Introduction to Basic Fundamental Alpha Factors

Definition of Alpha Factors

Alpha factors are quantitative metrics used in investment strategies to predict the future performance of assets relative to a market benchmark. These factors can be based on various attributes, including fundamentals, technical indicators, sentiment, and more. The primary goal of alpha factors is to identify opportunities where the market price deviates from an asset's intrinsic value, allowing investors to generate excess returns, or "alpha."

Background

In 2016, cyclical stocks surged, leading to a significant shift in market style. This change affected the relative strengths of various alpha factors. While the continued strength of cyclical stocks remains uncertain, several trends—such as increased IPO activity, tighter market regulation, and the expansion of quantitative products in the Chinese A-shares market—suggest that traditional small-cap and technically biased low-liquidity alpha factors may weaken. Conversely, valuation and profitability-based fundamental factors are likely to become more influential as the market matures.

Despite these trends, many investors doubt the effectiveness of fundamental factors in the Chinese stock market, with concerns about a potentially weakened correlation between price data and fundamentals. This project aims to find out whether these doubts are justified by quantitatively assessing the performance of fundamental alpha factors.

To understand the efficacy of fundamental alpha factors, I took 24 fundamental alpha factors from seven categories and tested their performance over the period from 2015 to 2024. This timeframe roughly corresponds to when China began to import quantitative trading practices. The focus on this period allows us to assess how these fundamental factors perform in a developing market like China’s A-shares as it integrates more sophisticated trading strategies. The analysis underscores the importance of profitability, valuation, and growth factors, which are expected to become more significant as the market matures.

Overview of Chinese-A-Share market(with comparison to US stocks market)

Historical Context

Before the Great Depression in 1929, individual retail investors dominated the US stock market, holding over 85% of market value. This led to rampant speculation. However, with enhanced financial regulation, the rise of asset management institutions, and the continuous development of derivatives markets, market competition intensified and market efficiency improved.

In comparison, the Chinese A-shares market shows significant differences:

Institutional Investors' Dominance:

As of 2021, institutional investors held 90% of the market value in the US, whereas in the Chinese A-shares market, institutional investors only controlled 18.7% of the market value.

Turnover Rate:

The overall turnover rate in the US market is relatively low, with a turnover ratio of approximately 68.43% as of 2019. In contrast, the Chinese A-shares market experienced an annual turnover rate of about 166.43% in 2022, largely due to speculative activities driven by the rise of small-cap growth stocks.

Listing and Delisting Mechanism:

The US market has a well-established mechanism for listing and delisting companies. Data shows that the number of companies listed and delisted annually is comparable, creating a dynamic market entry and exit environment. Conversely, the Chinese A-shares market primarily sees an influx of new listings without corresponding delistings, occasionally pausing IPOs, which strengthens the scarcity of quality small-cap stocks and the shell value of poor-quality stocks.

Market Cycles and Volatility:

The US stock market has longer bull markets and shorter bear markets with relatively lower volatility. For instance, the current bull market has lasted eight years post-financial crisis, and the previous bull market lasted five years from the 2002 dot-com bubble burst to the 2007 financial crisis. In contrast, the longest bull market in the Chinese A-shares market lasted just over two years, with bear markets averaging twice the duration of bull markets. The annualized volatility of the S&P 500 is around 20%, while the Chinese A-shares market experiences about 30% volatility, indicating more frequent and severe price swings.

Comparative Analysis

These differences highlight unique characteristics in each market. In the US, the dominance of institutional investors, lower turnover rates, effective listing and delisting mechanisms, and relatively stable market cycles contribute to an environment where fundamental factors such as profitability, valuation, and growth metrics are highly effective in predicting stock performance.

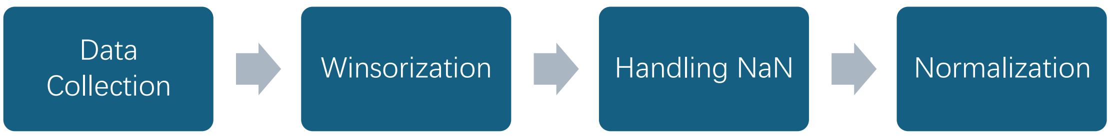
However, in the Chinese A-shares market, the prevalence of retail investors, higher turnover rates, less efficient listing and delisting processes, and more volatile market cycles raise questions about the effectiveness of fundamental factors. Many investors doubt that these factors, which are fundamental in nature, will prove as effective due to a potentially weakened correlation between price data and underlying fundamentals.

Objective of the Project

This project aims to investigate whether fundamental factors including profitability, valuation, and growth metrics are indeed effective in the Chinese A-shares market. By quantitatively assessing these factors from 2015 to 2024—a period that corresponds with the increasing adoption of quantitative trading in China—this research seeks to provide insights into whether these fundamental factors can be applied successfully in the Chinese market despite the differences highlighted above.

1.Testing Single Fundamental Alpha:

Data Processing Procedure



Constituent Stocks(winsorization):

The CSI All Share Index excludes stocks that have been listed for less than a quarter (unless their average daily market capitalization since listing ranks in the top 30 in the A-shares market). Additionally, it excludes stocks that are ST, *ST, or have suspended listings.

Normalization and Transformation:

We apply logarithmic or reciprocal transformations to several factors, including SP, Sales2EV, turnover rate, ILLIQ, and market capitalization. These transformations may cause the IC (Information Coefficient) signs for some factors to change.

Missing Values:

In this report, missing values are handled using the forward filling method.

2.Evaluate Single Alpha Trading Logic

In this methodology, we use the z-score of factors to analyze their effectiveness in predicting future stock returns. The steps involved are as follows:

Calculate Z-Scores:

For each period, compute the z-score for each factor across the cross-section of stocks.

Spearman Correlation:

Compute the Spearman rank correlation coefficient between the z-scores of the factors and the subsequent period's stock returns. The Spearman correlation measures the strength and direction of the association between two ranked variables.

Information Coefficient (IC):

Average the Spearman correlation coefficients across multiple periods to obtain the mean Information Coefficient (IC) for each factor. The IC reflects the predictive power of the factor:

If IC>0, the factor is positively correlated with future returns, and stocks are ranked in descending order of the factor values.

