A Study of Equity Investment Strategies for Volatility Management and Optimisation Based on Historical Volatility

Jiajing Li

Shanghai University of International Business and Economics, Shanghai 201600, China
DOI: 10.32629/memf.v5i6.3183

Abstract: This paper designs and optimizes a series of quantitative investment strategies for the Shanghai and Shenzhen stock markets (2012-2019), leveraging volatility management and multi-factor models with Wind database data, to boost returns and stabilize portfolios. Using MATLAB, we simulate and visualize strategy returns. The initial strategy selects low-volatility stocks for equal-weighted investment based on historical volatility, outperforming the market but yielding unstable returns. To improve, we propose: 1) allocating weights inversely proportional to volatility, 2) incorporating market return factors into a multi-factor model, and 3) enhancing strategy stability via rolling window analysis. The multi-factor model strategy demonstrates superior risk control and stable returns across time horizons, appealing to long-term investors. The optimized weighting strategy suits short-term, high-risk investors. Lastly, we assess the rolling window's impact on long and short-term investments to analyze its strengths and weaknesses for stock picking.

***Keywords*:** quantitative investment, volatility management strategy, weight allocation, multi-factor model, rolling window analysis.

1. Introduction

1.1 Intention

With the help of volatility management strategies, the aim is to increase returns, reduce volatility and grow returns.

1.2 Literature review

Volatility management is crucial in financial risk management, particularly given the increasing complexity and volatility of markets. Historical volatility, a key indicator of asset price fluctuations, underpins volatility management strategies.

Jiang Zhidan (2024)[1] in 'An Empirical Study of Turnover-Volatility Relations in the Chinese Stock Market' highlights a significant correlation between turnover and volatility, highlighting a growing demand for liquidity investment through the SV-VOL model. Lan Yang (2023)[2], in 'Trait Volatility Pricing in the Chinese Bond Market', explores trait volatility's cross-sectional pricing, revealing a positive correlation between corporate bond idiosyncratic volatility and yields.

Ying Liu (2023)[3], in 'Deep Learning for Volatility Forecasting and VaR Measurement', finds that the LSTM-GARCH fusion model, blending traditional econometrics with deep learning, excels in volatility forecasting and enhances VaR measurement accuracy. Yongfeng Wei and Wei Zhao (2022)[4], in 'Momentum Strategies, Collapse, and Risk Management in the Chinese Commodity Futures Market', study momentum strategies and collapse, identifying a momentum collapse driven by the losers' portfolio's option-like nature, sensitizing time-varying beta to market volatility. They propose a dynamic weighted momentum strategy for risk management[5].

These momentum strategies and volatility management methods confirm correlations between volatility, returns, stock prices, and volumes. This paper builds on basic momentum investment strategies, integrating factor modeling and window size adjustments to explore a theoretically more stable volatility management strategy, examining the return-volatility relationship.

1.3 Innovative points of this study

Combining volatility management with a multi-factor model: We augment the basic strategy by incorporating a market return factor, considering both volatility and market returns to optimize investments.

Optimizing weight allocation: We allocate weights inversely proportional to volatility, normalizing to sum to one, mitigating subjectivity and instability in the portfolio.

Rolling Window Analysis: This method adjusts the time period over which volatility and market return factors are calculated in order to analyse market changes over the short and long term. By varying the window size of the historical data, the multi-factor model with a 50-month window length was validated and found to perform best in terms of return and volatility for short-term investments.

Dynamic adjustment strategy: Tailoring investment strategies to different window lengths and factor combinations enhances yields while effectively managing risk.

2. Strategy implementation

2.1 Initial strategy principle

This strategy implements an equity investment strategy based on historical volatility.

Strategy Principle: Calculating Historical Volatility: We select underlying stocks from currently available historical data and compute their volatility over a specified window length, which reflects risk. For instance, we use 20 months of data.

Volatility Management: We prioritize stocks with lower volatility for portfolio construction, assuming they pose less risk. Portfolio weights are determined accordingly.

Lagged Volatility Calculation: We rely on lagged historical volatility for investment decisions, emphasizing long-term trends to avoid short-term noise. This approach enhances portfolio management by accurately capturing long-term risk

Equal Weight Investment: We build a portfolio of 50 low-volatility stocks, each equally weighted to ensure diversification and robustness, minimizing individual stock risk.

Innovation: This strategy integrates risk management into investment decisions, aiming for robust performance through volatility control.

2.2 Initial strategy performance and summary

The investment strategy outperformed the broader market for a period but subsequently declined. Over seven years, its cumulative return exhibited volatility, contrasting with the relatively flat performance of the SSE index. Notably, from 2013 to 2016, the strategy's cumulative return significantly surpassed the SSE Index, highlighting its market outperformance. However, it peaked in 2016 and declined thereafter, indicating insufficient return stability.

