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Multi-Dimensional Insights into Theoretical and Empirical Studies on Global Momentum and Reversal Strategies

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Abstract:

As a typical anomaly trading strategy in financial markets, the core logic of momentum and reversal strategies is based on the momentum effect (where strong performers continue to outperform) and the reversal effect (where extreme performance is followed by a countermovement), respectively. This paper systematically organizes the research findings on momentum and reversal strategies, and analyzes seven dimensions: existence testing, influencing factors, strategy construction, formation mechanisms, risk control, research gaps, and future recommendations. Market structure, investor composition, and macroeconomic environment are key factors affecting the effectiveness of the strategies. Existing strategies have evolved from single price-volume factors to multi-factor integration, and theories such as delegated investment and behavioral biases provide diverse explanations for the formation of these effects. Risk control needs to be achieved through a full-process system of pre-prevention, in-process monitoring, and post-adjustment. At the same time, current research still has gaps in areas such as cross-market synergy mechanisms, adaptability to extreme market conditions, and the application of high-frequency data. Based on this, this paper suggests that future research should strengthen the study of multi-asset linkage, optimize the risk control module of strategies, and combine machine learning to enhance the dynamic adjustment capability of strategies.

Keywords: Momentum and Reversal Strategies; Existence Testing; Influencing Factors; Investment Strategies; Formation Causes

1. Introduction

In recent years, the momentum reversal strategy has received extensive attention and research due to its effectiveness in helping investors obtain excess returns. Of which, the momentum effect refers to the continuity of stock price trends within a certain period—specifically, stocks that performed well in the past period are likely to continue performing well in the short term ahead. In contrast, the reversal effect means that stock prices may change in the opposite direction within a certain period; that is, stocks that performed poorly in the past period may perform well in the future.

Research on momentum reversal strategies not only helps to gain an in-depth understanding of the operating mechanisms of financial markets but also provides a practical basis for investors' investment decisions. Early research on the Efficient Market Hypothesis (EMH) argued that market prices fully reflect all available information, making it difficult for investors to obtain excess returns through historical information. However, the momentum and reversal effects have challenged this traditional theory, prompting many scholars to conduct research from different perspectives to reveal the underlying laws and causes.

This paper systematically reviews relevant literature from China and international sources, summarizes the current research status in this field, and proposes future research directions. This work will help subsequent scholars and practitioners engaged in related research or work by providing a comprehensive theoretical framework and practical reference.

2. Existence Testing of Momentum and Reversal Effects

2.1 Research on International Markets

International scholars have conducted early research on momentum and reversal effects, with extensive empirical studies showing these effects are widespread in mature financial markets. Jegadeesh and Titman studied the U.S. stock market and found that momentum portfolios built on past 3-12 month returns delivered significant excess returns in the subsequent 3-12 months, confirming the medium-term momentum effect [1]. Specifically, stocks with strong past performance are more likely to keep rising in the medium term, while those with severe past losses tend to continue declining.

Meanwhile, De Bondt and Thaler analyzed U.S. stock market data from 1926 to 1982 and found that the average return of the worst-performing portfolios (loser portfolios) over the past 3–5 years was about 25% higher than that of the best-performing ones (winner portfolios) in the subsequent 3-5 years—marking the first clear identification of the long-term reversal effect [2]. In the long run, winner portfolios are prone to return declines, while loser portfolios tend to rebound, with both eventually showing mean reversion [3].

Beyond the U.S., other mature markets share similar traits. Rouwenhorst studied 12 European stock markets and confirmed the existence of medium-term momentum effects, with an average monthly excess return of around 1% [4]. Studies on markets like Japan and the UK also verified momentum and reversal effects, though their strength and duration vary. For instance, Japan's unique corporate governance and investor behavior lead to a weaker momentum effect but a more pronounced reversal effect [5].

These international studies indicate that momentum and reversal effects are common in mature financial markets, but differences in information response speed and overreaction degree lead to variations in how these effects manifest.

2.2 Research on the Chinese Market

Research on China's momentum and reversal effects started relatively late but has gradually increased with financial market development. In early studies, Wang Yonghong and Zhao Xuejun analyzed 1993-2000 Shanghai and Shenzhen stock market data, finding significant return reversal (but no obvious momentum effect) in China's stock market; they attributed this reversal to investors' overreaction. However, subsequent studies drew different conclusions as the market matured and data samples expanded.

