Do Volatility-Managed Portfolios Work? Empirical Evidence from the Chinese Stock Market ⋆

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Abstract

Using data from the Chinese stock market, we have found that the main empirical findings in Moreira and Muir (2017) break down. Based on the new empirical findings, we exploit a comprehensive set of 99 equity strategies in the Chinese stock market to analyze the economic value of managed portfolios. Based on these 99 equity trading strategies, we find that there exists no systematic gain from scaling the original portfolios using volatility. Our empirical results suggest that one should be careful to use volatility-managed portfolios in practice as the expected performance gains are rather limited.

Keywords: Volatility-managed portfolios; Realized volatility; Anomaly investment; Chinese stock market

JEL Classification: C80, G11, G12

⋆ I am grateful for helpful discussions from Tao Zeng and Xiaobin Liu. All errors are my own. Yaohan Chen, School of Economics, Singapore Management University, 90 Stamford Road, Singapore 178903. Email: yaohan.chen.2017@phdecons.smu.edu.sg.

1 Introduction

Volatility played a vital role in financial decision making, including, for instance, derivatives pricing, portfolio selection, and risk management (Engle, 2004). Early studies such as Fleming, Kirby, and Ostdiek (2001) and Fleming, Kirby, and Ostdiek (2003) document the advantage of using volatility information to improve the portfolio performance. More recent studies further document the gain associated with volatility-managed portfolios of trading strategies (for instance, Ang, 2014; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Moreira and Muir, 2017, 2019; Eisdorfer and Misirli, 2020).

The basic idea of the volatility-managed portfolio is to scale the original portfolios (strategies) by taking conservative positions in the underlying factors when volatility was high and taking more aggressively levered positions following periods of low volatility. This idea can be generally understood from the global minimum variance portfolio in the conventional optimal portfolio theory (see Basak, Jagannathan, and Ma, 2009).

Let Σ denote the variance-covariance matrix of assets and μ denote the corresponding expected returns of assets. Then the optimal portfolio theory suggests that the optimal allocation weights, $\boldsymbol{w}$, assigned to assets contained in the global minimum variance portfolio is proportional $\Sigma^{-1}\mu$. If μ is fixed, then the magnitude of each element in $\boldsymbol{w}$ is proportional to Σ^{-1}. Consequently, volatility management can be heuristically interpreted as putting smaller weights on assets with greater volatility and larger weights on those with less volatility.

However, all these documented successes of using volatility to manage portfolios are mainly restricted to one or a few strategies (factors). Specifically, those portfolios studied in Ang (2014) are mainly about conventional benchmark factors (Fama-French factors) while both the discussions in Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) are restricted to momentum-related trading strategies. By contrast, Moreira and Muir (2017) make the corresponding discussions mainly based on 10 leading factors that are widely used in empirical asset pricing literature by adding some recently proposed strategies such as the betting-against-beta strategy in Frazzini and Pedersen (2014). In this regard, those empirical findings fail to provide a broad view demonstrating how general these volatility-managed portfolios can perform improvements in comparison to the unmanaged ones. This issue has been noticed in Cederburg, O'Doherty, Wang, and Yan (2020). In particular, Cederburg, O'Doherty, Wang, and Yan (2020) accentuate that, although using the set of leading factors as anomaly portfolios (as in Moreira and Muir, 2017) for analysis reconciles well with the leading asset pricing models, it fails to accommodate the recent findings from some machine learning methods that a larger set of anomalies (firm-level characteristics) is needed to be jointly studied (see Kelly, Pruitt, and Su, 2019; Kozak, Nagel, and Santosh, 2020; Kozak, 2020). In other words, although there exists a widely acknowledged base for volatility-managed portfolios, their performance is far from reaching a consensus.

Other than the debate between Moreira and Muir (2017) and Cederburg, O'Doherty, Wang, and Yan (2020), Barroso and Detzel (2021) further points out that the documented extra gain from managing equity portfolios via volatility-timing vanishes once transaction costs of specific forms are accounted (for instance, the look-ahead bias considered in Liu, Tang, and Zhou, 2019). Last but not least, all the existing studies on this topic mainly focus on using data constructed from the U.S. stock market. Rarely is there any empirical analysis on whether this volatility-based strategy works in other stock markets.

We begin this paper by applying the *market* volatility-timing strategy in Moreira and Muir (2017) to the Chinese stock market. To our surprise, we find that some documented empirical findings for the U.S. market do not hold in the Chinese stock market. As a result, our research motivation naturally stems from asking to what extent shall we support using information associated with volatility for portfolio management for gaining performance improvement? Or put it in another way, is volatility management as a portfolio management strategy still broadly applicable to other markets even without accounting for some recently proposed explanations (for instance those interpretations made from accommodating trading costs, Liu, Tang, and Zhou, 2019; Barroso and Detzel, 2021) for the controversial performance of volatility-managed portfolios?

As for the measurement for portfolio performance, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) assess whether investors can improve the anomaly portfolios' performances by scaling holding positions of the original portfolios based on comparing the Sharpe ratios of "volatility-managed" portfolios with those earned by the corresponding unscaled strategies. This is the so-called direct comparison. We follow this approach as in Cederburg, O'Doherty, Wang, and Yan (2020) to compare the volatility-managed portfolios with the un-managed ones directly. Specifically, we construct a relative comprehensive 99 equity (anomaly) portfolios using data collected from the Chinese stock market and the associated 99 volatility-managed anomaly portfolios. We find that for these 99 volatility-managed anomaly portfolios, only 14 of them can generate statistically significant Sharpe ratio differences, which suggests that there exists no systematic evidence to support that investors can earn performance improvements from scaling the original anomaly portfolios using the volatility of previous period.

Apart from the direct comparison using the Sharpe ratios, we also apply another empirical method using spanning regression to check whether we can obtain performance gain by adjusting the holding positions via lagged volatility. In comparison to measuring performance gain using the Sharpe ratios directly, spanning regression was initially suggested in Moreira and Muir (2017). The essence is rooted in the appraisal ratio closely related to the asset pricing model test or comparison (see Gibbons, Ross, and Shanken, 1989; Barillas and Shanken, 2018). The main objective of this spanning regression methodology is to check whether there exists a statistically significant alpha by running univariate time-series regression using monthly excess returns (we will come back on this and discuss it more in detail both in Section 2 and Section 4). Given this objective associated with spanning regression, we can see that the major implication of spanning regression is whether investors can construct a new portfolio with higher Sharpe ratio by combining the volatility-managed portfolio with the original un-managed portfolio. This is why it is usually referred to the combination strategy in the literature. By applying spanning regression on our constructed broader sample of anomaly portfolios (99 equity trading strategies) in the Chinese stock market, we find 71 out of 99 volatility-managed anomaly portfolios earn positive alphas but with only 16 of them are statistically significant at a generally acceptable significance level. Besides, we also find another 8 volatility-managed portfolios earn significantly negative in-sample alpha generated from spanning regression. Thus, we have 24 anomaly portfolios in all that can be acceptably regarded as gaining performance improvement by combing the original ones with the ones scaled via volatility.

The rest of the paper is summarized as follows: In Section 2, we review some basic concepts about volatility-managed portfolios and some technical details that have been discussed in literature. In Section 3, we discuss how we collect, clean, and construct anomaly portfolios in the Chinese stock market. In Section 4, we conduct the empirical analysis of this paper to check the performance of volatility-managed portfolios. Finally, Section 5 concludes this paper.

2 Volatility-managed Portfolios: A Review

2.1 Construction of volatility-managed portfolios

As suggested in Moreira and Muir (2017), the basic idea for constructing volatility-managed portfolios is scaling an excess return by the inverse of its conditional variance. Thus, in each month the volatility-managed strategy increases or decreases risk exposure to the volatility-managed portfolio according to the conditional variance. The managed portfolio is then[1]

$$f^{\sigma}_{t+1} = \frac{c}{\hat{\sigma}^2_t(f)} f_{t+1}, \tag{2.1}$$

where f_{t+1} is the buy-and-hold portfolio excess return, $\hat{\sigma}^2_t(f)$ is a proxy for the portfolio's conditional variance with $\hat{\sigma}^2_t(f)$ constructed by using previous month's realized variance defined by

$$\hat{\sigma}^2_t(f) = RV^2_t(f) = \sum_{d=1/22}^{1} \left(f_{t+d} - \frac{\sum_{d=1/22}^{1} f_{t+d}}{22} \right)^2. \tag{2.2}$$

In practice, when there are no 22 trading days in a month, we may the use the alternative proxy for conditional variance suggested in Cederburg, O'Doherty, Wang, and Yan (2020) as follows

$$\hat{\sigma}^2_t(f) = \frac{22}{J_t} \sum_{j=1}^{J_t} \left(f^j_t \right)^2. \tag{2.3}$$

where $j = 1, \ldots, J_t$ index days in month t and f^j_t is the excess return for a given portfolio (factor) on day j of month t. The constant c in (2.1) controls the average exposure of the strategy. It is

[1] Since f_{t+1} generally refers to factors, which are usually constructed as portfolios based on the cross-sectional sort on asset-specific characteristics, the volatility-managed portfolio can be alternatively interpreted as "PoP", namely the portfolio of portfolios.

selected to make the managed portfolio, f^{σ}_{t+1}, have the same unconditional standard deviation as the un-managed portfolio, f_{t+1}. In this paper, we use the method of Cederburg, O'Doherty, Wang, and Yan (2020) (i.e. (2.3)) to calculate realized volatility.

