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Volatility and returns: Evidence from China†

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Abstract

Size, value, and momentum factors and industry portfolios in the Chinese A-share stock market tend to have higher returns in the months following high volatility. Due to this positive relationship between lagged volatility and returns, volatility-managed portfolios of Moreira and Muir (Volatility-managed portfolios. *Journal of Finance*, *72*, 1611–1644), which reduce portfolio exposure when volatility is high, are spanned by the original portfolios and do not improve the investor's opportunity set. Volatility-scaled portfolios, which increase portfolio exposure in volatile times, are not spanned by the original portfolios and expand the investor's opportunity set. The investor's mean–variance frontier shifts into more desirable regions when volatility-scaled portfolios are included.

KEYWORDS

portfolio choice, return forecasting, volatility management

JEL CLASSIFICATION

G10; G11; G12; G15

There is strong theoretical basis to believe risk and return are positively related. Risk-averse investors value higher returns and lower volatility, so risky investments must offer higher returns in equilibrium. In his groundbreaking work on Modern Portfolio Theory, Markowitz (1952, 1959) demonstrates how investors can quantify their risk–return trade-off by measuring portfolio expected returns against portfolio volatility. Since Markowitz, asset pricing theory and empirics have largely been built around measuring and testing various forms of risk–return trade-offs. Modern asset pricing models often imply that in equilibrium, investors must take on additional risk if they want higher returns.

The empirical evidence between risk and return is less clear. In its most basic form, a positive risk–return trade-off implies higher volatility is associated with higher returns. Although there is a large literature on this topic,

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evidence of a positive risk–return trade-off has been mixed. Campbell and Hentschel (1992) and French, Schwert, and Stambaugh (1987) find a positive relationship between conditional expected returns and conditional variance, whereas Campbell (1987) and Glosten, Jagannathan, and Runkle (1993) find a negative relationship. Contradictory empirical results may be partially attributed to different research designs, but may also reflect a weak relationship buried in noisy data. Whereas much of the existing literature focuses on the U.S. markets, we turn our attention to the Chinese A-share stock market.

Established in 1991, China's A-share stock market has gone through rapid development. It has become the second-largest stock market in the world with a market capitalization of $5 trillion by August 2016 (Chen & Chi, 2018). While the Chinese stock market shares some similar characteristics as other large economies (Carpenter, Lu, & Whitelaw, 2015), it does have its unique institutional features. For example, according to official statistics from both the Shanghai and Shenzhen stock exchanges, more than 80% of the trading volume can be attributed to retail investors. In contrast, institutional investors dominate trading in the U.S. stock market. As retail and institutional investors may have different goals and can behave differently, asset prices may be impacted in different ways in a retail-dominated market compared to an institution-dominated market.

Our paper investigates the empirical relationship between volatility measures and returns for China's A-share stock market. We document a key empirical fact about volatility and returns: there is a positive relationship between lagged volatility and future returns. Figure 1 illustrates this positive risk–return trade-off for the A-share value-weight market portfolio. We compute a time series of monthly realized volatility using daily observations. We then sort the volatility time series into five buckets, and we track the portfolio returns in the following month. In the most volatile quintile, the annualized average return in the following month is 20%, the highest across all quintiles. In the least volatile quintile, the annualized average return in the following month is −7%, the lowest of all quintiles. The intermediate quintiles have average returns somewhere between the two extreme quintiles.

The Chinese evidence stands in sharp contrast to the U.S. evidence shown by Moreira and Muir (2017), where expected returns show a lack of variation across the five volatility buckets for the U.S. value-weight market portfolio. For China's A-share stock market, higher volatility appears to be associated with higher future returns. We also find that lagged change in volatility to be positively associated with future returns. These patterns hold for market returns, Fama and French (1992) factors, momentum (Carhart, 1997), and 63 industry portfolios defined by the Global Industry Classification Standard (GICS) level-3 code.

A positive relationship between lagged volatility and returns has important implications for using volatility as a portfolio management tool. Moreira and Muir (2017) demonstrate that for the U.S. stock market, scaling portfolio returns inversely proportional to lagged variance produces higher Sharpe ratios and large alphas relative to the original portfolios. Because volatility positively forecasts returns in the Chinese A-share stock market, the Moreira and

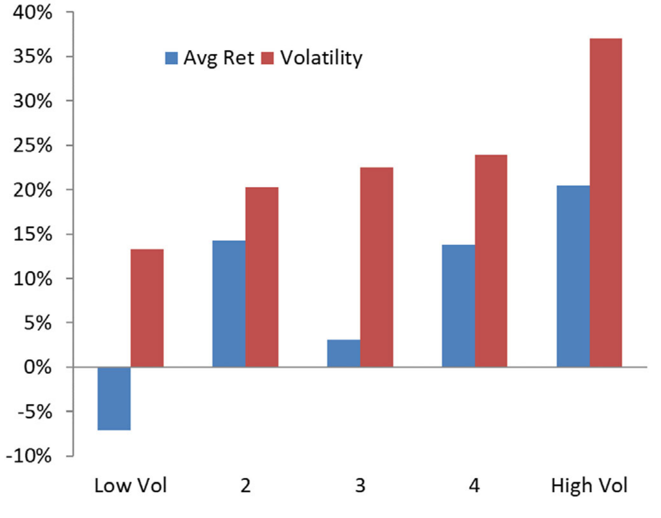

FIGURE 1 Volatility quintiles, value-weight Chinese A-share stock market. We sort monthly realized volatility of the value-weight A-share market portfolio into five buckets and track the portfolio volatility and returns for the following month. Average returns and volatility are annualized. The sample is from January 1998 to December 2017

Muir (2017) approach is not suitable for China; managing the portfolio exposure to be inversely proportional to lagged variance ignores the positive predictive power of lagged volatility. When volatility is high, volatility-managed portfolios prescribe reducing portfolio exposure, leaving the investor underinvested exactly when future expected returns are high. Volatility-managed portfolios are spanned by the original portfolios: time series regressions of volatility-managed portfolios on the original portfolios have negative intercepts. Volatility-managed portfolios do not help the investor improve his investment opportunity set.

