

Innovative Alpha Strategies for the Chinese A-Share Market: Stable Turnover Momentum Enhanced by Idiosyncratic Volatility

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Abstract: This paper focuses on optimizing momentum strategies by addressing key limitations in traditional approaches. To enhance strategy performance, the study introduces three critical factors: price curve stability, turnover rate stability, and idiosyncratic information distribution. These enhancements are designed to improve the effectiveness of momentum strategies, particularly in the context of the Chinese A-share market. Using the CSI 300 and CSI 1000 datasets from 2019 to 2024, the study evaluates these optimized strategies. The results demonstrate that the enhanced momentum portfolio can deliver substantial annualized returns, even under daily trading conditions with high transaction costs. The findings show that these improved alpha strategies provide a robust framework for balancing risk and return in both volatile and stable market environments, offering valuable insights for investors in the Chinese stock market.

Keywords: Idiosyncratic, Momentum, Enhancement, Chinese A-share market, Fama-French Model, Volatility

1. Introduction

The A-share market in China is distinguished by its unique structure and rapid growth, positioning it as a critical component of the global financial system. As one of the world's largest stock markets, it garners significant attention from both domestic and international investors. However, despite its attractiveness, the A-share market often experiences failures in momentum effect application, repeated reversal phenomena, high return volatility, high idiosyncratic volatility and other issues, which are not conducive to investors accurately assessing investment strategy performance.

In the A-share market, understanding and applying various types of information is extremely important. This includes price data, price-volume relationships, market information, and individual stock fundamental information, all of which are crucial for optimizing investment strategy performance. However, many traditional Alpha strategies often rely on fundamental analysis or overall market index analysis. This kind of alpha establishment may not be able to capture the unique characteristics of individual stocks in the market, thus missing out on arbitrage opportunities.

Momentum strategy, as the cornerstone of quantitative investment, has become a widely researched topic and is well known for its significant profitability in many stock markets. The

pioneering research by Jegadeesh and Titman [1] demonstrated that buying past winners and selling past losers in the U.S. stock market can yield substantial excess returns. This discovery has sparked numerous subsequent studies, reinforcing the broad applicability of the momentum effect across various markets and asset classes. In recent years, the latest developments in the field of quantitative finance have driven the development of models that enhance momentum alpha generation by analyzing stock-specific characteristics. The momentum effect - where recent winners continue to rise and losers continue to fall - represents a significant anomaly challenging traditional probability theory. Based on this view, many studies have combined idiosyncratic factors with momentum strategies. Fama and French [2] argued that their three-factor model could not explain momentum returns, calling it a "major anomaly." This has led to further research, with idiosyncratic momentum strategies becoming a prominent example: calculating stock residuals in a market multi-factor model as idiosyncratic returns and selecting based on this. Blitz [3] and Chaves [4] have documented strong performance of idiosyncratic momentum strategies in the U.S. and 23 international stock markets, proposing strategies that are significantly better than traditional momentum methods.

Despite these advancements, momentum strategy as a cornerstone strategy has significant shortcomings in information processing and has not effectively utilized the idiosyncratic information of individual stocks in traditional strategy development. Its deficiencies are mainly reflected in the following three aspects:

1. Insufficient information on price curve evolution
2. Insufficient information on the price-volume relationship
3. Insufficient information on individual stock characteristics

This paper addresses these three key shortcomings of momentum strategies by proposing various optimization solutions. These solutions target each of the three key deficiencies by introducing price curve stability factors, turnover rate stability factors to enhance strategy stability, and finally utilizing idiosyncratic information distribution factors to improve strategy's annualized performance. This study conducted comprehensive backtesting of various single-alpha-strategy and multi-alpha-strategy involved in the strategies before and after optimization. In a daily trading environment, taking into account trading costs to simulate real trading conditions, innovative conclusions and practical trading recommendations were drawn. The optimized strategies ultimately achieved substantial annualized returns under daily trading conditions. In conclusion, this study seeks to advance the understanding of Alpha strategies in the A-share market by specifically addressing the informational processing shortcomings of momentum strategies, with a particular focus on the enhancing effect of idiosyncratic information distribution. The findings aim to provide valuable insights for both academic researchers and practitioners, ultimately contributing to more informed investment practices in this pivotal emerging market. The dataset and trading strategy framework used in this study are all open-sourced at: [IamTinyman/Stocks \(github.com\)](https://github.com/IamTinyman/Stocks)

The structure of this paper is organized as follows: Chapter 2 describes the dataset, trading costs, and the process framework employed in the strategy development and backtesting experiments. Chapter 3 reviews the historical research on momentum strategies and idiosyncratic volatility factors, as well as the challenges associated with them. Chapter 4 introduces the primary methods used to develop the Stable Turnover Momentum strategy enhanced by idiosyncratic volatility. Chapter 5 presents the backtesting results and their analysis. Finally, Chapter 6 concludes the paper.

2. Datasets and Trading Framework

2.1. Datasets

Although the use of data from Bloomberg is common in the stock market literature, data for the Chinese stock market is not available. In this paper, we used a dataset provided by Winds, a vast and

accurate financial data platform. In this study, we retrieved the most recent history of the daily open-close prices, total market capitalization, and PE ratios for stocks traded in Shanghai Stock Exchange (SSE), Shenzhen Stock Exchange (SZSE) from June 3rd, 2019 to July 1st, 2024. In this paper, we choose CSI 300 index and CSI 1000 index as the datasets for strategy testing. The CSI 300 index includes 300 stocks with the largest market capitalization and best liquidity in China's A-share market, covering major industries and areas of the market. This makes the index a better proxy for the overall performance of large Chinese companies. The CSI 1000 index, which consists mainly of 1,000 smaller stocks, represents the market performance of small and medium-sized companies. This combination allows the pool of shares to cover a wide range of markets, from large to small and medium-sized companies. At the same time, the stocks of CSI 300 are more actively traded because of their large market value and strong liquidity, which is particularly important for high-frequency trading strategy testing or backtesting that requires frequent trading. Although China Securities 1000 includes small and medium-sized enterprises, it also ensures certain market liquidity and trading activity, making the backtest results more valuable for practical operation.