IC<0, the factor is negatively correlated with future returns, and stocks are ranked in ascending order of the factor values.

Stock Selection:

Based on the z-score rankings, create portfolios:

Top 10% Minus Bottom 10% Long-Short Portfolio: Go long on the top 10% of stocks and short the bottom 10%.

Long-Only Portfolio: Go long on the top 10% of stocks.

2.Performance Evaluation:

Assess the effectiveness of each factor by analyzing the performance metrics of the constructed portfolios:

PnL (Profit and Loss)

Definition: The daily gain or loss of the portfolio, representing the net change in value from one day to the next.

Long PnL

Definition: The profit or loss from long positions, where securities are bought with the expectation that their prices will rise.

Short PnL

Definition: The profit or loss from short positions, where securities are sold with the expectation of repurchasing them at a lower price.

Cumulative Long PnL

Definition: The total profit or loss from long positions accumulated over time.

Cumulative Short PnL

Definition: The total profit or loss from short positions accumulated over time.

Excess Return

Definition: The return of the portfolio relative to a benchmark, typically the average return of the overall market.

Turnover Ratio

Definition: The frequency at which the assets in the portfolio are traded.

Cumulative IC (Information Coefficient)

Definition: The cumulative sum of the Information Coefficient, which measures the correlation between predicted and actual returns.

IC Monotonicity Distribution Among Groups

Definition: The distribution of IC values across different quantiles or groups.

Size Exposure and Industry Exposure

Definition: The exposure of the portfolio to different market capitalizations and industry sectors.

Sharpe Ratio

Definition: Measures the risk-adjusted return of the portfolio.

Maximum Drawdown

Definition: The largest peak-to-trough decline in the portfolio's value.

Factor Definition and Explanation:

	Factor_Name	Explanation
VALUE	• BP_LF	• Newest Book Value/Market Cap
	• EP_TTM	• TTM Earnings/Market Cap
	• SP_TTM	• TTM Sales/Market Cap
	• CFP_TTM	• TTM Operating Cash Flow/Market Cap
	• EBIT2EV	• EBIT/Enterprise Value
	• SALES2EV	• TTM Sales / (Market Cap + Latest Financial Report Total Non-current Liabilities - Latest Financial Report Cash)
PROFIT	• ROA	• Return on Assets
	• ROE	• Return on Equity
	• GrossMargin	• Gross Profit Margin
GROWTH	• SalesGrowth_Qr_YOY	• Quarterly Year-over-Year Sales Growth
	• ProfitGrowth_Qr_YOY	• Quarterly Year-over-Year Profit Growth
	• OCFGrowth_YOY	• Year-over-Year Operating Cash Flow Growth
OPERATION	• AssetTurnover	• Asset Turnover
	• Debt2Asset	• Debt to Asset Ratio
LIQUIDITY	• TO_1M	• 1-Month Average Daily Turnover Rate Calculated with Circulating Shares
	• ILLIQ	• Price Impact of Trading One Billion RMB Daily
	• AmountAvg_1M_3M	• Average Daily Trading Volume over the Past Month / Average Daily Trading Volume over the Past Three Months
TECH&REVERSE	• Ret1M	• 1-Month Return Reversal
	• Momentumlast6M	• Adjusted Closing Price / Adjusted Closing Price from 6 Months Ago - 1
	• Momentumave1M	• Price Increase Compared to the Recent 1-Month Average Price
	• PPReversal	• Ping Pong Reversal Factor
	• CGO_3M	• Capital Gains Overhang (3 Months)
OTHER	• RealizedVolatility_3M	• Standard Deviation of Daily Returns Over the Past Three Months
	• MaxRet	• Maximum Daily Return of the Last Month

Factor Performance:

	Factor_Name	Annual Return	IC	IC_IR	Sharpe Ratio	Maximum Retreat	Factor Stability	TvrRatio
VALUE	BP_LF	-0.089	-0.0195		-0.928	0.118	0.9588	0.0877
	EP_TTM	-0.108	-0.0016		-1.011	0.152	0.964	0.0733
	SP_TTM	-0.083	-0.0012		-0.852	0.103	0.9529	0.0875
	CFP_TTM	-0.026	-0.0019		-0.285	0.014	0.97	0.0788
	EBIT2EV	0.1034	-0.0011		1.208	0.086	0.9839	0.0778
	SALES2EV	0.0892	-0.0008		0.912	0.125	0.996	0.0893
PROFIT	ROA	0.0771	0.0007		1.026	0.043	0.9638	0.0604
	ROE	0.025	-0.0001		0.318	0.089	0.8316	0.075
	GrossMargin	0.0631	0.0005		0.291	0.2116	0.9087	0.0833
GROWTH	SalesGrowth_Qr_YOY	0.0313	0.0008		0.245	0.1147	0.8976	0.0648
	ProfitGrowth_Qr_YOY	0.0561	0.0113		0.582	0.07	0.8208	0.0773
	OCFGrowth_YOY	0.0065	-0.0002		0.006	0.0658	0.8085	0.0781
OPERATION	AssetTurnover	0.0358	0.0027		1.009	0.021	0.9798	0.0468
	Debt2Asset	0.0159	-0.0025		0.2517	0.039	0.993	0.0478
LIQUIDITY	TO_1M	0.1887	-0.0071		2.2131	0.055	0.8865	0.0932
	ILLIQ	0.2127	0.03		1.8336	0.097	0.0919	3.3326
	AmountAvg_1M_3M	0.2997	-0.014		3.979	0.048	0.5092	0.2322
TECH& REVERSE	Ret1M	0.2401	-0.0112		1.911	0.1184	0.1078	0.8708
	Momentumlast6M	0.1698	-0.0081		1.725	0.0743	0.8102	0.3363
	Momentumave1M	-0.078	-0.0015		-0.518	0.1261	0.0429	1.0134
	PPReversal	0.6832	-0.0425		5.726	0.2457	0.0019	3.2518
	CGO_3M	0.1153	-0.0072		0.837	0.1088	0.5689	0.8632
OTHER	RealizedVolatility_3M	0.1212	-0.0012		1.025	0.1512	0.9689	0.0778
	MaxRet	-0.1553	-0.003		-1.515	0.1641	0.4864	0.2777

Backtest Period: 2015-04-22 to 2024-06-17

Overview of Factor Performance in the Chinese A-Share Market

Value Factors

Traditional value factors exhibit suboptimal performance within the Chinese A-share market. These factors show significant negative year-over-year (YoY) returns and an insignificant Information Coefficient (IC) value, on the order of magnitude 0.0001. The lack of strong performance and statistical significance suggests that traditional value factors may not serve as effective indicators for this market during the examined period.

