Volatility-managed Portfolios in the Chinese Equity Market

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Abstract

This study investigates the effectiveness of the volatility-timing strategy in the Chinese equity market. We find that the volatility-managed portfolio (VMP) consistently outperforms its original counterpart, both in individual factor analysis and mean-variance efficient multifactor assessment, and the results are robust in out-of-sample setup. Notably, the outperformance is mostly driven by stocks with high arbitrage risk, short-selling constraints, relatively smaller size, and lottery preferences. Further, the multifactor portfolio constructed from the volatility-managed strategy outperforms other portfolios especially in turmoil periods such as high sentiment and low macroeconomic confidence periods. Our findings suggest that in the Chinese equity market with typical trading frictions, volatility timing strategies consistently gain profitable performance.

Keywords: Timing Strategy, Volatility-managed Portfolio (VMP), Chinese Equity Market

JEL Classification: *G11, G12, G13*

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1. Introduction

Timing strategies hold a pivotal role in classical asset pricing theory and investment practice. One prominent timing strategy is the volatility timing, first coined by Moreira and Muir (2017), who observed that a volatility-managed portfolio that takes less risk when volatility is high produces higher Sharpe ratio and larger utility gains for investors. Challenging the rational asset pricing theory of the positive risk-return tradeoff, the weakening and even reverse risk-return correlation during highly volatile periods provides novel insights. Following literature discuss the real benefits of volatility timing strategy and hold controversial conclusions. Further expanding the factor domain to 103 individual equity strategies in the U.S. market, Cederburg, O'Doherty, Wang, and Yan (2020) poses a challenge to the implementation of this timing strategy under out-of-sample setups. Barroso and Detzel (2021) argues that the strong abnormal returns of managed market factor cannot be explained by the limit-to-arbitrage hypothesis. In contrast, DeMiguel, Martin-Utrera, and Uppal (2021) supports the efficacy of the strategy by constructing a multifactor portfolio with conditionally time-varying weights under out-of-sample setups.

In this study, we comprehensively examine the existence and sources of gains of volatility timing strategy in the Chinese equity market with abundant arbitrage opportunities and strict trading frictions. [1] The high volatility patterns tracing to temporary policy shocks and short-term retail herding makes the market unique relative to the institution-dominated U.S. equity market (see Figure 1(a)). In particular, with some exogenous shocks and the government's strong stability-maintaining incentive, highly volatile periods and stable periods can be relatively easy to identify (see Figure 1(b), where highly volatile periods are denoted as grey shades and stable periods are denoted as green shades). For example, the A-share index was severely volatile during China's participation in the WTO in late 2001, the 2008 global finance crisis with the following "four-trillion-yuan" stimulus package, the 2015 stock market crash, and the Covid-19 breakout.

[1] The Chinese equity market is well-known for several features of speculative trading, high participation of retail investor, salient investor sentiment, and inferior corporate governance. Existing literature include Allen, Qian, and Qian (2005); Mei, Scheinkman, and Xiong (2005); Xiong and Yu (2011); Jiang and Kim (2020); Carpenter, Lu, and Whitelaw (2021); He and Wei (2022).

Intriguingly, almost each volatile period was followed by a relatively low-volatile period shortly due to government efforts to maintain market stability. This feature is beneficial for our empirical identification and make the volatility-timing strategy an appealing and critical focus for factor investing in the Chinese equity market.

Our sample includes all China's A-Share stocks spanning from January 2000 to June 2022. We perform our analyses on a monthly basis and construct monthly volatility-managed factors scaled by total volatility of each factor in the previous month. More specifically, we first evaluate nine representative factors in three widely-used factor models, including the China's four-factor model (Liu, Stambaugh, and Yuan, 2019), the replication of Fama-French five-factor model (Fama and French, 2015), and the q-factor model (Hou, Xue, and Zhang, 2015). Then, following the literature (e.g., Green, Hand, and Zhang, 2017; Leippold, Wang, and Zhou, 2022; Liu, Stambaugh, and Yuan, 2019; Hou, Qiao, and Zhang, 2023), we construct other 62 representative firm characteristics and form the associated factors. Overall, the whole universe of 71 factor strategies including above nine pricing factors and 62 characteristic-sorted factors fall into seven categories: trading friction, value, risk, past return, profitability, investment, and the A-share market index. In terms of the evaluation of volatility-timing managed factor performance against original factors, one method is the alpha test obtained from regressing managed factor returns on original factor returns. The other refers to the Sharpe ratio difference test developed by Jobson and Korkie (1981) with Memmel (2003) correction.

We provide several findings. First, from the aspect of individually investing in risky factors, across nine commonly-used pricing factors, all managed value factors gain significantly positive regression alphas, indicating that original value factors uniformly underreact to volatility shocks. In the more comprehensive universe of 71 trading strategies, 55 strategies earn positive alphas in regression test, with 34 strategies demonstrating significantly positive alphas, and 14 factors displaying significantly positive Sharpe ratio improvement at the significance level of 10%. The outperformance is also observed in the strategy of optimally investing in both individual risky factors and the risk-free asset. In general, volatility-managed factors typically outperform original factors in categories of value, risk, trading friction, and past returns. Intriguingly, 12-month momentum, CAPM beta, and idiosyncratic risk factors, which are well-documented as unconditionally insignificant factors in China, gain significantly positive risk premium conditional on volatility shocks.

Second, the mean-variance efficient multifactor portfolio spanned from all the managed factors demonstrate superior performance compared to that spanned by the corresponding original factor portfolios, and the result is economically and significantly robust under the out-of-sample setup. The gains mainly result from the lowest volatility of the managed portfolio. To mitigate potential sample noises, instead of directly utilizing the whole set of 71 factors, we form the multifactor portfolio using factors with economic improvement. In line with Ledoit and Wolf (2022), we employ the nonlinear shrinkage methodology in estimating the sample covaraince matrix when forming the optimal weights in the multifactor portfolio. This approach addresses the singularity issue of covaraince matrix arising from the exceeding number of cross-sectional assets relative to the short time period typical in the Chinese equity market. [2] Notably, the multifactor portfolios constructed from the volatility-managed factors achieves annualized in-sample Sharpe ratio of 1.91, surpassing the Sharpe ratio of 1.42 achieved by portfolios including both original factors and volatility-managed factors, as well as the corresponding original factors or the equal-weighted naïve diversification strategy. Consistent with in-sample results, the volatility-timing multifactor portfolio yields the highest annualized out-of-sample Sharpe ratio of 1.59.

Third, we suggest that the strong limit-to-arbitrage in the Chinese equity market explains the outperformance of volatility-timing strategy. We measure limit-to-arbitrage with idiosyncratic risk, short selling constraint, and size, and maximum returns within the past one month. We partition all stocks into two or three groups based on cross-sectional magnitudes of limit-to-arbitrage and then form corresponding 71 managed factors within each group. In order to obtain identification of the effects of limit-to-arbitrage on managed factors and ensure consistent volatility information across groups, we scale each portfolios

[2] The Chinese equity market opens from 1990, leaving appropriate examination relatively short. We display the results of using whole set of 71 factors in Appendix, and the empirical results are similar.

with the same leverage used in the originally managed portfolios. The findings consistently indicate that abnormal returns concentrate in stocks with high limit-to-arbitrage across all measurement. Thus, stock-level limit-to-arbitrage well explain the apparent underreaction of prices to volatility shocks. Furthermore, given high investor sentiment and strong macroeconomic condition, we asses the economic performance of the different multifactor portfolios. The results indicate that the portfolios constructed from managed factors significantly outperform original strategies following turmoil periods with high investor sentiment and low macroeconomic confidence.

Our paper is closely related to literature on volatility timing strategy. In addition to the first strand of literature comprehensively covering the gains and sources of volatility-timing factors(e.g., Moreira and Muir, 2017; Cederburg, O'Doherty, Wang, and Yan, 2020; Barroso and Detzel, 2021; DeMiguel, Martin-Utrera, and Uppal, 2021; Neuhierl, Randl, Reschenhofer, and Zechner, 2023), existing literature also suggest other methods of volatility management including downside risk, asymmetric variance, and implied volatility index (Wang and Yan, 2021; Schwarz, 2021; Tang, 2019; Bozovic, 2023). Their findings suggest that aside from total volatility information, other volatility information also efficiently enhance the performance over original factors. However, neither downside risk nor asymmetric risk management shows significant outperformance in our sample factors. Another strand of literature focus on factor timing in the Chinese stock market. Existing literature points out that performance gains in factor timing strategies in the Chinese equity market (Tang, Jiang, Qi, and Huang, 2021; Ma, Liao, and Jiang, 2023). As for volatility-managed strategies, Chi, Qiao, Yan, and Deng (2021) document that volatility-managed portfolios underperform original counterparts, but the analysis is limited to a relatively narrow domain of individual factors. In this context, to our knowledge, our study is the first to comprehensively analyze volatility-managed strategy in the Chinese equity market.

The remainder of this paper is organized as follows. Section 2 presents sample description and construction of volatility-timing strategies. Section 3 discusses performance across full universe of individual factors. Section 5 presents empirical results of mean-variance efficient multifactor portfolios under both in-sample and out-of-sample tests. Section 6 identifies economic channels driving the outperformance including limit to arbitrage, investor sentiment, macroeconomic confidence level. Finally, Section 7 concludes the paper.

2. Data and methodology

2.1. Sample description

We construct a large cross-section of individual stocks that include all China's A share stocks listed on the main board of the Shanghai and Shenzhen stock exchanges, the GEM (Growth Enterprises Market), and STAR (Science & Technology Innovation) boards. The sample ranges from January 2000 to June 2022, in total, 270 months. Similar to Liu et al. (2019), we apply several filters to the data: (i) excluding those stocks listed less than six months, (ii) excluding those stocks with fewer than 120 trading records in the past 12 months or fewer than 15 trading records in the past month, (iii) retention of the largest 70% stocks on the basis of market capitalization each month to avoid shell-value concerns. Stock trading data are obtained from Wind Information Inc. (WIND), a major financial data provider in China, and accounting data and one-month risk-free rate are obtained from China Stock Market and Accounting Research (CSMAR), another major financial data provider in China.

We replicate and update nine widely-used factor returns following exactly the same procedures as in the literature. First, Liu, Stambaugh, and Yuan (2019) take into account the China-specific institutional settings and propose an observable factor model, in which a size factor SMB is constructed by excluding the smallest 30% of firms to eliminate potential shell contamination concerns, and a value factor VMG is constructed based on the earnings-price ratio, which subsumes the book-to-market ratio in capturing value effects in China. They also construct a sentiment factor PMO based on turnover given that the Chinese stock market is largely dominated by retail investors. The second well-documented factor model is the q-factor model developed by Hou, Xue, and Zhang (2015), in which an investment factor (I/A) and a profitability factor (ROE) capture time-varying patterns of expected return. Another pricing model we consider is the popular Fama-French five-factor model (Fama and French, 2015), which includes a value factor(HML), an investment factor (CMA), and a profitability factor (RMW). In total, we obtain excess returns of 9 factors: MKT, SMB, VMG and PMO factors from LSY-4 model, ROE and I/A factors from q-4 model, as well as HML, RMW and CMA factors from FF-5 model. The nine pricing factors will be used for the following preliminary analysis.

In addition, following the literature (see, e.g., Green, Hand, and Zhang, 2017; Leippold, Wang, and Zhou, 2022; Hu, Pan, and Wang, 2018; Liu, Stambaugh, and Yuan, 2019; Hou, Qiao, and Zhang, 2023), we construct 70 representative firm characteristics, and construct a broader set of 62 double-sorted factors in total based on each firm characteristic. The portfolios are formed by sorting on the size median across the whole sample stocks and then sorting on 30th and 70th percentile breakpoints of each firm characteristic. Portfolio returns are value-weighted average of stock returns. Detailed descriptions and categories of characteristics show in Table A1 and Table A2. The nine well-documented pricing factors and the comprehensive 62 factors fall into 6 categories: trading friction, value, risk, past return, profitability, and investment.