2.2. Market Neutralization

In the trading process described below and in the acquisition of data for trading backtesting experiments, all investment portfolios were subjected to market-neutral processing. The specific procedure is as follows: After calculating the Alpha values for all stocks in the stock pool, we rank them and select the top 10% and bottom 10% for investment consideration. Depending on their Alpha values, the top 10% are designated as either long or short positions, while the bottom 10% are assigned to the opposite side. The Alpha values within the selected long or short positions are then standardized, ensuring that the absolute sum of all adjusted Alpha values within each position equals 0.5. The weights of the standardized Alphas within the portfolio are managed in two ways: either by scaling according to their original Alpha values or by assigning equal weights to all stocks in the portfolio. This process ensures that the total investment amount for long and short positions is identical for each investment, thereby meeting the criteria for market neutrality.

$$\text{Sorted(Raw Alpha)} = \{\alpha_1, \alpha_2, \dots, \alpha_N\} \quad (\alpha_1 < \alpha_2 < \dots < \alpha_N) \quad (1)$$

$$k_1 = 0.10 \times N \quad k_2 = 0.90 \times N \quad (2)$$

$$\alpha_i = \begin{cases} \frac{\alpha_i}{2 \sum_{i=1}^{k_1} |\alpha_i|}, & \text{if } 1 \leq i \leq k_1 \\ 0, & \text{if } k_1 < i < k_2 \\ \frac{\alpha_i}{2 \sum_{i=k_2}^N |\alpha_i|}, & \text{if } k_2 \leq i \leq N \end{cases} \quad (3)$$

$$\alpha_i = \begin{cases} \frac{1}{2k_1}, & \text{if } 1 \leq i \leq k_1 \\ 0, & \text{if } k_1 < i < k_2 \\ \frac{1}{2(N - k_2)}, & \text{if } k_2 \leq i \leq N \end{cases} \quad (4)$$

Raw Alpha represents the initial Alpha value we calculated. In Formula (1), we rank all Alphas within the stock pool, where k_1 and k_2 in Formula (2) correspond to the positions of the top 10% and bottom 10% of the sorted Alpha sequence, respectively. Formulas (3) and (4) outline two approaches for managing the weights of the standardized Alphas within each portfolio. Formula (3) scales the

Alpha weights in the portfolio according to their original values, whereas Formula (4) assigns equal weights to all stocks in the portfolio.

2.3. Transaction Cost

Given the high trading frequency of this strategy (daily trading) and the broad scope of the selected stock pool, transaction costs are a critical factor to consider. The transaction cost structure established for this strategy is as follows:

Transaction Fee: 0.00341% (applied to both buy and sell transactions, calculated based on the total transaction value of each trade).

Stamp Duty for Sale: 0.1% (applied to the seller, calculated based on the total transaction value at the time of sale).

Bid-Ask Spread and Slippage Cost: Both of these costs are dynamically estimated for each trade based on daily stock price information and trading volume liquidity, and are applicable to both buy and sell transactions.

The Transaction Fee and Stamp Duty for Sale are statutory transaction fees regulated by the government and trading institutions in the Chinese A-share market.

Slippage cost refers to the difference between the actual execution price of a trade and the expected price. Factors such as high market volatility, low liquidity, or strict trading time constraints can all contribute to slippage. Similarly, the bid-ask spread represents the difference between the buying price and the selling price. When executing trades, discrepancies between the buying price, the selling price, and the real-time stock prices depicted on candlestick charts can be attributed to market volatility and liquidity conditions.

Roll's [5] covariance model derives the bid-ask spread by analyzing the trading direction (i.e., whether initiated by the buyer or seller) and the probability of price reversal. This model is a classic approach for estimating effective spreads using low-frequency price information. The bid-ask spread in this model is expressed as the arithmetic square root of the first-order autocovariance of stock returns: $S = 2\sqrt{-cov(\Delta p_t, \Delta p_{t-1})}$, where Δp_t represents the log return of the stock at time t . Although this method is straightforward and feasible, the positive correlation between returns can render it ineffective, presenting empirical challenges. Moreover, Roll's spread model is essentially a simple inventory handling cost model and does not explicitly indicate the relationship between bid-ask spreads and effective bid-ask spreads.

Corwin and Schultz [6] introduced a simple and practical method for estimating bid-ask spreads, known as the High-Low method, which is based on intraday price ranges. Through numerical simulations and empirical tests, they demonstrated that their High-Low spread model exhibits a higher correlation with basic relative effective spreads compared to Roll's model. This paper adopts Corwin and Schultz's method, and the estimation process proceeds as follows:

$$HLR = \frac{High}{Low} \quad (5)$$

$$\beta = \frac{\sum(\log(HLR))^2}{2(n-1)} \quad (6)$$

$$\gamma = \frac{\log(\prod HLR)}{n} \quad (7)$$

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} \quad (8)$$

$$\text{Spread} = 2(e^{\alpha} - 1) \quad (9)$$

The final spread obtained is a joint estimate of Slippage Cost and Bid-Ask Spread.

2.4. Trading Process

Our portfolio employs a daily trading strategy that excludes overnight information. The alpha for each trading day is calculated using prices from the final 5 minutes before market close. Portfolio rebalancing occurs just before the close, with positions closed during the last 5 minutes of the following trading day, and new positions established immediately based on the calculated alpha for the upcoming day, while maintaining a constant GMV (Gross Market Value).

For backtesting, we utilize a range of metrics, including annualized returns (long, short, and total), annualized volatility, maximum drawdown, win rate, and information ratio (IR). These metrics rigorously evaluate the investment strategies, aiming to provide a comprehensive assessment of their performance.

In the subsequent charts and data, total PNL includes all trading costs, whereas the long and short return portfolios do not account for these costs. Note that there may be differences compared to traditional calculation methods. The benchmark for maximum drawdown is GMV, which remains constant throughout.

3. Literature Review

A momentum strategy is a trading rule that involves buying past winners and selling past losers, with rankings derived from historical data. Conversely, a reversal (contrarian) strategy buys the worst performers and sells the best performers, also based on historical rankings. In their seminal study, Jegadeesh and Titman [1] document that momentum trading can generate excess returns in the US stock market, even when accounting for variations in the duration of the formation and holding periods. Subsequent studies, such as those by Asness, Moskowitz, and Pedersen [7], and Bianchi et al. [8], further support their conclusions.