To see the role of c in (2.1), first note that he unconditional variance of f^{σ}_{t+1} can be calculated as follows

$$\begin{aligned}\text{Var}\left[f^{\sigma}_{t+1}\right] &= \text{Var}\left\{\text{Var}_t\left[f^{\sigma}_{t+1}\right]\right\} \\ &= \text{Var}\left[\frac{c}{\hat{\sigma}^2_t(f)}\hat{\sigma}^2_{t+1}(f)\right] = \text{Var}\left[f_{t+1}\right].\end{aligned}$$

Thus, if both the unconditional variances of f^{σ}_{t+1} and f_{t+1} are fixed at specific magnitude, say $\sigma^2(f)$. Then the scaling constant c is essentially the solution to the following equation

$$\text{Var}\left[\frac{c}{\hat{\sigma}^2_t(f)}\hat{\sigma}^2_{t+1}(f)\right] = \sigma^2(f).$$

Since realized volatility measures integrated volatility, by replacing $\hat{\sigma}^2_t$ with integrated volatility σ^2_t we have

$$\text{Var}\left[\frac{c}{\sigma^2_t(f)}\sigma^2_{t+1}(f)\right] = \sigma^2(f)$$

In the stochastic volatility literature, the log volatility is normally assumed to follow a Gaussian AR(1) process. Consequently, we have

$$\ln\left[\sigma^2_{t+1}(f)\right] = \rho\ln\left[\sigma^2_t(f)\right] + e_{t+1}, \quad e_{t+1} \overset{i.i.d.}{\sim} \mathcal{N}\left(0, \sigma^2\right).$$

If we further assume $\rho = 1$, then we can have the following analytically tractable connection between the scaling constant c and the unconditional variance $\sigma^2(f)$:

$$\begin{aligned}\text{Var}\left[\frac{c}{\sigma^2_t(f)}\sigma^2_{t+1}(f)\right] &= c^2\,\text{Var}\left[\frac{\sigma^2_{t+1}(f)}{\sigma^2_t(f)}\right] \\ &= c^2\left[\exp\left(\sigma^2\right) - 1\right]\exp\left(\sigma^2\right) = \sigma^2(f).\end{aligned}$$

To pin down the scaling constant c in practice, we can simply use the empirical measure as the probability measure. In particular, we can calculate the sample variance of the original factors, f_{t+1} and the sample variance of the volatility-managed counterpart (unscaled by c), $f_{t+1}/\hat{\sigma}^2_t(f)$. Then we set c to ensure the following equation hold

$$\widehat{\text{Var}}\left[f_{t+1}\right] = c^2\widehat{\text{Var}}\left[f_{t+1}/\hat{\sigma}^2_t(f)\right], \tag{2.4}$$

where $\widehat{\text{Var}}[\cdot]$ denotes the sample variance.

In our setting, we always assume that investors have access to the risk-free asset. This is to facilitate the use of the excess returns for constructing portfolios using arbitrary combination weights. To see this, recall the classical portfolio selection theory (Markowitz, 1952), where we usually adopt a vector denoted by $\boldsymbol{w}$ to represent the portfolio weights. Thus, If there are n assets (including both the risky and the risk-free assets), then $\boldsymbol{w} = (w_1, \ldots, w_n)^\top$. In the literature we usually impose a restriction $\sum_{i=1}^{n} w_i = 1$. This restriction is not necessary if we focus on returns of the risky assets in excess of returns of the risk-free asset. Without loss of generality, we may assume that the n-th asset is the risk-free asset. Then for the remaining $(n-1)$ risky assets, we can specify the corresponding weights arbitrarily and then set the weight of the risk-free asset, w_n, to ensure the restriction (i.e. $\sum_{i=1}^{n} w_i = 1$) satisfied. In other words, for any risky asset index by i for $i = 1, \ldots, n-1$, the excess return $R_i^e = R_i - R_f$ can be combined to construct portfolios using arbitrary weights $(w_1, \ldots, w_{n-1})^\top$. In subsection 3.1, we will discuss more in detail how we construct zero-investment long-short portfolios based on cross-sectional characteristics (i.e. $w_n = 1$).

2.2 Motivation from the stylized fact about market portfolio

In this section, we use the market portfolio as an illustration of some stylized effects in the U.S. market and the Chinese stock market. Based on the data-cleaning technique of Jensen, Kelly, and Pedersen (2022), we find the empirical result, found by Moreira and Muir (2017) in the U.S market and used as the intuition for justifying volatility-managed portfolios, does not necessarily hold in the Chinese stock market. These empirical findings motivate the analysis in Section 4 for checking whether volatility management helps improve portfolio performance in the Chinese stock market.

Specifically, for the U.S. market, Moreira and Muir (2017) find that there is a strong (positive) relationship between the lagged volatility and the current volatility and that the mean-variance trade-off (measured as the average return divided by the variance) of the current period is negatively related to the volatility in the previous period. We can replicate these empirical findings via the following implementation. First, for each month contained in the data sample, we calculate realized volatility associated with the market portfolio (i.e. the value-weighted return) using daily data. Then, we group months by the previous month's realized volatility and plot volatility and mean-variance trade-off over the subsequent month. This is summarized as follows,

[Place Figure 1 about here]

As we can see from Figure 1, for the U.S. market, we observe a positive relationship (as in Moreira and Muir, 2017) between the volatility of the current period and the volatility of the previous month, and the negative relationship between the mean-variance trade-off of the current period and the volatility of the previous month. However, when we apply the same procedure to the Chinese stock market we find that, while the positive relationship between the volatility of the current month and the volatility of the previous month still exists, the mean-variance trade-off of the current month is not negatively correlated with the volatility of the previous month. In addition to this, we also compare the cumulative market return of the U.S. market and that of the Chinese stock market. This is summarized in Figure 2. Specifically, in Figure 2(a) we plot the cumulative value-weighted return of the U.S. market from 1926; in Figure 2(b), we plot the cumulative value-weighted return of the U.S. market from 1991, which also is the beginning of the sample period of the Chinese stock market. In Figure 2(c) we plot the cumulative value-weighted market return of the Chinese stock market. Figure 2(a) and Figure 2(b) jointly imply that for investments made in the U.S. equity market, in the long run, it pays to scale the market portfolio via volatility by decreasing the risk exposure when the market is volatile. However, Figure 2(c) implies that the advantage of the scaled market portfolio vanishes in the Chinese stock market. The value-weighted return of one-unit money invested in the Chinese stock market starting from 1991 generates a higher payoff in the long run than that from the volatility-managed counterpart.

[Place Figure 2 about here]

Given these empirical findings for the market portfolio, the empirical success of the volatility-managed portfolio in other stock markets is questionable.

3 Data

In cross-sectional asset pricing studies, it is important for researchers to carefully construct cross-sectional equity characteristics. In this section, we first briefly discuss the recent literature on constructing cross-sectional equity characteristics for asset pricing studies and explain how we use the existing methods to construct equity characteristics in the Chinese stock market. Then we discuss how characteristic-managed portfolios are constructed based on daily returns of individual assets in the Chinese stock market. We use these constructed characteristic-managed portfolios as the proxy for anomaly portfolios.

3.1 Individual equity characteristic data

Following Harvey and Liu (2014, 2015); Harvey, Liu, and Zhu (2016); Mclean and Pontiff (2016); Green, Hand, and Zhang (2017); Hou, Xue, and Zhang (2018); Gu, Kelly, and Xiu (2019); Demiguel, Martín, Nogales, and Uppal (2020); Freybergerk, Neuhierl, and Weber (2019); Kozak, Nagel, and Santosh (2020); Kozak (2020), we obtain firm-level equity characteristic data. Several standard data-cleaning routines are available in the literature. The method of Chen and Zimmermann (2020) is a successful response to the call for transparency and cooperation (Welch, 2019). Besides, Jensen, Kelly, and Pedersen (2022) provides a more comprehensive analysis by constructing a global dataset in response to the recent discussions on the replication crisis in empirical asset pricing studies.[2] We combine both the data cleaning routines in Chen and Zimmermann (2020) and Jensen, Kelly, and Pedersen (2022) to replicate 99 finance and accounting anomaly variables in the Chinese stock market from 1996 to 2020. All the data (including returns and accounting data) are obtained from

[2] Jensen, Kelly, and Pedersen (2022) also makes their replication procedures and data publicly available at `https://github.com/bkelly-lab/ReplicationCrisis`.