2.2. Construction of volatility-managed portfolios

To start with, we define realized variance for factor k at the end of month t as the summation of squared daily returns:

$$\sigma^2_{k,t} = \frac{21}{D}\sum_{d=1}^{D} f^2_{k,t-d} \tag{1}$$

Then, following Moreira and Muir (2017), we form volatility-managed portfolios as follows:

$$f^{\sigma}_{k,t} = \frac{c_k}{\sigma^2_{k,t-1}} f_{k,t} \tag{2}$$

where $f_{k,t}$ denotes kth buy-and-hold excess return in month t, $f^{\sigma}_{k,t}$ denotes excess return after managing with volatility, $\sigma^2_{k,t-1}$ denotes kth realized variance of daily returns in month $t-1$, and constant c_k guarantees that managed portfolio returns and original factor returns achieve the same level of unconditional variance over the full sample period. [3]

Notably, recent papers point out that estimating constant scaling parameter c_k using full sample period induce inherent look-ahead bias for real-time investors(Cederburg, O'Doherty, Wang, and Yan, 2020; Bozovic, 2023), who could only observe information available up to month t. To tackle this concern, we estimate $c_{k,t-1}$ within the minimum training period starting from $t = 1$ through 12, and then estimate $c_{k,t-1}$ iteratively from month 1 through $t-1 (t > 13)$. Within each in-sample training period, $c_{k,t-1}$ ensures that original factors and managed factor have the same level of variance. Managed factor return at out-of-sample month t is then calculated based on Equation 2. [4]

Two performance measures are implemented to quantify performance differences. The first measurement is alpha significance from the spanning regression documented in Moreira and Muir (2017). Specifically, we regress volatility-managed portfolio returns on raw factor returns to obtain α_k:

$$f^{\sigma}_{k,t} = \alpha_k + \beta_k f_{k,t} + \epsilon_{k,t} \tag{3}$$

The significantly positive α_k indicates that successfully volatility-managed factor spans the mean-variance frontier against the original version. The intuition follows from the equivalent validity between spanning test and utility gains from optimal allocation of portfolios.

However, Cederburg, O'Doherty, Wang, and Yan (2020) indicate that alpha significance only insures that $\bar{f}^{\sigma}_{k,t} > \rho \bar{f}_{k,t}$, where $0 < \rho < 1$, thus providing the lower bound of managing success. Under more stringent conditions of $\bar{f}^{\sigma}_{k,t} > \bar{f}_{k,t}$, which implies that Sharpe ratio of the managed version is strictly higher than the original version given equal unconditional variance for both versions of factors, alpha significance may cause overstating concerns. To settle the overstating concerns, the second measurement im-

[3]For robustness check, we scale monthly individual factor returns with realized variance of daily returns over the previous three months. We also scale monthly individual factor returns with realized variance of market daily returns, and the empirical results are robust.

[4]The estimation process are mainly applied in out-of-sample setups in this study. For robustness check of in-sample results in Section 3, we also iteratively estimate $c_{k,t-1}$ starting from $t = 12$. The empirical results are similar to estimating constant c_k within the whole sample period and are available upon request.

plements the Sharpe ratio difference test, developed by Jobson and Korkie (1981) with Memmel (2003) correction. The analytical formula shows as follows:

$$\Delta SR(f^{\sigma}_{k,t}, f_{k,t}) = SR(f^{\sigma}_{k,t}) - SR(f_{k,t}) \tag{4}$$

Given equal unconditional variance for both versions of factors, the test statistic of Sharpe ratio difference, $\Delta SR(f^{\sigma}_{k,t}, f_{k,t})$, is asymptotically distributed as the standard normal distribution, in which the statistical inference can be then applied.

2.3. Investment strategy

This study mainly considers two types of investing strategies: the first strategy invests in only risky assets, and the other strategy refers to the complete strategy, which optimally allocate between the risk-free asset as well as the risky assets(Cederburg, O'Doherty, Wang, and Yan, 2020). Specifically, consider a mean-variance investor with risk aversion of $\gamma = 2$, who maximizes her expected utility by investing in both risky factors and risk-free asset: [5]

$$\max_{w} U(w) = w^{\top}\hat{\mu} - \frac{\gamma}{2} w^{\top}\hat{\Sigma} w \tag{5}$$

where w denotes an $K \times 1$ vector of factor weights, $\hat{\mu}$ is mean excess factor returns, and $\hat{\Sigma}$ is variance-covariance matrix of excess factor returns. The optimal factor weights can be solved through the first-order derivative of Equation 5:

$$\widehat{w} = \frac{1}{\gamma}\hat{\Sigma}^{-1}\hat{\mu} \tag{6}$$

and $1 - \sum_{i=1}^{K} \hat{w}_i$ denotes the share of risk-free asset.

In following empirical tests, the domain of risky assets in the complete strategy includes original factors, managed factors.

[5] Empirical results are robust to different values of risk aversion parameter of $\gamma = 5$.

3. Empirical findings

To obtain a general overview of volatility-managed performance, we first evaluate the economic gains from direct investments in risky factors, covering from a preliminary analysis of nine well-documented pricing factors in Section 3.1 to the broader domain of 71 factors in Section 3.2. Then, we evaluate the performance of investing in the complete strategy in Section 3.3.

3.1. Common factors

Panel A of Table 1 displays summary statistics of mean excess returns and Sharpe ratio across nine pricing factors. For value and profitability factors of VMG, ROE, HML, and RMW, they almost uniformly earn higher risk premium after managed with total volatility at the 5% level of significance. For example, the VMG factor in the original strategy achieves the highest monthly excess return of 0.94% across all pricing factors, and the managed counterpart earns an even more impressive risk premium of 1.17% per month. In addition, for trading friction factor of PMO, the monthly risk premium in the managed strategy achieves 0.68% at the 1% level of significance, but the magnitude is slightly decreasing relative to its original counterpart. For market factor MKT and SMB, which are the focus of existing research, the volatility-managed strategy still may not resurrect the plain performance in the original strategy given the decreasing value of average returns. For I/A or CMA factor, the managed strategy only slightly elevate the performance.

In terms of performance comparison, in accordance with summary statistic findings, Panel B and Panel C of Table 1 both demonstrate that the managed strategy efficiently enhances factor performance. For instance, out of the nine factors examined, seven factors exhibit positive alphas, and six of them generate increasing magnitudes of Sharpe ratio. Notably, all value factors generate significantly positive alphas relative to their original counterparts, with a significance level of 5%.

The findings in Table 1 demonstrate that pricing signals within various groups exhibit cross-sectional discrepancy with regard to their sensitivity to volatility information. These preliminary results suggest that the factor domain cannot be confined to a limited sample of only nine pricing factors, highlighting the need for a broader perspective in the following analysis. Besides, investing in managed value factors has the potential to enhance the mean-variance frontier for investors.

3.2. Other factors

In this section, we extent our analysis to the entire universe of 71 factors in order to comprehensively analyze performance improvement of managed strategies. The whole universe of factors fall into seven categories of trading friction, value, risk, past return, profitability, investment, and the A-share market return. Quantifying performance differences of managed portfolio against original counterparts, Table 2 summarizes the number of positive or negative alpha values, as well as significantly positive or negative alpha values obtained from spanning regression. More rigorously, Table 2 presents the number of increased or decreased magnitudes of the Sharpe ratios, and the number of significantly increasing or decreasing trends observed.

Generally speaking, the outperformance of volatility-managed strategy against the original version dominates the adverse performance over the full sample period. Panel A of Table 2 shows that out of 71 strategies, 55 volatility-managed strategies gain positive alphas, with 34 significant alphas at the 10% level of significance. In terms of the Sharpe ratio difference test, 47 managed strategies gain increased magnitudes of Sharpe ratio, with 14 strategies showing significantly increasing improvement at the 10% level of significance. Panel B of Table 2 shows that all these strategies with strong performance are constructed from other firm characteristics besides the commonly-used factors, indicating the importance of conducting a complete analysis in order to fully understand the volatility-managed strategy. Furthermore, breaking the whole universe into seven trading categories, Panel C of Table 2 reveals that the superior performance of volatility-managed strategies can be primarily attributed to factors in value, risk, and trading friction groups. For instance, among 12 value factors, 9 factors exhibit significantly positive alphas, while

4 factors exhibit a significant improvement in the Sharpe ratio improvement. Detailed summary statistics of each factor strategy are listed in Table A3.

To further investigate the sources of enhanced performance of managed strategy, we display factors with significantly positive α and improved Sharpe ratio in detail. Loosely speaking, for the general overview, the enhanced performance is contingent on the significance level of 10%. Column (1) and (2), (4) and (5) of Table 3 present mean excess returns and Sharpe ratio of both the original and managed strategies, respectively, while Column (3) and (6) present magnitudes of α from spanning regression and the Sharpe ratio difference.[6] Clearly, value, profitability, and trading friction factors contribute the largest proportion to the superior performance of volatility-managed strategy.

3.2.1. Momentum factors

Volatility-timing strategies also elevate several factor performance to a large margin, especially for some typical factors without unconditional predictability in the Chinese stock market. The most intriguing evidence from Table 3 is that, insignificant factor returns constructed from the 12-month momentum, CAPM beta, and CAPM idiosyncratic volatility in the full sample all transform into conditionally profitable strategies at a significance level of 5%. [7] For instance, for 12-month momentum factor, the managed version generates the significantly predictive return of 0.71% per month, compared with the mere return of 0.11% in the original strategy.

3.2.2. Risk factors

Factor of CAPM beta generates a significantly conditional return of 0.54% per month, compared with the unconditional return of 0.19%. Managed version of factor constructed from CAPM idiosyncratic risk generates the highest monthly excess return of 0.98%. The possible explanations might be that original 12-month momentum factor as well as sys-

[6] All factors gaining significant Sharpe ratio improvement also gain significantly positive alphas from the spanning regression, but not vice versa.

[7] There are eight unconditionally profitable factors in total in the full sample, which are, namely, 12-month momentum, CAPM beta, CAPM idiosyncratic volatility, volatility, turnover, operating accruals, Ohlson's O-score and change in tax expense.

tematic risk factors may not capture the hedging effect of historical volatility information.

Collectively, empirical evidence indicates that volatility-timing strategy applied for factor returns elevates pricing efficiency in the Chinese equity market. In terms of the characteristic importance, groups of value, trading friction, risk and profitability significantly contribute to the outperformance of managed strategy.

3.3. Complete strategy

In this section, we analyze the performance of different combinations of assets including both the risky assets and the risk-free asset. We construct the following three mean-variance efficient portfolios with the optimal weights of risky assets given in Equation 6: the combination of the original factors and the risk-free asset (original strategy), the combination of the volatility-managed factors and the risk-free asset (managing strategy), and original factor, volatility-managed factor and risk-free asset (combined strategy), respectively.

Consistent with results of direct investment in risky factors shown in Table 2, the managing and combined strategies uniformly generate favourable performance over the original strategies, and the empirical results is robust to out-of-sample test. Panel A of Table 4 presents that out of 71 strategies, 47 managed strategies gain increased Sharpe ratio improvement against original strategies, with 11 strategies exhibiting significant Sharpe ratio improvement under level of 10%. The combined approach demonstrates a notably enhanced Sharpe ratio improvement over the entire set of 71 strategies.

Panel B of Table 4 shows that the superior results are robust to out-of-sample setups. We adopt a rolling estimation window from month 1 to t to estimate optimal factor weights in Equation 6, and forecast tangency portfolio excess returns at month $t+1$. [8] DeMiguel et al. (2009) point out concerns about moment conditions when estimating optimal portfolio weights within a short period of in-sample window. Thus, given that the whole sample period in the Chinese stock market is only 270 months, which is much shorter than that in the developed markets, we at least take the first one-third (90 months)

[8] To caution against structural change in the data generating process, we also use fixed window of $t = 90$ to conduct out-of-sample estimation. The results are robust.

as the cutoff to start out-of-sample evaluations. 46 combined strategies gain improved Sharpe ratio, with 10 strategies significant under level of 10%.

4. Other methods of volatility management

Other risk components implying the impact of market crashes or extreme cases underlying the Chinese equity market also attract attention recently(Sun, Wang, and Zhu, 2022). Following Barndorff-Nielsen et al. (2008), we further decompose total realized variance in Equation 1 into upside and downside semivariance in month t as follows,

$$\begin{aligned} \sigma^2_{u,k,t} &= \frac{21}{D}\sum_{d=1}^{D} f^2_{k,t-d}\mathbb{1}_{f_{k,t-d}>0} \\ \sigma^2_{d,k,t} &= \frac{21}{D}\sum_{d=1}^{D} f^2_{k,t-d}\mathbb{1}_{f_{k,t-d}\leq 0} \end{aligned} \tag{7}$$

where $\mathbb{1}_{f_{k,t-d}>0}(\mathbb{1}_{f_{k,t-d}\leq 0})$ is an indicator function taking the value of 1 if the day $t-d$ return is positive (negative), and zero otherwise. Then, we calculate the asymmetric variance of factor k as the difference between upside and downside semivariance normalized by total variance, which proxies for skewness realized variance:

$$\frac{\sigma^2_{u,k,t} - \sigma^2_{d,k,t}}{\sigma^2_{k,t}} \tag{8}$$

We measure the managing ability of downside realized variance and asymmetric variance on original factors, which have been analyzed in the pricing ability in equity market (Cederburg, O'Doherty, Wang, and Yan, 2020; Bollerslev, Li, and Zhao, 2020). Empirically, to ensure enough number of daily observations, we set the estimation window as of the previous three months. [9]

However, neither downside volatility nor asymmetric volatility management strategies excel over total volatility strategy, shown in Table A4 and A5. The evidence suggest that Chinese pricing factors are uniformly more sensitive to total volatility management.