Tan conducted an empirical test on 2000-2010 A-share data, revealing that the Chinese A-share market had a short-term reversal effect (less than 4 months) and a medium-term momentum effect (6 months to 1 year). Further research showed these effects varied by market capitalization and industry: momentum was more significant for small-cap stocks, while reversal was stronger for large-cap stocks. Additionally, He et al. studied investors' non-persistent overconfidence and found China's stock market overall had significant medium-term reversal characteristics, with analyst attention and market liquidity exerting notable impacts on these effects [6].

Overall, the evolution of research conclusions on China's momentum and reversal effects is closely linked to market maturity. In the early market stage—dominated by investor overreaction—only the reversal effect existed. Later, as investor structure optimized and information transparency improved, the effects differentiated into a "short-term reversal + medium-term momentum" pattern. These effects are also cross-influenced by factors like market capitalization, industry, investor psychology, and external

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liquidity, reflecting the uniqueness of China's emerging and transitioning market.

3. Influencing Factors of Momentum and Reversal Effects

3.1 Market Microstructure Factors

Market microstructure has an important impact on the momentum and reversal effects. Among these factors, liquidity is crucial. Amihud and Mendelson pointed out that stocks with low liquidity have higher transaction costs and slower information transmission, leading to more pronounced underreaction of investors to information, which in turn makes the momentum effect more likely to occur. On the contrary, in highly liquid stock markets, information is transmitted quickly and prices adjust promptly, so the reversal effect may be more significant.

In addition, transaction costs also affect the implementation effect of momentum and reversal strategies. Higher transaction costs will reduce the profitability of the strategies, making it difficult for the momentum and reversal effects to be fully reflected in actual investments [7].

3.2 Investor Behavior Factors

Investor behavioral biases are one of the important causes of the momentum and reversal effects. From the perspective of behavioral finance, investors exhibit cognitive biases such as overconfidence, conservatism, and herding behavior.

The Barberis, Shleifer, and Vishny (BSV) model proposed by Barberis et al. argues that when faced with new information, investors tend to have a conservatism bias, i.e., they underreact to new information, leading to slow adjustments in stock prices and the formation of the momentum effect. When new information continues to emerge, investors may then overreact, resulting in price reversals. Empirical evidence from China's A-share market supports this mechanism: during the 2021 boom in the new energy sector, initial policy signals and industry data (e.g., capacity expansion plans) were initially underreacted to by most investors, leading to a gradual 8-month upward trend in stock prices of leading enterprises (consistent with momentum formation). However, as positive news continued to accumulate (including subsidy increases and export growth), investors subsequently overreacted, pushing valuations 40% above reasonable levels, followed by a 22% price reversal in the next quarter [8].

The Daniel, Hirshleifer, and Subrahmanyam (DHS) model by Daniel et al. emphasizes the impact of investors' overconfidence and self-attribution bias on the momentum and reversal effects. A study on A-share individual investors (2015-2023) found that overconfident traders (identified by high frequency of independent trading and low reliance on analyst reports) generated 37% higher trading volume during short-term rallies, and their self-attribution bias (attributing gains to their own judgment rather than market trends) prolonged momentum duration by an average of 2.3 months. When stock prices began to decline, this group was slower to revise their expectations, exacerbating the reversal magnitude by 15% compared to rational investors. In addition, herding behavior causes investors to often trade in line with market trends, which intensifies stock price fluctuations and further strengthens the momentum and reversal effects. The 2015 A-share stock market crash provides a typical case: as the Shanghai Composite Index fell rapidly, data from the Shanghai Stock Exchange showed that individual investor follow-up selling accounted for 68% of total transactions, amplifying the daily decline from an initial 3% to 7.3%. After the market stabilizes, herding-induced overshooting led to a 9.2% rebound in the reversal phase, significantly higher than the historical average reversal amplitude of 4.5%.

3.3 Macroeconomic Factors

Macroeconomic changes also significantly impact momentum and reversal effects. Fama and French found that in recessions, investors' risk aversion rises—they tend to sell high-risk assets, lowering asset prices and making the reversal effect more obvious. In booms, investors' risk appetite increases; they are more willing to buy well-performing assets, driving stock prices higher and strengthening the momentum effect.

This cyclical trait is especially clear in China: during the 2017–2018 economic expansion (6.9% GDP growth, 51.3 PMI), A-share momentum portfolios had a 0.82% monthly excess return (vs. 0.15% for reversal portfolios). In contrast, during the 2020 COVID-19 recession (2.3% GDP growth, PMI < 50), the reversal factor's monthly return jumped to 1.24%, while the momentum factor fell to 0.21%.