We propose an alternative construction, volatility-scaled portfolios, which increases portfolio exposure when volatility is high and decreases portfolio exposure when volatility is low. This portfolio management technique takes advantage of the positive relationship between lagged volatility and future returns observed in Chinese A-share stock market. Volatility-scaled portfolios are not spanned by the original portfolios and can expand the investor's opportunity set. In spanning regressions of volatility-scaled portfolios on the original portfolios, the intercepts are economically large, ranging between 1 and 6% per year. Our results are unchanged if we use GARCH volatility forecasts, rather than lagged volatility, to adjust portfolio exposure.

We also quantify the change in the investor's opportunity set by comparing the mean–variance frontier formed using the original portfolios, and the frontier formed using the original portfolios plus volatility-scaled portfolios. The mean–variance frontier including volatility-scaled portfolios subsumes the mean–variance frontier excluding them, moving the investor's feasible set towards higher-return and lower-volatility portfolios. As higher Sharpe ratio portfolios become available, the investor's expanded choice set can improve his risk–return trade-off. Overall, the investor is better off adding volatility-scaled portfolios to his investment mix.

We consider the predictions of several leading asset pricing models including habit formation of Campbell and Cochrane (1999), disaster risk of Wachter (2013), long-run risk of Bansal and Yaron (2004), and the intermediary-based model of He and Krishnamurthy (2013). Moreira and Muir (2017) show that these models imply zero or negative intercepts in spanning regressions of volatility-managed portfolios onto the original portfolios, which they reject for the U.S. markets. For the Chinese A-share stock market, indeed we find zero or negative intercepts for volatility-managed portfolios, consistent with the leading asset pricing models.

Our paper fits into the literature on risk–return trade-offs in the Chinese A-share stock market. Kong, Liu, and Wang (2008) use MIDAS, a mixed-frequency technique, and finds no relationship between volatility and returns for the aggregate stock market from 1993 to 2001. However, they find a positive trade-off for 2001 to 2005. Chen (2015) adopts a GARCH-M specification to find a positive risk–return relationship for the Shenzhen Stock Exchange but not for the Shanghai Stock Exchange.[1] Lee, Chen, and Rui (2001) also use GARCH-M but does not find any relation between expected returns and risk. Compared to these papers, we consider factors including size, value, and momentum, as well as industry portfolios to study risk–return trade-offs beyond the market portfolio.

More broadly, our paper is related to the empirical literature documenting risk–return relationships. Much of the existing work focuses on the U.S. markets. French et al. (1987) apply a GARCH-M model to find a positive relationship between expected risk premiums and volatility. Campbell and Hentschel (1992) find evidence of "volatility feedback" using a model that combines GARCH and the Campbell and Shiller (1988a, 1988b) identity. Campbell (1987) finds a negative relationship between conditional variance and stock returns using a variety of linear models. Glosten et al. (1993) use a modified GARCH-M model and find a negative relationship between conditional mean and variance for monthly returns. Compared to these studies, our paper takes a simple and straightforward approach to investigate investigates the relationship between realized volatility and returns in China. For the Chinese stock market, clear empirical patterns emerge without the need of sophisticated statistical techniques. We also consider the economic impact of our statistical findings through exploring the use of volatility measures in portfolio management.

Applying volatility measures in portfolio management is a central theme of our paper. Moreira and Muir (2017) document that scaling portfolios by the inverse of their lagged variance improves the performance of the original portfolios. Qiao, Yan, and Deng (2018) show that scaling portfolios using the inverse of their downside variance further improves the investor's opportunity set. In contrast to these approaches, our paper demonstrates that in the Chinese A-share stock market, reducing portfolio exposure when volatility is high is suboptimal, because high volatility is associated with high returns next period. Our alternative portfolio management tool, volatility-scaled portfolios, accounts for this stylized fact in the Chinese A-share stock market and helps expand the investor's opportunity set.

Our paper is organized as follows. Section 1 examines the relationship between volatility measures and returns. Section 2 investigates the portfolio management implications of time-varying volatility and returns, including analysis on volatility-managed portfolios and volatility-scaled portfolios. Section 3 provides a discussion of our empirical findings. Section 4 concludes. Appendix A includes the GICS-industry mapping information.