[9]We also instead set time period as six months, and the empirical results are similar. Results are available upon request.

5. Portfolio analyses

In this section, we compare the performance of following four types of tangency portfolios, which are optimally spanned by: i) naïve strategy of equal-weighted combination of original factors as the benchmark model, ii) the original factors and risk-free asset, iii) the volatility-managed factors and risk-free asset, and iv) the original factors, corresponding volatility-managed factors, and risk-free asset, respectively. In terms of the selection of factors to optimally span the tangency portfolios, in a loosely manner, we mainly show performance results from a sample of $N = 34$ factors with significantly positive alphas or improved Sharpe ratios in Table 3. The chosen factors comprise almost half number of risky factors in the full sample, indicating that the $N = 34$ factors are rather representative. To circumvent potential concerns of the prior selection of characteristics, we also use full set of $N = 71$ factors to form associated tangency portfolios, and the similar results are shown in Table A6 and Table A7.

The fact that the large cross-sectional number of factors combined with a relatively short time period in the Chinese equity market may induce estimation noise or extreme leverage of factors when estimating the optimal factor weights. The following three concerns need to be tackled with. The first is that following Campbell and Thompson (2008) and DeMiguel, Martin-Utrera, and Uppal (2021), we discipline the optimal weights of factors by assignment a nonnegative weight for all risky factors. The second is that the leverage constraint for each factor is imposed as 5 to exclude extreme outliers, and in empirical tests, we find that the constraint level is robust to as low as 1 or unconstrained leverage. Last but not least, especially in terms of the combined strategy with twice the number of selected factors, as well as under out-of-sample estimation without ample number of observations in the early stage, the estimation of sample covariance matrix eigenvalues may include noise. We implement the methods in Ledoit and Wolf (2022) to shrink the eigenvalues of the estimated sample covariance of excess returns. [10]

[10] Ledoit and Wolf (2022) design a nonlinear shrinkage estimator derived under the Frobenius loss, Inverse Stein's loss, and minimum variance loss.

5.1. In-sample analysis

We start from in-sample performance over the full sample period. Table 5 displays the average returns, standard deviations, and annualized Sharpe ratios of above four tangency portfolios. One of the findings is that, all three tangency portfolios exhibit superior performance compared to the benchmark model at a significance level of 1%, thereby confirming the effectiveness of employing a time-varying asset allocation strategy. More importantly, tangency portfolio constructed from only managed factors achieves the highest annualized Sharpe ratio of 1.91. It is closely followed by the combination strategy, which gets a Sharpe ratio of 1.42. Both of the two multifactor models exhibit a significant superiority over the original version, which only yields a Sharpe ratio of 1.22. The primary source of economic benefits can be attributed to the implementation of a volatility-timing approach. Notably, multifactor constructed from only volatility factors delivers the lowest monthly standard deviation of 0.93% among all the strategies, which contributes to the highest Sharpe ratio we observed.

We also explore how the performance of the multifactor evolves over time. Figure 2 presents cumulative excess returns of four multifactors. To ensure returns of different portfolios are comparable, we normalize variance of all portfolios to ensure that the magnitude remains the same as the equal-weighted strategy. Figure 2 shows that cumulative return of volatility managed strategy clearly dominates other three strategies and increase steadily during all period. For instance, around global finance crisis in 2008 and the Chinese stock market crash in 2015 shaded in grey region, except for the flat trend of volatility managed strategy, all other three strategies suffer from fluctuation and downturn to varying degrees.

Overall, the evidence suggests that original factors are sensitive to historical volatility signals, and employing a volatility-managed multifactor approach that fully incorporates the information content of volatility leads to beneficial performance outcomes.

5.2. Out-of-sample analysis

In this section, we evaluate whether in-sample improvement of tangency portfolio continues to outperform counterparts under out-of-sample setup. Out-of-sample estimation is implementable for a real-time mean-variance investor, and the empirical result provides important intuition to the real effect of managed strategy. Considering statistical requirements of proper estimation of optimal weights of $t >> N$, we implement the rolling window estimation with at least $t = 120$ months to start out-of-sample scheme. The covariance matrix of factor excess returns are estimated with Ledoit and Wolf (2022) method to exclude potential errors induced by the short span of time periods.

Table 6 shows that outperformance of managed strategy is consistent with in-sample results without potential look-ahead bias. Table 6 presents out-of-sample average mean, standard deviation, annualized Sharpe ratio, and results of Sharpe ratio difference test. Though Sharpe ratios of all strategies with time-varying optimal weights decrease to some extent, the dominance of two managed versions over the original version still persist. The tangency portfolio constructed from only managed factors still achieves the lowest monthly standard deviation of 0.93% and the highest annualized Sharpe ratio of almost 1.60, and the combined strategy achieves a standard deviation of 3.10% and a Sharpe ratio of 1.20. [11]

Consistent with patterns in Figure 2, Figure 3 plots out-of-sample excess cumulative return of all trading strategies. Cumulative return plots of the volatility strategy and combined strategy are steadily increasing across all periods, immune to all stock market crashes shaded in grey regions.

Table A6 and A7 reports results of tangency portfolio constructed from the whole universe of 71 factors, and the economic performance is robust to the prior selection of factors. Considering fairly larger cross-sectional number of factors, we impose estimation correction of Ledoit and Wolf (2021) across all strategies and both in-sample and out-of-sample setups. Table A6 reveals that in-sample multifactors spanned from two versions

[11] For robustness check of the selection of out-of-sample window, Table **??** presents similar results out-of-sample estimation results starting from $t = 90$. The starting of estimation window is fairly robust.

of managed factors provide significantly higher Sharpe ratio than that spanned by the original version or benchmark model. The outperformance is persistent shown in Table A7 under out-of-sample setup.

In general, above empirical evidence suggests that volatility timing strategy is significantly profitable in the Chinese equity market from both perspective of individual factor and mean-variance efficient multifactor analysis. We suggest that the significance of volatility timing effect in China may be attributed to several factors, including the variability of volatility across different categories of factors, the substantial portion of retail investors with behavioral biases and speculative needs, and the dynamic nature of macroeconomic conditions. Rigorous channel analyses are shown in the following section.

6. Possible explanations

In this section, we examine the economic mechanisms driving the superior performance of volatility-managed strategy, particularly associated with prominent features of high limit-to-arbitrage and large retail trading in the Chinese equity market. Further, investor sentiment and macroeconomic conditions also determine the speed of mispricing correction. To aggregate abundant volatility information available for investors, we investigate performance of the multifactor portfolios under different market conditions.

6.1. Limit-to-arbitrage

The Chinese equity market has typical features of high arbitrage risk and strictly restrictive short-selling, binding the pricing correction and lowering the speed of restoring to equilibrium returns(Gu, Kang, and Xu, 2018; Wan, 2020; Hong, Li, Wang, and Wang, 2023). Barroso and Detzel (2021) points out that the abnormal returns of volatility-managed factors may be driven by limit-to-arbitrage regulations, which prevents arbitrageurs from trading aggressively and results in underreaction to volatility signals. Hence, we hypothesize that higher limit-to-arbitrage renders the existence of mispricing alpha obtained by the volatility-managed portfolios.

We construct several proxies for limit-to-arbitrage. The first variable is the idiosyncratic risk, IV, which is calculated as the standard deviation of daily excess returns on Liu, Stambaugh, and Yuan (2019) three factor model over the previous one month. The second related variable is qualification of short-sell constraint. The Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) launched a pilot scheme of margin trading and short selling since March 2010, and gradually enlarge the list of designated stocks. Obviously, stocks not included in the designation list face higher short selling constraints without elimination of overpricing. Third, small stocks are well documented to be risky and costly to arbitrage (Baker and Wurgler, 2006). At the end of each month, we partition all stocks into value-weighted portfolios based on the sample median of IV. For short selling constraint proxy, we partition sample stocks with or without short selling constraint based on the monthly designation lists. Size portfolios are sorted into the decile portfolios, and we consider top 30% stocks as large stocks, and the bottom 30% as small stocks. [12] Then, In order to obtain identification of the effects of limit-to-arbitrage on managed factors and ensure consistent volatility information across groups, we form managed factor returns using the same level of leverage from the full sample:

$$f^{\sigma}_{k,s,t} = \frac{c_k}{\sigma^2_{k,t-1}} f_{k,s,t} \tag{9}$$

where s refers to low- and high-LTA groups. Consistent with our hypothesis, the escalation of the volatility-managed strategy concentrates in stocks with high LTA. Panel A and B of Table 7 shows that managed factors earn larger magnitudes of mispricing alpha in stocks with high IV. Panel C and D of Table 7 shows that managed factors earn larger magnitudes of mispricing alpha in stocks with short selling constraint. Panel E and F of Table 7 shows that managed factors earn larger magnitudes of mispricing alpha in stocks with smaller size. [13] Besides, we also perform the comparison based on lottery

[12] We classify stocks with or without designation based on the status of the last trading day of each trading month. Related data are retrieved from CSMAR. Following Liu et al. (2019), our sample has deleted stocks with the bottom 30% market capitalization across the whole sample of A-share stocks. To better capture the attributes of small stocks, we categorize stocks in the lowest 30% of market capitalization from the remaining 70% of full sample stocks, rather than relying on the sample median as the case of IV.

[13] Another commonly used proxy for arbitrage risk is the institutional ownership(Nagel, 2005), which defines as the market capitalization of domestic institutional holdings scaled by market capitalization of outstanding A shares. However, in the Chinese equity market typical of large proportion of retail

preference, and the results are shown in Table A8.

6.2. Sentiment

Retail investors account for 85% trading volume in the Chinese equity market, who are documented to hold heterogeneous belief toward asset prices, irrationally speculate, and induce higher investor sentiment(Han and Li, 2017). High sentiment also account for excess volatility shocks and valuation difficulty, and thus deteriorate conditional mean-variance relation(Baker and Wurgler, 2006; Yu and Yuan, 2011; Stambaugh, Yu, and Yuan, 2012, 2015). The typical issue raises concerns about whether original portfolios could time volatility risk properly and could be overvalued. We thus argue that performance variation of different trading strategies is conditional on investor sentiment. Following Baker and Wurgler (2006) and Du, Liang, Chen, and Tu (2022), we adopt the monthly investor sentiment index for the Chinese stock market using the first principal component of the six investor sentiment proxies. The sentiment proxies include: close-end fund discount rate (CEFD), share turnover (TURN), the number of IPOs (NIPO), first-day returns on IPOs (RIPO), the equity share in new issues (EQTI), and the dividend premium (PDIV). [14] We define month t as a high- (low-)sentiment period if the investor sentiment index in month $t-1$ is above (below) the median over the full sample period.

Contrary to common sense of high sentiment attenuating the link between conditional risk-return tradeoff for small stocksYu and Yuan (2011), Panel A of Table 8 shows that mean-variance factor exhibits higher return following high sentiment periods, indicating that multifactor strategies, which integrates ample information compared with single anomaly, tend to be undervalued during high sentiment periods. This may due to

trading, the effect of institutional ownership is limited to explain the outperformance of VMPs. Results are available upon request.

[14] Hou, Qiao, and Zhang (2023) adopts the volatility premium instead of dividend premium in the Chinese equity market, for only giants payout dividends in the early stage. The volatility premium is calculated as the month-end natural log of the ratio of the value-weighted average market-to-book ratio of high volatility stocks to that of low volatility stocks. High and low volatility stocks are stocks in the top and bottom three deciles, respectively, based on the variance of monthly returns in the previous year. We test that sentiment effect is robust to different constructions. All raw data are retrieved from CSMAR.

the fact that retail investors trade aggressively or hold heterogeneous valuations towards small firms, but overlook investing demand for "factor of factors" during high-sentiment period (Yuan, 2015; Baker and Wurgler, 2006), causing higher future expected returns. Conversely, though managed portfolios achieve better performance following low sentiment realizations but the elevation is not significant, suggesting that sentiment cannot explain payoffs derived from volatility timing. Panel B of Table 8 further shows that volatility-managed strategy achieves significantly higher trade-off than other strategies following low sentiment period under level of 5%, indicating that managed version provides valuation benefits during low-sentiment periods.

6.3. Macroeconomic confidence

Macroeconomic conditions also determine asset prices.[15] Empirically, Lemmon and Portniaguina (2006) associates economic fundamentals to the small-stock premium, which are retrieved from two survey data covering U.S. consumer confidence and consumer sentiment. Motivated by underlying determining component of economic fundamentals, we investigate the relationship between macroeconomic confidence level and future risk-return tradeoff. Monthly macroeconomic confidence index is released by National Bureau of Statistics[16], which generally consist of investor consumption, industrial production, investment, employment, and income to denote short-term economic trend. Contrarily to speculative property underlying sentiment or arbitrage risk discussed above, the confidence index captures the fundamentally macroeconomic conditions covering both nation-wide investing prospects and residence welfare.[17] We define month t as a high-(low-)confidence period if the macroeconomic confidence index in month $t-1$ is above (below) the median.