the Center for Research in Security Prices (`CRSP`), `Compustat`, and the China Stock Market & Accounting Research (`CSMAR`) database, all of which can be downloaded from the Wharton Research Data Service (WRDS). These anomaly variables are normalized as in Freybergerk, Neuhierl, and Weber (2019) so that each characteristic is normalized over the cross-sectional dimension to take a value between 0 and 1. More precisely,

$$rc_{i,t}^{s} = \frac{\text{rank}\left(c_{i,t}^{s}\right)}{n_t + 1}, \tag{3.1}$$

where $c_{i,t}^{s}$ denotes the originally unscaled firm-level equity characteristic (indexed by superscript s) associated with stock i at time t and n_t denotes the total number of individual assets available for observations at time t. $\text{rank}(\cdot)$ denotes the cross-sectional ranking order of specific variable. Then, for each rank-transformed characteristic $rc_{s,t}^{i}$, we center it around the cross-sectional mean and divide it by the sum of average deviations from the cross-sectional mean for available stocks. Hence, we have,

$$z_{i,t}^{s} = \frac{\left(rc_{i,t}^{s} - \overline{rc}_{t}^{s}\right)}{\sum_{i=1}^{n_t}\left|rc_{i,t}^{s} - \overline{rc}_{t}^{s}\right|}, \tag{3.2}$$

where

$$\overline{rc}_{t}^{s} = \frac{1}{n_t}\sum_{i=1}^{n_t} rc_{i,t}^{s}.$$

Each column of Z_t is $\left(z_{1,t}^{s}, \ldots, z_{n_{t,1}}^{s}\right)^{\top}$. It is known in practice that individual characteristic data is imbalanced panel dat. For this reason, we exploit n_t rather than N to emphasize the time-varying cross-sectional dimension.[3]

3.2 Characteristic-managed portfolios

Annual accounting data is realigned with monthly return data based on the following annual rebalancing rule. Returns at the monthly frequency from July of year t to June of year $t+1$ are matched to the annual accounting variables in December of $t-1$. This is also the mechanism in which we realign data to construct cross-sectional equity characteristic data. For monthly rebalancing to construct the daily characteristic-managed portfolios, a similar scheme applies. That is, to construct the daily characteristic-managed portfolios in month $t+1$ based on equity s, returns at the daily frequency are matched with the normalized characteristics $z_{i,t}^{s}$ in month t and $z_{i,t}^{s}$ are used as the weights for constructing the daily characteristic-managed portfolios. Characteristics normalized as in (3.2) ensure the managed portfolios, to some extent, mimic the long-short trading strategies so that we can use the normalized characteristics as the weights for constructing portfolios. These normalized variables are then used to construct 99 characteristic-managed portfolios. Monthly

[3] This also implicitly suggests that for each cross-section we only use those individual assets available as observations both for the corresponding returns and specific characteristics (indexed by s).

portfolios will be mainly used for comparison analysis such as calculating the IS Sharpe ratios and running univariate spanning regression; while daily managed portfolios will be used for calculating realized volatility for each month. More comprehensive descriptions of these anomaly variables are listed in the appendix along with acronyms used in our replication procedure. The corresponding studies, where these anomaly variables were initially proposed, are listed in the appendix as well.

Following the cutting-edge data cleaning technique, we can approximately construct 400 anomaly variables with approximately 153 of them are regarded as the representative factor-related variables. In another paper, Chen (2022) selects 123 anomaly variables from 1995 to 2020 to construct characteristic-managed portfolios by requiring that those selected anomaly variables should overall keep at least 80% of the sample as observations and the corresponding observations with missing anomaly variables are directly discarded. However, in this paper, we want to keep data as informative as possible about the cross-sectional information and hence select those anomaly variables **without missing observations** from 1996 to 2020, which finally shrinks the anomaly universe from 123 anomaly variables to 99 anomaly variables. We construct the 99 characteristic-managed portfolios (or equity strategies) used for analysis in the main context with this filtered anomaly universe.

4 Empirical Analysis

4.1 Direct comparison on anomaly augmented portfolios

Using 99 equity strategies based on the cross-sectional characteristics in the Chinese stock market, we make following comparison by calculating and comparing the in-sample mean of returns and Sharpe ratios for both the original anomaly long-short portfolios and the associated volatility-managed portfolios. The results are summarized as follows

[Place Figure 3 about here]

[Place Figure 4 about here]

To assign statistical meaning to the corresponding comparison, we use the method of Wright, Yam, and Yung (2014), which improves the procedure using the Sharpe ratios for comparing portfolio performance (see Jobson and Korkie, 1981; Lo, 2002; Ledoit and Wolf, 2008; Leung and Wong, 2008) by accommodating richer statistical properties of excess returns under more general assumptions. More technical details can either be referred via the original paper of Wright, Yam, and Yung (2014) or Pav (2021, 2022). We summarize the results as follows,

Table 1

		Sharpe ratio difference	
Sample	Total	$\Delta SR > 0$ [Signif.]	$\Delta SR < 0$ [Signif.]
All trading strategies	99	60[11]	39[3]

Note: In the table above, ΔSR refers to the difference between absolute value of the Sharpe ratios associated with original anomaly portfolios (f_{t+1}) and volatility-managed portfolios (f^{σ}_{t+1}). We demonstrate the number of absolute value of the Sharpe ratios differences that are positive, negative and significant at 5% level (in square brackets).

As we can see from Table 1, among all the 99 anomaly-based strategies we have checked for the Chinese stock market, the performances of 60 trading strategies are seemingly improved by readjusting the holding positions via the lagged volatility given that the in-sample absolute values of the Sharpe ratios of these 60 volatility-managed portfolios increase ($\Delta SR > 0$) in comparison to those of original anomaly portfolios. However, for these 60 anomaly portfolios whose performance can be seemingly improved by scaling the holding positions using lagged volatility, only 11 of them enjoys statistically significant improvements in the Sharpe ratios (based on the methodology in Wright, Yam, and Yung, 2014). By contrast, the remaining 39 anomaly portfolios cannot directly enjoy improvements in the Sharpe ratios ($\Delta SR < 0$) via managing lagged volatility. Besides, for these 39 anomaly portfolios, we can only see statistically different performance differences (based on the increments in the absolute value of the Sharpe ratios) between the original anomaly portfolios and the volatility-managed ones. Finally, we summarize $14 (= 11 + 3)$ anomalies for which the original anomaly portfolios or volatility-managed ones witness statistically significant differences in the absolute value of the Sharpe ratios in the following table.

[Place Table 2 about here]

4.2 Spanning regression approach for comparison

The empirical methodology exploited in Moreira and Muir (2017) is based on following time-series regression of the volatility-managed portfolio on the original factors,

$$f^{\sigma}_{t+1} = \alpha + \beta f_{t+1} + \epsilon_{t+1} \tag{4.1}$$

(4.1) is a straightforward empirical methodology with the empirical implication as follows: a positive intercept (α) implies that volatility timing increasing the Sharpe ratios relative to the original factors (Moreira and Muir, 2017). However, the increment in the Sharpe ratios suggested from spanning regression must correspond to a new portfolio combining both the volatility-managed portfolio and un-managed portfolio. Alpha alone does not necessarily imply the increment in the Sharpe ratio of f^{σ}_{t+1} in direct comparison to f_{t+1}. This viewpoint involves the following discussion about the connection between alpha and the Sharpe ratio of a single scaled portfolio (i.e. f_{t+1} alone) and the connection between alpha and the Sharpe ratio of the augmented portfolio that combines both the scaled portfolio and the unscaled portfolio (i.e. f^{σ}_{t+1} and f_{t+1}).

Cederburg, O'Doherty, Wang, and Yan (2020) hold the opinion that a positive alpha in (4.1) is a lower bar for declaring success of managed portfolio relative to the Sharpe ratio difference. Recall our main target for comparison: managed portfolio f^{σ}_{t+1} and the original anomaly portfolio f_{t+1}. Intuitively, this can be interpreted as follows: a significant alpha in (4.1) only requires that $\bar{f}^{\sigma}_{t+1} > \hat{\beta}\bar{f}_{t+1}$, where $\bar{f}^{\sigma}_{t+1}$ and $\bar{f}_{t+1}$ refer to sample time-series mean of volatility-managed portfolios and sample time-series mean of original volatility portfolios respectively; $\hat{\beta}$ refers to estimation of correlation coefficient between f^{σ}_{t+1} and f_{t+1} by running OLS using (4.1). However, this requirement is not enough for guaranteeing $\left|\bar{f}^{\sigma}_{t+1}\right| > \left|\bar{f}_{t+1}\right|$, which is essentially the requirement for having an improved IS Sharpe ratio by using volatility to scale the original anomaly portfolios.[4] Specifically, suppose we obtain $\hat{\beta}$ from running spanning regression in (4.1) as $\hat{\beta} = 0.7$ while at the same time $\bar{f}^{\sigma}_{t+1} = 0.9 \times \bar{f}_{t+1}$, which suggests that

$$\hat{\alpha} = \bar{f}^{\sigma}_{t+1} - \hat{\beta}\bar{f}_{t+1} = 0.9 \times \bar{f}_{t+1} - 0.7 \times \bar{f}_{t+1} = 0.2 \times \bar{f}_{t+1},$$

then the volatility-managed portfolio still fails to generate IS increment in the Sharpe ratio. Besides, note that

$$\begin{aligned}
\hat{\beta} &= \frac{\sum_{t+1}\left(f^{\sigma}_{t+1} - \bar{f}^{\sigma}_{t+1}\right)\left(f_{t+1} - \bar{f}_{t+1}\right)}{\sum_{t+1}\left(f_{t+1} - \bar{f}_{t+1}\right)^2} \\
\hat{\alpha} &= \bar{f}^{\sigma}_{t+1} - \hat{\beta}\bar{f}_{t+1}
\end{aligned}$$

