984	-0.0849
	wl	-0.0487※	-0.3324※	0.9870※	-0.0936	0.2798※
	t	-4.3401	-2.4090	-4.4905	-1.0605	-1.1958
9 months	wp	-0.2934	-0.0206	0.0853	-0.4832	0.0519
	lp	0.0238	-0.0394	0.3085	-0.5293	-0.2085
	wl	-0.3172※	0.0188※	-0.2232※	0.0461※	0.2604※
	t	-4.7922	-8.5792	-5.5912	-3.7257	-7.9083
12 months	wp	-0.7083	-0.3582	0.3849	0.2048	-0.3028
	lp	0.2925	0.2490	-0.0294	0.2084	-0.0247
	wl	-1.0008※	-0.6072※	0.4143※	-0.0036※	-0.2781※
	t	-5.0284	-9.3962	-7.2975	-7.3374	-9.8217
18 months	wp	-0.9240	0.0108	0.1052	-0.4937	0.2806
	lp	0.0284	-0.2420	0.1083	-0.0284	0.2874
	wl	-0.9524※	0.25284※	-0.0030※	-0.4653※	-0.0068※
	t	-8.06059	-7.7146	-0.0415	-2.7705	-9.0339
24 months	wp	-0.0183	-0.0083	0.0398	-0.0408	-0.2084
	lp	0.0482	0.0029	0.0184	-0.1294	0.1083
	wl	-0.0665※	-0.0112	0.0214※	0.0886※	-0.3167※
	t	-5.1487	-0.5971	-2.6853	-8.9878	-9.2583
30 months	wp	-0.2948	-0.1294	0.2948	0.0698	-0.2949
	lp	0.0290	0.1084	0.0108	-0.0908	0.2844
	wl	-0.3238	-0.2378	0.2840	0.1606※	-0.5793※
	t	-0.9548	-0.7403	-0.0126	-5.6271	-8.7080
36 months	wp	0.2084	-0.2850	0.0203	-0.3985	0.5082
	lp	0.0129	0.0940	0.2984	-0.2084	0.2952
	wl	0.1955	-0.379※	-0.2781※	-0.1901※	0.213※
	t	-1.8446	-3.6409	-2.0442	-3.9977	-6.2831
48 months	wp	-0.0024	0.2044	-0.2049	0.0385	-0.0108
	lp	0.0597	0.1094	-0.2943	-0.0044	0.2044
	wl	-0.0621※	0.095※	0.0894※	0.04285※	-0.2152※
	t	-8.873	-7.2558	-8.5790	-5.5865	-6.3009
60 months	wp	-0.0070	0.1939	0.1033	-0.0188	0.4298
	lp	-0.2934	0.0139	-0.0210	-0.1944	0.0039
	wl	0.2864※	0.1800※	0.1243※	0.1756※	0.4259※
	t	-2.8769	-5.2485	-8.0858	-6.7919	-8.9324
Hold period q	Forming period p	24 months	30 months	36 months	48 months	60 months
3 months	wp	0.0428	0.2490	0.1932	0.3942	0.1038
	lp	-0.0208	-0.0283	-0.0286	-0.0246	-0.0612
	wl	0.06364※	0.27734※	0.22180※	0.4188※	0.1650※