3. Optimisation strategy proposed

3.1 Optimising strategy principles

Due to the problem of high volatility and instability of the initial strategy, which may increase the investment risk, the equal weight allocation method is adjusted for this. That is, a certain number of stocks (100) are selected and the number of investments also increased compared to the original strategy is used to reduce instability. Equal scaling of the inverse of volatility is used to allocate weights, and the final sum is normalised to 1, avoiding subjectivity and arbitrariness in the weight allocation process, which is used to resist instability.

3.2 Optimising strategy performance

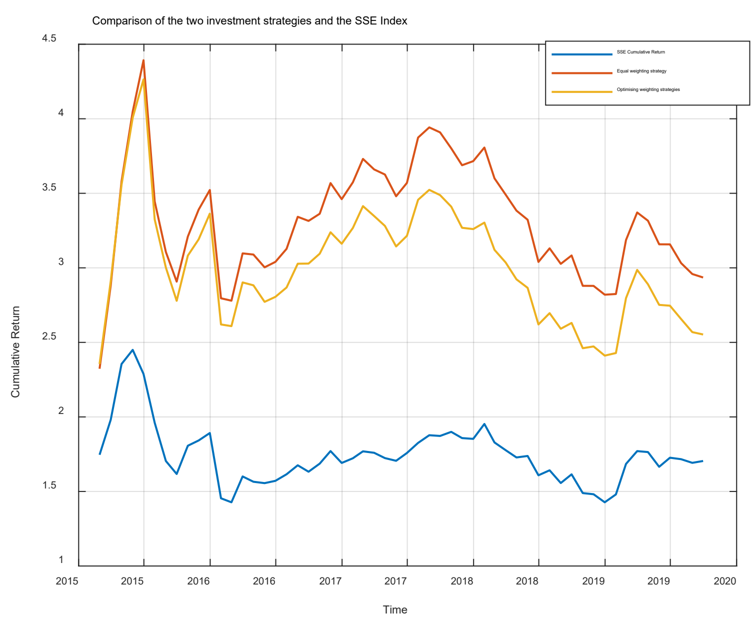

Figure 1. Two Optimised Momentum Strategies vs. Basic Strategy Returns

3.3 Optimising strategy summary

Optimally weighted strategies (red line) outperform equally weighted strategies (blue line) in terms of cumulative returns at short-term points in time. This suggests that optimised weighting strategies may have higher potential for short-term returns.

However, from a stability perspective, while the optimised weighting strategy performs better than the equal weighting strategy in some periods, it also has a more volatile curve. This means that optimised weighting strategies may offer higher potential returns, but also come with greater risk. So while it is still outperforming the broader market, it is not well protected against risk instability.

4. Multi-factor optimisation strategies

4.1 Optimising strategy principles

Building on the previous strategy, we consider stability and investment return. We augment the original volatility management strategy by incorporating a market return factor to construct a multi-factor model. This factor, representing overall market return, is calculated using historical data of market indices (e.g., CSI 300). By equally weighting both factors, we multiply the normalized value of each by its weight and sum the results to obtain a weighted score. The market's attractiveness and risk level are assessed based on this score; a high score indicates high yield with relatively low risk, suggesting an ideal investment time. Based on the composite score, we select 100 stocks for equal weighting.

4.2 Optimising strategy performance

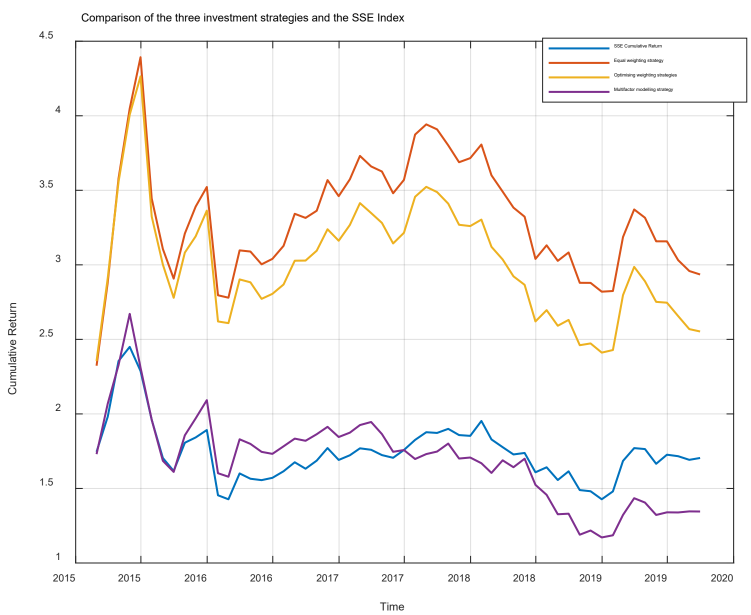

Figure 2. Three Optimised Momentum Strategies vs. Basic Strategy Returns

4.3 Optimising strategy summary

Compared to equal-weighted and optimized-weighted strategies, the multi-factor model strategy yields a smoother return curve over most periods. While fluctuations may occur at certain times, volatility remains lower, indicating superior risk control. Despite lower returns, the higher stability largely addresses the issue of insufficient return stability, making it suitable for long-term investment by risk-averse investors.