In the momentum trading literature, commodities are often ranked based on their log-returns during the formation period, from highest to lowest (hereafter referred to as “winners,” “middle,” and “losers,” corresponding to the top, middle, and bottom terciles of historical performance). Portfolios are then constructed by taking long positions in the winners and short positions in the losers for momentum strategies, or the reverse for reversal strategies. However, the effectiveness of momentum strategies is largely contingent upon the stability of trends in the selected stocks. Momentum strategies tend to be more successful with stocks that exhibit relatively stable performance, as evidenced not only in their raw market returns but also after adjusting for market factors.

The stability of an individual stock can be assessed from various perspectives, including the stability of its price curve, trading volume, and other factors. Considerable research has been conducted in this area. For instance, Moskowitz and Grinblatt [9] found in their study of the US stock market that stocks with lower volatility and smoother price movements tend to perform better under momentum strategies. These stocks exhibit clear price trends, allowing market participants to more confidently rely on past price behavior to predict future movements. Furthermore, Grundy and Martin [10] discovered that momentum strategies perform better when price curves are smooth, as smooth price curves typically reflect stable market expectations and consistent fund inflows or outflows, thereby reducing the negative impact of price volatility on momentum strategies. Regarding trading volume, Lee and Swaminathan [11] found a significant relationship between changes in trading volume and future stock returns. Specifically, stocks with more stable trading volumes tend to exhibit more stable price trends, making it easier to generate sustained momentum effects.

Apart from market factors, the stability of individual stock trends is also influenced by specific characteristics of the stocks. Although research in this area is relatively limited, Jegadeesh and Titman [1] were among the first researchers to systematically record the momentum effect at the individual stock level. They emphasized that individual stock momentum is often related to company-specific fundamental factors, rather than just being driven by market fluctuations. They found that stocks that continue to exhibit strong momentum characteristics, even after removing market factors, often provide investors with higher excess returns. In the field of quantitative finance trading, there is a class of factors used to measure individual stock factors in the market environment: idiosyncratic factors.

Idiosyncratic factors refer to the part of a stock that cannot be explained by systematic risk factors. Stock volatility is often seen as a risk characteristic, with some of the volatility attributed to broader market factors, while the unexplained portion is classified as idiosyncratic volatility. Unlike the volatility that reflects all information, idiosyncratic volatility often reflects the impact of company-specific information or events on stock prices. The Fama-French three-factor model is a foundational framework in this research area. Ang, Hodrick, Xing, and Zhang [12] used U.S. stock data to measure idiosyncratic volatility by the standard deviation of residuals from the three-factor model. Their research results show a significant negative correlation between idiosyncratic volatility and cross-sectional expected returns. Additionally, Fu's [13] research also indicates that stocks with stable momentum, even after removing market volatility, tend to generate more significant excess returns.

In summary, the effectiveness of traditional momentum strategies largely depends on the stability of individual stocks. However, this stability is often difficult to assess through a one-dimensional price curve and typically requires a large amount of information, including market data, fundamental analysis, and price-volume dynamics, aspects that are often overlooked by traditional momentum strategies. The limitations of traditional momentum strategies in information processing can be summarized in the following three key areas.

3.1. Insufficient information on price curve evolution

Traditional momentum strategies typically only focus on the formation and holding periods. When constructing traditional momentum strategies, the input information of the strategy usually only includes price differences at the specified start and end of a time window, overlooking the evolution of price trajectories. This approach fails to fully utilize the curve trajectory information of prices, which is often crucial in actual trading scenarios.

3.2. Insufficient information on the price-volume relationship

Momentum strategies often focus solely on price differences or returns. In constructing these strategies, the input information is typically limited to price data, without considering trading volume. This approach neglects the significance of the price-volume relationship. Even among stocks with rising prices, subsequent price trends can vary significantly depending on whether trading volume is increasing or decreasing.

3.3. Insufficient information on individual stock characteristics

Insufficient information on individual stock characteristics Momentum strategies frequently focus only on the final price performance of individual stocks. The input information in traditional momentum strategies generally reflects only the final outcome after a stock has been influenced by both company-specific factors and broader market dynamics. However, the stability of a single stock is closely related to company-specific fundamentals, events, and information, rather than being solely driven by market fluctuations.

4. Methods

4.1. Overview

In the Literature Review section of Chapter 3, this paper identified three key shortcomings in the use of incoming information in traditional momentum strategies. This chapter will address each of these shortcomings in detail. The structure of this chapter is as follows:

Section 4.2 introduces the Stable Turnover Momentum, which optimizes traditional momentum strategies by incorporating a scaling factor. This approach specifically targets the first two shortcomings: the insufficient consideration of price curve evolution and the inadequate integration of the price-volume relationship.

Section 4.3 presents the Idiosyncratic Information Distribution, which extends the traditional concept of Idiosyncratic Volatility. By constructing a single Alpha factor based on Idiosyncratic Volatility, this method assesses the proportion of stock-specific information in the market and confirms the negative relationship between Idiosyncratic Volatility and returns.

In Section 4.4, the Idiosyncratic Information Distribution is employed to refine the stock selection process. By constructing multi-factor investment portfolios, the Stable Turnover Momentum strategy from Section 4.2 is further optimized, effectively addressing the third shortcoming of traditional momentum strategies.

4.2. Stable Turnover Momentum Alpha

To address the first limitation, we propose the novel Stable Momentum Alpha, underpinned by the following economic rational:

By capitalizing on the disposition effect and investors' tendency to overlook consistent small gains, we select stocks that exhibit relatively higher returns with steady, incremental increases to generate profits. Short-term investors often favor stocks with larger price jumps and higher volatility for quick gains, leading to the frequent undervaluation of stocks with smaller, more stable price increases. If investors demonstrate delayed reactions to such information, this indicates market inefficiency. Exploiting this inefficiency aligns with Eugene Fama's Efficient Market Hypothesis, thereby opening avenues for arbitrage opportunities.

The construction process of the proposed Alpha is as follows: This alpha consists of three factors: one primary factor and two scaling factors. The primary factor driving the alpha is the 20 days' return factor (Formula (10)). The other two factors are the Win Rate Deviation (WRD) factor (Formula (11)) and the Return Stability (RS) factor (Formula (12 - 14)).