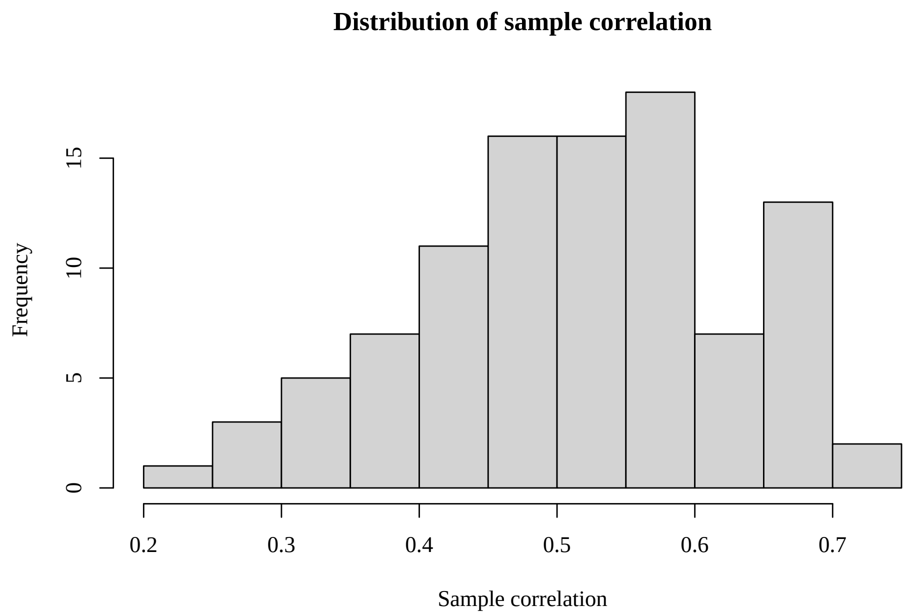
and that

$$\hat{\rho}_{f^{\sigma}_{t+1}, f_{t+1}} = \frac{\sum_{t+1}\left(f^{\sigma}_{t+1} - \bar{f}^{\sigma}_{t+1}\right)\left(f_{t+1} - \bar{f}_{t+1}\right)}{\sqrt{\sum_{t+1}\left(f^{\sigma}_{t+1} - \bar{f}^{\sigma}_{t+1}\right)^2}\sqrt{\sum_{t+1}\left(f_{t+1} - \bar{f}_{t+1}\right)^2}}$$

where $\hat{\rho}_{f^{\sigma}_{t+1}, f_{t+1}}$ denotes the sample correlation between f^{σ}_{t+1} and f_{t+1}. Since, by construction, f^{σ}_{t+1} and f_{t+1} have the same sample correlation, $\hat{\beta} = \hat{\rho}_{f^{\sigma}_{t+1}, f_{t+1}}$. We calculate all the sample correlations between f^{σ}_{t+1} and f_{t+1} for the 99 anomaly portfolios and summarize the distribution of the sample correlations as follows. We can see from the figure that for the 99 equity anomaly portfolios, the sample correlations between the original ones and the volatility-managed ones range approximately from 0.21 to 0.72, which suggests obtaining statistically significant alpha from spanning regression and having a relatively low absolute value for the IS Sharpe ratios of volatility-managed portfolios is possible.

A statistically significant alpha indicates that the optimal ex post combination of scaled and unscaled factors expands the mean-variance frontier relative to the original factor. This combination strategy allows investors to allocate wealth both in the volatility-managed portfolios and the original anomaly portfolios. Gibbons, Ross, and Shanken (1989) and Barillas and Shanken (2018) link

[4] This is because by construction f^{σ}_{t+1} and f_{t+1} share the same unconditional (sample) standard deviation.



the intercept (alpha) with the Sharpe ratio by taking the ratio of the estimated alpha to the standard error in linear regression (i.e. the so-called appraisal ratio, $AR = \hat{\alpha}/\hat{\sigma}_\epsilon$) and show that the appraisal ratio can be used to characterize the extent to which the augmented portfolios can increase the slope of the mean-variance frontier. This argument can be directly applied in the volatility-managed portfolio setting for discussing the connection between statistically significant alpha and the performance gain measured as the increment in the Sharpe ratio that is obtained from the combination strategy, as noted Cederburg, O'Doherty, Wang, and Yan (2020). Specifically, for the investor who has the access to the risk-free security, under the standard optimal portfolio allocation theory as in Markowitz (1952), his optimal ex post allocation rule is proportional to $\hat{\Sigma}^{-1}\hat{\mu}$, where $\hat{\Sigma}$ is 2×2 matrix as the sample variance-covariance matrix of $\left[f^{\sigma}_{t+1}, f_{t+1}\right]^{\top}$ and $\hat{\mu}$ is a 2×1 vector with each entry denoting the time-series sample mean of f^{σ}_{t+1} and f_{t+1} respectively, thus $\hat{\mu} = \left[\bar{f}^{\sigma}_{t+1}, \bar{f}_{t+1}\right]^{\top}$. Since, by construction, f^{σ}_{t+1} and f_{t+1} have the same sample standard deviation, we show that

$$
\begin{aligned}
\hat{\Sigma} &= \begin{bmatrix} \hat{\sigma}^2(f) & \hat{\rho}_{f^{\sigma}_{t+1}, f_{t+1}} \sigma_{f^{\sigma}_{t+1}} \sigma_{f_{t+1}} \\ \hat{\rho}_{f^{\sigma}_{t+1}, f_{t+1}} \sigma_{f^{\sigma}_{t+1}} \sigma_{f_{t+1}} & \hat{\sigma}^2(f) \end{bmatrix} \\
&= \hat{\sigma}^2(f) \begin{bmatrix} 1 & \hat{\rho}_{f^{\sigma}_{t+1}, f_{t+1}} \\ \hat{\rho}_{f^{\sigma}_{t+1}, f_{t+1}} & 1 \end{bmatrix}
\end{aligned}
$$

and correspondingly

$$\hat{\Sigma}^{-1} = \left[\hat{\sigma}^2(f)\left(1 - \hat{\rho}^2_{f^\sigma_{t+1},f_{t+1}}\right)\right]^{-1} \begin{bmatrix} 1 & -\hat{\rho}_{f^\sigma_{t+1},f_{t+1}} \\ -\hat{\rho}_{f^\sigma_{t+1},f_{t+1}} & 1 \end{bmatrix}.$$

Then we have the optimal ex post allocation rule associated with the volatility-managed portfolio is

$$x^*_\sigma = \frac{\bar{f}^\sigma_{t+1} - \hat{\rho}_{f^\sigma_{t+1},f_{t+1}}\bar{f}_{t+1}}{\hat{\sigma}^2(f)\left(1 - \hat{\rho}^2_{f^\sigma_{t+1},f_{t+1}}\right)} = \frac{\hat{\alpha}}{\hat{\sigma}^2(f)\left(1 - \hat{\rho}^2_{f^\sigma_{t+1},f_{t+1}}\right)}. \tag{4.2}$$

(4.2) has the direct implication that $\hat{\alpha}$ obtained from spanning regression determines the wealth allocated to the scaled portfolios. Besides,

$$AR^2 = SR^2(f^\sigma, f) - SR^2(f) \tag{4.3}$$

where $SR^2(f^\sigma, f)$ refers to the IS squared Sharpe ratio of combination strategy comprising both f^σ (managed portfolio) and f (original portfolio).

We run time-series spanning regression of the form in (4.1) and report both the estimated coefficients and the associated Newey and West (1987) t-statistics with three lags (Kelly, Moskowitz, and Pruitt, 2021). We summarize the results from univariate spanning regression in Table 3 and more detailed spanning regression estimation results in Table 4 for those anomaly portfolios with significant estimated alpha.

[Place Table 3 about here]

[Place Table 4 about here]

Given the results summarized in Table 3 and Table 4, we find that among all the 99 anomaly portfolios, 71 volatility-managed portfolios have a positive estimate of alpha in univariate spanning regression while the remaining 28 volatility-managed portfolios have a negative estimate of alpha in univariate spanning regression. However, since all the original anomaly portfolios are constructed as the long-short portfolios based on the univariate sort on the associated equity characteristic, the sign associates with the negative alpha can readily shifted to positive by taking revere holding positions. In other words, the main implication of spanning regression is whether an investors can obtain an increment in the Sharpe ratio by combining the volatility-managed portfolios and the original anomaly portfolios. This increment can be reflected in the appraisal ratio associated with alpha and, accordingly, in whether the estimated alpha in the univariate spanning regression is statistically significant or not matters more for evaluating the corresponding performance gain. For this purpose, we see from Table 3 and Table 4 that among all the 99 anomaly portfolios we investigate, only 24 of them generate statistically significant alpha in the univariate spanning regression. This low ratio

($24/99 \approx 24\%$) suggests that scaling the holding positions of the original portfolios using the lagged volatility is not a successful strategy for improving the portfolio performance.