Intuitively, Panel A of Table 9 shows that gains of multifactor strategy generally

[15] Classical consumption-based asset pricing model include Lucas(1987), Epstein and Zin(1989), Bansal and Yaron(2004), Backus, Routledge, and Zin(2008), etc.

[16] See: http://www.stats.gov.cn/zs/tjws/tjfx/202301/t20230101_1903945.html. The Chinese confidence index captures typical business cycles to the extent that it precipitously shrinks during 2008 financial crisis, 2015 stock market crash, and 2019 breakout of pandemic.

[17] The time series correlation between macroeconomic confidence index, sentiment, and arbitrage risk is -4.72% and 6.58%, illustrating that confidence index indeed capture different aspects of economic development.

derive from market conditions with high confidence level: Sharpe ratio of unmanaged strategies halves following low confidence level. The evidence suggests that after going through macroeconomic depression, investors uniformly hold conservative beliefs toward future investments and even underreact to temporarily optimistic shocks, resulting in even lower future returns. Comparatively, however, for volatility-managed portfolios considering volatility risk, the performance is relatively robust to worse macroeconomic conditions with magnitude of decreasing Sharpe ratio -0.09. This indicates that the managed strategy typically provides hedging benefits during macroeconomic shrinkage periods. Panel B of Table 9 corroborates that managed version achieves significantly robust outperformance against original strategies following low confidence period.

Overall, economic mechanism results show that managed version achieves higher risk-return tradeoff during low investor sentiment, low idiosyncratic volatility, and high macroeconomic confidence periods. It is intuitive given that Chinese equity market exhibits high degree of retail investor trading and opaque trading environment. Furthermore, compared with other trading strategies, managed version achieves robust superior hedging performance against other strategies during higher investor sentiment, easily arbitraging and lower macroeconomic confidence periods.

7. Conclusion

In this study, we analyze the factor timing strategy of volatility strategy in the Chinese equity market to the complete domain using 9 commonly-used pricing factors and extending to the 71 representative factors. The empirical results imply that volatility timing strategies demonstrate favourable performance against original factors from the perspective of both the individual factor analysis and mean-variance efficient multifactor analysis, and the results are robust under out-of-sample setups. Specifically, the outperformance is primarily attributed to factors related to value, risk, profitability, and trading friction. For instance, the 12-month momentum factor and the CAPM model-implied risk factors turn into conditionally profitable investment strategies.

We examine economic mechanisms driving the outperformance of volatility timing strategies, and stocks with high limit-to-arbitrage typically gain significant improvement managed with volatility. Further, the portfolio analyses show that the managed multifactors achieve robust risk-return tradeoff during turmoil market states, particularly during high investor sentiment and low macroeconomic confidence periods.

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Table 1: Summary statistics for pricing factors

Panel A reports monthly mean excess returns(%) with t-statistic in parentheses and annualized Sharpe ratios of original version(S1) and managed version(S2) across 9 pricing factors. Panel B reports spanning regression α of managed factors on original factors and R-squared in Equation 3. Panel C reports Sharpe ratio difference test, developed by Jobson and Korkie (1981) with Memmel (2003) correction, between volatility-managed strategies and original factors. The sample period spans from January 2000 to June 2022. Reported statistics are p-value and z-statistics. Standard errors are adjusted with Newey and West (1987) five lag correction.

	MKT	SMB	VMG	PMO	ROE	I/A	HML	RMW	CMA
Panel A: Summary statistics									
Original factor strategy									
Return	0.676	0.501*	0.940***	0.779***	0.734***	-0.172	0.643**	0.784***	0.112
	(1.47)	(1.80)	(4.04)	(3.48)	(3.27)	(-1.325)	(2.20)	(4.87)	(0.89)
Sharpe ratio	0.287	0.383	0.861	0.786	0.669	-0.304	0.458	0.748	0.016
Vol-managed factor strategy									
Return	0.383	-0.403	1.174***	0.677***	1.082***	-0.035	0.942***	0.773***	0.216
	(0.83)	(-1.445)	(5.03)	(3.07)	(4.83)	(-0.272)	(3.36)	(4.06)	(1.35)
Sharpe ratio	0.176	-0.305	1.061	0.647	1.017	-0.057	0.707	0.857	0.285
Panel B: Spanning regressions									
α	-0.078	-0.689***	0.529***	0.200	0.599***	0.090	0.593**	0.289**	0.208*
	(-0.25)	(-2.97)	(2.98)	(1.08)	(3.57)	(0.92)	(2.55)	(2.13)	(1.68)
R-squared	0.542	0.319	0.458	0.337	0.460	0.446	0.327	0.514	0.401
Panel C: Sharpe ratio difference									
Diff	-0.111	-0.688	0.200	-0.139	0.349	0.247	0.249	0.108	0.269
p-value	0.354	0.010	0.250	0.319	0.119	0.185	0.200	0.355	0.172
z-statistic	-0.376	-2.332	0.673	-0.471	1.181	0.896	0.840	0.373	0.945

Table 2: Economic Performance for volatility-managed factors and original factors

This table summarizes number of observations from spanning regressions and Sharpe ratio difference test across 71 factors. Alpha test from spanning regressions are given in Equation 3. Sharpe ratio difference test validity between volatility-managed version and original version is shown in Equation 4. Panel A reports results for the complete set of 71 factors. Panel B shows results for factors and anomaly portfolios. Panel C breaks down results to seven types of trading categories.The sample period spans from January 2000 to June 2022. The significance level is set as 10%. Standard errors are adjusted with Newey and West (1987) five lag correction.

		Univariate regressions		Sharpe ratio difference	
	N	Alpha > 0 [Signif.]	Alpha < 0 [Signif.]	SR > 0 [Signif.]	SR < 0 [Signif.]
Panel A: Whole sample					
All trading strategies	71	55 [34]	16 [5]	47 [14]	24 [5]
Panel B: By category					
Factors	9	7 [5]	2 [1]	6 [0]	3 [0]
Anomaly portfolios	62	48 [29]	14 [4]	41 [14]	21 [5]
Panel C: By trading strategy type					
Investment	12	9 [4]	3 [1]	9 [0]	3 [1]
Past return	5	2 [1]	3 [1]	2 [1]	3 [1]
Profitability	23	20 [11]	3 [0]	16 [4]	7 [0]
Risk	6	4 [3]	2 [1]	4 [2]	2 [2]
Trading frictions	12	9 [6]	3 [2]	7 [3]	5 [2]
Value	12	11 [9]	1 [0]	9 [4]	3 [0]
Market	1	0 [0]	1 [0]	0 [0]	1 [0]

Table 3: Analysis for factors with significant economic improvement

This table summarizes analysis of factors with significant alpha from spanning regression or Sharpe ratio improvement under significance level of 10%. Column (1), (2) and (3) reports monthly mean(%) of original version, volatility-managed version, and alpha of spanning regression from regressing volatility-managed factors on original factors. Column (4), (5) and (6) displays Sharpe ratio of original factors, volatility-managed factors, and the difference between them. The sample period spans from January 2000 to June 2022. Factors are ranked by order of categories. Factors with bold font are those that unconditionally unprofitable strategies transforming into conditionally profitable strategies under significance level of 5%. ***/**/* indicate the significant at 1%, 5% and 10% confidence level, respectively. Standard errors are adjusted with Newey and West (1987) five lag correction.

	Acronym	Category	Spanning regression			Sharpe ratio test		
			Original (1)	Vol (2)	α (3)	Original (4)	Vol (5)	Diff (6)
1	**mom12m**	Past return	0.105	0.713***	0.640***	0.097	0.659	0.56***
3	lev	Investment	0.166	0.479*	0.381*	0.136	0.259	0.123
4	lgr	Investment	0.184*	0.276**	0.161*	0.364	0.319	-0.046
5	**noa**	Investment	0.194	0.300**	0.169*	0.302	0.479	0.177
2	cashspr	Profitability	0.042	0.299*	0.271**	0.057	0.409	0.35**
6	**chtx**	Profitability	0.169	0.380***	0.262***	0.312	0.701	0.39**
7	pchsale_pchrect	Profitability	0.214**	0.382***	0.231***	0.454	0.811	0.36**
8	salerev	Profitability	0.286*	0.549***	0.352***	0.370	0.711	0.34**
9	chpm	Profitability	0.377***	0.469***	0.209**	0.701	0.582	-0.120
10	fscore	Profitability	0.842***	0.895***	0.248**	1.057	1.043	-0.015
11	**oscore**	Profitability	0.216	0.327**	0.168*	0.316	0.367	0.051
12	pchquick	Profitability	0.026	0.136	0.117*	0.058	0.074	0.017
13	tb	Profitability	0.358**	0.473***	0.233**	0.544	0.571	0.027
14	**beta**	Risk	0.19	0.541***	0.406***	0.198	0.562	0.36**
15	**idiovol**	Risk	0.36	0.979***	0.766***	0.301	0.820	0.52***
16	**volatility2**	Risk	0.39	0.694***	0.437**	0.312	0.351	0.039
17	dolvol	Trading frictions	0.760***	1.313***	0.891***	0.646	1.116	0.47**
18	ear	Trading frictions	0.444***	0.689***	0.504***	0.720	1.118	0.40**
19	**turn**	Trading frictions	0.38	0.791***	0.543***	0.318	0.662	0.34*
20	maxret2	Trading frictions	0.545***	0.622***	0.278*	0.553	0.363	-0.191
21	mo12turn	Trading frictions	0.619**	0.956***	0.578***	0.524	0.443	-0.081
22	std_turn	Trading frictions	1.208***	1.335***	0.708***	1.068	0.738	-0.330
23	egr	Value	0.475***	0.730***	0.397***	0.610	0.938	0.33*
24	operprof	Value	0.712***	0.998***	0.506***	0.711	0.997	0.29*
25	roc	Value	0.560***	0.885***	0.487***	0.615	0.972	0.36**
26	roeq	Value	0.629***	0.912***	0.487***	0.689	0.999	0.31*
27	cfp	Value	0.325***	0.420***	0.174**	0.555	0.723	0.168
28	roic	Value	0.739***	0.743***	0.233**	1.013	0.877	-0.136
29	sp	Value	0.438**	0.695***	0.427***	0.448	0.641	0.193
30	VMG	Value	0.940***	1.174***	0.529***	0.861	1.061	0.200
31	ROE	Profitability	0.734***	1.082***	0.599***	0.669	1.017	0.349
32	HML	Value	0.643**	0.942***	0.593**	0.458	0.707	0.249
33	RMW	Profitability	0.784***	0.773***	0.289**	0.748	0.857	0.108
34	CMA	Investment	0.112	0.216	0.208*	0.016	0.285	0.269

Table 4: Combined strategy for individual factors

This table summarizes number of observations of combined strategies. Combined strategy include mean-variance optimal combination of original factors and risk-free asset, volatility-managed factors and risk-free asset, and original factors, managed factors and risk-free asset. This table reports comparison results of managed strategy against original strategy, as well as combined strategy against original strategy. Panel A reports in-sample results and Panel B presents out-of-sample results. Out-of-sample period starts from month $t = 91$ since January 2000 with recursive estimation scheme. Scaling parameter c is estimated iteratively. The sample period spans from January 2000 to June 2022. Standard errors are adjusted with Newey and West (1987) five lag correction.

	N	Univariate regressions		Sharpe ratio difference	
		Alpha > 0 [Signif.]	Alpha < 0 [Signif.]	SR > 0 [Signif.]	SR < 0 [Signif.]
Panel A: In-sample results					
Managing strategy					
All trading strategies	71	64 [31]	7 [0]	47 [11]	24 [2]
Factors	9	8 [5]	1 [0]	5 [0]	4 [0]
Anomaly portfolios	62	56 [26]	6 [0]	42 [11]	20 [2]
Combined strategy					
All trading strategies	71	71 [32]	0 [0]	71 [10]	0 [0]
Factors	9	9 [5]	0 [0]	9 [0]	0 [0]
Anomaly portfolios	62	62 [27]	0 [0]	62 [10]	0 [0]
Panel B: Out-of-sample results					
Managing strategy					
All trading strategies	71	64 [31]	7 [0]	46 [11]	25 [2]
Factors	9	8 [5]	1 [0]	3 [0]	6 [0]
Anomaly portfolios	62	56 [26]	6 [0]	43 [11]	19 [2]
Combined strategy					
All trading strategies	71	71 [32]	0 [0]	46 [10]	25 [1]
Factors	9	9 [5]	0 [0]	4 [0]	5 [0]
Anomaly portfolios	62	62 [27]	0 [0]	42 [10]	20 [1]

Table 5: In-sample result for mean-variance efficient factor

Panel A of this table presents in-sample result for mean-variance efficient factor spanned by original factors and risk-free rate(S1), volatility-managed factors and risk-free rate(S2), and combination of original factors, volatility-managed factors and risk-free rate(S3). Equal-weighted average of original factors are taken as the benchmark model(S0). Panel B reports Sharpe ratio difference test between managed portfolio and original portfolio, and test between combination portfolio and original portfolio. The sample period spans from January 2000 to June 2022.