5. Optimisation strategies for rolling window analysis

5.1 Optimising strategy principles

Based on the previous strategy, the multi-factor model reduces the investor's risk while reducing the investor's return, so the following attempts are made to increase the return while maintaining stability by changing the window size. After studying and verifying the different window sizes from 10-60, i.e., using historical data of different dimensions, it is found that the return with a window size of 50 months is, on a combined basis, the window with the highest return and the lowest volatility except for the window of 20 months. Hence the window length is changed to 50 months for the study below.

5.2 Optimising strategy performance

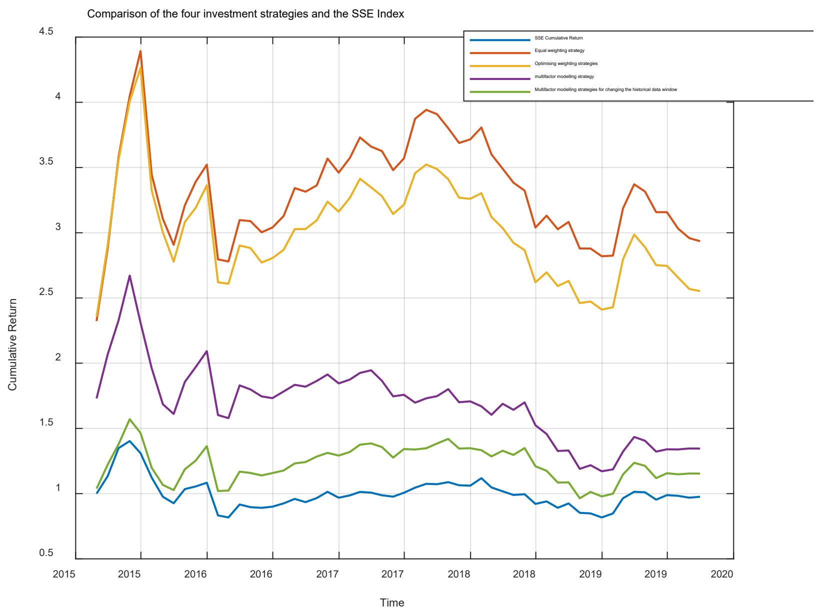

Figure 3. Four Optimised Momentum Strategies and Basic Strategy Returns vs. Sensex

5.3 Optimising strategy summary

The 50-month multifactor modelling strategy offers smoother returns than the 20-month version and is better suited for short-term investments due to its higher short-term yield.

The cumulative return of the strategy with an extended historical window (green line) is smoother and less volatile, suggesting stable returns with lower risk during market fluctuations. It also demonstrates resilience during downturns, with a smaller retracement compared to the equal weighting, optimized weighting, and general multi-factor strategies, highlighting its advantage in stabilizing returns.

6. Conclusion

This paper simulates quantitative investment in Shanghai and Shenzhen stocks for the eight years 2012-2019, using volatility management strategies, as well as multi-factor models and other components, changing the historical data window, etc. It is found that the advantages of multi-factor model strategies lie in their lower volatility and higher risk stability, and although returns are lower than equal-weighted and optimally-weighted strategies for some time periods, their smoother growth curve makes Although returns are lower than those of Equal Weight and Optimised Weight strategies in some time periods, their smoother growth curve makes them more stable and predictable over long periods of time, making them suitable for investors who want to achieve stable returns over the long term. Equal Weight and Optimised Weight strategies are suitable for investors with a higher risk tolerance who are looking for higher returns in the short term.

References

[1] Zhidan Jiang. Research on Volume-Volatility Relation in Chinese Stock Market [D]. Jilin University,2024. DOI:10.27162/d.cnki.gjlin.2024.003276.

[2] Yang Lan. An empirical study of the impact of idiosyncratic volatility on corporate bond yields in China [D]. Shanghai University of Finance and Economics,2023.DOI:10.27296/d.cnki.gshcu.2023.000529.

[3] Ying Liu. Empirical research on stock index volatility prediction and VaR measurement based on deep learning [D]. Anhui University of Finance & Economics,2023.DOI:10.26916/d.cnki.gahcc.2023.000657.

[4] Wei Y F, Zhao W. Momentum strategy, momentum crashes, and risk management: an empirical research based on

Chinese commodity futures market[J]. Journal of University of Chinese Academy of Sciences,2022,39(5):593-614. DOI:10.7523/j.ucas.2020.0049.
[5] Jiawei Yan, Jingxiao Qian. Can fund investors benefit from volatility management?[R]. Hua An Securities Research Institute.