Profit, Growth, and Operation Factors

In contrast, profit, growth, and operation factors outperform traditional value factors. These factors collectively generate overall positive returns, though they also lack significant IC values. Despite the absence of strong statistical significance, the consistent positive performance indicates that these factors could be more reliable indicators of potential returns compared to traditional value factors.

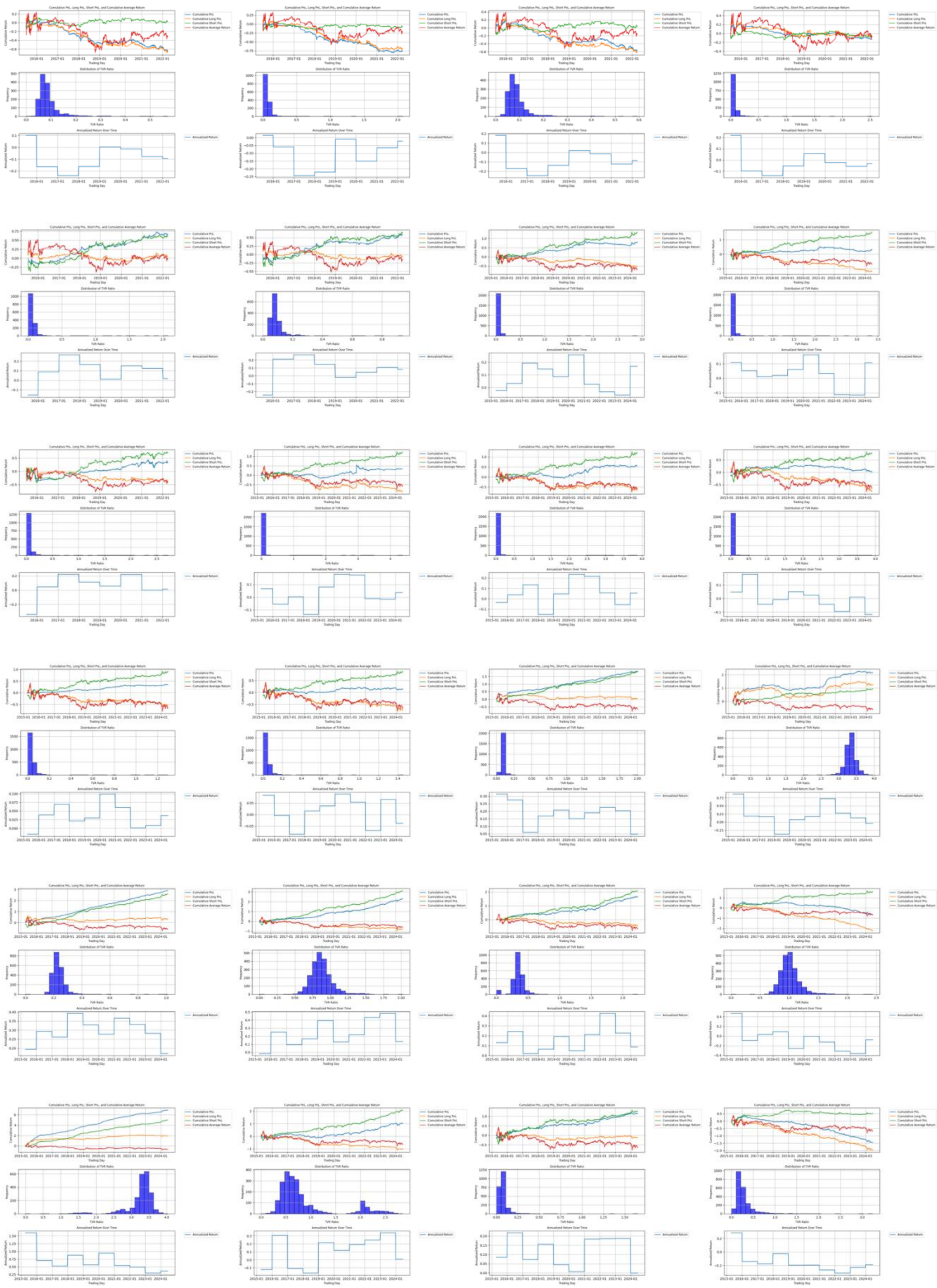
Liquidity and Reversal Factors

Liquidity and reversal factors, while classified as fundamental, are predominantly price-volume based due to the nature of the data utilized in their calculations. These factors show superior performance relative to other fundamental factors, producing relatively high returns with more statistically significant IC values. However, their stability, as indicated by the factor stability coefficient, is notably low. This instability leads to a high turnover ratio in daily trading, potentially increasing transaction costs and posing execution challenges for large institutions.

A detailed examination of cross-sectional and time-series data will be conducted to further explore the specific drivers behind the performance of these factors. This comprehensive analysis aims to enhance our understanding of the underlying dynamics and provide valuable insights for optimizing factor-based investment strategies in the Chinese A-share market.)

PNL TVRRATIO Distribution, and Annualized Return Analysis:

(The following graphs are aligned in the same order as the previous graph, from the top left to the bottom right.)



Cumulative PnL, Long PnL, Short PnL, and Cumulative Average Return
Distribution of TVR Ratio
Annualized Return Over Time

In the PnL analysis, the blue line represents the cumulative long and short PnL, the yellow line denotes the PnL from long positions, the green line illustrates the PnL from short positions, and the red line serves as the benchmark, representing the average return of all stocks in the Chinese A-share market.

Observations

From the analysis, it is evident that for nearly all fundamental factors, the PnL generated from short positions outperforms that from long positions. An exception is noted for the ILLIQ factor, which shows periods where the long PnL exceeds the short PnL.