	Mean	Standard deviation	Sharpe ratio
[S0] Equal-weighted factor	0.439	1.758	0.864
[S1] Original factor	0.760	2.150	1.224
[S2] Vol-managed factor	0.513	0.931	1.909
[S3] Combined strategy	1.421	3.459	1.423
SR difference test			
[S2]-[S1]	0.684	[S3]-[S1]	0.199
p-value	**0.001**	p-value	**0.005**
z-statistic	3.416	z-statistic	2.817
[S2]-[S0]	1.044	[S3]-[S0]	0.559
p-value	**0.000**	p-value	**0.000**
z-statistic	5.462	z-statistic	8.395

Table 6: Out-of-sample result for mean-variance efficient factor

Panel A of this table presents out-of-sample result for mean-variance efficient factor spanned by original factors and risk-free rate(S1), volatility-managed factors and risk-free rate(S2), and combination of original factors, volatility-managed factors and risk-free rate(S3). Equal-weighted average of original factors are taken as the benchmark model(S0). Panel B reports Sharpe ratio difference test between managed portfolio and original portfolio, and test between combination portfolio and original portfolio. The sample period spans from January 2000 to June 2022. Out-of-sample period starts from month $t = 121$ since January 2000 with recursive estimation scheme. We shrink sample covariance matrix eigenvalues in Ledoit and Wolf (2021) across all strategies.

	Mean	Standard deviation	Sharpe ratio
[S0] Equal-weighted factor	0.488	1.510	1.120
[S1] Original factor	0.668	2.437	0.949
[S2] Vol-managed factor	0.428	0.928	1.598
[S3] Combined strategy	1.076	3.102	1.202
SR difference test			
[S2]-[S1]	0.649	[S3]-[S1]	0.253
p-value	**0.011**	p-value	**0.015**
z-statistic	2.540	z-statistic	2.439
[S2]-[S0]	0.478	[S3]-[S0]	0.082
p-value	**0.007**	p-value	0.343
z-statistic	2.718	z-statistic	0.949

Table 7: Limit-to-arbitrage analysis

This table summarizes the number of observations from spanning regressions and Sharpe ratio difference test across 68 factors in groups of different levels of limit-to-arbitrage constraint. Limit-to-arbitrage constraints are measured with three proxies: the idiosyncratic risk which is the standard deviation of daily excess returns on Liu, Stambaugh, and Yuan (2019) three factor model over the previous one month, the short selling constraint, and size, which is the total market capitilization over the previous one month respectively. Each month, we sort stocks into two value-weighted decile portfolios based on the proxy of the limit-to-arbitrage constraint. Alpha test from spanning regressions are given in Equation 3. Sharpe ratio difference test between volatility-managed version and original version is shown in Equation 4. Panel A and B report results for measure of idiosyncratic risk, Panel C and D report results for the stocks with or without short selling constraint, and Panel E and F for stocks of different size. The sample period spans from January 2000 to June 2022. The significance level is set as 10%. Standard errors are adjusted with Newey and West (1987) five lag correction.

		Univariate regressions		Sharpe ratio difference	
	N	Alpha > 0 [Signif.]	Alpha < 0 [Signif.]	SR > 0 [Signif.]	SR < 0 [Signif.]
Panel A: High idiosyncratic risk					
All trading strategies	68	59 [42]	12 [3]	48 [11]	23 [7]
Factors	7	6 [5]	3 [0]	5 [3]	4 [3]
Anomaly portfolios	61	53 [37]	9 [3]	43 [8]	19 [4]
Panel B: Low idiosyncratic risk					
All trading strategies	68	45 [16]	26 [5]	26 [4]	45 [12]
Factors	7	5 [2]	4 [1]	4 [1]	5 [3]
Anomaly portfolios	61	40 [14]	22 [4]	22 [3]	40 [9]
Panel C: Non designated stocks					
All trading strategies	68	52 [29]	16 [1]	41 [11]	27 [1]
Factors	7	4 [1]	3 [0]	2 [1]	5 [1]
Anomaly portfolios	61	48 [28]	13 [0]	39 [10]	22 [0]
Panel D: Designated stocks					
All trading strategies	68	40 [11]	28 [5]	25 [1]	43 [12]
Factors	7	4 [1]	3 [1]	4 [0]	3 [3]
Anomaly portfolios	61	36 [10]	25 [4]	21 [1]	40 [9]
Panel E: Small size					
All trading strategies	68	55 [38]	13 [2]	43 [14]	25 [3]
Factors	7	6 [4]	1 [0]	4 [2]	3 [0]
Anomaly portfolios	61	49 [34]	12 [2]	39 [12]	22 [3]
Panel F: Large size					
All trading strategies	68	44 [18]	24 [5]	26 [5]	42 [14]
Factors	7	4 [1]	3 [1]	3 [1]	4 [3]
Anomaly portfolios	61	40 [17]	21 [4]	23 [4]	38 [11]

Table 8: Sentiment effect analysis

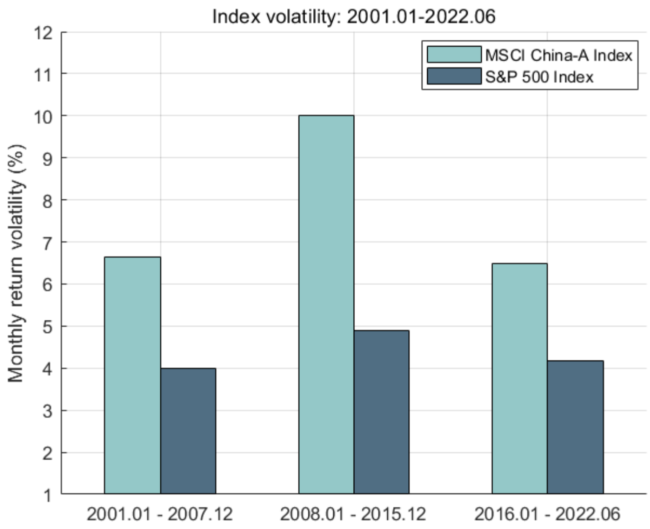
This table presents sentiment effect analysis of out-of-sample mean-variance efficient factor spanned by original factors and risk-free rate(S1), volatility-managed factors and risk-free rate(S2), and combination of original factors, volatility-managed factors and risk-free rate(S3). Sentiment periods are partitioned into high- and low- periods based on sample median. Equal-weighted average of original factors are taken as the benchmark model(S0). This table also reports Sharpe ratio difference test between high sentiment and low sentiment period for each strategy. Out-of-sample period starts from month $t = 121$ since January 2000 with recursive estimation scheme.

Panel A: Summary statistics				
		Mean	Standard deviation	Sharpe ratio
[S0] Equal-weighted factor	High sentiment	0.586	1.405	1.446
	Low sentiment	0.390	1.612	0.838
		Diff	p-value	z-statistic
	Low-High	-0.608	0.328	-0.978
[S1] Original factor	High sentiment	1.050	3.439	1.058
	Low sentiment	0.941	4.054	0.804
		Diff	p-value	z-statistic
	Low-High	-0.254	0.672	-0.424
[S2] Vol-managed factor	High sentiment	0.506	1.015	1.728
	Low sentiment	0.681	1.658	1.424
		Diff	p-value	z-statistic
	Low-High	-0.304	0.623	-0.491
[S3] Combined strategy	High sentiment	2.172	5.579	1.349
	Low sentiment	2.795	9.364	1.034
		Diff	p-value	z-statistic
	Low-High	-0.315	0.610	-0.510
Panel B: Sharpe ratio difference test				
High sentiment	[S2]-[S1]	Diff	p-value	z-statistic
		0.670	**0.081**	1.742
	[S2]-[S0]	Diff	p-value	z-statistic
		0.282	0.320	0.995
Low sentiment	[S2]-[S1]	Diff	p-value	z-statistic
		0.620	**0.051**	1.951
	[S2]-[S0]	Diff	p-value	z-statistic
		0.586	**0.012**	2.527

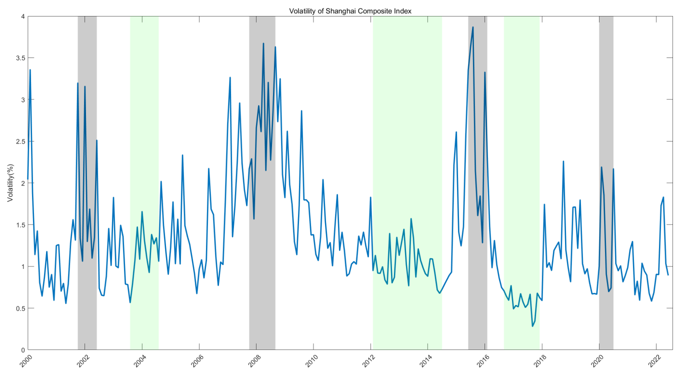
Table 9: Macroeconomic confidence analysis

This table presents macroeconomic confidence effect analysis of out-of-sample mean-variance efficient factor spanned by original factors and risk-free rate(S1), volatility-managed factors and risk-free rate(S2), and combination of original factors, volatility-managed factors and risk-free rate(S3). Confidence periods are partitioned into high- and low- periods based on sample median. Equal-weighted average of original factors are taken as the benchmark model(S0). This table also reports Sharpe ratio difference test between high confidence and low confidence period for each strategy. Out-of-sample period starts from month $t = 121$ since January 2000 with recursive estimation scheme.

Panel A: Summary statistics				
		Mean	Standard deviation	Sharpe ratio
[S0] Equal-weighted factor	High confidence	0.635	1.486	1.481
	Low confidence	0.341	1.530	0.772
		Diff	p-value	z-statistic
	Low-High	-0.709	0.235	-1.187
[S1] Original factor	High confidence	1.079	3.110	1.202
	Low confidence	0.912	4.310	0.733
		Diff	p-value	z-statistic
	Low-High	-0.469	0.424	-0.799
[S2] Vol-managed factor	High confidence	0.485	1.060	1.584
	Low confidence	0.703	1.627	1.497
		Diff	p-value	z-statistic
	Low-High	-0.088	0.884	-0.146
[S3] Combined strategy	High confidence	2.269	5.542	1.418
	Low confidence	2.698	9.392	0.995
		Diff	p-value	z-statistic
	Low-High	-0.423	0.469	-0.725
Panel B: Sharpe ratio difference test				
High confidence	[S2]-[S1]	Diff	p-value	z-statistic
		0.383	0.173	1.362
	[S2]-[S0]	Diff	p-value	z-statistic
		0.103	0.575	0.561
Low confidence	[S2]-[S1]	Diff	p-value	z-statistic
		0.764	**0.039**	2.065
	[S2]-[S0]	Diff	p-value	z-statistic
		0.724	**0.007**	2.677



(a) Return volatility



(b) A-share volatility

Figure 1: Volatility patterns of the Chinese equity market

Figure 1(a) displays monthly return volatilities (%) of MSCI China A-share index and S&P 500 index over time. Figure 1(b) shows realized volatility of daily returns of Shanghai Stock Market Index.