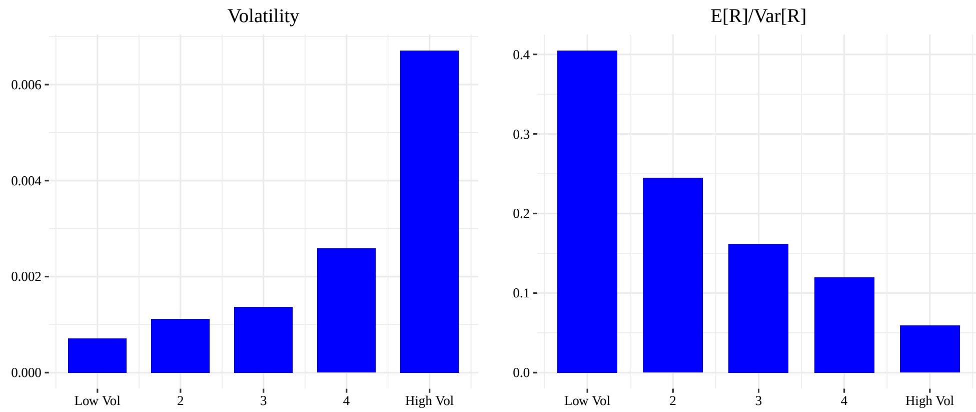
5 Conclusion

This paper examines the performance of volatility-managed portfolios in the Chinese stock market. Using the standard empirical methods to collect, clean, and construct data from the Chinese stock market, we apply the standard empirical strategies to investigate whether an investor can adjust the holding positions of portfolios based on volatility to improve the performance of the original anomaly portfolios in the Chinese stock market. Our empirical results are similar to those in Cederburg, O'Doherty, Wang, and Yan (2020) for the U.S. equity market . That is, the performance of volatility-managed portfolios degrades within a broad sample of anomaly portfolios (103 trading strategies in the U.S. equity market). Based on our analysis of the Chinese stock market using 99 equity trading strategies, we also find that there exists no desired performance gain systematically by scaling anomaly portfolios using the lagged volatility as suggested in Moreira and Muir (2017).

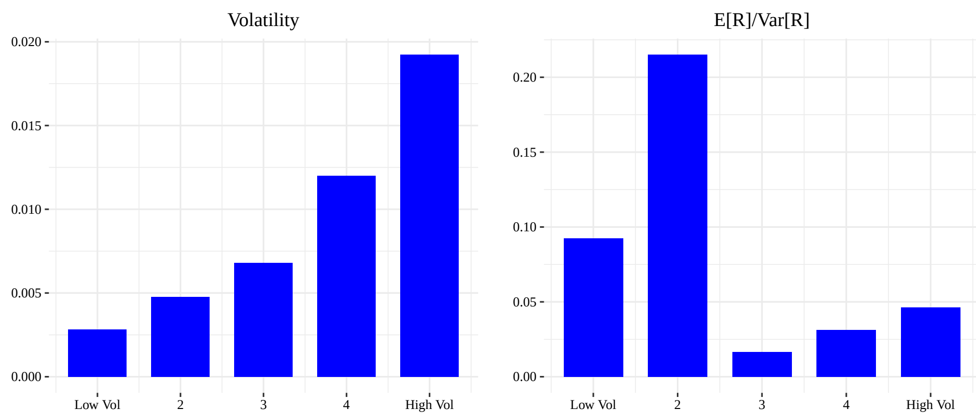
Figures and Tables

Figure 1

(a) The U.S. Market



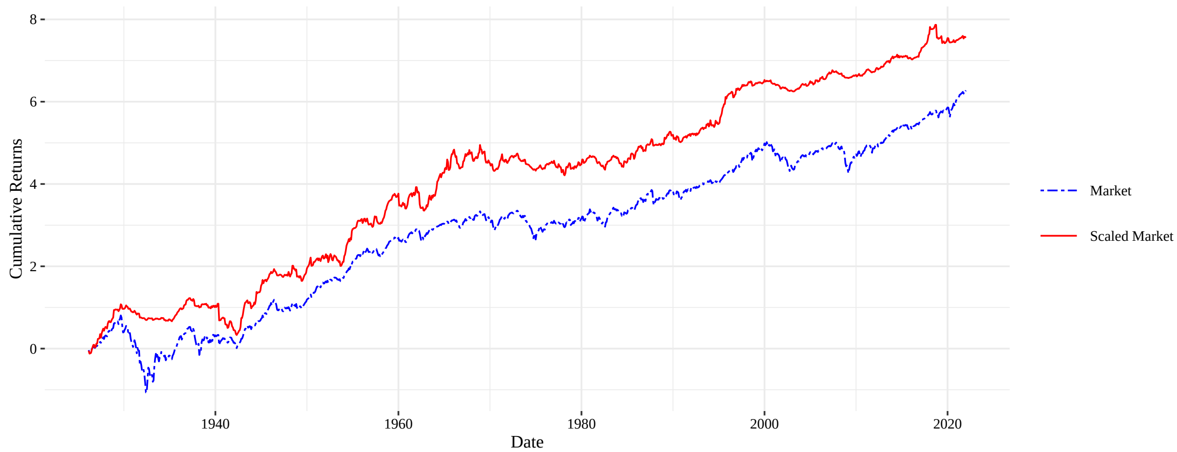
(b) The Chinese Market



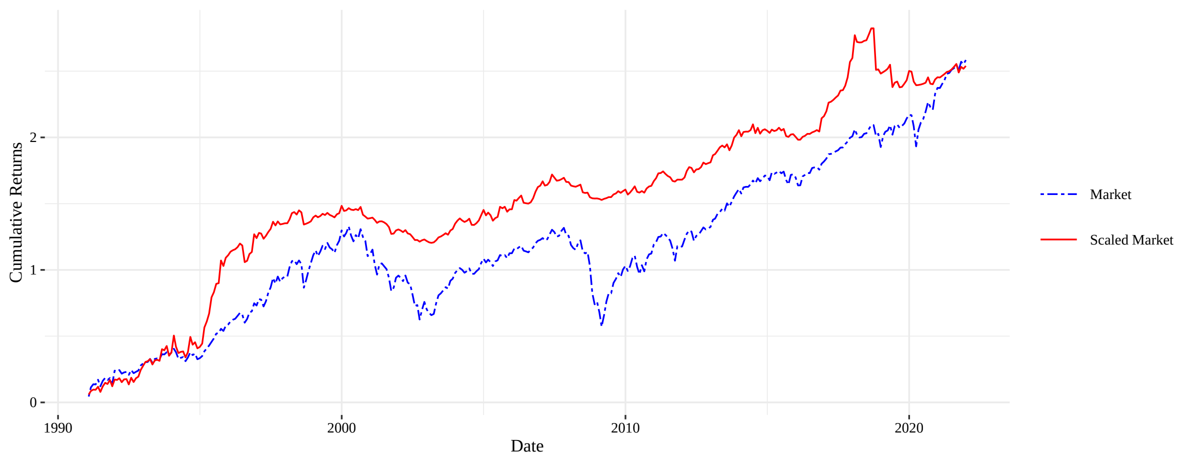
Note: In the figure above, we demonstrate results generated from sorting on the previous month's volatility both for the U.S. market (a) and the Chinese stock market (b). Specifically, we use (2.3) to calculate realized volatility for each month. With this obtained monthly time series of realized volatility, we sort all the months into five buckets based on realized volatility of the previous month. Then for each bucket, we calculate average volatility (on the left for each panel), average return, and the ratio of average return over average volatility as the mean-variance trade-off (on the right for each panel). For the U.S. market, there is an observed positive relationship between volatility and lagged volatility, and a negative relationship between mean-variance trade-off and lagged volatility. For the Chinese stock market, the positive relationship between volatility and lagged volatility still exists as expected, but negative relationship between mean-variance trade-off and lagged volatility breaks.