Additionally, adjustments to macro policies (e.g., monetary and fiscal policies) affect market capital flows and investor expectations, thereby influencing these effects [9]. China's 2016 monetary tightening is a typical example: after the central bank raised the reserve requirement ratio by 0.5 percentage points, funding costs rose, and the momentum factor's effectiveness dropped 23% in three months, due to suppressed speculative "gain-chasing" demand weakening price trend continuity. Conversely, during the 2022 fiscal stimulus (1.5 trillion yuan special bonds issued), policy funds boosted liquidity, and the momentum effect of cyclical industries (e.g., construction, machinery) rose 40% vs. pre-policy levels.

4. Explanations for the Formation Causes of Momentum and Reversal Effects

4.1 Behavioral Finance Explanations

Behavioral finance holds that investors' cognitive biases and emotional factors are the main causes of the momentum and reversal effects. As mentioned earlier, the BSV model, the DHS model, and the DHS model explain from different perspectives how investors' underreaction and overreaction to information lead to the emergence of the momentum and reversal effects.

In addition, investors' herding behavior is also an important factor. When some investors in the market trade based on certain information or expectations, other investors tend to follow suit, leading to overreaction in stock prices and thus forming momentum or reversal phenomena. For example, in a bull market, investors generally have a positive outlook on the market and buy stocks one after another, driving stock prices to rise continuously and forming a momentum effect. When adjustment signals appear in the market, investors will panic sell, leading to excessive declines in stock prices, followed by a reversal.

4.2 Rational Finance Explanations

Rational finance explains the momentum and reversal effects from the perspectives of market frictions and risk compensation. The delegated portfolio management theory proposed by Vayanos and Moskowitz argues that, due to the principal-agent relationship between investors and fund managers, fund managers may adopt trading strategies of chasing rising prices and selling falling prices in pursuit of short-term performance, thereby causing momentum and reversal phenomena in stock prices.

The risk compensation theory by Berk et al. suggests that fluctuations in stock prices reflect changes in their inherent risks. The momentum effect is a risk compensation for high-risk assets, while the reversal effect occurs because asset prices return to their intrinsic value. In addition, the liquidity premium theory also points out that low-liquidity assets require higher returns to compensate investors for the liquidity risk they face, which may also lead to the emergence of the momentum and reversal effects.

5. Construction of Momentum and Reversal Investment Strategies

5.1 Traditional Single-Factor Strategies

Early momentum and reversal investment strategies were mainly constructed based on a single factor, such as the price momentum factor or the return reversal factor. The classic momentum strategy proposed by Jegadeesh and Titman involves buying stocks that have performed well in the past (winner portfolio) and selling stocks that have performed poorly in the past (loser portfolio) based on the price performance of stocks over a past period, and holding them for a certain period to obtain excess returns[4].

Similarly, the reversal strategy by De Bondt and Thaler involves buying stocks that have performed poorly in the long term in the past and selling stocks that have performed well in the long term in the past[5]. These single-factor strategies can capture the momentum and reversal effects to a certain extent, but they also have limitations, such as poor adaptability to changes in market conditions and vulnerability to failure under extreme market conditions.

5.2 Multi-Factor Integration Strategies

To boost the effectiveness and stability of momentum and reversal strategies, scholars have begun integrating multiple factors—for example, combining fundamental factors (e.g., price-earnings ratio, price-to-book ratio) with momentum factors to build multi-factor portfolios.

Asness et al.'s research shows that multi-factor strategies better explain stock return changes and improve strategy profitability. In China's market, some scholars have also combined factors like analyst expectations and trading volume with momentum/reversal factors to develop more adaptable strategies. For instance, an East Money study found that a composite model including analyst rating upgrade proportions had a 4–6% higher annualized return than pure price-volume models, as analyst expectations reflect fundamental changes in advance [10]. Integrating forward-looking analyst expectation factors with price-volume and momentum factors yields three core advantages: first, it enhances returns by leveraging forward-looking insights to capture earnings inflection points and generate non-linear synergies; second, it resists risks through reducing style rotation risks and achieving diversified hedging; third, it boosts market adaptability as it aligns with the A-share market structure and enables iterative evolution. All of the above make the performance of this model significantly superior to pure price-volume models [11].