1 | THE RELATIONSHIP BETWEEN RETURNS AND VOLATILITY

1.1 | Data

We collect Chinese A-share stock market data from WIND®. We include all publicly listed stocks in the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Our dataset includes daily stock returns, trading status, market capitalization, high, low, open, close, value-weighted average price, and major index returns (SSE50, CSI300, and CSI500), book value at the end of each June, industry classifications following GICS, and IPO dates. Our sample is from January 1998 to December 2017.[2]

We construct stock return factors using the Chinese A-share data. The market premium, RmRf, is taken as the value-weight one-month return on publicly listed A-share stocks on the Shanghai and Shenzhen stock exchanges minus the risk-free rate captured by the 3-month Chinese household deposit rate. We construct the size and value factors using a similar procedure as Fama and French (1992). Each stock is categorized as "big" or "small" based on whether it is above or below the median market capitalization at the end of each June. The book-to-market ratio (BM) is calculated as the shareholder's equity (less minority equity) divided by the total market capitalization. The book value comes from the last available financial report that has been released on the appointed day. Stocks are classified as "high," "medium," or "low" based on the BM at the end of each June. Stocks with top 30% BM are classified as "high." The bottom 30% is classified as "low." The 30th to 70th percentile BM stocks are classified as "medium." Six portfolios are formed using market cap and BM breakpoints: small/high, small/medium, small/low, big/high, big/medium, and big/low.

In addition to annual assignment of stocks into the six portfolios, we also consider monthly assignment. The market capitalization breakpoints each month is the median market capitalization at the end of the last month. For BM breakpoints, stocks are classified as "high," "medium," or "low" depending on its BM at the end of last month. To calculate a stock's BM in month t, we define the numerator as its equity's book value from the latest available financial report at the end of month $t-1$, and the denominator as its total market capitalization at the end of month $t-1$. For example, to calculate a stock's BM in June, we check the latest available financial statement available by the end of May (from the first quarter) and extract the shareholder equity's book value. We then take the stock's total market capitalization value at the end of May. We divide the book value by the total market capitalization to arrive at the stock's BM. We form six portfolios using the market capitalization and BM breakpoints, as the annual sort, at the end of each month.

Within each of the six portfolios, value-weight returns are computed. The size factor, SMB, is the equal-weight average of small/high, small/medium, and small/low portfolios minus the equal-weight average of big/high, big/medium, and big/low portfolios. HML is constructed as the equal-weight average of small/high and big/high minus the equal-weight average of small/low and big/low. Factors constructed with annual assignment (Fama & French, 1992) are referred to as SMB_Annual and HML_Annual, and factors constructed with monthly assignment are SMB_Monthly and HML_Monthly. We compute monthly returns for both monthly and annually-assigned factors.

For the momentum factor, we compute cumulative past returns from 12 months prior to the current date to 2 months prior, skipping the most recent month (Jegadeesh & Titman, 1993). The breakpoints for past performance are the 30th and 70th percentiles. The bottom 30% past performers are classified as "losers"; the top 30% of past performers are classified as "winners." The middling performers are classified as "neutral." Each month, we form six portfolios combining past performance and market capitalization: small/loser, small/neutral, small/winner, big/loser, big/neutral, and big/winner. The momentum factor, MOM, is constructed as the equal-weight average of small/winner and big/winner minus the equal-weight average of small/loser and big/loser.

We present summary statistics for the factors in Table 1. In China's A-share stock market, the size factor is positively priced with significant t-statistic and economic magnitude. SMB_Annual has an average monthly return of 0.86% (t = 2.8); and SMB_Monthly has an average monthly return of 1.15% (t = 3.4). The value factor is also positively priced with significant t-statistic and economic magnitude. HML_Annual has an average monthly return of 0.41% (t = 1.7); and HML_Monthly has an average monthly return of 1.05% (t = 3.9). In comparison, the momentum factor MOM is not priced, with an average monthly return of −0.22% (t = −0.8).

Industry portfolios are value-weight portfolios using GICS definition (see Appendix A). We omit Real Estate Management & Development, GICS code 601020, because it only contains 13 months of returns. We focus on 63 industry portfolios for our analysis.

1.2 | Contemporaneous volatility measures and returns

We start by looking at the contemporaneous relationship between volatility measures and returns. Monthly realized volatility of factors and industry portfolios are constructed using daily returns. We regress monthly returns onto realized volatility in the same month:

$$f_t = a + b\sigma_t + \eta_t \tag{1}$$

where f_t is the return at time t for factors or industry portfolios. σ_t is the month t standard deviation of f_t constructed using daily observations. b is the regression coefficient which measures the comovement between returns and volatility. a is a constant and η_t is the time t residual. The regression coefficient b and the associated t-statistics for long-short factors are shown in the top panel of Table 2.

The contemporaneous relationship between returns and volatility is weak for factors. Market, SMB_Annual, HML_Annual, and SMB_Monthly all show statistically insignificant coefficients. For the two factors that have significant coefficients, MOM shows a negative relationship between volatility and same period returns, whereas HML_Monthly shows a positive relationship. To improve statistical power, we run a pooled regression including all factors, including fixed effects for each factor to allow for cross-sectional differences in average returns. The pooled regression coefficient is −0.03 with a t-statistic, clustered by portfolio and by time, of −0.8.