4.2.1. Win Rate Deviation (WRD)Factor

This factor primarily measures the stability of a stock's win rate. If a stock has consistently risen or fallen within a specific historical timeframe, this scaling factor will have a higher value. Conversely, if the stock has shown mixed performance in the past, the value of this factor will be lower. The final raw alpha is derived by multiplying these three factors together.

4.2.2. Return Stability (RS)Factor

This factor assesses the stability of a stock's price. Significant price changes within a specific historical timeframe leading to a higher value for this scaling factor, while minimal price fluctuations over the same period yield a lower value.

$$Return_{20} = \frac{p_t - p_{t-20}}{p_{t-20}} \quad (10)$$

$$WRD_{20} = |2 \cdot WR_{20} - 1| \quad (11)$$

$$AR_{20} = \frac{1}{20} \sum R_t \quad (12)$$

$$MDR_{20} = \max[|R_t|] \quad (13)$$

$$RS_{20} = \frac{1}{|AR_{20}| + MDR_{20}} \quad (14)$$

$$SM_{20} = Return_{20} \cdot WRD \cdot RS_{20} \quad (15)$$

P_t represents the price at a specific time t , while R_t denotes the daily return at that time. WR stands for Win Rate, representing the winning/losing rate of the stock over the previous period. AR stands for Average Return, indicating the average daily return of the stock during the same period. MDR represents Max Daily Return, which is the maximum daily return of the stock in that period. The resulting SM is the Stable Momentum, an Alpha value obtained by multiplying several factors, with the subscript “20” indicating a formation period of 20 trading days.

To address the second limitation, we propose an optimization to the novel Stable Momentum Alpha as follows:

Stocks that have exhibited positive returns in the recent past, particularly those with low turnover rates, are more likely to sustain their upward trajectory. As a result, the combination of low turnover and stable trading may yield a superior weighted portfolio. Building on this premise, stocks with low and stable turnover rates are more likely to exhibit momentum consistent with historical trends. Since the primary objective of the original Alpha is to identify stocks exhibiting stable growth or decline, incorporating this scaling factor can enhance the performance of stocks with low and stable turnover rates in the long position portfolio. Similarly, for short positions, a low and stable turnover rate suggests a more consistent downward trend. Therefore, this scaling factor can be employed to reinforce the stability of the original Alpha, thereby reducing its return volatility.

$$ATR_{20} = \frac{1}{20} \sum_{i=1}^{20} TR_i \quad (16)$$

$$TR_vol_{20} = \text{std}(TR_{20}) \quad (17)$$

$$TS_{20} = \frac{1}{e^{(ATR_{20} + TR_vol_{20})}} \quad (18)$$

$$STM_{20} = Return_{20} \cdot WRD_{20} \cdot RS_{20} \cdot TS_{20} \quad (19)$$

TR denotes the Turnover Rate, ATR denotes the Average Turnover Rate, std represents the standard deviation, and TS stands for Turnover Stability, with the subscript 20 indicating that a 20-day time window is used for calculating these factors. STM denotes Stable Turnover Momentum, with

$Return_{20}$, WRD_{20} RS_{20} being the factor in formula (15)

After obtaining the original Alpha values, we neutralize them using formulas (1)(2)(3) from Section 2.2, selecting the top 10% of Alpha values to construct long positions and the bottom 10% to construct short positions. The weights of each alpha within each portfolio are determined by the weights of the original Alpha values.

4.3. Idiosyncratic Information Distribution

4.3.1. Alpha Construction

Idiosyncratic volatility, defined as the volatility of the residuals, represents the component of stock return volatility after removing market factors. We hypothesize that it is closely tied to the overall volatility of stock returns. Specifically, the total volatility of a stock's returns can be decomposed into market volatility and idiosyncratic volatility. In the dataset we collected, this hypothesis is supported by the high average correlation coefficient of 0.88 observed between idiosyncratic volatility and overall return volatility across the entire stock universe.

Ross [15] and Andersen [16] demonstrated through theoretical and empirical research that stock price volatility is directly linked to the flow of information into the stock. Ross's theoretical model further posits that in an arbitrage-free equilibrium market, stock price volatility should precisely equal the volatility of information flow. The uniformity of information distribution in the stock market significantly influences investor trading behavior and, consequently, the responsiveness of stock prices to information. Due to the uneven distribution of information, certain stocks may exhibit higher idiosyncratic volatility.

Building on these insights, we introduce the idiosyncratic volatility-to-return volatility ratio as a novel alpha factor. We employed the Fama-French three-factor model to construct a linear regression framework (Formula (20)), from which we extracted the idiosyncratic volatility. (Formula (21)) The Alpha factor is derived by dividing idiosyncratic volatility by total return volatility (Formula (22))

$$r(i, t) = \alpha(i, t) + \beta(i, t) \cdot MKT_t + \eta(i, t) \cdot SMB_t + \lambda(i, t) \cdot HML_t + \varepsilon(i, t) \quad (20)$$

$$IV_{20} = \text{std}(\varepsilon(i, t)) \quad (21)$$

$$IID_{20} = \frac{IV_{20}}{Vol_{20}} \quad (22)$$

MKT denotes the market risk premium, defined as the difference between the return of the market portfolio and the risk-free rate. In this context, MKT is computed by weighting the returns of individual stocks based on their market capitalization. SMB captures the return differential between small-cap and large-cap stocks, where the stocks are divided according to market capitalization in a 1:1 ratio. HML represents the return differential between stocks with high and low book-to-market ratios, categorized using a 3:4:3 distribution based on their book-to-market values. $\varepsilon(i, t)$ denotes the residual. IV stands for Idiosyncratic Volatility, while IID refers to Idiosyncratic Information Distribution. The subscript 20 indicates that a 20-trading-day time window is used in the construction of the linear regression model.

A higher Alpha value indicates that a greater proportion of idiosyncratic information is present in the stock, making it more influenced by its own fundamentals or specific events. This suggests that the stock's price changes are driven more by internal factors rather than broader market movements. Additionally, this Alpha can be used as a standalone trading strategy, as there is a documented negative correlation between idiosyncratic volatility and returns. By normalizing idiosyncratic volatility through its ratio to total return volatility, we achieve a form of standardization, where exceptionally high or low ratios may signal potential market mispricing. Arbitrageurs can capitalize on this by hedging positions between stocks with high and low idiosyncratic volatility, potentially securing arbitrage profits with greater stability than using idiosyncratic volatility alone as an Alpha factor.