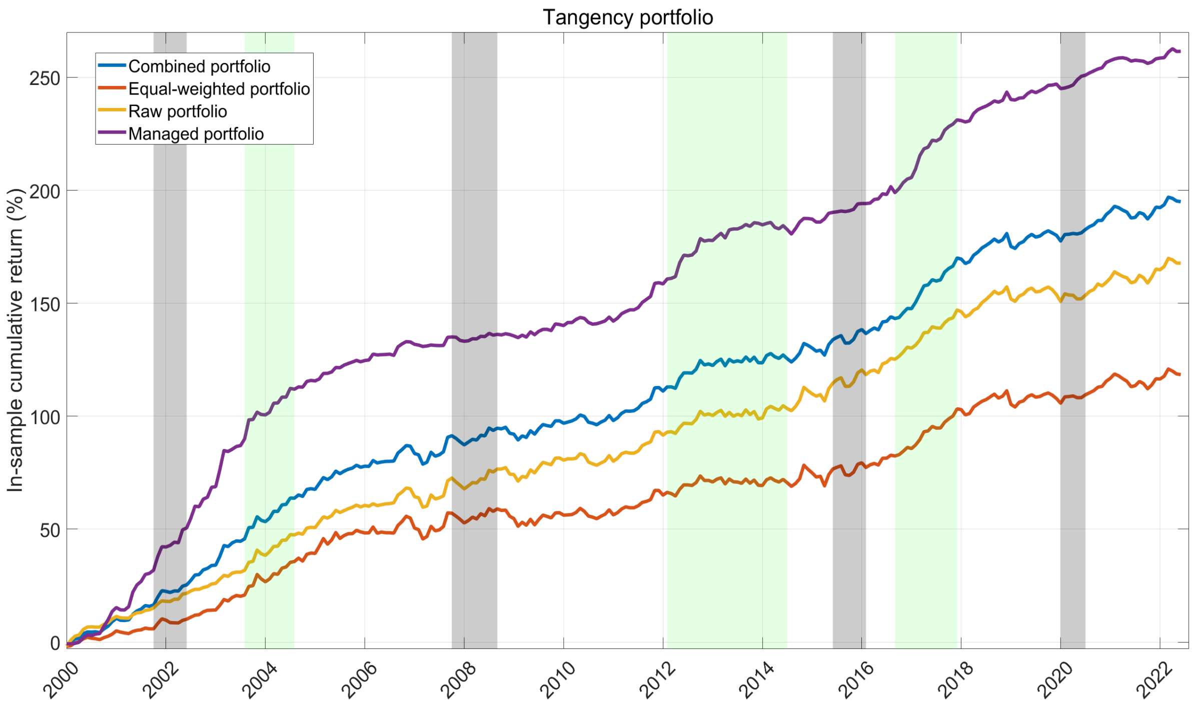


Figure 2: In-sample cumulative return of tangency portfolio

This figure displays in-sample cumulative return of tangency portfolio spanned by original factors(denoted as yellow), volatility factors(denoted as purple) and combination of original factors and volatility factors(denoted as blue), respectively. Equal-weighted average of original factors are used as the benchmark model(denoted as red). The factors are chosen as 34 individual factors with improved performance managing with total volatility. The sample period spans from January 2000 to June 2022.

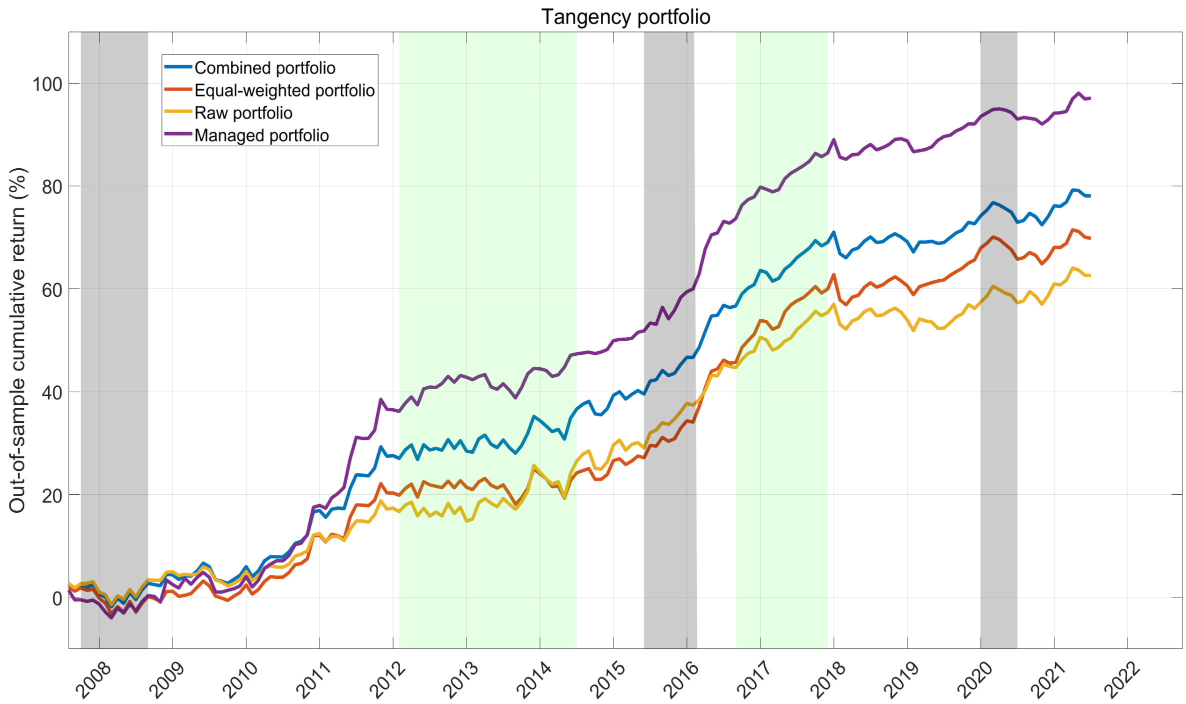


Figure 3: Out-of-sample cumulative returns of tangency portfolios

This figure displays out-of-sample cumulative return of tangency portfolio spanned by original factors(denoted as yellow), volatility factors(denoted as purple) and combination of original factors and volatility factors(denoted as blue), respectively. Equal-weighted average of original factors are used as the benchmark model(denoted as red). The factors are chosen as 34 individual factors with improved performance managing with total volatility. Out-of-sample period starts from month $t = 91$ since January 2000 with recursive estimation scheme. We shrink sample covariance matrix eigenvalues in Ledoit and Wolf (2021) across all strategies.

Internet Appendix
(not for publication)

Volatility-managed Portfolios in the Chinese Equity Market

Table A1: Definition of Firm Characteristics

No.	Acronym	Stock Characteristics Definition	Data Source	Frequency	Literature
1	acc	acc = [(Δ CA - Δ CASH) - (Δ CL - Δ STD - Δ TP) - Dep]/ Total Assets; where Δ represents the difference between two consecutive periods, CA, CASH, CL, STD, TP and Dep denote current assets, cash/cash equivalents, current liabilities, non-current liabilities due within one year, notes payable, income tax payable, depreciation and amortization expense, respectively.	CSMAR	Semi-annual	Sloan, 1996
2	absacc	Absolute value of acc.	CSMAR	Semi-annual	Bandyopadhyay, Huang and Wirjanto, 2010
3	abturn	The ratio of its average daily share turnover within month t to its average daily share turnover over the past 12 months/ A firm's abnormal turnover is calculated as the ratio of its average daily turnover over the past 20 days to its average daily turnover over the past 250 days. A firm's daily turnover is calculated as its share trading volume divided by its total shares outstanding.	WIND	Monthly	Liu,Stambaugh and Yu, 2019
4	Mo12turn	The average daily share turnover over the past 250 days. A firm's daily turnover is calculated as its share trading volume divided by its total shares outstanding.	WIND	Monthly	Liu,Stambaugh and Yu, 2019
5	agr	Annual percent change in total assets.	CSMAR	Annual	Cooper, Gulen, and Schill, 2008
6	beta	Estimated market beta from weekly excess returns and value weighted market excess returns for 3 years ending month t-1 with at least 52 weeks of returns.	WIND	Monthly	Fama and MacBeth, 1973
7	idiovol	Standard deviation of residuals of weekly excess returns on weekly value weighted market excess returns for 3 years prior to month end(ending in month t-1).	WIND	Monthly	Ali, Hwang and Trombley, 2003
8	betadimson	CAPM beta is estimated using the past 12 months(month t-11 through t, inclusive) of daily excess returns with a five-lag Dimson (1979) correction.	WIND	Monthly	Dimson, 1979
9	bm	Book value of equity divided by month-end market capitalization, where book value of equity is defined as total shareholders' equity excluding minority interests, and market capitalization as close price multiplied by total shares outstanding.	CSMAR, WIND	Monthly	Rosenberg, Reid and Lanstein, 1985
10	cash	Cash and cash equivalents divided by average total assets(quater t and t-1).	CSMAR	Quarterly	Palazzo, 2012
11	cashdebt	Earnings divided by total liabilities, where earnings is defined as in Liu,Stambaugh and Yu(2019).	CSMAR, WIND	Quarterly	Ou and Penman, 1989
12	cashspr	Quarter-end market capitalization plus long-term debt minus total assets divided by cash and equivalents.	CSMAR	Quarterly	Chandrashekar and Rao, 2006
13	cfp	Operating cash flows divided by quarter-end market capitalization.	CSMAR	Quarterly	Desai, Rajgopal, and Venkatachalam, 2004
14	chato	Change in sales divided by average total assets.	CSMAR	Quarterly	Soliman, 2008
15	chinv	Change in inventory scaled by total assets.	CSMAR	Quarterly	Thomas and Zhang, 2002
16	chmom	Cumulative returns from months t-6 to t-1 minus months t-12 to t-7.	WIND	Monthly	Gettleman and Marks, 2006
17	chpm	Change in income before extraordinary items scaled by sales.	CSMAR, WIND	Quarterly	Soliman, 2008
18	chtx	Percent change in taxes from quarter t-1 to t.	CSMAR	Quarterly	Thomas and Zhang, 2011
19	cp	Cash flow equals the net change in cash or cash equivalents between the two most recent cash flow statements. A stock's CP is the ratio of cash flow to the product of last month-end's close price and total shares.	CSMAR, WIND	Monthly	Liu,Stambaugh and Yu, 2019
20	distress	distress =(-20.26NIMTAAVG+1.42TLMTA-7.13EXRETAVG+1.41 SIGMA-0.045RSIZE-2.13CASHMTA+0.075MB-0.058PRICE- 9.16) where	CSMAR, WIND	Monthly	Stambaugh and Yuan, 2017
21	dolvol	Natural logarithm of trading volume times price per share from month t-2.	WIND	Monthly	Chordia, Subrahmanyam and Anshuman, 2001
22	ear	Sum of daily returns in three days around earnings announcement.	WIND	Quarterly	Kishore, Brandt, Santa-Clara, and Venkatachalam, 2008
23	egr	Quarterly percentage change in book value of equity.	CSMAR	Quarterly	Richardson, Sloan, Soliman and Tuna, 2005

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No.	Acronym	Stock Characteristics Definition	Data Source	Frequency	Literature
24	ep	Earnings equals the most recently reported net profit excluding nonrecurrent gains/losses. A stock's EP is the ratio of earnings to the product of last month-end's close price and total shares.	WIND	Quarterly	Liu,Stambaugh and Yu, 2019
25	fscore	The composite score, F, is the sum of the individual binary signals: Fscore = Froa + Fdroa + Fcf/a + Facc + Fdmargin + Fdturn + Fdlever + Fdliquid. For the sake of simplicity, we refer readers to the Appendix B. of Hou, Qiao and Zhang(2020, WP) for more details.	CSMAR	Quarterly	Piotroski, 2000; Hou, Qiao and Zhang, 2020
26	gma	Revenue minus cost of goods sold divided by lagged total assets.	CSMAR	Quarterly	Novy-Marx, 2013
27	grCAPX	Percent change in capital expenditures from year t-1/2 to year t.	CSMAR	Semi-annual	Anderson and Garcia-Feijoo, 2006
28	herf	Sum of squared percent sales in industry for each company.	CSMAR	Quarterly	Hou and Robinson, 2006
29	hire	Percent change in number of employees.	CSMAR	Annual	Bazdresch, Belo and Lin, 2014
30	ill	Average of daily (absolute return/RMB volume)*1,000,000 in month t.	WIND	Monthly	Amihud, 2002
31	invest	The sum of annual change in fixed assets and annual change in inventories divided by lagged total assets.	CSMAR	Annual	Chen and Zhang, 2010
32	lev	Total liabilities divided by quarter-end market capitalization.	CSMAR, WIND	Quarterly	Bhandari, 1988
33	lgr	Quarterly percent change in total liabilities.	CSMAR	Quarterly	Richardson, Sloan, Soliman and Tuna, 2005
34	lm	[(Number of volumes¡150000 in month t-1) + (1/sum of daily turnover in month t-1)/deflator]*(21/NoTD), where NoTD is the total number of trading days over the month t-1, and deflator is maxTurnover in month t-1+1 for all stocks in each month.	WIND	Monthly	Liu, 2006; Hou, Qiao and Zhang, 2021
35	maxret	Maximum daily return from returns during month t-1.	WIND	Monthly	Bali, Cakici and Whitelaw, 2011
36	maxret2	Following Liu,Stambaugh and Yu(2019), maximum daily return from returns during month t.	WIND	Monthly	Liu,Stambaugh and Yu, 2019
37	mom12m	11-month cumulative returns ending one month before month end(month t-12 to month t-1).	WIND	Monthly	Jegadeesh, 1990
38	mom1m	1-month cumulative return(month t).	WIND	Monthly	Jegadeesh and Titman, 1993
39	mom6m	5-month cumulative returns ending one month before month end(month t-6 to month t-1).	WIND	Monthly	Jegadeesh and Titman, 1993
40	mom36m	Cumulative returns from months t-36 to t-13.	WIND	Monthly	Jegadeesh and Titman, 1993
41	mve	Natural log of market capitalization at end of month t-1.	WIND	Monthly	Banz, 1981
42	noa	(Operating asset - Operating liability)/lagged Total asset. Operating asset equals total assets minus cash and short-term investment, and Operating liability equals total assets minus short-term debt, long-term debt, minority interest, book preferred stock, and book common equity.	CSMAR	Quarterly	Liu,Stambaugh and Yu, 2019
43	operprof	Quarterly operating profit divided by lagged common shareholders' equity, where common shareholders' equity is defined as total shareholders' equity excluding minority interests.	CSMAR	Quarterly	Fama and French, 2015; Leippold, Qian and Zhou, 2022
44	op	Operating revenue minus cost of goods sold, interest expense, selling expense, general and administrative expense, all divided by the total shareholder equity.	CSMAR	Quarterly	Fama and French, 2015
45	oscore	O = -1.32 - 0.407 log(TA) + 6.03TLTA - 1.43WCTA + 0.076CLCA - 1.72OENEG - 2.37NITA - 1.83FUTL + 0.285IN2 - 0.521CHIN. For the sake of simplicity, we refer readers to the Appendix B. of Hou, Qiao and Zhang(2020, WP) for more details.	CSMAR, WIND	Quarterly	Ohlson, 1980
46	pchgm_pchsale	Percentage change in gross margin minus percentage change in sales.	CSMAR	Quarterly	Abarbanell and Bushee, 1998
47	pchquick	Percentage change in quick ratio.	CSMAR	Quarterly	Ou and Penman, 1989
48	pchsale_pchrect	Quarterly percentage change in sales minus quarterly percentage change in receivables.	CSMAR	Quarterly	Abarbanell and Bushee, 1998
49	pchsale_pchxsga	Quarterly percentage change in sales minus quarterly percentage change in management expenses.	CSMAR	Quarterly	Abarbanell and Bushee, 1998
50	pchsaleinv	Quarterly percentage change in sales-to-inventory.	CSMAR	Quarterly	Ou and Penman, 1989