Figure 2

(a) The U.S. Market



(b) The U.S. Market from 1991



(c) The Chinese Market

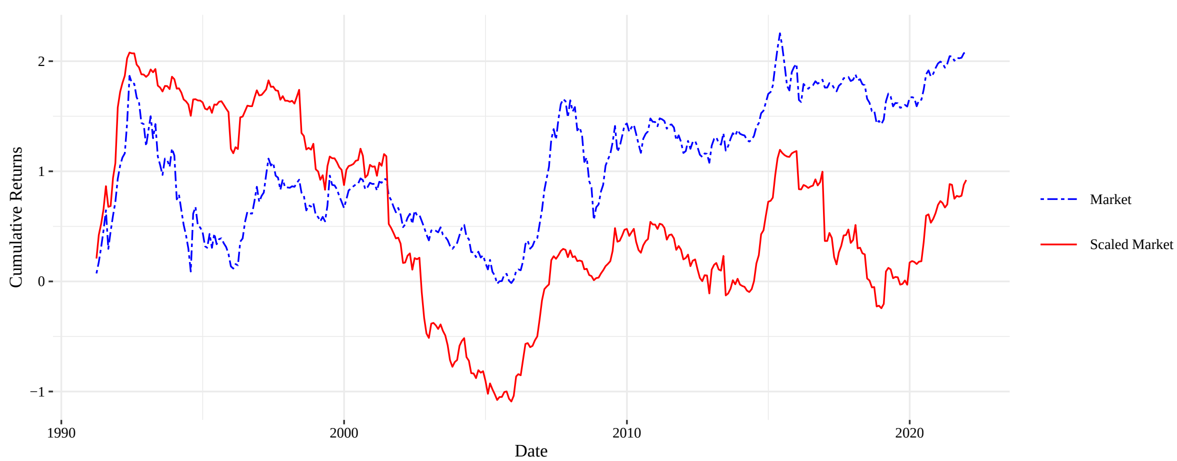
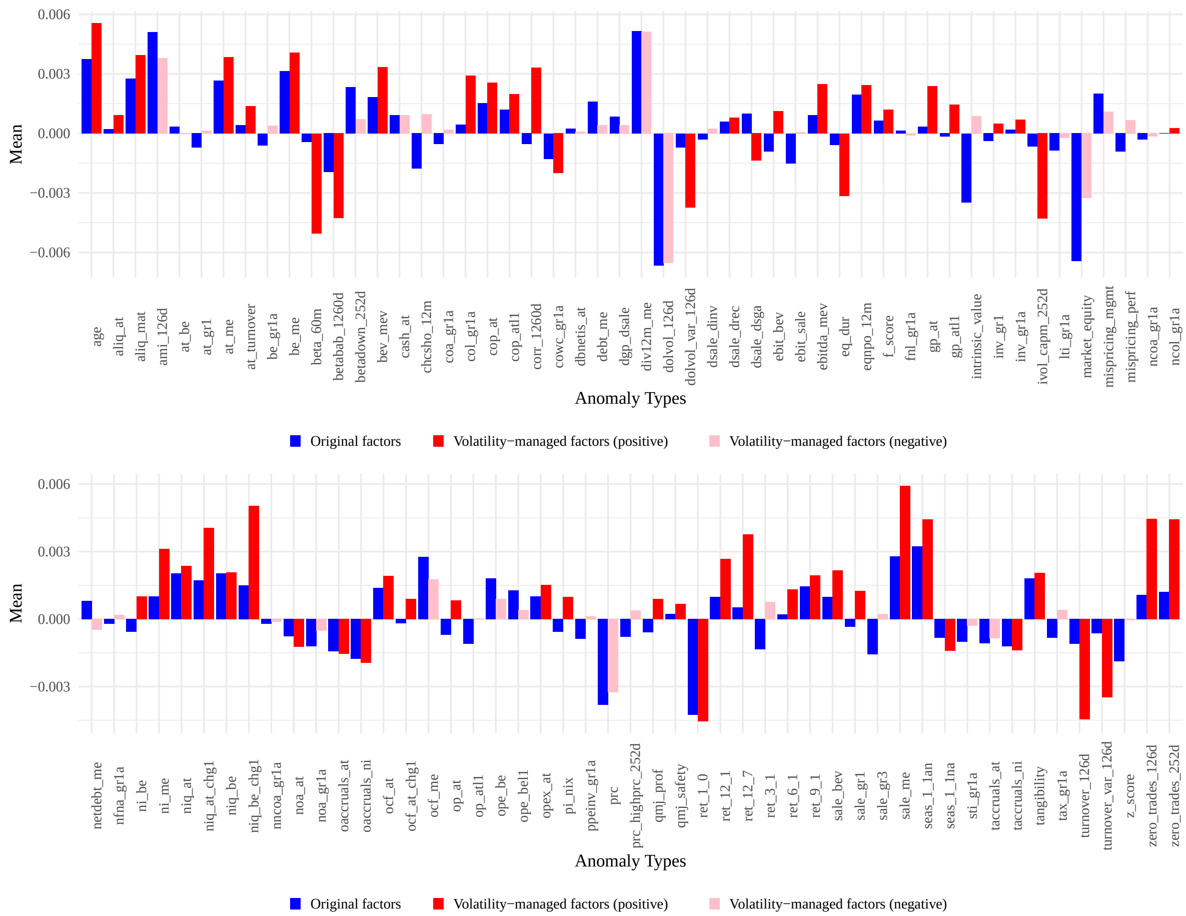
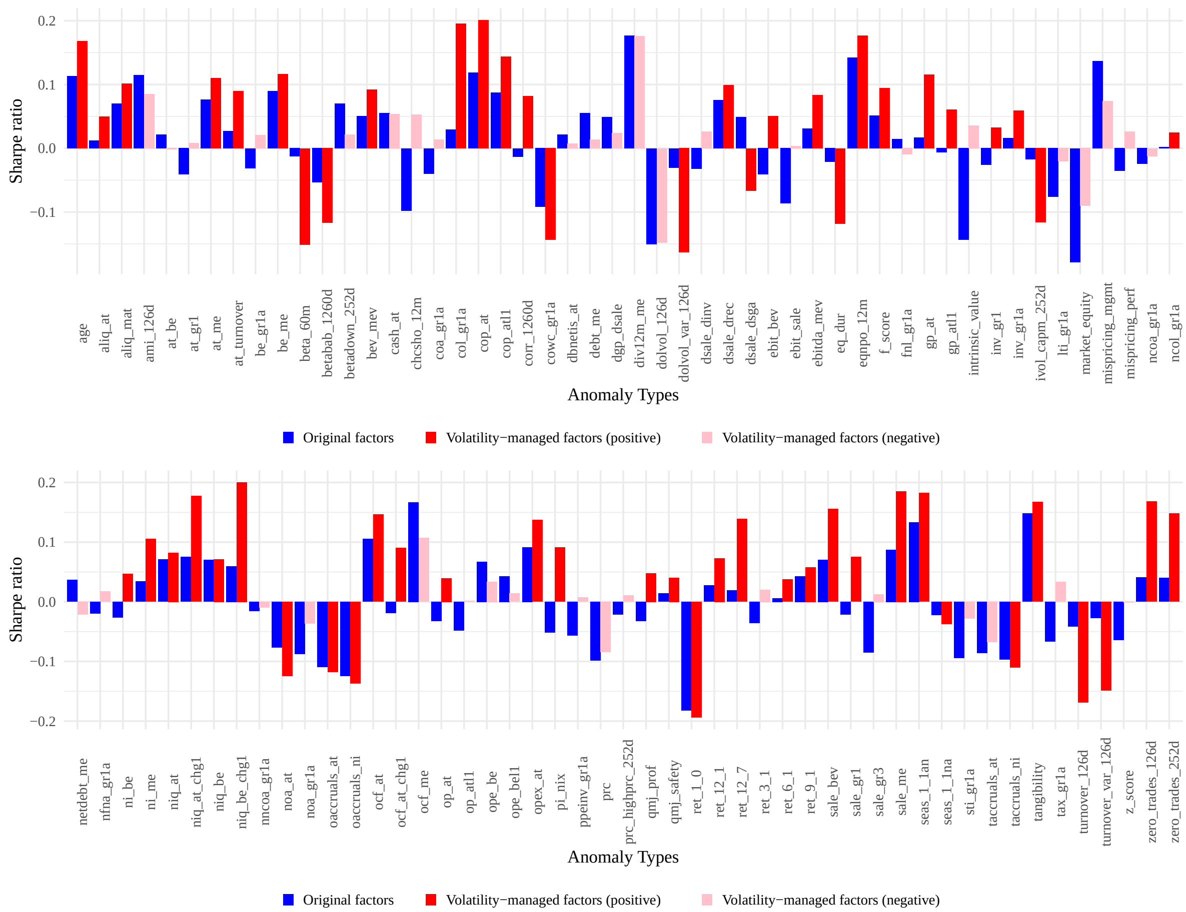


Figure 3



Note: In the figure above, we summarize the results of comparing IS (in-sample) mean of original anomaly portfolios and the associated volatility-managed portfolios. Both the original anomaly portfolios and the volatility-managed portfolios are at monthly frequencies and data spans from January 1996 to December 2020 (i.e. 25 years in total). As we have discussed in the main context, we use f_{t+1} to denote the original portfolio in month $t+1$ and $f_{t+1}^{\sigma} = \frac{c}{\hat{\sigma}_t^2(f)} f_{t+1}$ to denote the volatility-managed portfolio in month $t+1$. c is a constant chosen so that f_{t+1} and f_{t+1}^{σ} have the same sample unconditional standard deviation over the full sample period. There are three kinds of bars in this figure: the blue bars indicate the original factors (portfolios), the red bars indicate the volatility-managed factors (portfolios) that exhibit **larger** absolute value of IS mean in comparison to the corresponding original factors (portfolios), and the pink bars indicate the volatility-managed factors that exhibit **smaller** absolute value of IS mean in comparison to the corresponding original factors (portfolios).