TABLE 1 Summary statistics of factor returns, 1998–2017. The market risk premium, RmRf, is the value-weight 1-month return on publicly listed A-share stocks on the Shanghai and Shenzhen exchanges minus the risk-free rate captured by the three-month Chinese household deposit rate. We form size and value factors using the Fama and French (1992) methodology, rebalancing the portfolios annually (SMB_Annual and HML_Annual). We also consider monthly rebalanced size and value factors SMB_Monthly and HML_Monthly. The momentum (MOM) factor is rebalanced monthly. T-statistics are reported in parentheses. * and ** indicate statistical significance at the 10 and 5% levels, respectively

	RmRf	SMB_Annual	HML_Annual	MOM	SMB_Monthly	HML_Monthly
Average returns	0.82%	0.86%**	0.41%*	−0.22%	1.15%**	1.05%**
	(1.4)	(2.8)	(1.7)	(−0.8)	(3.4)	(3.9)

TABLE 2 Contemporaneous relationship between volatility measures and returns for factor portfolios

	RmRf	SMB_Annual	HML_Annual	MOM	SMB_Monthly	HML_Monthly	Pooled
	Returns on volatility						
b	−0.06	−0.11*	0.07	−0.14**	−0.05	0.19**	−0.03
	(−1.4)	(−1.7)	(1.4)	(−2.6)	(−0.8)	(4.1)	(−0.8)
R^2	0.8%	1.2%	0.9%	2.8%	0.3%	6.6%	0.8%
N	240	234	234	228	239	239	1,414
	Returns on change in volatility						
b^{ch}	−0.11**	−0.38**	0.15**	0.10	−0.40**	0.12**	−0.10**
	(−2.1)	(−5.7)	(2.4)	(1.6)	(−5.8)	(2.2)	(−2.3)
R^2	1.8%	12.4%	2.4%	1.1%	12.3%	2.0%	1.9%
N	239	233	233	227	238	238	1,408

Notes: We regress monthly returns of factors on the contemporaneous volatility and change in volatility. The top panel shows results for regressions of factor returns on its volatility from the same month. $f_t = a + b\sigma_t + \eta_t$. The bottom panel shows results for regressions of factor returns onto the contemporaneous change in volatility. $f_t = a^{ch} + b^{ch}\Delta\sigma_t + \eta_t^{ch}$. The data are from January 1998 to December 2017. *T*-statistics are shown in parentheses. The rightmost column shows coefficients from a pooled regression including all factors, including fixed effects by factors. For the pooled regression, the *t*-statistics are clustered by factor and time. * and ** indicate statistical significance at the 10 and 5% levels, respectively. *N* is the number of observations.

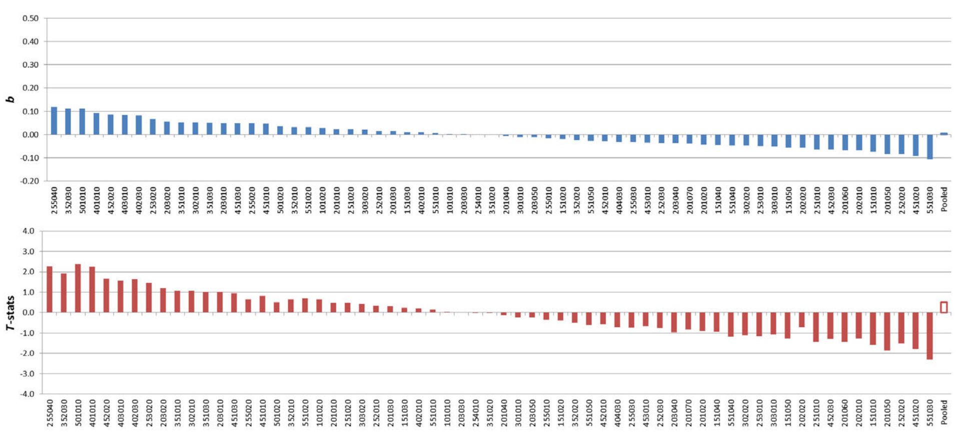

FIGURE 2 Regression of monthly returns on volatility for industry portfolios. We regress industry portfolio returns on the contemporaneous month volatility. $f_t = a + b\sigma_t + \eta_t$. For ease of presentation, regression coefficients *b* and the associated *t*-statistics are sorted from the largest to smallest *b*. The rightmost (unshaded) bar shows the pooled regression coefficient including industry fixed effects. The *t*-statistic for the pooled regression is clustered by industry and by time. The data are from January 1998 to December 2017. We mark each industry by its GICS level-3 code. We list the GICS-industry mapping in Appendix A

Because we have a large number of industry portfolios, showing individual point estimate and *t*-statistics can result in an overwhelmingly large table. We choose to present our industry portfolio results using bar graphs, following Qiao et al. (2018). Results for 63 industry portfolios are shown in Figure 2. To visually capture the variation across numerous industries, we present the regression coefficients that are ordered from the largest to the smallest. The associated *t*-statistics are also ordered from the largest to the smallest coefficient. This presentation allows us to more easily observe how many coefficients are statistically significant, and how many are positive.

Some portfolios show a small positive relationship between returns and volatility, whereas other portfolios show a small negative relationship. There are 32 industry portfolios with positive coefficients and 31 portfolios with negative coefficients. The pooled regression coefficient is economically small, with a *t*-statistics of 0.5. Like the U.S. stock market, the Chinese A-share stock market shows a weak contemporaneous relationship between volatility and returns for a broad set of portfolios.

Next, we explore the relationship between volatility innovations and returns. For the U.S. stock market, there is a "leverage effect" for market returns: negative returns are associated with larger increases in volatility than positive returns of the same magnitude (Campbell & Hentschel, 1992; Glosten et al., 1993). Unconditionally, this effect leads to a negative correlation between volatility innovations and returns. We examine the relationship between volatility innovations and returns in the Chinese A-share stock market, using monthly change in volatility as a measure of volatility innovations. Our regression specification is as follows:

$$f_t = a^{ch} + b^{ch}\Delta\sigma_t + \eta_t^{ch} \tag{2}$$

where $\Delta\sigma_t = \sigma_t - \sigma_{t-1}$ is the first difference in monthly realized volatility. a^{ch} and η_t^{ch} are the intercept coefficient and regression residual. b^{ch} is the regression coefficient measuring the relationship between portfolio returns f_t and $\Delta\sigma_t$.