Table 6 Existential verification results *(Continued)*

	t	-9.5661	-6.4948	-4.5017	-4.3875	-6.5235
6 months	wp	-0.0242	0.1084	-0.3942	0.0329	0.2494
	lp	0.6092	0.0903	-0.3934	-0.2820	-0.3028
	wl	-0.6334※	0.01812※	-0.0087※	0.31494※	0.5522※
	t	-4.7564	-2.3861	-5.7409	-9.4873	-9.6719
9 months	wp	0.2058	0.5038	0.4846	0.2045	0.5028
	lp	0.4080	-0.0920	0.2058	0.0385	-0.3040
	wl	-0.2022※	0.5958	0.2788※	0.1660	0.8068※
	t	-7.3042	-1.2111	-7.6711	-1.7727	-2.5962
12 months	wp	0.3856	-0.4941	0.3494	0.3842	-0.0794
	lp	-0.5927	0.3859	0.4928	-0.3842	-0.5938
	wl	0.9783※	-0.88※	-0.1434※	0.7684※	0.5144※
	t	-7.2787	-8.0722	-2.9770	-7.2284	-5.0118
18 months	wp	0.1958	-0.1858	-0.0184	0.1540	-0.1885
	lp	0.0593	0.0284	-0.1084	-0.3749	0.0563
	wl	0.13653※	-0.2142※	0.09※	0.5289※	-0.2448※
	t	-9.0714	-9.6582	-3.3249	-8.1674	-4.2962
24 months	wp	-0.0183	0.1098	0.1282	0.2853	0.0828
	lp	0.2945	-0.2084	-0.0173	0.2943	-0.2084
	wl	-0.3128※	0.3182※	0.1455※	-0.0090	0.2912※
	t	-3.5671	-5.7649	-3.3872	-1.3965	-7.8998
30 months	wp	0.3930	-0.0109	-0.0014	0.0194	0.1854
	lp	-0.1050	0.0335	0.1042	-0.1988	-0.4851
	wl	0.498※	-0.0444	-0.1056※	0.2182※	0.6705※
	t	-1.2578	-1.7227	-3.6256	-5.0381	-6.5537
36 months	wp	0.0189	-0.3940	-0.2840	-0.0018	-0.1030
	lp	-0.2848	0.0592	-0.2020	-0.0188	-0.0128
	wl	0.3037※	-0.4532※	-0.0820※	0.0170	-0.0902※
	t	-5.7673	-8.9516	-4.3568	-0.61444	-8.8585
48 months	wp	0.3095	-0.0240	0.4085	0.2953	0.0044
	lp	-0.1084	0.3848	-0.0220	-0.0140	0.0199
	wl	0.4179※	-0.4088※	0.4305※	0.3093※	-0.0155
	t	-1.7304	-5.2197	-2.3661	-3.6702	-1.1061
60 months	wp	0.1088	-0.0053	-0.2420	-0.0110	-0.0399
	lp	0.2842	-0.0910	0.2985	0.0503	0.0018
	wl	-0.1753※	0.0857※	-0.5405※	-0.0613※	-0.0417※
	t	-2.5214	-2.6269	-5.2042	-9.6926	-4.9969

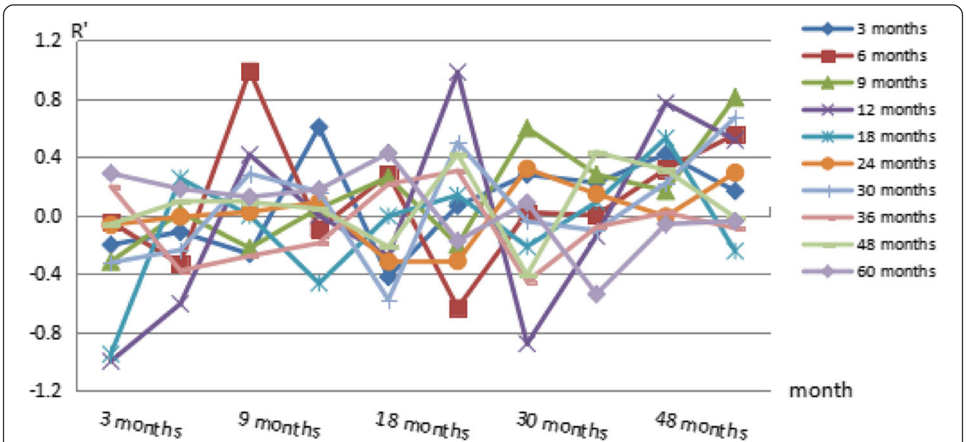

Fig. 6 Sorting period W-L combinations or different holdings monthly rate of change (adjusted)

Tables 7 and 8 show the results of the correlation regression. The results in Table 7 are almost negative. However, if BM can return the risk, it should be positive. Therefore, the regression of (24) indicates that the BM value cannot be used to return the risk but can be used to characterize corporate risk (Penman, 1991).

In the mixed regression in Table 8, the BETA coefficient is less significant, and the fluctuation varies greatly compared to the regression results in Table 7. After adding the industry dummy variable, we found that the coefficient of BETA has no significance. This shows that company risk impacts the BM ratio. Thus, the industry's special factors capture risk more effectively than BETA.