Figure 4



Note: In the figure above, we summarize the results of comparing IS (in-sample) Sharpe ratio of original anomaly portfolios and the associated volatility-managed portfolios. Both the original anomaly portfolios and the volatility-managed portfolios are at monthly frequencies and data spans from January 1996 to December 2020 (i.e. 25 years in total). As we have discussed in the main context, we use f_{t+1} to denote the original portfolio in month $t+1$ and $f^{\sigma}_{t+1} = \frac{c}{\hat{\sigma}^2_t(f)} f_{t+1}$ to denote the volatility-managed portfolio in month $t+1$. c is a constant chosen so that f_{t+1} and f^{σ}_{t+1} have the same sample unconditional standard deviation over the full sample period. There are three kinds of bars in this figure: the blue bars indicate the original factors (portfolios), the red bars indicate the volatility-managed factors (portfolios) that exhibit **larger** absolute value of IS Sharpe ratio in comparison to the corresponding original factors (portfolios), and the pink bars indicate the volatility-managed factors that exhibit **smaller** absolute value of IS Sharpe ratio in comparison to the corresponding original factors (portfolios).

Table 2

Anomaly Types	ΔSR	p-value
Market beta [**Low Risk**]	0.1382	0.0232
Net stock issues [**Value**]	-0.0449	0.0029
Change in current liabilities [**Investment**]	0.1660	0.0081
Coefficient of variation for dollar trading volume [**Profitability**]	0.1330	0.0176
Return on net operating assets [**Profitability**]	0.0097	0.0354
Profit margin [**Profit Growth**]	-0.0834	0.0395
Gross profits-to-assets [**Quality**]	0.0986	0.0358
Intrinsic-value [**Value**]	-0.1079	0.0003
Change in quarterly return on equity [**Profit Growth**]	0.1408	0.0230
Taxable income-to-book income [**Seasonality**]	0.0393	0.0105
Price momentum $t-12$ to $t-7$ [**Momentum**]	0.1196	0.0115
Share turnover [**Low Risk**]	0.1269	0.0179
Coefficient of variation for share turnover [**Profitability**]	0.1216	0.0478
Number of zero trades with turnover as tiebreaker (6 months) [**Low Risk**]	0.1273	0.0179

Table 3

Sample	Total	Univariate spanning regression $\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]
All trading strategies	99	71[16]	28[8]

Note: This table summarizes results from spanning regressions for 99 anomaly trading strategies in the Chinese stock market. The spanning regression is the one that we have discussed in the main context, given by $f^{\sigma}_{t+1} = \alpha + \beta f_{t+1} + \epsilon_{t+1}$, where $f^{\sigma}_{t+1}(f_{t+1})$ is the monthly return for the volatility-managed (original) portfolio. For each regression, this table reports the number of alphas that are positive, positive and significant approximately at 2.5% level (i.e. we set critical value for the corresponding t-stat as 2), negative, and negative and significant at the 5% level. We assess the statistical significance of alpha using Newey and West (1987) adjusted standard errors.

Table 4

Anomaly Types	$\hat{\alpha}$	t-stat($\hat{\alpha}$)	$\hat{\beta}$	t-stat($\hat{\beta}$)	R^2	AR^2
Firm age [**Low Leverage**]	0.0043	2.4911	0.3260	5.6823	0.1033	0.0193
Market beta [**Low Risk**]	-0.0049	-2.7247	0.3948	3.4379	0.1530	0.0252
Frazzini-Pedersen market beta [**Low Risk**]	-0.0033	-2.0269	0.4978	4.2988	0.2453	0.0109
Change in current liabilities [**Investment**]	0.0027	3.2492	0.3859	2.8768	0.1461	0.0398
Cash-based operating profits-to-book assets [**Quality**]	0.0017	2.6395	0.5866	6.6950	0.3419	0.0262
Change in current operating working capital [**Accruals**]	-0.0015	-2.2617	0.4246	2.9854	0.1775	0.0133
Dividend yield [**Value**]	0.0029	2.0264	0.4342	4.6806	0.1858	0.0121
Dollar trading volume [**Size**]	-0.0034	-2.8954	0.4768	3.9751	0.2248	0.0287
Return on net operating assets [**Profitability**]	0.0018	2.0774	0.7038	8.1265	0.4937	0.0126
Equity duration [**Value**]	-0.0029	-2.0033	0.4429	4.0892	0.1935	0.0146
Equity net payout [**Value**]	0.0014	2.2130	0.5512	5.4834	0.3015	0.0140
Gross profits-to-assets [**Quality**]	0.0022	2.5263	0.6172	7.1965	0.3788	0.0178
Idiosyncratic volatility from the CAPM (252 days) [**Low Risk**]	-0.0039	-2.4611	0.5827	7.1438	0.3373	0.0170
Change in quarterly return on equity [**Profit Growth**]	0.0036	2.9183	0.2465	2.9236	0.0576	0.0268
Change in quarterly return on equity [**Profit Growth**]	0.0046	3.3454	0.2598	2.8428	0.0644	0.0367
Taxable income-to-book income [**Seasonality**]	0.0013	2.5581	0.5083	6.9227	0.2559	0.0186
Price momentum $t-12$ to $t-7$ [**Profit Growth**]	0.0035	2.8083	0.6086	5.5528	0.3683	0.0256
Asset turnover [**Quality**]	0.0016	2.5226	0.5651	4.7138	0.3171	0.0197
Sale to market [**Value**]	0.0050	2.8300	0.3464	3.5571	0.1171	0.0273
Year 1-lagged return, annual [**Profit Growth**]	0.0029	2.4769	0.4581	3.5126	0.2072	0.0186
Share turnover [**Low Risk**]	-0.0039	-3.1728	0.5469	3.9528	0.2968	0.0303
Coefficient of variation for share turnover [**Profitability**]	-0.0032	-2.5662	0.4076	3.3853	0.1634	0.0227
Number of zero trades (6 months) [**Low Risk**]	0.0039	3.1689	0.5451	3.9584	0.2948	0.0303
Number of zero trades (12 months) [**Low Risk**]	0.0038	2.6714	0.5318	4.2990	0.2804	0.0224

Note: This table summarizes detailed estimation results from univariate spanning regression for anomaly portfolios with statistically significant alpha. R^2 refers to the adjusted R-square as the measure of IS regression fitting. AR^2 refers to the squared appraisal ratio with $AR = \hat{\alpha}/\hat{\sigma}_{\epsilon}$ and $\hat{\sigma}_{\epsilon}$ refers to the standard deviation of residual in univariate spanning regression.

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Appendix

A Anomaly variables used in Chinese stock market

We summarize the main cross-sectional equity characteristics (firm-level characteristics) used in empirical analysis of this paper. We follow the cutting-edge data-cleaning routine proposed in Jensen, Kelly, and Pedersen (2022) to replicate following 99 equity characteristics in Chinese stock market. In each item, we list the brief descriptions of corresponding anomaly variables with the acronym (in typewriter format collected in parenthesis) and in general the category (in bold collected square brackets) it belongs to in finance and accounting literature. We also list the corresponding literature that initially proposes equity characteristics. The corresponding information and description inherit directly from Jensen, Kelly, and Pedersen (2022) and readers should refer to documentation released along with Jensen, Kelly, and Pedersen (2022) for more about construction details.

1. Firm age (`age`) [**Low Leverage**], Jiang, Lee, and Zhang (2005).
2. Liquidity of book assets (`aliq_at`) [**Investment**], Ortiz-Molina and Phillips (2014).
3. Liquidity of market assets (`aliq_mat`) [**Low leverage**], Ortiz-Molina and Phillips (2014).
4. Amihud measure (`ami_126d`) [**Size**], Amihud (2002).
5. Book leverage (`at_be`) [**Low leverage**], Fama and French (1992).
6. Asset growth (`at_gr1`) [**Investment**], Cooper, Gulen, and Schill (2008).
7. Assets-to-market (`at_me`) [**Value**], Fama and French (1992).
8. Capital turnover (`at_turnover`) [**Quality**], Haugen and Baker (1996).
9. Change in common equity (`be_gr1a`) [**Investment**], Richardson, Sloan, Soliman, and İrem Tuna (2005).
10. Book-to-market equity `be_me` [**Value**], Rosenberg, Reid, and Lanstein (1985).
11. Market beta (`beta_60m`) [**Low Risk**], Fama and Macbeth (1973).
12. Frazzini-Pedersen market beta (`betabab_1260d`) [**Low Risk**], Frazzini and Pedersen (2014).
13. Downside beta (`betadown_252d`) [**Low Risk**], Ang, Hodrick, Xing, and Zhang (2006).
14. Book-to-market enterprise value (`bev_mev`) [**Value**], Penman, Richardeson, and Tuna (2007).
15. Cash-to-assets (`cash_at`) [**Low Leverage**], Palazzo (2012).
16. Net stock issues (`chcsho_12m`) [**Value**], Pontiff and Woodgate (2008).