Cumulative PnL Performance

In terms of cumulative PnL, Reversion and Liquidity factors generally outperform other factors. Factors such as TO_1M, AmountAvg_1M_3M, Ret_1M, Momentum6M, Momentum1M, and PPReversal consistently provide positive annualized returns, indicating their stability and reliability in profit generation. Conversely, Value Factors exhibit the poorest performance, with an overall negative PnL. Specifically, the EP_TTM factor consistently delivers negative annualized returns over the years.

Turnover Ratio

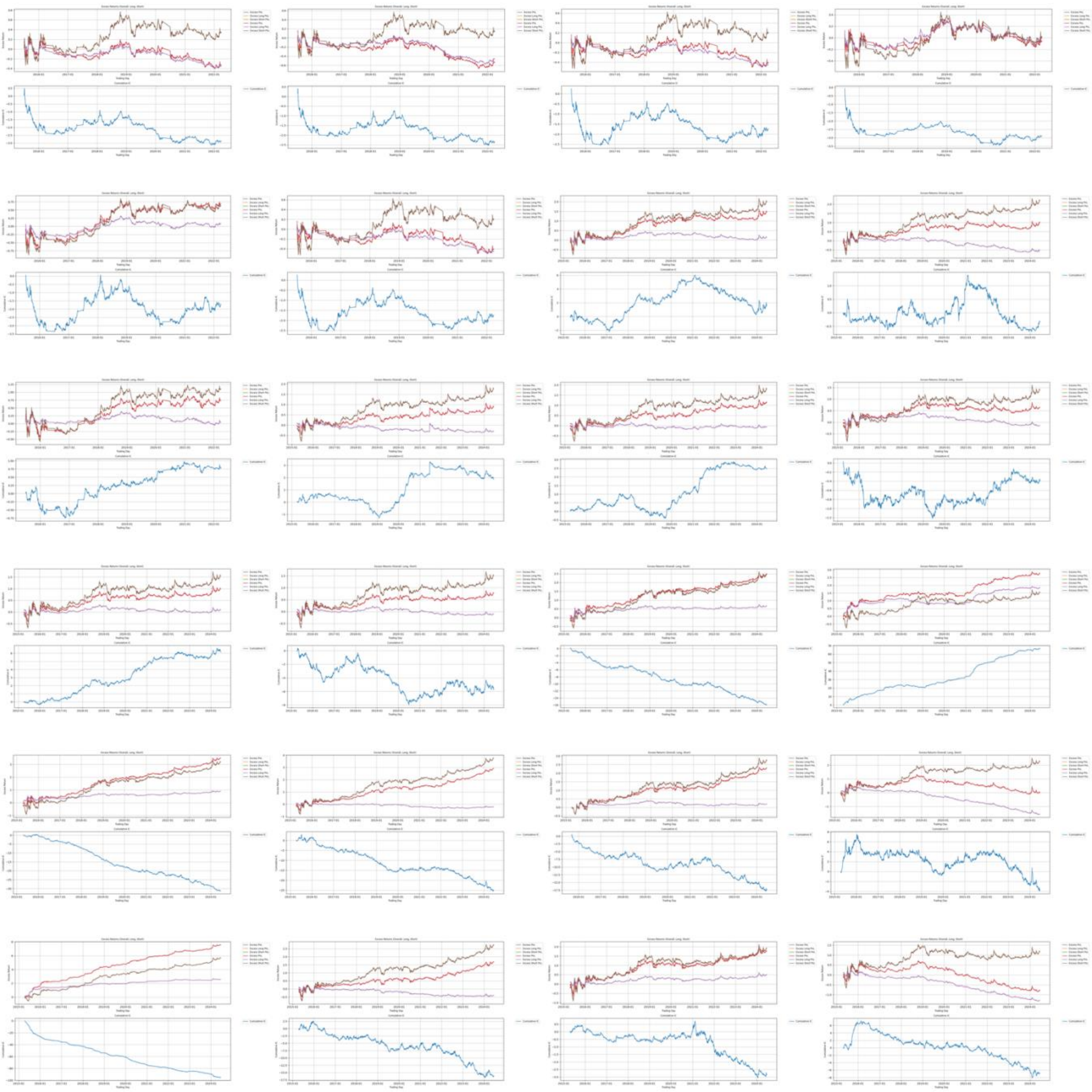
An examination of turnover ratios reveals that traditional fundamental factors, such as value, growth, and profit factors, exhibit relatively low turnover ratios (below 0.1). This low turnover is attributed to the infrequent issuance of fundamental data, which is typically updated monthly, quarterly, or annually. In contrast, technical, reversion, and liquidity factors display high turnover ratios (exceeding 0.8), as these factors rely on daily updated data.

The fundamental data in financial reports often lack standardization, and some companies may not include key elements required for the calculation of value, profit, and growth factors, resulting in a significantly reduced stock pool. On the other hand, technical and reversion factors, which depend solely on price and volume data, encompass a larger stock pool as this data is available for all tradable stocks.

Implications for Large Institutions

The lower turnover ratio of value factors offers a distinct advantage for large institutions due to their lower frequency and reduced transaction costs. Furthermore, the lower frequency of turnover minimizes the impact on the market, especially for large shareholders (top 10 in certain companies), as frequent turnover can be visible to other investors and potentially trigger panic selling.

Excess PNL and Cumulative IC:

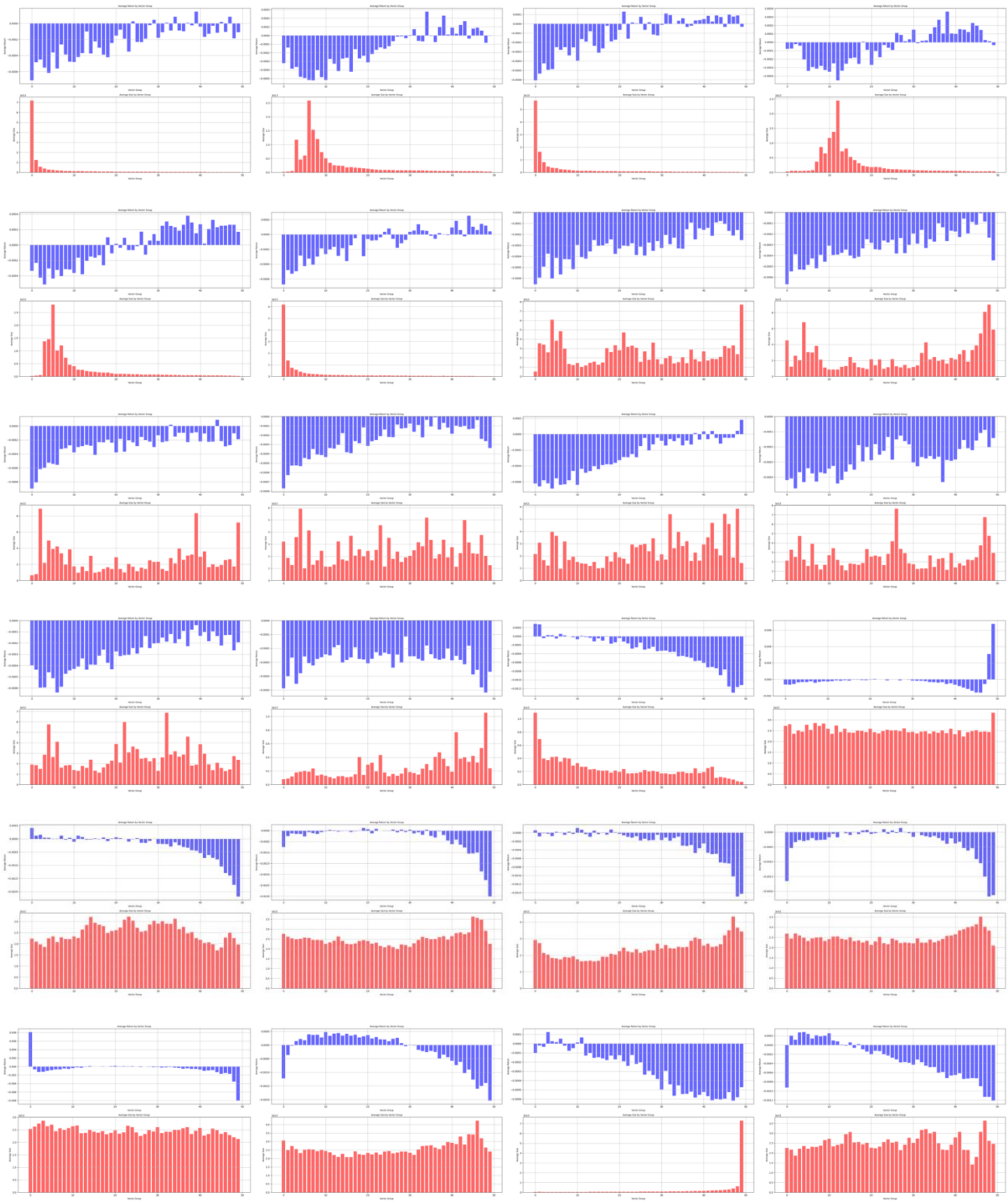


This section provides complementary information on the factors by plotting excess return against the average return of the entire market and examining the cumulative Information Coefficient (IC) to assess the stability and monotonicity of fundamental factors.

Cumulative IC Analysis

The cumulative IC of value factors is observed to be highly volatile and lacks a clear direction. This volatility suggests a weak correlation between alpha values and future returns, which may explain the underperformance of value factors. Conversely, reversion and liquidity factors display a more directional and linear cumulative IC. This linearity indicates a stronger predictive power, which accounts for the superior performance of these factors compared to others.

Alpha Vector Grouping Analysis(Monotonicity, size industry exposure)



The grouping analysis is conducted based on the construction of the portfolio (as previously mentioned, top 10% against bottom 10% depending on the sign of IC values). In this analysis, stocks are divided into 50 groups based on their fundamental factor values in ascending order.

The grouping analysis indicates a stronger correlation between negative returns and extreme vector values than with positive returns. This finding helps explain why short PnL constitutes a larger portion than long PnL for almost all fundamental factors. Additionally, the Value, Profit, Growth, and Operation factors exhibit nearly negative correlations across all vector groups, suggesting a lack of explanatory and predictive power. This explains their underperformance relative to other factors. Conversely, the Liquidity factor demonstrates stronger monotonicity and correlation between vector and future return, generating higher returns than the previous four factors. The Reversion factor shows the strongest monotonicity, indicating the highest explanatory power. Notably, factors such as PPReversal, despite not showing strong monotonicity in the middle groups, exhibit extremely strong correlations in the most extreme groups, which are the groups selected for portfolio construction, potentially resulting in the highest PnL.

Regarding size exposure, the Value and Profit factors display significant variation in market cap among different vector groups, suggesting that portfolios constructed from these factors will not concentrate stocks into certain market caps. Different sizes of companies tend to react differently to market conditions. Conversely, the Reversion and Liquidity factors exhibit less variation in market cap among the vector groups, indicating higher size exposure. Large-cap stocks might be more stable and less volatile, while small-cap stocks might offer higher growth potential but with higher risk. This diversity can help smooth out portfolio performance over time. Additionally, different size groups might be more or less sensitive to various economic factors. Large-cap stocks might be more resilient during economic slowdowns due to their established market positions, while small-cap stocks might perform better during economic expansions. A diverse portfolio can hedge against different market trends and reduce overall systematic risk.