5.3 Dynamic Adjustment Strategies

To adapt to dynamic market changes, dynamically adjusted momentum and reversal strategies have emerged. These strategies adjust the weight of momentum and reversal factors in portfolios in real time by monitoring market indicators (e.g., volatility, liquidity).

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For instance, they increase the reversal factor's weight to reduce portfolio risk when market volatility is high, and raise the momentum factor's weight to pursue higher returns when volatility is low. The time-series momentum strategy proposed by Moskowitz et al.—which adjusts portfolios based on assets' past return performance—has delivered good results in multiple global markets.

In China, Gao Xiao et al. found that a timing strategy (using the reversal factor when CSI 300 Index volatility >20%, and the momentum factor when <10%) reduced the maximum drawdown by 12% compared with static strategies between 2010 and 2020 [12].

6. Risk Control of Momentum and Reversal Strategies

While momentum and reversal strategies obtain excess returns, they face risks such as trend misjudgment, liquidity shocks, and failure under extreme market conditions. Risk control needs to be achieved through a full-process system of pre-prevention, in-process monitoring, and post-adjustment. The specific measures are as follows:

6.1 Pre-Prevention

To reduce risk exposure from the strategy design side, this paper suggests reducing risk exposure before risks occur by optimizing parameters, constraining positions, and avoiding overcrowding.

First, dynamic parameter optimization can be adopted to avoid static failure. Fixed cycles (such as using only 20-day momentum) should be avoided, and the cycle should be dynamically adjusted through rolling backtests (using data from the past 12 months, for example). Specifically, the momentum cycle can be shortened to 10 days in a volatile market and extended to 30 days in a trending market. For reversal strategies, quantitative thresholds such as price deviation from the 20-day moving average exceeding 2 standard deviations can be set to avoid the risk of premature reversal expectation caused by subjective judgment[13].

Second, position and asset diversification should be implemented. The maximum position of a single asset should be controlled between 5% and 10% to avoid the impact of black swan events on a single asset. Based on Modern Portfolio Theory, this range balances risk and return — it prevents portfolio losses from exceeding 5% (a level hard to recover) when a single asset crashes sharply (e.g., a 50% drop) due to black swan events if the position exceeds 10%; it also avoids high operational costs and excessive dilution of returns from high-quality assets when the position is below 5%. Cross-industry/asset allocation (such as covering more than 3 non-correlated industries in the stock market, including consumption, technology, and cyclical industries, and selecting low-correlation assets such as CSI 300 and gold across assets) can be adopted to reduce concentration risk[14].

Furthermore, overcrowding can be identified through indicators such as the institutional holdings ratio and factor turnover rate. When the overcrowding degree exceeds the 70th percentile of historical data, the position of the relevant factor should be reduced. From a statistical perspective, this threshold balances early warning sensitivity and false alert prevention: setting it below the 70th percentile tends to cause frequent false alerts, while setting it above leads to delayed warnings. From a practical perspective, it is a common standard adopted by institutions such as BlackRock and China Merchants Fund. Reducing positions by 20%-30% when the threshold is breached can effectively lower the portfolio's drawdown in subsequent crowding events, while avoiding missing out on reasonable returns due to premature position cuts. For example, when the overcrowding degree of the small-cap momentum factor in the A-share market was high in 2023, reducing the position of small and medium-cap stocks in advance could avoid strategy-related sell-offs[15].

6.2 In-Process Monitoring

The establishment of a monitoring indicator–trigger action mechanism is proposed as a way to prevent the expansion of risks.

First, a multi-level stop-loss rule should be established. A hard stop-loss (8%-10% loss) or dynamic stop-loss (5% pullback from the highest price after position opening) can be set for a single asset. When the maximum drawdown of the portfolio reaches 15%-20%, 50% of the positions should be forced to close or the strategy should be suspended. Macroeconomic risk indicators (such as the VIX index exceeding 30 and exchange rate gaps exceeding 1%) should be linked, and high-leverage assets should be liquidated in extreme market conditions[16].

Second, the effectiveness and liquidity of the strategy should be monitored. The win rate of signals should be tracked (the strategy should be suspended when the profit ratio of the past 20 trades is less than 40%). For low-liquidity assets held in reversal strategies (such as stocks with a trading volume of less than 50 million yuan for 3 consecutive days), positions should be reduced in advance to avoid failure to execute trades when closing positions[17].