Overall, ROE and BM do not correlate with BETA, and BM is less relevant to BETA. But BM and ROE are related, and BM will cause change in the ROE. This leads to the following conclusion: the BM factor is the fundamental reason that models can explain the medium-term momentum and long-term reversal. In other words, the BM effect does have an impact on medium-term momentum and long-term reversal.

Test conclusions

Through the previous interpretation of the mid-momentum and the long-term reversal of the two anomalies, we confirm that BM, as an influencing factor, does have some explanatory power of the two visions in the US stock market. On the other hand, the interpretation also explains that the BM effect does cause part of the mid-momentum and long-term reversal to generate excess returns. The BM effect can only partially

Table 7 Cross-sectional regression with BM as the dependent variable and BETA as the independent variable year by year

	Cons	BETA	Adj.R^2
2010	0.2554	-0.1546	0.0655
2011	0.4229	-0.2986	0.0055
2012	0.3500	-0.2014	0.0204
2013	0.4476	-0.1012	0.0253
2014	0.2759	-0.0281	0.0062
2015	0.3939	-0.2399	0.0772

Table 8 A comparison of the results of year-round mixed regression with account-to-market ratio

Panel A: No dummy variables						
Independent variable	2010	2011	2012	2013	2014	2015
Cons	0.8302	1.2207	1.2830	0.7492	0.9298	1.0593
BETA	-0.0824	-0.0240	-0.3023	-0.0427	-0.6222	-0.3812
ROE	1.1221	1.8324	0.8066	1.4899	1.0270	1.9774
Panel B: There are dummy variables						
Independent variable	2010	2011	2012	2013	2014	2015
Intercept	0.7045	0.9152	0.6048	0.5362	0.5065	1.0709
BETA	-0.0783	-0.0656	-0.1084	-0.0936	-0.0676	-0.0905
ROE	1.3985	1.7643	1.3274	1.5536	1.5359	1.7982

explain the two visions. There is no in-depth study on this subject, and it is not the focus of this paper. However, we believe that this issue will create a meaningful research direction. Of course, if there is change in the future, we would consider conducting more detailed research. Additionally, BM as a model impact factor is one for which the sample data are easy to obtain and calculate, which is a rare advantage.

For the model capacity's difference with respect to mid-momentum and long-term reversal, we speculate that the reason may be that the book value and the market value are infinitely close to the same mean when the time lengthens.

Overall, the research results are of great importance. First, the MC model has a good ability to predict earnings, but company's basic data is not easy to obtain. The explaining of stock mid-momentum and long-term reversal is convenient.

For the model's ability to predict and explain, first, we identify whether the model's capabilities are limited to return forecasts. Second, we identify whether this conclusion can be applied to other financial indicator forecasts. In other words, we identify whether the principles used in MC model construction can be exploited in different aspects of research in the future. Third, does this new model only apply to the above two types of visions, or is it possible to have explanatory power for other stock market anomalies? If the new model is applied to other stock market visions, what will be the consequence? This study only presents ideas, and future practical application is required. However, this new model will have deep significance for future research.

Research prospects

Our study uses a newly constructed model to prove the existence of medium-term momentum and long-term reversal, but it also obtains the intrinsic relationship between the BM factor and these two visions. This is undoubtedly a great improvement in the field of financial market vision research. Based on this research, the author suggests that the following points should be discussed in depth.

First, the US market has significant mid-term momentum and long-term reversal. China, as a representative developing country, may have the same characteristics, which is contrary to the stated effective market hypothesis. Second, the MC model is used to predict future earnings and to explain financial visions in this paper. Thus, we can infer whether this model has good ability in other financial markets and even in other nonfinancial sectors. Future discussion will be based on existing research. Third, since the BM factor does have a considerable internal relationship with medium-term momentum and long-term reversal, the BM factor also presents some explanatory power for other visions in the financial market. This research question will become our future main research direction.

Robustness test

Control the sample age

When the model is calculated for the model coefficients and results, the sample used is the initial training sample from 1980 to 1994. When we use the complete model to test the performance of quarterly log returns, we use a sunken sample from June 2010 to June 2016. According to the empirical analysis conducted by Kelly and Pratt (2013), we need to consider the estimated deviation of the expected return due to the different sample. Therefore, to avoid this deviation, we choose the sample data from January 1996 to December 2009, which is a set of sample data at different time intervals to test the sample sensitivity.