When applying the idiosyncratic volatility factor and Idiosyncratic Information Distribution in a single-factor trading strategy, we neutralize them using formulas (1), (2), and (4) from Section 2.2 to confirm the negative correlation between idiosyncratic volatility and returns. We then select the top

10% of Alpha values to construct short positions and the bottom 10% to construct long positions, with each portfolio's Alpha weights being equally distributed.

4.3.2. Single Alpha Performance

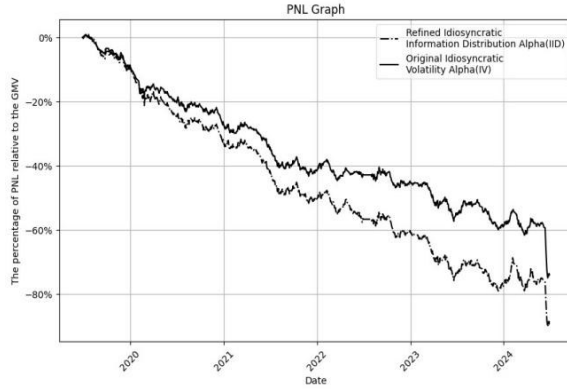


Figure 1: Pnl on IV & IID Alpha

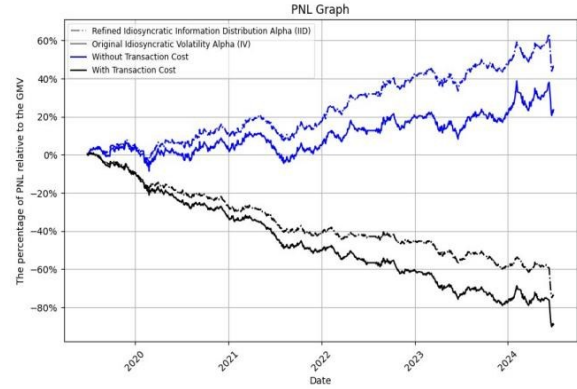


Figure 2: Pnl on IID Alpha (Transaction Cost)

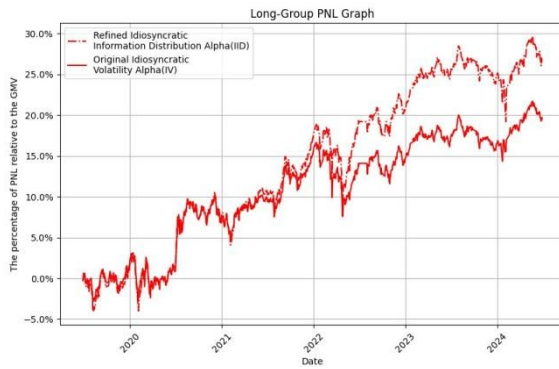


Figure 3: Long-Group Pnl on IV & IID alpha

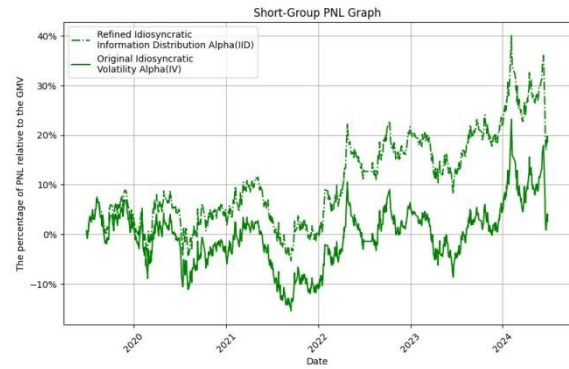


Figure 4: Short-Group Pnl on IV & IID alpha

Table 1: IV & IID Alpha Statistics

	Version	Annual Return	Long Return	Short Return	Volatility	Max Drawdown	IR	Win Rate
2019-2020	Idiosyncratic Volatility Idiosyncratic Information Distribution	-26.41%	6.53%	-9.69%	7.50%	27.25%	-3.52	48.41%
		-21.12%	7.09%	-3.15%	6.54%	21.96%	-3.23	50.40%
2020-2021	Idiosyncratic Volatility Idiosyncratic Information Distribution	-20.17%	2.16%	-0.99%	7.46%	21.41%	-2.70	46.43%
		-17.11%	2.85%	2.79%	6.79%	18.32%	-2.52	49.21%
2021-2022	Idiosyncratic Volatility Idiosyncratic Information Distribution	-10.73%	3.48%	10.92%	7.68%	12.45%	-1.40 -	47.62%
		-4.72%	7.49%	15.26%	7.06%	7.39%	0.67	50.79%
2022-2023	Idiosyncratic Volatility Idiosyncratic Information Distribution	-14.13%	4.73%	1.60%	8.60%	21.58%	-1.64 -	50.40%
		-9.48%	8.01%	4.42%	7.96%	16.81%	1.19	53.17%
2023-2024	Idiosyncratic Volatility Idiosyncratic Information Distribution	-23.52%	1.66%	1.30%	12.84%	21.52%	-1.83 -	53.17%
		-27.86%	0.05%	-0.29%	11.85%	24.40%	2.35	55.61%
Annualized	Idiosyncratic Volatility Idiosyncratic Information Distribution	-18.49%	4.08%	0.82%	8.88%	91.35%	-2.08 -	49.05%
		-15.37%	5.54%	4.10%	8.13%	75.89%	1.89	51.69%

Figures 1-4 display the performance of Idiosyncratic Volatility (IV) (Formula (21)) and Idiosyncratic Information Distribution (IID) (Formula (22)) across various metrics, including total PnL, PnL without transaction costs, and the performance of long-short portfolios from July 3, 2019, to July 1, 2024. Table 1 provides the corresponding statistical data.

The data in Table 1 segmented by year ranges from July 1st of the current year to July 1st of the following year.

The calculation of Annual Return, Volatility, Max Drawdown and IR accounts for transaction costs, but the calculation of Long Return, Short Return, and Win Rate did not account for transaction costs. Additionally, the PNL curves in Figure 3 and Figure 4 were also calculated without considering transaction costs.