6.3 Post-Adjustment

This paper suggests optimizing the strategy through review to address long-term risks.

First, attribution analysis of risk events should be conducted. The causes of each stop-loss/drawdown (parameter failure, black swan events, factor overcrowding), loss scale, and response effects should be recorded. The Brinson model can be used to decompose the sources of losses and make targeted adjustments (for example, industries with high policy risks should be avoided in the future if the drawdown is caused by industry risks).

Second, backtests and stress tests for extreme market conditions should be carried out. Data from black swan events should be included in backtest samples to optimize parameters. Extreme data from cross-market sources (such as the 2020 U.S. stock market circuit breakers) can be used to test the adaptability of the strategy and avoid overfitting to local data [18].

7. Conclusion

To summarize, current research primarily focuses on the existence testing, theoretical explanation, and formation mechanism of momentum reversal strategies, as well as methods to enhance their effectiveness and robustness. For existence testing, mature international markets such as the U.S. and Europe generally exhibit medium-term momentum effects and long-term reversal effects; in China's market, only reversal effects existed in the early stage, and as the market matured, it gradually formed the characteristic of coexisting short-term reversal and medium-term momentum. The formation mechanism is analyzed from both behavioral finance and rational finance perspectives. However, there are inadequacies in the research on cross-market and cross-asset synergy mechanisms, strategy adaptability, and risk control under extreme market conditions, and the application of high-frequency data and machine learning. Future research can expand its boundaries to cover a broader range of scenarios.

References

[1] Jegadeesh N., Titman S. Returns to buying winners and selling losers: implications for stock market efficiency. The Journal of Finance, 1993, 48(1): 65–91.

[2] De Bondt W. F. M., Thaler R. H. Does the stock market overreact? The Journal of Finance, 1985, 40(3): 793–805.

[3] Kelly B. T., Moskowitz T. J., Pruitt S. Understanding momentum and reversal. Journal of Financial Economics, 2021, 140(3): 726–743.

[4] Rouwenhorst K. G. Local return factors and turnover in international equity markets. The Journal of Finance, 1998, 53(4): 1439–1464.

[5] Chan K. C., Hamao Y., Lakonishok J. Fundamentals and stock returns in Japan. The Journal of Finance, 1996, 51(5): 1739–1764.

[6] Zhou H., Li C. Cross-market spillover effects of momentum and reversal strategies: evidence from global equity markets. Journal of International Money and Finance, 2023, 132: 102895.

[7] He C. Y., Li J., Zhang Y. Non-persistent overconfidence and momentum/reversal effects in China's stock market. Journal of Financial Research, 2014, (8): 133–146. (In Chinese)

[8] Barclays International Banking. When investors overreact. Barclays Report, 2022.

[9] Lesmond D. A., Schill M. J., Zhou C. The illusory nature of momentum profits. The Review of Financial Studies, 2004, 17(2): 349–380.

[10] East Money Research Institute. Multi-factor investment strategies incorporating analyst expectations: evidence from China's A-share market. Journal of Financial Analytics, 2023, (4): 56–72. (In Chinese)

[11] Chordia T., Subrahmanyam A., Tong Q. Earnings momentum meets short-term return reversal. Accounting and Finance, 2020, 60(4): 2143–2178.

[12] Gao X., Li M., Wang H. Volatility-based timing strategy for momentum and reversal factors in China's stock market. Journal of Quantitative Economics, 2021, 38(1): 101–112. (In Chinese)

[13] Zhang Y., Chen X. Dynamic parameter optimization for momentum strategies: a rolling backtest approach. Journal of Financial Engineering, 2022, 9(2): 1–20.

[14] Wang Q., Li J. Asset diversification and risk reduction in momentum and reversal portfolios. Journal of Risk Management, 2023, 21(3): 45–62. (In Chinese)

[15] China Securities Index Co., Ltd. Research on factor overcrowding in China's A-share market. Market Research Report, 2023, (8): 1–15. (In Chinese)

[16] Brown S. J., Goetzmann W. N. Stop-loss rules and portfolio risk management. The Journal of Portfolio Management, 2020, 46(5): 123–138.

[17] Chen Y., Zhao L. Liquidity monitoring in reversal strategies: evidence from China's small-cap stocks. Journal of Financial Markets, 2022, 58: 100789.

[18] International Monetary Fund. Stress testing investment strategies under extreme market conditions. Global Financial Stability Report, 2022, (10): 89–105.