We present the factor results in the lower panel of Table 2 and industry portfolio results in Figure 3. There is still considerable variation across the factor portfolios, with three factors showing positive coefficients and three showing negative coefficients. In particular, the market excess returns show a negative relationship between volatility innovations and returns, corresponding to the U.S. result. The size factor also shows a negative relationship; both SMB_Annual and SMB_Monthly have negative and statistically significant regression coefficients. In contrast, value and momentum factors show a positive relationship between volatility innovations and returns. The pooled regression shows a statistically significant coefficient of −0.10 across the six factors.

We turn our attention to the industry portfolios in Figure 3. Figure 3 follows the presentation in Figure 2 and orders the regression coefficients (and their *t*-statistics) from the largest to the smallest. Please note that the same portfolio may be in different horizontal positions in Figure 2 and in Figure 3. Many regression coefficients are

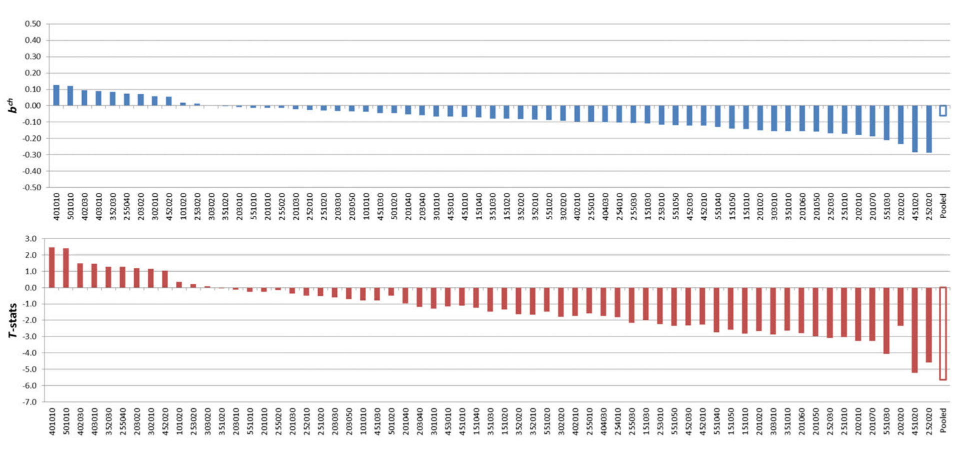

FIGURE 3 Regression of monthly returns on change in volatility for industry portfolios. We regress industry portfolio returns on the change in volatility. $f_t = a^{ch} + b^{ch}\Delta\sigma_t + \eta_t^{ch}$. For ease of presentation, regression coefficients b^{ch} and the associated *t*-statistics are sorted from the largest to smallest b^{ch}. The rightmost (unshaded) bar shows the pooled regression coefficient including industry fixed effects. The t-statistic for the pooled regression is clustered by industry and by time. The data are from January 1998 to December 2017. We mark each industry by its GICS level-3 code. We list the GICS-industry mapping in Appendix A

negative and economically large, ranging between −0.1 and −0.4. Fifty of 63 industries display a negative relationship between returns and the change in volatility; 13 industries show a positive relationship. Furthermore, the *t*-statistics are larger compared to those in Figure 2, and many of the negative coefficients are statistically significant at the 5% level. With a *t*-statistic exceeding 5, the pooled regression coefficient is statistically significant at the 1% level.

Overall, the contemporaneous relationship between returns and volatility is weak, whereas the relationship between returns and volatility innovations is stronger and typically negative. The results in this section are similar to those for the U.S. markets. In the United States, there is also a weak relationship between returns and volatility: Campbell and Hentschel (1992) and French et al. (1987) find a small positive relationship between returns and volatility, whereas Campbell (1987) and Glosten et al. (1993) find a negative relationship. Returns and volatility innovations are negative correlated for the U.S. markets (Engle & Ng, 1993). In the next section, we examine the relationship between returns and lagged volatility measures, where we discover important differences to the U.S. markets.

1.3 | Lagged volatility measures and returns

There is a large literature exploring the ability of volatility to forecast futures returns. The prevailing empirical finding for the U.S. markets is that there is limited, if any, relationship between past volatility of a portfolio and future portfolio returns. We measure the relationship between lagged volatility and current period returns through forecasting regressions:

$$f_t = \gamma + \delta\sigma_{t-1} + \varepsilon_t \tag{3}$$

where f_t is the portfolio return at time t. σ_{t-1} is the portfolio standard deviation at time $t-1$ constructed using daily observations. γ is the intercept and ε_t is the residual. δ is the forecasting coefficient. A positive δ indicates that higher volatility in the previous month is associated with higher returns in the current month.

The top panel of Table 3 presents the forecasting coefficients and the associated t-statistics for factor portfolios. Four of the six factors show positive coefficient. For the two negative coefficients, HML_Annual has an economically and statistically small coefficient, whereas MOM shows a large negative coefficient which is statistically significant. The pooled regression coefficient is 0.04 and not statistically significant. Figure 4 presents the forecasting coefficient δ and *t*-statistics for industry portfolios. We see a positive risk–return trade-off: If last month's volatility was high, this month's return is likely to be higher. For the majority of industries, last month's volatility has some predictive power for this month's returns. Among 63 industry portfolios, only 2 have marginally negative δ. The pooled coefficient for industry portfolios has a large *t*-statistic of 6.8, which means we reliably estimate a positive relationship between return and lagged volatility for industry portfolios. The results in Figure 4, and Table 3 to a lesser extent, stand in contrast to the case for the U.S. stock market. For factors or industry portfolios in the U.S. markets, past month's volatility does not forecast this month's return (Moreira & Muir, 2017).