An analysis of the PnL curves shows that the shapes of the total PnL curve and the long-short curve before and after optimization are nearly identical. This suggests that the optimization process did not alter the underlying stock selection logic based on idiosyncratic volatility. Instead, it focused on further refining the selection and enhancing the returns of individual stocks to better capture the idiosyncratic volatility effect.

The data indicate that, for most of the period, IID outperforms IV in terms of annualized return, volatility, and drawdown. The most significant increase in annualized return was observed during the 2020-2021, with a notable rise of 5.99%. Although IID experienced a decline in returns during the Year 5, the win rate remained strong, surpassing 55%. These observations suggest that incorporating idiosyncratic volatility as a factor in the portfolio construction process may contribute to enhancing the stability of stock selection based on specific factors, reducing the potential high volatility associated with idiosyncratic factor-based selection, and potentially intensifying the unique characteristics of the idiosyncratic volatility factor.

However, while both the IV and IID single-factor strategies generate positive gross returns when excluding trading costs, their profits are insufficient to offset daily transaction costs. As a result, despite their positive correlation with market performance, strategies based solely on IV or IID factors cannot be effectively employed as viable strategies under high transaction cost conditions in daily trading.

4.4. Stable Turnover Momentum Enhanced by Idiosyncratic Volatility

To address the third limitation, we propose an innovative approach that optimizes the Stable Turnover Momentum strategy using IID information.

The stability of individual stock trends is influenced not only by market factors but also by stock-specific characteristics. Jegadeesh and Titman [1] were the first to systematically document the existence of the momentum effect in their seminal study, indicating that momentum at the individual stock level is often linked to company-specific fundamental factors rather than being solely driven by market fluctuations. Fu [13] supports this view, suggesting that stocks demonstrating stable momentum after eliminating market volatility often continue to generate significant excess returns. The effectiveness of momentum strategies largely depends on the trait effects of selected stocks, particularly those that continue to exhibit momentum characteristics after adjusting for market factors. This stability reflects the intrinsic characteristics of the stocks, rather than overall market volatility, and plays a crucial role in the success of momentum strategies.

Based on these insights, we propose that if stock selection based on momentum can effectively filter out market factors, the momentum effect may be enhanced. Therefore, by leveraging idiosyncratic volatility to enhance Stable Momentum Alpha, we hypothesize that if a stock's idiosyncratic volatility significantly impacts its return volatility, it can be considered to possess strong intrinsic characteristics and be less influenced by the market, thereby leading to a stronger momentum effect.

With this framework in mind, we construct the following investment portfolio:

Among all stocks in the stock pool, we first calculate the Idiosyncratic Volatility Index (IID) for each stock using Formulas (20)-(22), then select the top 10% with the highest IID as the new stock pool. Within this refined stock pool, we apply formulas (10)-(19) to construct the STM Alpha

investment portfolio. After obtaining the original Alpha values, we neutralize them using formulas (1)(2)(3) from Section 2.2, selecting the top 10% of Alpha values to construct long positions and the bottom 10% to construct short positions. The weights of each alpha within each portfolio are determined by the weights of the original Alpha values.

We name this investment strategy “STM-IV” (Stable Turnover Momentum Enhanced by Idiosyncratic Volatility.)

5. Results and Analysis

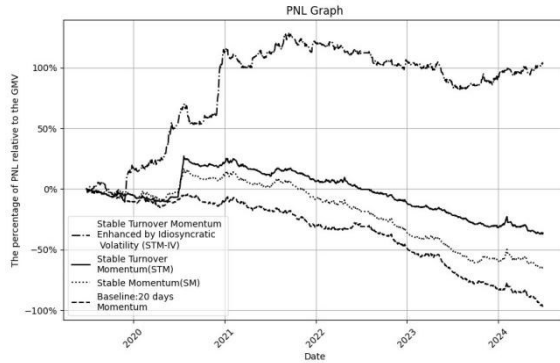


Figure 5: Pnl on Baseline & SM & STM & STM-IV Alpha

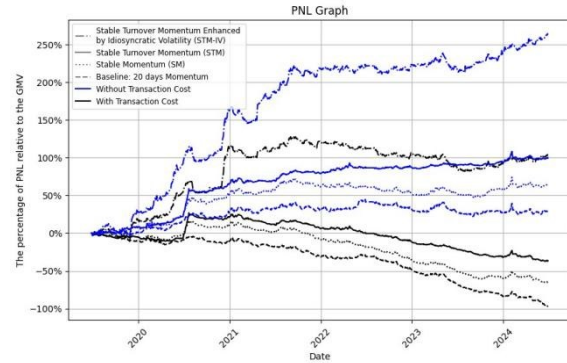


Figure 6: Pnl on Baseline & SM & STM & STM-IV Alpha (Transaction Cost)

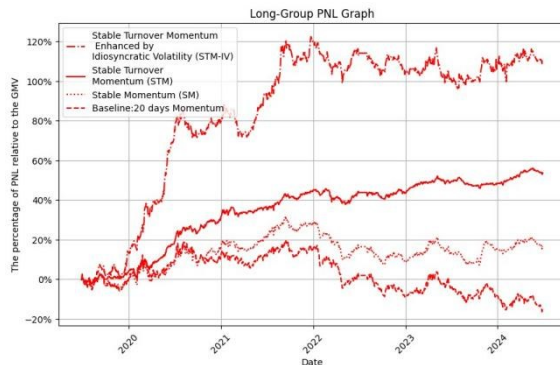


Figure 7: Long-Group Pnl on Baseline & SM & STM & STM-IV Alpha

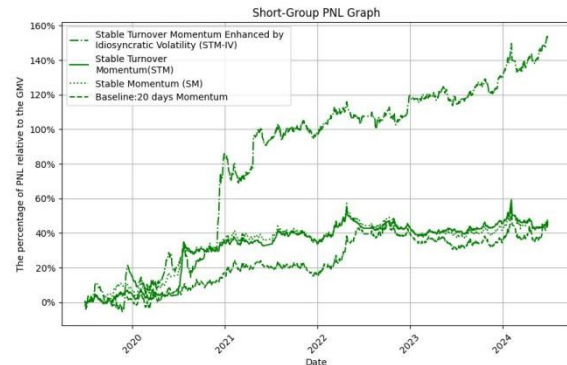


Figure 8: Short-Group Pnl on Baseline & SM & STM & STM-IV Alpha

Figures 5-8 present the total PnL performance, PnL without transaction costs, and the performance of long-short portfolios for the momentum strategies from July 3, 2019, to July 1, 2024. The strategies include Baseline, which represents the traditional momentum strategy (Formula (10)); SM, which addresses the first shortcoming (Formula (15)); STM, which tackles the first two shortcomings (Formula (19)); and STM-IV, the final optimized investment portfolio strategy that addresses all three limitations. The corresponding statistical data are provided in Table 2.