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No.	Acronym	Stock Characteristics Definition	Data Source	Frequency	Literature
51	pctacc	Same as acc except that the numerator is divided by the absolute value of net income; if net income = 0 then net income set to 0.01 for denominator.	CSMAR	Semi-annual	Hafzalla, Lundholm and VanWinkle, 2011
52	quick	Quick ratio, (current assets - inventory) / current liabilities.	CSMAR	Quarterly	Ou and Penman, 1989
53	roaq	Income before extraordinary items divided by one quarter lagged total assets.	CSMAR, WIND	Quarterly	Balakrishnan, Bartov and Faurel, 2010
54	roe	The ratio of a firm's earnings to book equity, where book equity is defined as total shareholders' equity excluding minority interests	CSMAR, WIND	Quarterly	Liu,Stambaugh and Yu, 2019
55	roeq	Income before extraordinary items divided by lagged common shareholders' equity.	CSMAR, WIND	Quarterly	Hou, Xue and Zhang, 2015
56	roc	EBIT/(Net working capital + Net fixed assets)	CSMAR	Quarterly	Brown and Rowe, 2007
57	roic	EBIT/Enterprise Value(ceq+lt-che)	CSMAR, WIND	Quarterly	Brown and Rowe, 2007
58	rsup	Sales from quarter t minus sales from quarter t-1 divided by quarter-end market capitalization.	CSMAR	Quarterly	Kama, 2009
59	salecash	Quarterly sales divided by cash and cash equivalents.	CSMAR	Quarterly	Ou and Penman, 1989
60	saleinv	Quarterly sales divided by total inventory.	CSMAR	Quarterly	Ou and Penman, 1989
61	salerev	Quarterly sales divided by accounts receivable.	CSMAR	Quarterly	Ou and Penman, 1989
62	sgr	Quarterly percentage change in sales.	CSMAR	Quarterly	Lakonishok, Shleifer and Vishny, 1994
63	skewness	Skewness of a stock's daily returns from month t.	WIND	Monthly	Hou, Xue and Zhang, 2019
64	sp	Quarterly sales divided by quarter-end market capitalization.	CSMAR	Quarterly	Barbee, Mukherji and Raines, 1996
65	std_turn	Monthly standard deviation of daily share turnover in month t. Daily share turnover is defined as daily trading volume scaled by daily shares outstanding.	WIND	Monthly	Chordia, Subrahmanyam and Anshuman, 2001
66	tang	(Cash holdings + 0.715*receivables + 0.547*inventory + 0.535*fixed assets)/total assets.	CSMAR	Quarterly	Almeida and Campello, 2007
67	tb	Tax income, defined as net income plus income expense, divided by net income.	CSMAR, WIND	Quarterly	Lev and Nissim, 2004
68	turn	Average monthly trading volume for month t-3 to t-1 scaled by number of shares outstanding in month t.	WIND	Monthly	Datar, Naik and Radcliffe, 1998
69	volatility	The standard deviation of daily returns from month t-1.	WIND	Monthly	Ang, Hodrick, Xing and Zhang, 2006
70	volatility2	The standard deviation of daily returns from month t.	WIND	Quarterly	Ang, Hodrick, Xing and Zhang, 2006

Table A2: Groups of Characteristics

This table categorizes 70 firm characteristics into six groups, including investment, past return, profitability, risk, trading friction and value following Leippold, Wang, and Zhou (2022).

Panel A: Investment			
absacc	Absolute accruals	acc	Working capital accruals
chinv	Change in inventory	grCAPX	Growth in capital expenditures
hire	Employee growth rate	invest	Capital expenditures and inventory
lev	Leverage to market capitalization	lgr	Growth in long-term debt
noa	Operating accruals	pctacc	Percent change in accruals
Panel B: Past return			
chmom	Change in 6-month momentum	mom6m	6-month momentum
mom12m	12-month momentum	mom36m	36-month momentum
mom1m	1-month momentum		
Panel C: Profitability			
cash	Cash to total assets	cashdebt	Earnings to total liabilities
cashspr	Cash productivity	chpm	Change in profit margin
chato	Change in asset turnover	fscore	Composite F score
chtx	Change in tax expense	oscore	Ohlson's O-score
gma	Gross profitability	pchquick	Percent change in quick ratio
pchgm_pchsale	Percent change in gross margin - percent change in sales	pchsale_pchxsga	Percent change in sales - percent change in SG&A
pchsale_pchrect	Percent change in sales - percent change in A/R	quick	Quick ratio
pchsaleinv	Percent change in sales-to-inventory	salecash	Sales to cash
rsup	Revenue surprise	salerev	Sales to inventory
saleinv	Sales to receivables	tb	Tax income to book income
tang	Debt capacity/firm tangibility		
Panel D: Risk			
beta	CAPM market beta	betadimson	Dimson-adjusted CAPM market beta
idiovol	Idiosyncratic return volatility	skewness	Skewness of a stock's daily returns
volatility	Volatility of daily return at month t-1	volatility2	Volatility of daily return at month t
Panel E: Trading frictions			
abturn	One month abnormal turnover	maxret	Maximum daily return at month t-1
mo12turn	Average daily share turnover	maxret2	Maximum daily return at month t
herf	Industry sales concentration	mve	Market capitalization
dolvol	Yuan trading volume	std_turn	Standard deviation of daily share turnover
ear	Earnings announcement return	turn	Share turnover
ill	Standard deviation of residuals	lm	Turnover-adjusted number of zero daily trading volume
Panel F: Value			
bm	Book-to-market equity	operprof	Quarterly operating profit to common shareholders' equity
cfp	Operating cash flows to market capitalization	op	Operating profitability to market capitalization
cp	Cash to market capitalization	roaq	Return on assets
egr	Growth in common shareholder equity	roe	Earnings to book equity
sgr	Sales growth	roeq	Earnings to lagged book equity
ep	Earnings to market capitalization	roc	Return on capital
sp	Leverage to market capitalization	roic	Return on invested capital

Table A3: Summary statistics for anomaly factors

This table reports summary statistic of average mean return(%), t-value, and annualized Sharpe ratio across whole set of factors over the whole sample period. Volatility-managed factor returns are scaled with 1-month realized total volatility of each individual factor. ***/**/* indicate the significant at 1%, 5% and 10% confidence level, respectively. Standard errors are adjusted with Newey and West (1987) five lag correction.

		Original version			Managed version		
	Factor	Mean return	t-stas	Sharpe ratio	Mean return	t-stas	Sharpe ratio
1	absacc	0.044	(0.309)	0.065	-0.260*	(-1.825)	-0.385
2	acc	0.044	(0.416)	0.088	0.129	(1.225)	0.258
3	beta	0.19	(0.937)	0.198	0.541***	(2.667)	0.562
4	betadimson	0.016	(0.058)	0.012	-0.686**	(-2.504)	-0.528
5	cash	0.101	(0.868)	0.183	0.189	(1.622)	0.342
6	cashdebt	0.502***	(2.612)	0.551	0.482**	(2.507)	0.528
7	cashspr	0.042	(0.272)	0.057	0.299*	(1.940)	0.409
8	cfp	0.325***	(2.633)	0.555	0.420***	(3.401)	0.717
9	chato	0.319***	(2.768)	0.583	0.330***	(2.861)	0.603
10	chinv	0.098	(0.937)	0.198	0.154	(1.466)	0.309
11	chmom	0.11	(0.923)	0.195	0.022	(0.181)	0.038
12	chpm	0.377***	(3.326)	0.701	0.469***	(4.139)	0.873
13	chtx	0.169	(1.479)	0.312	0.380***	(3.327)	0.701
14	cp	0.038	(0.392)	0.083	-0.084	(-0.868)	-0.183
15	dolvol	0.760***	(3.063)	0.646	1.313***	(5.294)	1.116
16	ear	0.444***	(3.416)	0.72	0.689***	(5.301)	1.118
17	egr	0.475***	(2.894)	0.61	0.730***	(4.451)	0.938
18	fscore	0.842***	(5.015)	1.057	0.895***	(5.331)	1.124
19	gma	0.581***	(2.928)	0.617	0.479**	(2.412)	0.509
20	grCAPX	0.041	(0.348)	0.073	-0.03	(-0.254)	-0.053
21	herf	0.034	(0.234)	0.049	-0.165	(-1.138)	-0.24
22	hire	0.286**	(2.165)	0.456	0.292**	(2.213)	0.467
23	idiovol	0.36	(1.429)	0.301	0.979***	(3.892)	0.82
24	ill	0.690***	(2.602)	0.548	0.4	(1.511)	0.318
25	invest	0.084	(0.658)	0.139	0.17	(1.328)	0.28
26	lev	0.166	(0.645)	0.136	0.479*	(1.866)	0.393
27	lgr	0.184*	(1.728)	0.364	0.276**	(2.593)	0.547
28	lm	0.455*	(1.936)	0.408	0.483**	(2.058)	0.434
29	maxret	0.445**	(2.173)	0.458	0.440**	(2.152)	0.454
30	maxret2	0.545***	(2.625)	0.553	0.622***	(2.997)	0.632
31	Mo12turn	0.619**	(2.488)	0.524	0.956***	(3.840)	0.81

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		Original version			Managed version		
	Factor	Mean return	t value	Sharpe ratio	Mean return	t value	Sharpe ratio
32	mom12m	0.105	(0.458)	0.097	0.713***	(3.125)	0.659
33	mom1m	0.811***	(3.327)	0.701	0.089	(0.365)	0.077
34	mom36m	0.017	(0.109)	0.023	0.094	(0.593)	0.125
35	mom6m	0.102	(0.458)	0.096	-0.17	(-0.761)	-0.16
36	noa	0.194	(1.432)	0.302	0.300**	(2.215)	0.467
37	operprof	0.712***	(3.374)	0.711	0.998***	(4.731)	0.997
38	oscore	0.216	(1.501)	0.316	0.327**	(2.269)	0.478
39	pchgm_pchsale	0.066	(0.804)	0.169	0.115	(1.394)	0.294
40	pchquick	0.026	(0.274)	0.058	0.136	(1.425)	0.3
41	pchsale_pchrect	0.214**	(2.155)	0.454	0.382***	(3.847)	0.811
42	pchsale_pchxsga	0.085	(0.851)	0.179	0.024	(0.237)	0.05
43	pchsaleinv	0.313***	(3.253)	0.686	0.336***	(3.489)	0.736
44	pctacc	0.054	(0.546)	0.115	0.025	(0.257)	0.054
45	quick	0.078	(0.390)	0.082	-0.183	(-0.916)	-0.193
46	roaq	0.591***	(3.141)	0.662	0.511***	(2.714)	0.572
47	roc	0.560***	(2.917)	0.615	0.885***	(4.610)	0.972
48	roeq	0.629***	(3.266)	0.689	0.912***	(4.740)	0.999
49	roic	0.739***	(4.803)	1.013	0.743***	(4.826)	1.017
50	rsup	0.394***	(3.738)	0.788	0.387***	(3.668)	0.773
51	salecash	-0.007	(-0.078)	-0.016	-0.066	(-0.704)	-0.148
52	saleinv	0.063	(0.450)	0.095	0.209	(1.492)	0.315
53	salerev	0.286*	(1.755)	0.37	0.549***	(3.374)	0.711
54	sgr	0.335***	(2.936)	0.619	0.273**	(2.394)	0.505
55	skewness	0.376**	(2.518)	0.531	0.182	(1.219)	0.257
56	sp	0.438**	(2.123)	0.448	0.695***	(3.372)	0.711
57	std_turn	1.208***	(5.067)	1.068	1.335***	(5.602)	1.181
58	tang	0.293*	(1.885)	0.397	0.209	(1.350)	0.285
59	tb	0.358**	(2.581)	0.544	0.473***	(3.413)	0.72
60	turn	0.38	(1.507)	0.318	0.791***	(3.139)	0.662
61	volatility	0.363	(1.477)	0.311	0.382	(1.555)	0.328
62	volatility2	0.39	(1.479)	0.312	0.694***	(2.636)	0.556

Table A4: Downside volatility management

This table summarizes number of observations from spanning regressions and Sharpe ratio difference test across 71 factors managed with downside volatility. Alpha test from spanning regressions are given in Equation 3. Sharpe ratio difference test validity between volatility-managed version and original version is shown in Equation 4. Panel A reports results for the complete set of 71 factors. Panel B shows results for factors and anomaly portfolios. Panel C breaks down results to seven types of trading categories. The significance level is set as 10%.