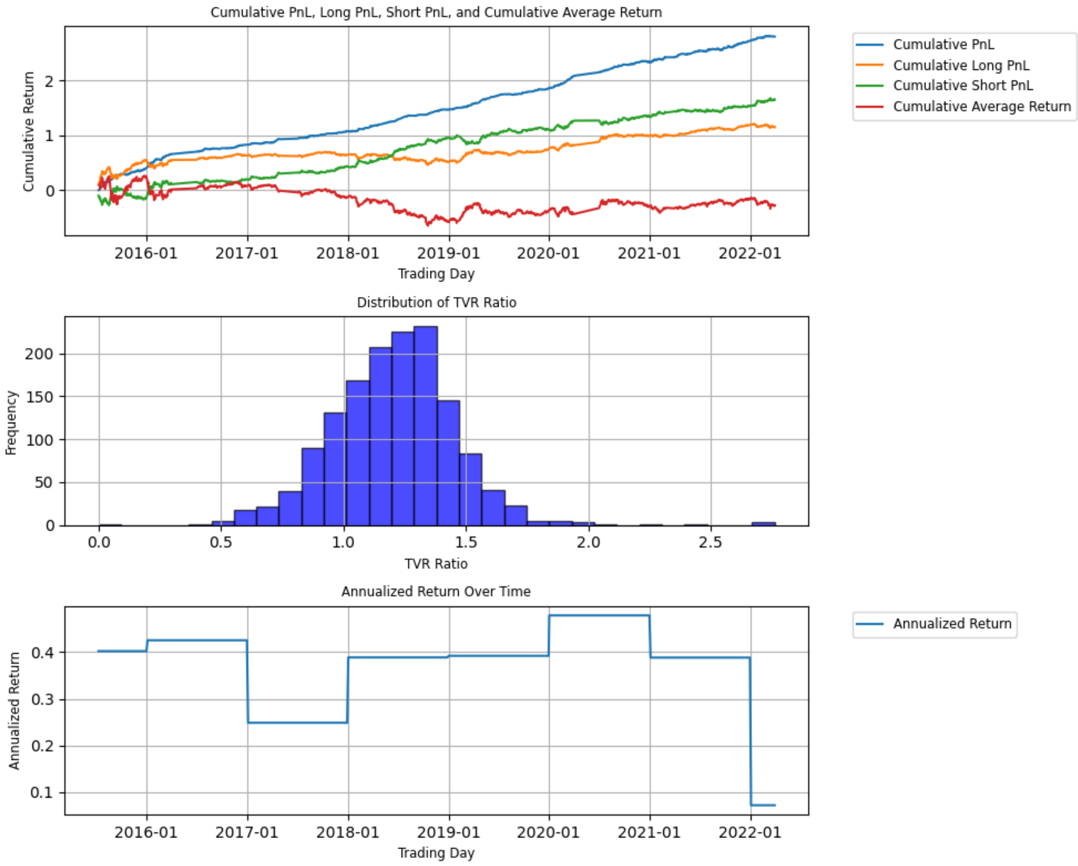
Analyzing size exposure reveals why portfolios constructed from Value, Profit, and Growth factors may be more conservative and less risky compared to those based on Reversion and Liquidity factors. This is reflected in the maximum drawdown (MDD) figures. For Value, Profit, and Growth factors, the MDD is typically less than 10%, whereas for Reversion and Liquidity factors, it is often above 10% and even exceeds 20% in some cases.

Single fundamental factors, despite differing in profit-generating abilities, exhibit several inherent issues such as lack of explanatory power, high industry and size exposure, and high turnover ratios. These issues reduce the robustness of the alpha. To construct a more robust alpha that combines the advantages and mitigates the disadvantages of individual factors, a combination approach is necessary. This research further investigates several methods of combination.

Even Weighted Alpha

An even weighted alpha is constructed by taking a linear combination of the individual alpha values. The signs of these values are determined by the sign of the IC value. If the IC value is positive, the alpha value is added to the even weighted alpha; if negative, it is subtracted. The combined alpha is then divided by the number of alpha values considered to generate the even weighted alpha. This approach aims to balance the contributions of each factor, leveraging their predictive strengths while minimizing individual weaknesses.