The data in Table 2 segmented by year ranges from July 1st of the current year to July 1st of the following year.

The calculation of Annual Return, Volatility, Max Drawdown and IR accounts for transaction costs, but the calculation of Long Return, Short Return, and Win Rate did not account for transaction costs. Additionally, the PNL curves in Figure 7 and Figure 8 were also calculated without considering transaction costs.

By analyzing the overall PnL curve and the long and short PnL curves of the baseline and the Stable Momentum (SM) strategy, we found that the shapes of the long and short positions in SM are largely similar to the baseline. This similarity indicates that introducing the price curve stability factor did not change the fundamental stock selection logic of the original momentum strategy. Statistical analysis shows that the improvement of SM relative to the baseline is mainly due to the increase in short positions. This improvement suggests that in certain market stages, such as in 2020 possibly due to the impact of the COVID-19 pandemic, some stocks experienced sharp short-term declines followed by reversals. The introduction of the price stability factor effectively reduced the weight of these stocks in the strategy, thereby mitigating their negative impact.

Table 2: Baseline & SM & STM & STM-IV Alpha Statistics

	Version	Annual Return	Long Return	Short Return	Volatility	Max Drawdown	IR	Win Rate
2019-2020	Baseline	-6.75%	17.23%	3.79%	7.04%	15.47%	-0.96	52.38%
	SM	7.05%	14.16%	21.01%	8.58%	9.58%	0.82	61.90%
	STM	8.14%	23.44%	15.28%	8.16%	10.61%	1.00	61.11%
	STM-IV	67.09%	82.60%	27.26%	19.79%	16.52%	3.39	60.71%
2020-2021	Baseline	-11.66%	-1.64%	15.07%	8.47%	14.78%	-1.38	52.78%
	SM	-2.97%	10.42%	17.64%	10.01%	15.96%	-0.30	56.75%
	STM	3.27%	12.44%	20.04%	10.53%	16.52%	0.31	57.54%
	STM-IV	51.75%	15.01%	73.20%	21.03%	17.12%	2.46	52.78%
2021-2022	Baseline	-15.13%	-16.24%	19.61%	9.14%	18.27%	-1.65	48.02%
	SM	-26.62%	-12.05%	4.24%	9.36%	28.26%	-2.84	47.22%
	STM	-16.65%	4.92%	4.78%	8.02%	18.41%	-2.08	46.03%
	STM-IV	-7.45%	12.79%	8.86%	15.70%	18.40%	-0.47	47.62%
2022-2023	Baseline	-40.91%	-8.67%	-5.36%	8.57%	42.78%	-4.77	43.25%
	SM	-34.70%	-2.88%	-4.88%	8.03%	36.23%	-4.32	49.60%
	STM	-23.24%	6.91%	-1.53%	6.18%	24.13%	-3.76	53.17%
	STM-IV	-27.25%	-10.36%	11.07%	14.45%	28.79%	-1.89	51.59%
2023-2024	Baseline	-27.55%	-7.14%	13.24%	9.30%	23.09%	-2.96	53.17%
	SM	-11.15%	7.65%	9.41%	9.46%	15.49%	-1.18	55.12%
	STM	-14.53%	5.51%	5.37%	8.19%	14.37%	-1.77	60.00%
	STM-IV	26.89%	13.67%	42.91%	14.24%	9.39%	1.89	57.07%
Annualized	Baseline	-19.98%	-3.18%	9.43%	8.52%	96.92%	-2.34	49.79%
	SM	-13.39%	3.43%	9.91%	9.14%	82.21%	-1.47	54.08%
	STM	-7.58%	11.16%	9.62%	8.37%	64.34%	-0.91	55.40%
	STM-IV	21.63%	22.95%	32.00%	17.53%	46.25%	1.23	53.83%

The long position performance in STM surpasses that of both SM and Baseline. This aligns with the economic principle discussed in Section 4.2. However, the performance of short positions in 2023-2024 did not maintain the returns observed in SM. In fact, both SM and STM underperformed the Baseline in short positions during this period. This outcome suggests that while the turnover stability factor allows STM to more effectively capture stable price growth and trading volume, it did not enhance short position returns as effectively. However, during periods of broader market declines—such as in 2023-2024 in the A-share market—stocks with higher trading volumes were more likely to continue their downward trajectory, meaning that shorting low turnover, stable-declining stocks may have reduced the strategy's performance. Statistical analysis shows that STM significantly outperforms SM in terms of increased annualized returns, reduced maximum drawdown, and lowered

volatility. This suggests that the turnover stability factor enhances the information ratio within the strategy, thereby improving its overall stability compared to SM and the Baseline.

Similar to the IV and IID strategies, although Baseline, SM, and STM all generated positive gross returns when excluding trading costs, their profits were insufficient to offset the high daily trading costs. Therefore, despite their positive correlation with market performance, these momentum strategies, even with partial enhancements, cannot be effectively deployed under daily trading conditions with high transaction costs. However, STM-IV not only covers these costs but also achieves an impressive annualized return rate of 21.63%.

Further analysis of the long and short PnL curves reveals that during periods of stability in the original STM (e.g., long positions in 2021-2022 and short positions in 2021 and 2023-2024), the enhanced STM-IV exhibits higher volatility and returns. This suggests that individual stock performance is increasingly driven by market conditions during these phases, with higher market beta and less pronounced momentum effects. In volatile market conditions, stocks exhibiting strong idiosyncratic characteristics tend to display more stable price trends. STM-IV's distinct stock selection logic enables it to effectively identify stocks with intrinsic momentum.