We also explore forecasting regressions using volatility innovations as measured by the first difference in monthly volatility:

$$f_t = \gamma^{ch} + \delta^{ch}\Delta\sigma_{t-1} + \varepsilon_t^{ch} \tag{4}$$

where $\Delta\sigma_{t-1} = \sigma_{t-1} - \sigma_{t-2}$ is the lagged first difference in monthly realized volatility. δ^{ch} is the forecast coefficient. The bottom panel of Table 3 and Figure 5 show the results of these forecasting regressions.

There is a positive but economically small relationship between factor returns and lagged volatility innovations: five of the six factor portfolios show positive coefficients, and the pooled coefficient is positive. However, the

TABLE 3 Relationship between lagged volatility measures and returns for factor portfolios

	RmRf	SMB_Annual	HML_Annual	MOM	SMB_Monthly	HML_Monthly	Pooled
	Returns on lagged volatility						
δ	0.01	0.21**	−0.02	−0.22**	0.29**	0.10**	0.04
	(0.3)	(3.3)	(−0.4)	(−4.1)	(4.4)	(2.1)	(1.2)
R^2	0.0%	4.6%	0.1%	6.9%	7.6%	1.8%	0.9%
N	239	233	233	227	238	238	1,408
	Returns on change in lagged volatility						
δ^{ch}	0.02	0.04	0.01	−0.05	0.09	0.08	0.03
	(0.4)	(0.6)	(0.2)	(−0.8)	(1.2)	(1.5)	(0.8)
R^2	0.1%	0.1%	0.0%	0.3%	0.6%	1.0%	0.8%
N	238	232	232	226	237	237	1,402

Notes: We regress monthly returns on factors on lagged volatility from the previous month and the change in lagged volatility. The top panel shows results for regressions of factor portfolios on the previous month volatility. $f_t = \gamma + \delta\sigma_{t-1} + \varepsilon_t$. The bottom panel shows results for regressions of portfolio returns on the lagged changed in volatility. $f_t = \gamma^{ch} + \delta^{ch}\Delta\sigma_{t-1} + \varepsilon_t^{ch}$. The data are from January 1998 to December 2017. *T*-statistics are shown in parentheses. The rightmost column shows coefficients from a pooled regression including all factors, including fixed effects by factors. For the pooled regression, the *t*-statistics are clustered by factor and time. * and ** indicate statistical significance at the 10 and 5% levels, respectively. *N* is the number of observations.

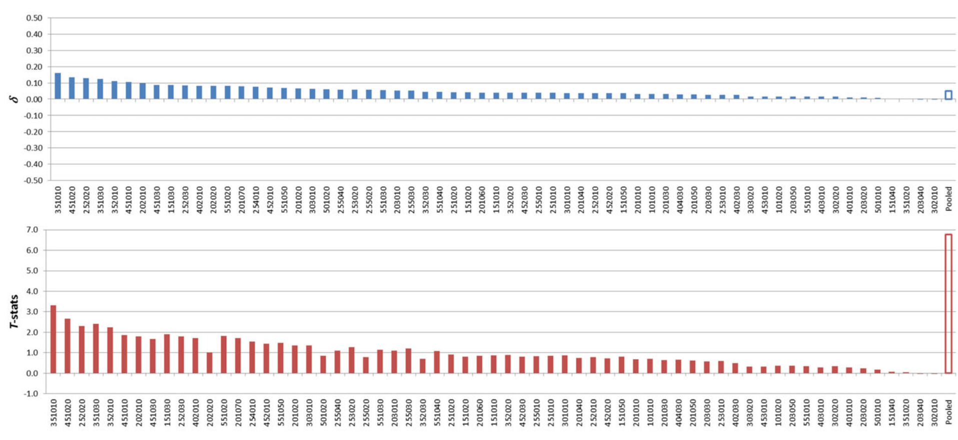

FIGURE 4 Regression of monthly returns on lagged volatility for industry portfolios. We regress industry portfolio returns on portfolio volatility from the previous month. $f_t = \gamma + \delta\sigma_{t-1} + \varepsilon_t$. For ease of presentation, forecasting coefficients δ and *t*-statistics are sorted from the largest to smallest δ. The rightmost (unshaded) bar shows the pooled regression coefficient including industry fixed effects. The *t*-statistic for the pooled regression is clustered by industry and by time. The data are from January 1998 to December 2017. We mark each industry by its GICS level-3 code. We list the GICS-industry mapping in Appendix A

magnitude of the coefficients is generally small, and the pooled coefficient is not statistically significant. Industry portfolios show a stronger result. In Figure 5, 55 of 63 industry portfolios show a positive coefficient. The pooled coefficient is 0.05 with a *t*-statistic of 6.1, indicating a reliably positive relationship between lagged volatility innovations and returns for industry portfolios. If volatility increased last month, returns are likely to be higher this month.