$$EW_{Alpha} = \frac{1}{n}\sum_{i=0}^{n} \frac{IC_i}{|IC_i|}\alpha_i$$


Cumulative PnL, Long PnL, Short PnL, and Cumulative Average Return
Cumulative Return
Trading Day
Cumulative PnL
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Distribution of TVR Ratio
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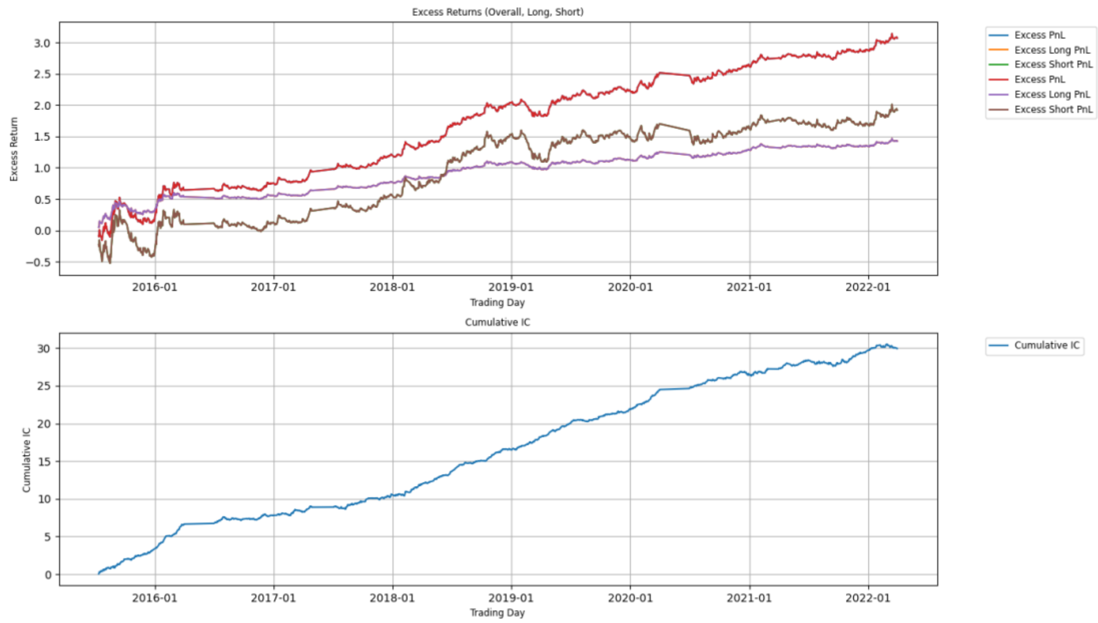
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Excess Return
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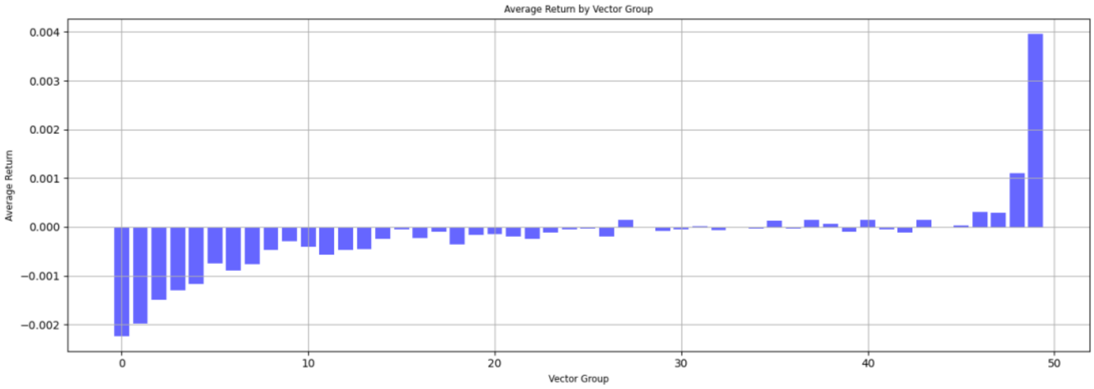
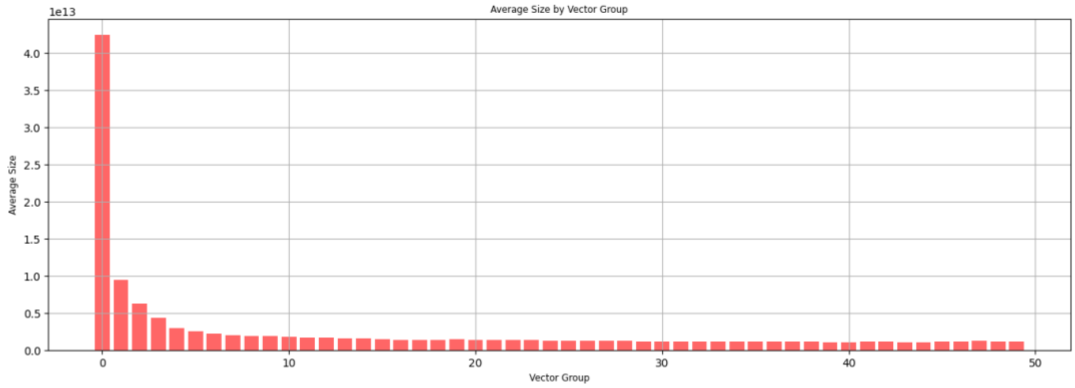
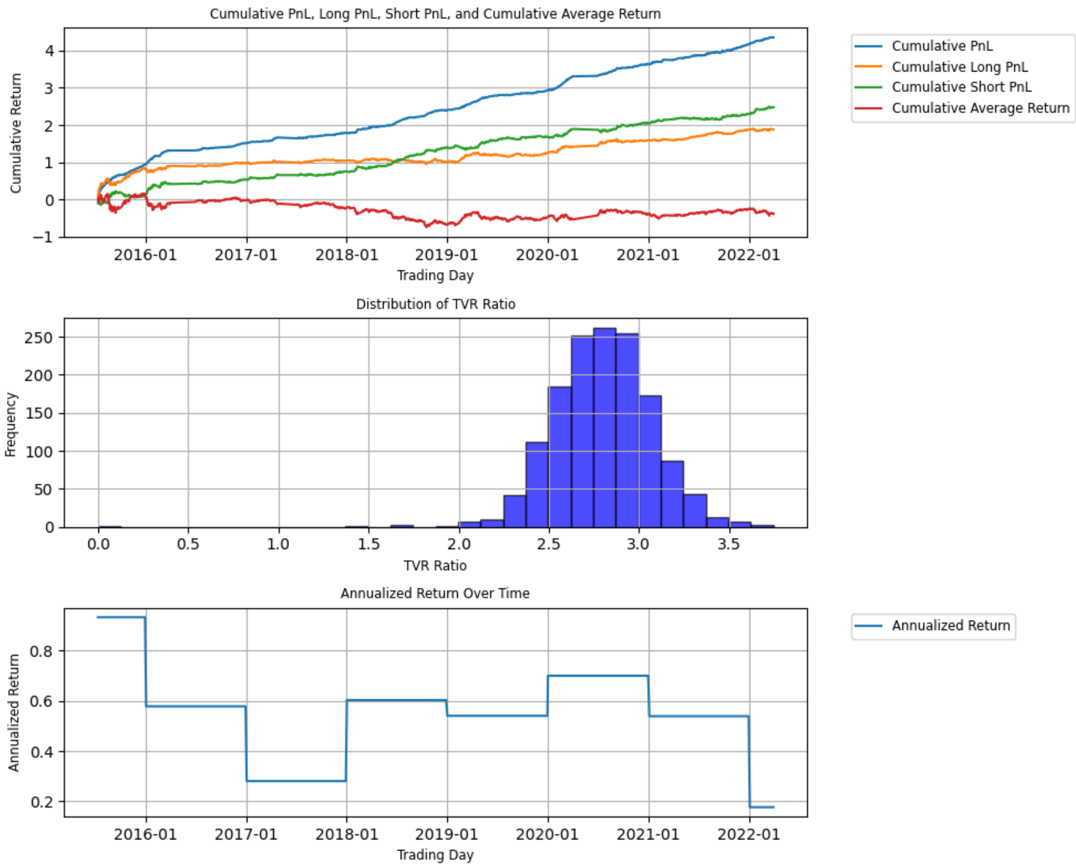




IC_Weighted Alpha

The logic behind IC weighted alpha is to maximize the effect of fundamental alpha with relatively strong explanatory power, and thus combine the alpha by IC.