To verify this conjecture, we conducted an in-depth analysis. We selected individual stocks from January to June 2020, a period characterized by strong long position performance, and December 2020, which saw strong short position performance from the STM-IV multi-head portfolio. Given the longer time horizon for long positions, we selected the top 20 stocks with the highest long returns during this period. For short positions, we selected the top 3 stocks with the highest short returns. For each stock, we calculated its STM Alpha value, STM-IV Alpha value, average Idiosyncratic Information Distribution (IID) value, and the IID value for all stocks during the corresponding period.

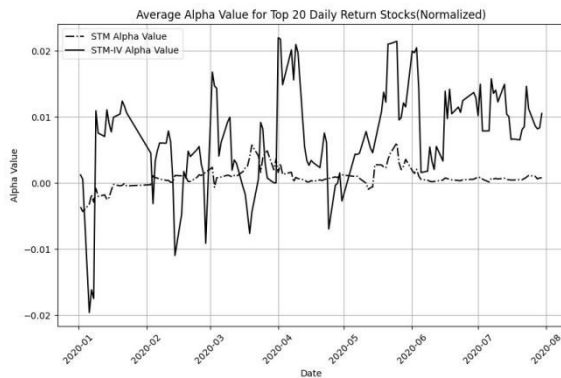


Figure 9: Average Alpha Value for Top 20 Daily Return Stocks (Normalized)

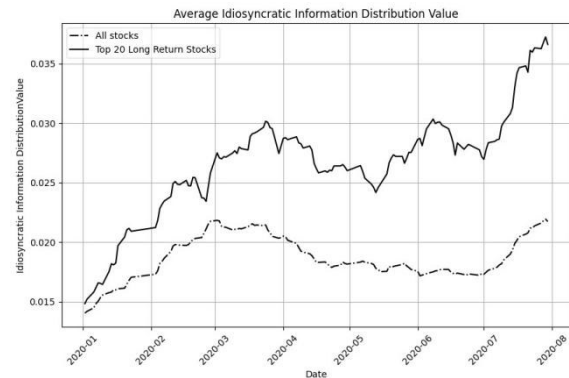


Figure 10: Average Idiosyncratic Information Distribution Value

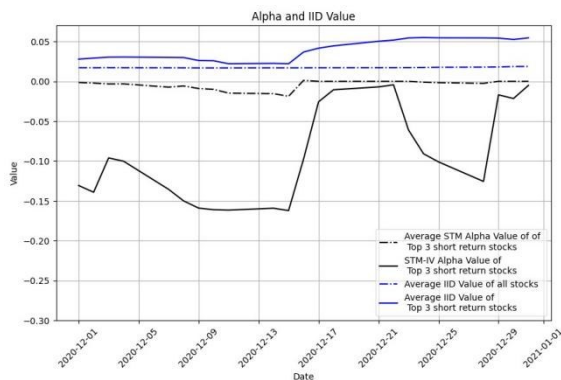


Figure 11: Alpha and IID Value



Figure 12: Price for Top 3 Short Return Stocks

Figure 9 presents the STM and STM-IV Alpha values for the top 20 stocks with the highest long returns under the STM-IV strategy during the first half of 2020. Figure 10 compares the average IID values for these 20 stocks with the average IID values for all stocks in the stock pool over the same period.

Figure 11 shows the STM and STM-IV Alpha values for the top 3 stocks with the highest short returns under the STM-IV strategy in December 2020, along with the average IID values for these 3 stocks and the overall stock pool during that time. Figure 12 illustrates the price movements of these 3 stocks throughout the period.

For both groups of stocks, the average IID value is significantly higher than the overall average for all stocks (as shown in Figures 10 and 11). This result provides support for our conjecture, and the price trend analysis of the top 3 stocks with the highest short returns (Figure 12) indicates that these stocks exhibit strong downward momentum, which the STM-IV strategy effectively captures and filters.

In conclusion, incorporating idiosyncratic information into momentum strategies and enhancing them with idiosyncratic volatility can significantly amplify their effectiveness. This approach can greatly enhance returns, especially after addressing the initial limitations of momentum strategies. However, due to our focus on stocks with strong idiosyncratic characteristics, this strategy exhibits higher volatility. Over the five-year period, the annualized volatility of STM-IV is even higher than that of the original STM strategy.

6. Conclusion

In this study, we investigated and optimized a traditional Alpha strategy—the Momentum strategy—within the context of the China A-share market. We introduced factors such as price curve stability, turnover rate stability, and idiosyncratic information distribution to address three key challenges associated with traditional momentum factors. Additionally, we validated and optimized idiosyncratic volatility as a standalone Alpha strategy, which exhibits a negative correlation with returns.

The final strategy proposed, Stable Turnover Momentum Enhanced by Idiosyncratic Volatility (STM-IV), was designed to overcome the limitations of traditional momentum strategies, particularly in terms of inadequate information utilization and strategy instability. By integrating factors such as win rate deviation and price change stability, we enhanced the overall effectiveness of the momentum strategy. The strategy was further stabilized by optimizing turnover rate stability, which reduced return volatility and maximum drawdown. Leveraging idiosyncratic information distribution amplified the strategy's return performance, significantly boosting its annualized return. Backtesting results suggest that the STM-IV strategy has the potential for sustained outperformance in the China A-share market, especially in daily trading with high transaction costs.

Moreover, our findings indicate that stock price momentum effects are more strongly influenced by individual characteristics—such as company fundamentals, specific corporate information, and events—than by broader market factors. This influence is particularly evident in stable momentum effects, which can amplify both positive and negative returns, albeit at the cost of increased volatility. These insights will assist investors in making more informed decisions about whether to incorporate idiosyncratic volatility information into their strategies, helping them to balance risk and return and ultimately construct more effective investment portfolios.

Additionally, our analysis of the final results and underlying data confirms the close relationship between stock momentum effects and idiosyncratic attributes. This also sets the direction for future research: building on the conclusions of this study, we plan to explore the deeper, more fundamental relationship between stock momentum effects and idiosyncratic attributes, further reducing the strategy volatility introduced by idiosyncratic information and thereby constructing more stable and effective strategies.

Acknowledgement

Jichen Zhang and Ziqing Chen contributed equally to this work and should be considered co-first authors.

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