Micro-cap stocks can drive empirical findings on the behavior of asset returns, due to their liquidity and market microstructure effects. To address this concern, we follow Liu, Stambaugh, and Yuan (2019) to exclude the bottom

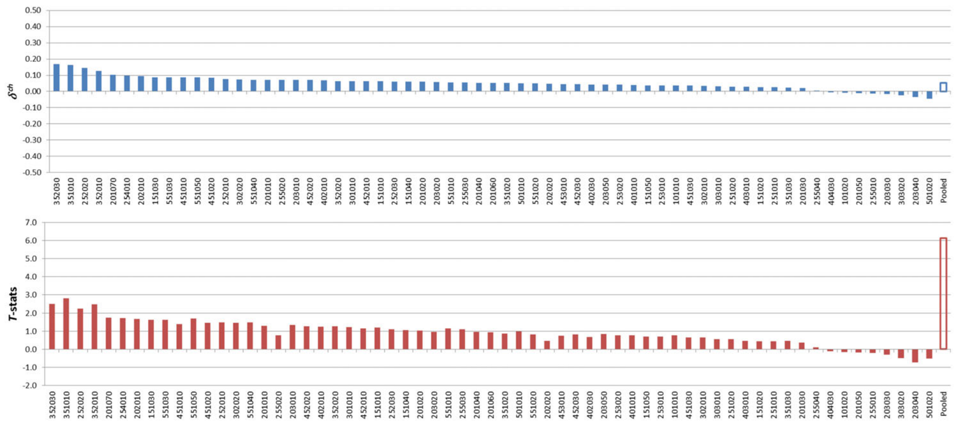

FIGURE 5 Regression of monthly returns on lagged volatility changes for industry portfolios. We regress industry portfolio returns on the first difference in portfolio volatility from the previous month. $f_t = \gamma^{ch} + \delta^{ch} \Delta\sigma_{t-1} + \varepsilon_t^{ch}$. For ease of presentation, forecasting coefficients δ^{ch} and t-statistics are ordered from the largest to smallest δ^{ch}. The rightmost (unshaded) bar shows the pooled regression coefficient including industry fixed effects. The t-statistic for the pooled regression is clustered by industry and by time. The data are from January 1998 to December 2017. We mark each industry by its GICS level-3 code. We list the GICS-industry mapping in Appendix A

30% of stocks by market capitalization, and we reproduce Figures 4 and 5 using the remaining 70%. We find that our results are not driven by the smallest market-capitalization stocks. More details are available in Appendix B.

The Chinese A-share stock market exhibits unique and intriguing patterns for the relationship between volatility and returns. There exists a weak or negative relationship between returns and contemporaneous volatility—qualitatively similar to the U.S. stock market. However, the positive relationship between lagged volatility or change in volatility and returns appears to be unique to the Chinese A-share stock market. For the U.S. stock market, there is no clear relationship between lagged volatility and current period returns (see Appendix C).

Typical asset pricing models imply a positive relationship between risk and return. For example, habit formation of Campbell and Cochrane (1999), disaster risk of Wachter (2013), long-run risk of Bansal and Yaron (2004), and the intermediary-based model of He and Krishnamurthy (2013) all exhibit positive risk–return trade-offs. Our empirical findings offer support for such theoretical predictions in the Chinese A-share market. In contrast, the lack of a clear relationship between risk and return for the U.S. markets, such as the findings in Moreira and Muir (2017), are puzzling in the context of theory.

The difference between the U.S. and Chinese stock markets has important implications for using volatility for portfolio management. We explore these implications in the following section.

2 | VOLATILITY IN PORTFOLIO MANAGEMENT

2.1 | Volatility-managed portfolios

Because lagged volatility and current period returns are not closely linked for the U.S. markets, scaling portfolios by their past volatilities improves their risk–return properties. Moreira and Muir (2017) exploit this idea and propose managing portfolio exposures to be proportional to the inverse of the lagged variance:

$$f_{t+1}^{MM} = \frac{c}{\sigma_t^2} f_{t+1} \tag{5}$$

where f_{t+1}^{MM} is the Moreira and Muir (2017) volatility-managed portfolio. f_{t+1} is the original portfolio. σ_t^2 is the variance estimated using the previous month's daily returns. c is a constant set such that f_{t+1}^{MM} and f_{t+1} have the same unconditional standard deviation. Moreira and Muir (2017) show that their volatility-managed portfolios are able to expand the investor's opportunity set.

We investigate the benefit of Moreira and Muir's (2017) portfolio construction in the Chinese A-share stock market. We first construct volatility-managed portfolios using the methodology from Moreira and Muir (2017), then we run the following spanning regression:

$$f_{t+1}^{MM} = \alpha + \beta f_{t+1} + \varepsilon_{t+1}^{MM} \tag{6}$$

The purpose of Equation (6) is to measure whether the volatility-managed portfolio f_{t+1}^{MM} can expand the investor's opportunity set relative to the original portfolio returns f_{t+1}. The coefficient of interest is α: if it is large and positive, f_{t+1} cannot span f_{t+1}^{MM}, and adding f_{t+1}^{MM} to the investor's set of investments improves his investment opportunities and expands his mean–variance frontier.

We present the estimated intercept α and the associated t-statistics in Figure 6. Across factor and industry portfolios, the majority of estimated intercepts is negative; 60 of 69 return series exhibit negative intercepts in the spanning regression. We do observe some large and positive intercepts. In particular, the largest positive estimated intercept is 7.9% for MOM. In comparison, the largest negative intercepts are even larger in magnitude. Nine industry portfolios show negative intercepts of −10% or greater.