		Univariate regressions		Sharpe ratio difference	
	N	Alpha > 0 [Signif.]	Alpha < 0 [Signif.]	SR > 0 [Signif.]	SR < 0 [Signif.]
Panel A: Whole sample					
All trading strategies	71	54 [27]	17 [6]	42 [6]	29 [6]
Panel B: By category					
Factors	9	7 [4]	2 [0]	5 [0]	4 [1]
Anomaly portfolios	62	47 [23]	15 [6]	37 [6]	25 [5]
Panel C: By trading strategy type					
Investment	12	7 [2]	5 [1]	7 [2]	5 [1]
Past return	5	2 [1]	3 [2]	2 [1]	3 [2]
Profitability	23	20 [10]	3 [1]	16 [0]	7 [1]
Risk	6	4 [1]	2 [1]	3 [1]	3 [0]
Trading frictions	12	9 [5]	3 [1]	5 [1]	7 [2]
Value	12	11 [8]	1 [0]	9 [1]	3 [0]
Market	1	1 [1]	0 [0]	0 [0]	1 [0]

Table A5: Asymmetric volatility management

This table summarizes number of observations from spanning regressions and Sharpe ratio difference test across 71 factors managed with asymmetric volatility. Alpha test from spanning regressions are given in Equation 3. Sharpe ratio difference test validity between volatility-managed version and original version is shown in Equation 4. Panel A reports results for the complete set of 71 factors. Panel B shows results for common factors and other factors. Panel C breaks down results to seven types of trading categories. The significance level is set as 10%.

		Univariate regressions		Sharpe ratio difference	
	N	Alpha >0 [Signif.]	Alpha <0 [Signif.]	SR >0 [Signif.]	SR <0 [Signif.]
Panel A: Whole sample					
All trading strategies	71	35 [2]	36 [3]	11 [1]	60 [28]
Panel B: By category					
Factors	9	6 [0]	3 [1]	2 [1]	7 [5]
Anomaly portfolios	62	29 [2]	33 [2]	9 [0]	53 [23]
Panel C: By trading strategy type					
Investment	12	9 [0]	3 [0]	7 [1]	5 [1]
Past return	5	2 [0]	3 [0]	0 [0]	5 [1]
Profitability	23	12 [1]	11 [1]	2 [0]	21 [8]
Risk	6	1 [0]	5 [0]	1 [0]	5 [2]
Trading frictions	12	4 [0]	8 [1]	0 [0]	12 [9]
Value	12	6 [1]	6 [1]	1 [0]	11 [7]
Market	1	1 [0]	0 [0]	0 [0]	1 [0]

Table A6: In-sample tangency portfolio for all sample factors

This table reports summary statistics of in-sample tangency portfolio spanned from full sample of 71 factors. Shrinkage estimation of sample covariance matrix eigenvalues for the combined strategy is applied. Bottom panel reports Sharpe ratio difference test. We shrink sample covariance matrix eigenvalues in Ledoit and Wolf (2021) across all strategies.

	Mean	Standard deviation	Sharpe ratio
[S0] Equal-weighted factor	0.345	0.805	1.485
[S1] Original factor	0.892	1.584	1.950
[S2] Vol-managed factor	0.659	0.957	2.384
[S3] Combined strategy	1.462	2.251	2.250
SR difference test			
[S2]-[S1]	0.434	[S3]-[S1]	0.300
p-value	**0.050**	p-value	**0.001**
z-statistic	1.957	z-statistic	3.221
[S2]-[S0]	0.899	[S3]-[S0]	0.765
p-value	**0.000**	p-value	**0.000**
z-statistic	4.337	z-statistic	8.402

Table A7: Out-of-sample tangency portfolio for all sample factors

This table reports summary statistics of out-of-sample tangency portfolio spanned from full sample of $N = 71$ factors. Bottom panel reports Sharpe ratio difference test. Out-of-sample period starts from month $t = 181$ since January 2000 with recursive estimation scheme to satisfy estimation requirement of $t >> N$. We shrink sample covariance matrix eigenvalues in Ledoit and Wolf (2021) across all strategies.

	Mean	Standard deviation	Sharpe ratio
[S0] Equal-weighted factor	0.364	0.653	1.933
[S1] Original factor	0.787	1.531	1.782
[S2] Vol-managed factor	0.593	0.954	2.152
[S3] Combined strategy	1.304	2.236	2.020
SR difference test			
[S2]-[S1]	0.371	[S3]-[S1]	0.238
p-value	0.363	p-value	0.250
z-statistic	0.909	z-statistic	1.149
[S2]-[S0]	0.219	[S3]-[S0]	0.087
p-value	0.418	p-value	0.643
z-statistic	0.811	z-statistic	0.464

Table A8: Lottery preference analysis

This table summarizes the number of observations from spanning regressions and Sharpe ratio difference test across 68 factors in three different groups of lottery preference. Each month, we sort stocks into value-weighted decile portfolios based on lottery preference, which is the maximum daily return over the previous one month. We define stocks in the bottom 30%, medium 40%, and top 30% deciles as stocks with low lottery preference, medium lottery preference, and high lottery preference, respectively. Alpha test from spanning regressions are given in Equation 3. Sharpe ratio difference test between volatility-managed version and original version is shown in Equation 4. Panel A, B, and C reports results for the stocks with low lottery preference, medium lottery preference, and high lottery preference, respectively. The sample period spans from January 2000 to June 2022. The significance level is set as 10%. Standard errors are adjusted with Newey and West (1987) five lag correction.

		Univariate regressions		Sharpe ratio difference	
	N	Alpha > 0 [Signif.]	Alpha < 0 [Signif.]	SR > 0 [Signif.]	SR < 0 [Signif.]
Panel A: Low lottery preference					
All trading strategies	68	42 [12]	28 [5]	24 [3]	46 [17]
Factors	7	5 [2]	4 [0]	3 [1]	6 [3]
Anomaly portfolios	61	37 [10]	24 [5]	21 [2]	40 [14]
Panel B: Medium lottery preference					
All trading strategies	68	54 [25]	17 [5]	38 [7]	33 [9]
Factors	7	6 [3]	3 [1]	4 [2]	5 [3]
Anomaly portfolios	61	48 [22]	14 [4]	34 [5]	28 [6]
Panel C: Large lottery preference					
All trading strategies	68	55 [39]	13 [6]	39 [9]	29 [6]
Factors	7	5 [4]	2 [1]	3 [1]	4 [1]
Anomaly portfolios	61	50 [35]	11 [5]	36 [8]	25 [5]

Table A9: Recession

This table presents recession period of in-sample mean-variance efficient factor spanned by original factors and risk-free rate(S1), volatility-managed factors and risk-free rate(S2), and combination of original factors, volatility-managed factors and risk-free rate(S3). Equal-weighted average of original factors are taken as the benchmark model(S0). Recession period refers to 2007 financial crisis, 2015 Chinese equity market crash, and 2020 Covid-19 breakout.

Panel A: Summary statistics				
		Mean	Standard deviation	Sharpe ratio
[S0] Equal-weighted factor	Recession	0.196	2.029	0.334
	Normal	0.520	1.655	1.089
[S1] Original factor	Recession	0.514	2.668	0.667
	Normal	0.842	1.945	1.500
[S2] Vol-managed factor	Recession	0.181	0.528	1.188
	Normal	0.624	1.008	2.145
[S3] Combined strategy	Recession	0.771	3.876	0.689
	Normal	1.640	3.288	1.727

Panel B: Sharpe ratio difference test				
Recession	[S2]-[S1]	Diff	p-value	z-statistic
		0.520	0.138	1.483
	[S2]-[S0]	Diff	p-value	z-statistic
		0.853	**0.010**	2.578
Normal	[S2]-[S1]	Diff	p-value	z-statistic
		0.645	**0.004**	2.878
	[S2]-[S0]	Diff	p-value	z-statistic
		1.056	**0.000**	4.854

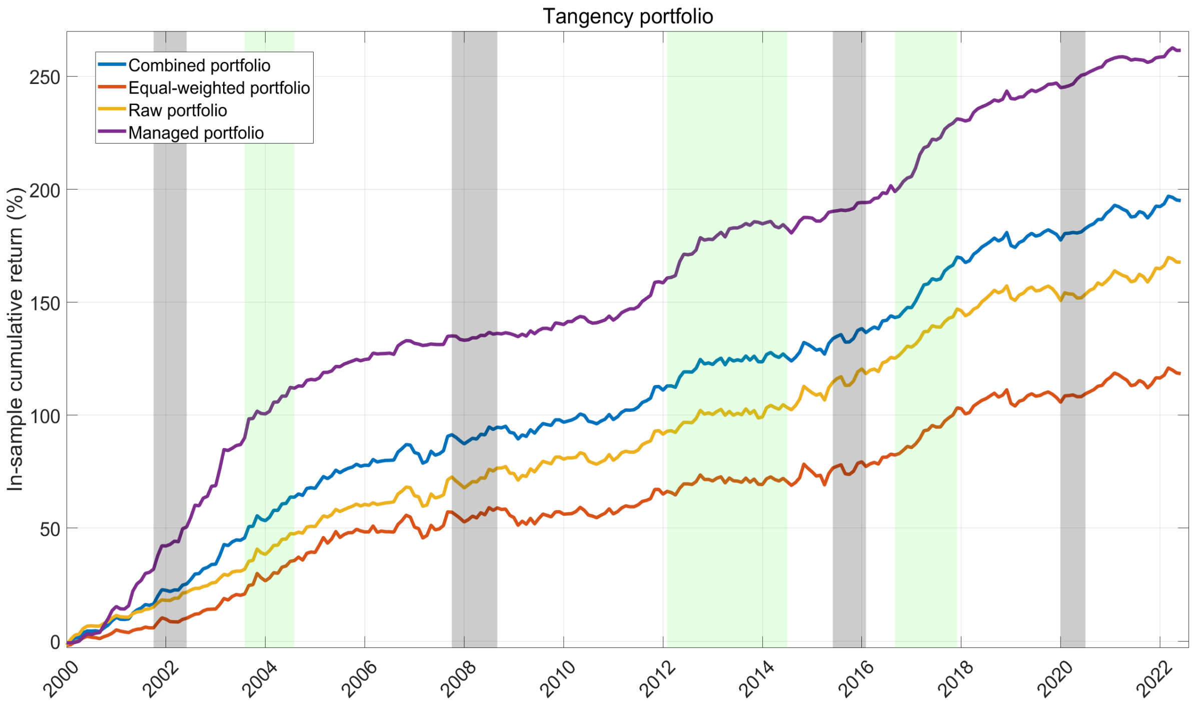

Figure A1: In-sample cumulative returns of tangency portfolios for full sample

This figure displays in-sample cumulative returns of tangency portfolios spanned by original factors(denoted as yellow), volatility factors(denoted as purple) and combination of original factors and volatility factors(denoted as blue), respectively. Equal-weighted average of original factors are used as the benchmark model(denoted as red). The factors are chosen as full sample of 71 individual factors. We shrink sample covariance matrix eigenvalues in Ledoit and Wolf (2021) across all strategies.