Figures 7 and 8 show the graphical representation of the slope coefficients after the same regression as that shown in Table 3 under different samples. Figure 9 includes the industry fixed effect. The two figures will have different test results considering the different running time. However, in the mathematical sense, these results are still significant, and the regression slope coefficient is stable with a certain economic significance.

Use roei,t−1 instead of roei,t

The next step concerns the choice of an auxiliary variable roei,t, which may lead to unreliability in the test results. That is, in the process of using the log ROE(roei,t) to replace the expected log ROE(hi,t)of the next period, it is likely that the MC model will not agree with the estimation of β2. If the final test result is moderate, this indicates that the lag value of ROE is a useful auxiliary variable, and this auxiliary variable can be used to weaken potential bias in the coefficient estimating process.

Panel A of Table 9 shows the summary statistics for the model estimate parameters using the auxiliary variable regression method. Additionally, the fourth column of the table records the statistical results of the F statistic.

The F statistic results for the fifth quartile were 93.1769, and the average quartile was 765.4844. The coefficient of roei,t increased from the least squares estimate 0.339625 (0.265) to the average score (median) of 0.494119 (0.3615). This result indicates that the results of the least squares estimation may be affected by the measurement error, resulting in an increase in the ROE coefficient estimation. In contrast, the coefficient variance changes from 0.198346 to 1.176139, almost 10 times that of the previous result. Thus, as previously proposed, there is a trade-off between the estimates of bias and efficiency. The constant coefficient estimates will increase mutations. The increase in all estimated coefficients' anomalies will inevitably lead to anomalies in the implicit model parameters. However, this can be reduced by adjusting the implicit persistence parameter (0.9999). The mean (median) of the model estimation parameters indicates that the long-term unconditional expectation decreases from the OLS estimates 0.056226 (0.041286) to 0.047367 (0.042206). The persistence parameter value

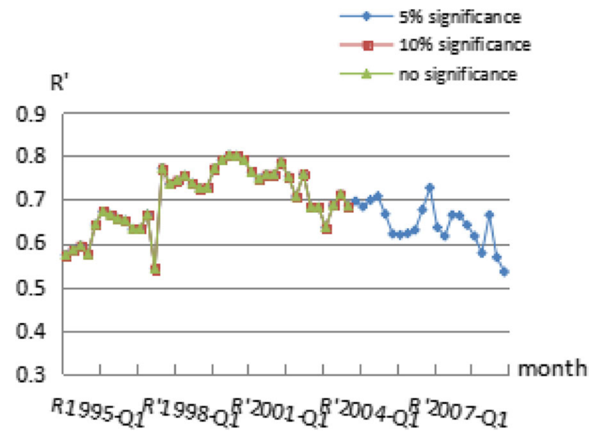

Fig. 7 Yield regression slope coefficient slope coefficient

corresponding is from 0.964003 (0.962121) to 0.961834 (0.960101). The mean (median) of implied persistence parameters is still relatively constant for log expected returns.

Panel B of Table 9 shows the re-processing of the results of Table 3, corresponding to the panel A auxiliary variable estimation results. "***", "**", "*" represent significance levels of 10%, 5%, and 1%, respectively. The fourth auxiliary variable roe(i, t+1) is used to predict the future expected return, and the others do not change significantly. Within three-years-ahead time conditions, we look for the return where the cross-section and the industry both have significant predictability. The log expected returns of the coefficients are 0.689 (0.6028), 0.636 (0.569), 0.556 (0.4902), and 0.521 (0.3502) for the 3, 12, 24, and 36 months, respectively. Under the industry fixed effect, each coefficient at a significance level of 1% is clearly not zero. Although they are still important, these coefficients are consistently lower than the OLS-based estimates.

In general, the use of roei,t−1 reduces the potential measurement estimation error in addition to the noise generated by the general parameter estimation. Therefore, the OLS estimate based on roei,t−1 may reduce the effective loss in the estimation process, which is also a motive to employ a more accurate model to forecasting returns in the first stage.