$$ICW_{Alpha} = \frac{1}{n}\sum_{i=0}^{n} IC_i \alpha_i$$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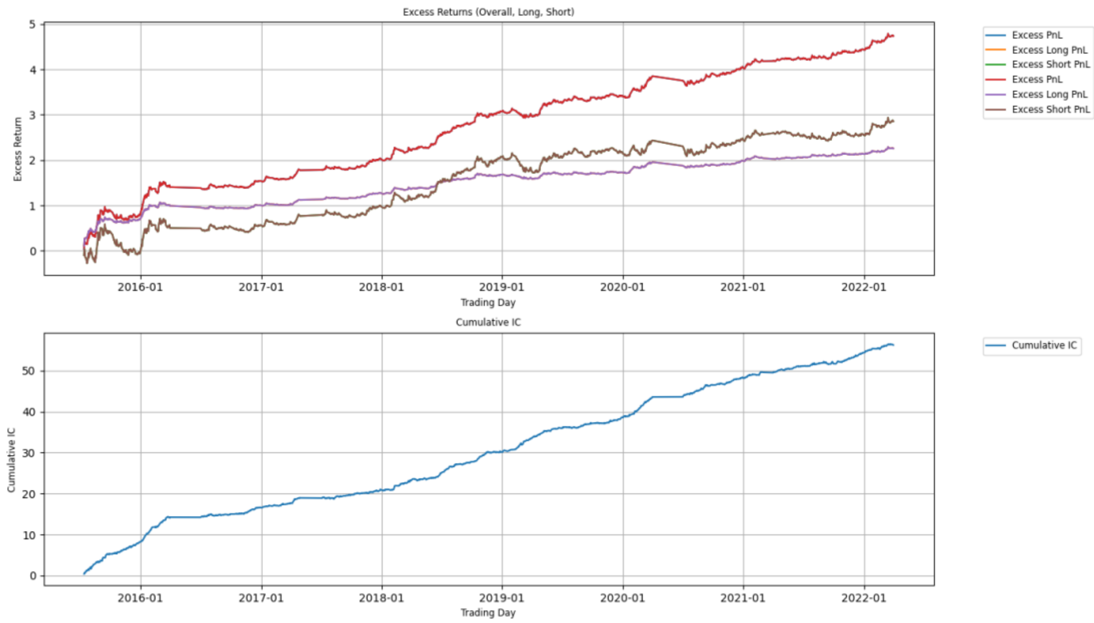
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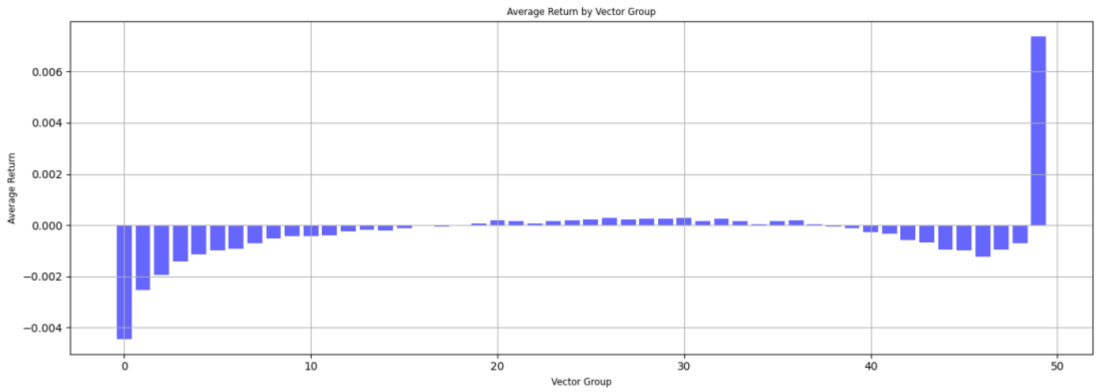

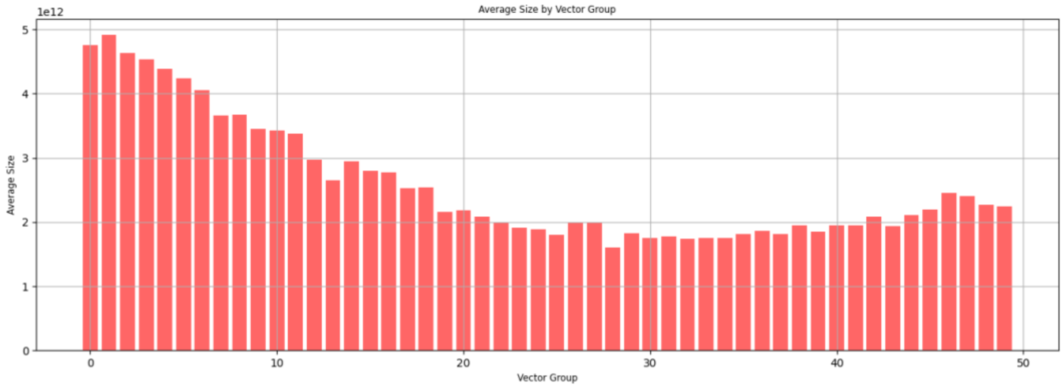

	Factor_Name	Annual Return	IC	IC_IR	Sharpe Ratio	Maximum Retreat	Factor Stability	TvrRatio
Simple Combo	Even_Weighted_Alpha(EWalpha)	0.374	0.0206		5.637	0.0376	0.7361	1.2056
	IC_Weighted_Alpha (ICWalpha)	0.556	0.0387		6.427	0.0457	0.0446	2.7985
	Average all factors	0.0831	-0.0032		0.832	0.102	0.729	0.474

As illustrated by the charts above, the monotonicity of the compound alpha is superior to any single alpha, consistently generating positive annual returns. This improvement is evident in the performance metrics, significantly enhancing both the annual return and Information Coefficient (IC) value compared to the average of all fundamental factors. Additionally, the compound alpha exhibits lower risk, as indicated by a reduced maximum drawdown. While the combination strategy does increase the turnover ratio significantly, it remains robust compared to the transaction fees involved.

One advantage of the compound alpha over reversion and liquidity factors is its higher monotonicity and lower size exposure. This reduces the systematic risk associated with size and improves the predictive power of the alpha. Thus, even though the compound alpha may generate lower returns than some reversion factors (such as PPReversal), it proves to be a better factor overall. It offers more stable and significant profits in the long run, making it a valuable strategy for sustained investment performance.

Conclusion：

This report primarily examines the effectiveness of factors in the A-share market. We tested various factors to determine their utility in the market. Overall, the liquidity and technical reversal factors in the A-share market demonstrated the most significant performance.

Next, we focused on the liquidity effect in the A-share market and the momentum effect in the U.S. stock market. It was found that the small-cap market style in the A-share market has been particularly prominent in recent years, while the reversal effect is also very notable.

Finally, we combined these factors to create a selection factor that exhibits strong explanatory power, a high Sharpe ratio, and enhanced stability. This composite factor offers a robust strategy for stock selection, capitalizing on the strengths of individual factors while mitigating their weaknesses.