17. Change in current operating assets (`coa_gr1a`) [**Investment**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

18. Change in current liabilities (`col_gr1a`) [**Investment**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

19. Cash-based operating profits-to-book assets (`cop_at`) [**Quality**], Haugen and Baker (1996).

20. Cash-based operating profits-to lagged book assets (`cop_atl1`) [**Quality**], Ball, Gerakos, Linnainmaa, and Nikolaev (2016).

21. Market correlation (`corr_1260d`) [**Seasonality**], Asness, Frazzini, Gormsen, and Pedersen (2020).

22. Change in current operating working capital (`cowc_gr1a`) [**Accruals**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

23. Net debt issuance (`dbnetis_at`) [**Net debt issuance**], Bradshaw, Richardson, and Sloan (2006).

24. Debt-to-market (`debt_me`) [**Value**], Bhandari (1988).

25. Change gross margin minus change sales (`dgp_dsale`) [**Quality**], Abarbanell and Bushee (1998).

26. Dividend yield (`div12m_me`) [**Value**], Litzenberger and Ramaswamy (1979).

27. Dollar trading volume (`dolvol_126d`) [**Size**], Brennan, Chordia, and Subrahmanyam (1998).

28. Coefficient of variation for dollar trading volume (`dolvol_var_126d`) [**Profitability**], Chordia, Subrahmanyam, and Anshuman (2001).

29. Change sales minus change inventory (`dsale_dinv`) [**Profit Growth**], Abarbanell and Bushee (1998).

30. Change sales minus change receivables (`dsale_drec`) [**Profit Growth**], Abarbanell and Bushee (1998).

31. Change sales minus change SG&A (`dsale_dsga`) [**Profit Growth**], Abarbanell and Bushee (1998).

32. Return on net operating assets (`ebit_bev`) [**Profitability**], Soliman (2008).

33. Profit margin (`ebit_sale`) [**Profit Growth**], Soliman (2008).

34. Ebitda-to-market enterprise value (`ebitda_mev`) [**Value**], Loughran and Wellman (2011).

35. Equity duration (`eq_dur`) [**Value**], Dechow, Sloan, and Soliman (2004).

36. Equity net payout (eqnpo_12m) [**Value**], Daniel and Titman (2006).

37. Pitroski F-score (f_score) [**Profitability**], Piotroski (2000).

38. Change in financial liabilities (fnl_gr1a) [**Debt Issuance**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

39. Gross profits-to-assets (gp_at) [**Quality**], Novy-Marx (2013).

40. Gross profits-to-lagged assets (gp_atl1) [**Quality**], Novy-Marx (2013).

41. Intrinsic-value (intrinsic_value) [**Value**], Frankel and Lee (1998).

42. Inventory growth (inv_gr1) [**Investment**], Belo and Lin (2012).

43. Inventory change (inv_gr1a) [**Investment**], Thomas and Zhang (2002).

44. Idiosyncratic volatility from the CAPM (252 days) (ivol_capm_252d) [**Low Risk**] Ali, Hwang, and Trombley (2003).

45. Change in long-term investments (lti_gr1a) [**Seasonality**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

46. Market equity (market_equity) [**Size**], Banz (1981).

47. Mispricing factor: Management (mispricing_mgmt) [**Investment**], Stambaugh and Yuan (2016).

48. Mispricing factor: Performance (mispricing_perf) [**Quality**], Stambaugh and Yuan (2016).

49. Change in noncurrent operating assets (nroa_gr1a) [**Investment**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

50. Change in noncurrent operating liabilities (ncol_gr1a)) [**Debt Issuance**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

51. Net debt-to-price (netdebt_me) [**Low Leverage**], Penman, Richardeson, and Tuna (2007).

52. Change in net financial assets (nfna_gr1a) [**Debt Issuance**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

53. Return on equity (ni_be) [**Profitability**], Haugen and Baker (1996).

54. Earnings-to-price (ni_me) [**Value**], Basu (1983).

55. Quarterly return on assets (niq_at) [**Quality**], Balakrishnan, Bartov, and Faurel (2010).

56. Change in quarterly return on assets (niq_at_chg1) [**Profit Growth**], Abarbanell and Bushee (1998).

57. Quarterly return on equity (`niq_be`) [**Profitability**], Hou, Xue, and Zhang (2015).

58. Change in quarterly return on equity (`niq_be_chg1`) [**Profit Growth**], Abarbanell and Bushee (1998).

59. Change in net noncurrent operating assets (`nncoa_gr1a`) [**Investment**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

60. Net operating assets (`noa_at`) [**Debt Issuance**], Hirshleifer, Hou, Teoh, and Zhang (2004).

61. Change in net operating assets (`noa_gr1a`) [**Investment**], Hirshleifer, Hou, Teoh, and Zhang (2004).

62. Operating accruals (`oaccruals_at`) [**Accruals**], Sloan (1996).

63. Percent operating accruals (`oaccruals_ni`) [**Accruals**], Hafzalla, Lundholm, and Winkle (2011).

64. Operating cash flow to assets (`ocf_at`) [**Profitability**], Bouchaud, Krüger, Landier, and Thesmar (2019).

65. Change in operating cash flow to assets (`ocf_at_chg1`) [**Profit Growth**], Bouchaud, Krüger, Landier, and Thesmar (2019).

66. Operating cash flow to market (`ocf_me`) [**Value**], Bouchaud, Krüger, Landier, and Thesmar (2019).

67. Operating cash flow to assets (`ocf_at`) [**Profitability**], Bouchaud, Krüger, Landier, and Thesmar (2019).

68. Operating profits-to-lagged book assets (`op_atl1`) [**Quality**], Ball, Gerakos, Linnainmaa, and Nikolaev (2016).

69. Operating profits to book equity (`ope_be`) [**Profitability**], Fama and French (2015).

70. Operating profits to lagged book equity (`ope_bel1`) [**Profitability**], Fama and French (2015).

71. Operating leverage (`opex_at`) [**Quality**], Novy-Marx (2010).

72. Taxable income-to-book income (`pi_nix`) [**Seasonality**], Lev and Nissim (2004).

73. Change PPE and Inventory (`ppeinv_gr1a`) [**Investment**], Lyandres, Sun, and Zhang (2008).

74. Price and share (`prc`) [**Size**], Miller and Scholes (1982).

75. Current price to high price over last year (`prc_highprc_252d`) [**Momentum**], George and Hwang (2004).

76. Quality minus Junk: Profitability (`qmj_prof`) [**Quality**], Asness, Frazzini, and Pedersen (2019).

77. Quality minus Junk: Safety (`qmj_safety`) [**Quality**], Asness, Frazzini, and Pedersen (2019).

78. Short-term reversal (`ret_1_0`) [**Size**], Jegadeesh (1990).

79. Price momentum $t-12$ to $t-1$ (`ret_12_1`) [**Momentum**], Jegadeesh and Titman (1993).

80. Price momentum $t-12$ to $t-7$ (`ret_12_7`) [**Profit Growth**], Novy-Marx (2012).

81. Price momentum $t-3$ to $t-1$ (`ret_3_1`) [**Momentum**], Jegadeesh and Titman (1993).

82. Price momentum $t-6$ to $t-1$ (`ret_6_1`) [**Momentum**], Jegadeesh and Titman (1993).

83. Price momentum $t-9$ to $t-1$ (`ret_9_1`) [**Momentum**], Jegadeesh and Titman (1993).

84. Asset turnover (`sale_bev`) [**Quality**], Soliman (2008).

85. Sale growth (1 year) (`sale_gr1`) [**Investment**], Lakonishok, Shleifer, and Vishny (1994).

86. Sale growth (3 years) (`sale_gr3`) [**Investment**], Lakonishok, Shleifer, and Vishny (1994).

87. Sale to market (`sale_me`) [**Value**], William C. Barbee, Mukherji, and Raines (1996).

88. Year 1-lagged return, annual (`seas_1_1an`) [**Profit Growth**], Heston and Sadka (2008).

89. Year 1-lagged return, nonannual (`seas_1_1na`) [**Momentum**], Heston and Sadka (2008).

90. Change in short-term investments (`sti_gr1a`) [**Seasonality**], Heston and Sadka (2008).

91. Total accruals (`taccruals_at`) [**Accruals**], Richardson, Sloan, Soliman, and İrem Tuna (2005).

92. Percent total accruals (`taccruals_ni`) [**Accruals**], Hafzalla, Lundholm, and Winkle (2011).

93. Asset tangibility (`tangibility`) [**Low Leverage**], Hahn and Lee (2009).

94. Tax expense surprise (`tax_gr1a`) [**Profit Growth**], Thomas and Zhang (2002).

95. Share turnover (`turnover_126d`) [**Low Risk**], Datar, Y. Naik, and Radcliffe (1998).

96. Coefficient of variation for share turnover (`turnover_var_126d`) [**Profitability**], Chordia, Subrahmanyam, and Anshuman (2001).

97. Altman Z-score (`z_score`) [**Low Leverage**], Dichev (1998).

98. Number of zero trades with turnover as tiebreaker (6 months) (`zero_trades_126d`) [**Low Risk**], Liu (2006).

99. Number of zero trades with turnover as tiebreaker (12 months) (`zero_trades_252d`) [**Low Risk**], Liu (2006).