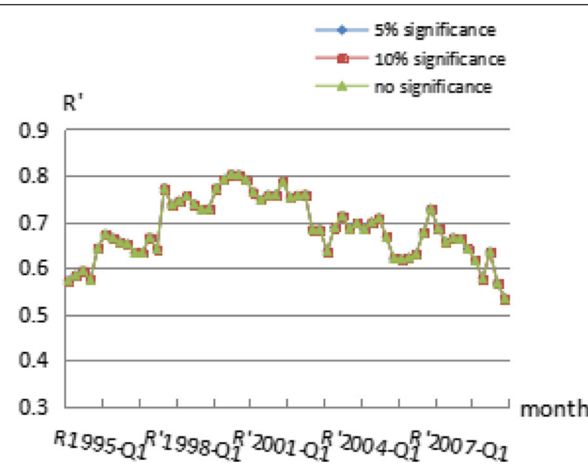

Fig. 8 Revenue regression (industry fixed effect)

Table 9 Supplementary variable estimation results

Panel A: Regression parameter summary								
Data	Regression coefficients				Implied parameters			
	cons	bm	roe	F	k	w	μ	
5th percentile	0.01378	0.01967	0.1149	93.1769	0.9374	0.7144	0.0248	
25th percentile	0.0254	0.0417	0.1557	257.869	0.9515	0.8075	0.0346	
mean	0.0323	0.0478	0.4942	765.484	0.9618	0.8563	0.0474	
median	0.0317	0.0495	0.3615	503.141	0.9601	0.8704	0.0422	
75th percentile	0.0375	0.0581	0.3813	1040.069	0.9679	0.9255	0.0519	
95th percentile	0.0558	0.0719	0.6032	2276.989	0.9904	0.9492	0.0865	
standard deviation	0.01386	0.0174	1.1761	789.7891	0.0176	0.0849	0.0212	
Panel B: Return of Regressions								
	3M (1)	12M (2)	24M (3)	36M (4)	3M (5)	12M (6)	24M (7)	36M (8)
$E[r_{(i,t+1)}]$	0.689***	0.636***	0.556***	0.521***	0.6028***	0.569***	0.4902***	0.3502***
	(0.013)	(0.0103)	(0.0295)	(0.0615)	(0.013)	(0.0098)	(0.0208)	(0.0421)
Cons	0.0343	0.0368	0.0329***	0.0319**	0.2492	0.22	0.21	0.195**
	(0.063)	(0.0132)	(0.0202)	(0.284)	(0.0492)	(0.0107)	(0.0150)	(0.254)
Number of observations	1681	1232	1025	957	1681	1232	1025	957
Fixed effects	no	no	no	no	yes	yes	yes	yes

Seasonal return

We choose the quarterly data rather than the month or year data at first, mainly because of the relatively modest amount of data. The study does not reveal excessive deviation because the time is too long or too short. However, using the quarterly data also has potential problems. Thus, we want to test the sensitivity of the results for the quarterly data and consider the potential of parameter estimation measurement error due to seasonal quarterly earnings.

For example, for the end of June 2010, we use the annual known logarithm return and observable annual BM and ROE to do a prediction at a time span selection from June 30, 2009 to June 30, 2010. This is the same as before using training samples from the years 1980 to 1995. The other estimates are similar to the quarterly earnings estimates method based on OLS.

From Table 10, we find that annual persistence parameter estimation is less than the quarter parameter most of the time, and the logarithm return and long unconditional expected return are optimal. Panel B is based on the annual proxy variable regression. At 12, 24, and 36 months of lead time, joint (not joint) industry fixed effects of holding period logarithmic expected return were 0.504 (0.482), 0.462 (0.405), and 0.462 (0.315), and the coefficient at 1% level is not significantly zero. However, we found that these coefficients are much smaller than the quarter, which means that the expected logarithmic return based on the annual financial statements data showed weaker earnings predictability.

The MC model's robustness test overall shows that the model is not very sensitive. Whether it adds a new auxiliary variable, changes the data age selection or the quarterly data to the annual data, the MC model has shown considerable stability. Thus, the model is not affected by too many external changes.

Table 10 Year data of least squares estimation results

Panel A: parameter estimation summary

Data	Regression coefficient				implicit parameter		
	cons	bm	roe	F	k	w	μ
5th percentile	0.013858	0.019755	0.12185	108.91885	0.943712	0.722926	0.01988
25th percentile	0.024605	0.039525	0.16875	180.5975	0.948106	0.837972	0.033205
mean	0.034328	0.048013	0.292219	1391.13566	0.961604	0.859725	0.053624
median	0.032565	0.05195	0.2425	271.368	0.957626	0.867538	0.04623
75th percentile	0.041725	0.061375	0.372	2300.75	0.970177	0.924935	0.058376
95th percentile	0.06029	0.065725	0.608	5129.3	0.990146	0.952434	0.125165
standard deviation	0.01578	0.0166	0.17457	1948.64092	0.016768	0.080108	0.036647

Panel B:Return regressions

	12M (2)	24M (3)	36M (4)	12M (6)	24M (7)	36M (8)
$E[r_{(i,t+1)}]$	0.504^{***}	0.462^{***}	0.34^{***}	0.482^{***}	0.405^{***}	0.315^{***}
	(0.0694)	(0.026)	(0.03)	(0.0272)	(0.0197)	(0.116)
Cons	-0.033	0.027^{***}	0.185^{**}	0.205	0.273^{**}	0.302^{**}
	(0.024)	(0.055)	(0.077)	(0.0429)	(0.056)	(0.0207)
Number of observations	1254	1162	936	1254	1162	936
Fixed effects	no	no	no	yes	yes	yes
Adj.R2	0.002	0.005	0.022	0.0102	0.009	0.0402

Conclusion

Progress and innovation

Although there are studies on stock market visions, this paper finds unexpected results in the research view and research methods. First, the focus of this article is to prove that medium-term momentum and long-term reversal exists and can be explained. Some studies prove that there are two types of visions. However, studies that explain the two visions are few. Second, the main research method we use in this study is the experimental method. We use the MC model with the BM factor, relying on a large number of sample data to prove the existence of medium-term momentum and long-term reversal. Additionally, we explain the existence of two types of visions. This research method is rare in the literature, which emphasizes the uniqueness of this study.

Analysis conclusion

The mid-momentum and long-term reversal of stock returns are two typical stock market anomalies that play a key role in the process of resource allocation. Explaining these two anomalies means that they can predict the excess returns that they generate providing greater autonomy and greater benefits with respect to investment choices.

This paper considers the difference between the CAPM model and the MC model, and thus introduces a novel and relatively simple model to explain mid-momentum and long-term reversal. The model has some explanatory power for both visions, and the ability to explain the mid-momentum is improved compared to other models.

After defining the model's ability to interpret the vision, the intrinsic mechanism of this interpretation is explored. Through a correlation analysis of several influencing factors in the model, we find that BM plays a key role in the interpretation of visions. Thus, we verify that the BM factor explains the mid-momentum and the long-term reversal, and the mid-momentum is more easily explained.

For some less in-depth study problems, we summarize the following. First, the BM effect has always been considered by investors as a type of stock market anomaly, and it can be quantified. Thus, we regard it as a basic indicator to join the model. Furthermore, we consider that if the BM as an impact factor clarifying other stock market visions, what level of ability will it show? Second, the whole model is rigorously derived, but there may be some inevitable omissions, particularly the impact of residuals that we cannot remove. Moreover, when we interpret the two visions, we cannot calculate how much of a role the residual plays.

Enlightenment to future research

We conclude that US stock market volatility forecasting is easier than before. Our studies play an irreplaceable role in this work. For mature markets, as in the United States, the emergence of the vision is inevitable. Therefore, considering the market factors when we study the vision will be meaningful. At minimum, this article provides some advancement based on the existing literature in explaining future visions. The suggested model can explain both the mid-term momentum and the long-term reversal, but it also finds the most fundamental explanatory factor that can interpret both visions.

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Authors' contributions

LW contribution: He is the first author of this paper and provides the most of the views and ideas towords the whole article conception and innovation. ZJ contribution: She as the second author, mainly assists the first author to complete the construction and writing of entire paper. Both authors read and approved the final manuscript.

Competing interests

The authors declare that we have no competing interests.

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