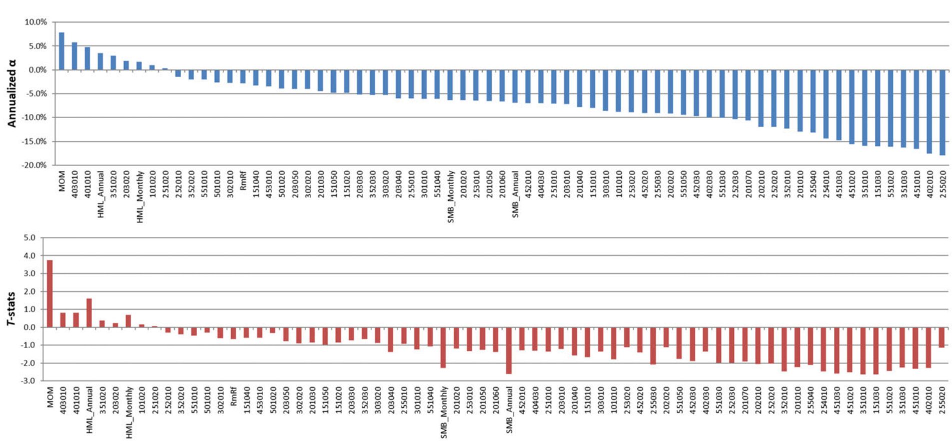

FIGURE 6 Spanning regressions of volatility-managed portfolios on the original portfolios. We construct volatility-managed portfolios of Moreira and Muir (2017): $f_{t+1}^{MM} = \frac{c}{\sigma_t^2} f_{t+1}$, where f_{t+1}^{MM} is the Moreira and Muir (2017) volatility-managed portfolio. f_{t+1} is the original portfolio. σ_t^2 is the variance estimated using last month's daily observations. c is a constant set such that f_{t+1}^{MM} and f_{t+1} have the same unconditional standard deviation. We then regress volatility-managed portfolio f_{t+1}^{MM} on the original portfolio f_{t+1}: $f_{t+1}^{MM} = \alpha + \beta f_{t+1} + \varepsilon_{t+1}^{MM}$. For ease of presentation, annualized figures of α and the associated t-statistics are sorted by α. The data are from January 1998 to December 2017. We mark each industry by its GICS level-3 code. We list the GICS-industry mapping in Appendix A

Figure 6 shows that scaling returns series by the inverse of past month's variance does not expand the investor's opportunity set relative to the original portfolios. This finding stands in contrast to the results in Moreira and Muir (2017) for the U.S. stock market, for which the authors find that volatility-managed portfolios are almost never spanned by the original portfolios and the intercept estimates are large and positive.

Our results differ from those from Moreira and Muir (2017) because there is a positive risk–return trade-off between lagged volatility and returns. If last month's volatility (or variance) is high, this month's returns are likely to be higher for the majority of our test portfolios. Managing portfolio exposure to be proportional to the inverse of past month's variance ignores this return predictability, increasing (decreasing) portfolio exposure when expected returns are low (high), and therefore weakens the portfolio risk–return trade-off. Because of this empirical fact unique to the Chinese A-share stock market, Moreira and Muir (2017) volatility-managed portfolios do not benefit Chinese A-share investors.

The big outlier in Figure 6 is momentum, for which the volatility-managed version is not spanned by the original factor. In fact, volatility-managed momentum has a statistically large intercept estimate of 7.9% per year. In Table 3, for the momentum factor, past volatility and the change in past volatility showed negative predictive coefficients for the next month's returns. When volatility is high, expected returns for momentum for the next month is likely to be low, and when volatility is low, expected returns for momentum is like to be high. Therefore, managing portfolio exposure to be proportional to the inverse of past month's variance can improve the risk–return trade-off of momentum returns through exploiting this negative predictive relationship.

If volatility-managed portfolios do not expand the investor's opportunity set for the A-share stock market, can volatility still be useful for portfolio management? We exploit the positive return predictability of lagged volatility, and we propose an alternative portfolio management methodology that does expand the investor's opportunity set for the Chinese A-share stock market.

2.2 | Volatility-scaled portfolios

In the Chinese A-share stock market, higher volatility in 1 month is associated with higher returns in the following month. Rather than managing portfolio exposure to be inversely proportional to lagged variance, we consider volatility-scaled portfolios that increase exposure when volatility is high and decrease exposure when volatility is low. Such portfolio construction takes advantage of the positive association between lagged volatility and future returns. Volatility-scaled portfolio f^{σ}_{t+1} for return series f_{t+1} is constructed as follows:

$$f^{\sigma}_{t+1} = \frac{\sigma_t}{k} f_{t+1} \tag{7}$$

where σ_t is the standard deviation estimated using daily observations in month t. k is a constant chosen such that f^{σ}_{t+1} and f_{t+1} have the same unconditional standard deviation.

We conduct spanning tests for volatility-scaled portfolios, similar to those for volatility-managed portfolios:

$$f^{\sigma}_{t+1} = \alpha^{\sigma} + \beta^{\sigma} f_{t+1} + \varepsilon^{\sigma}_{t+1} \tag{8}$$

The spanning regression results are shown in Figure 7. Thirty-two of 69 return series have intercepts that range from 1 to 6% per year; 45 series have positive intercepts. Momentum and the industry portfolio 351020, "Health Care Providers & Services," are two portfolios that have economically large negative intercept estimates, indicating the volatility-scaled portfolios of these two return series are spanned by the original return series. Momentum has the only statistically large negative intercept. Overall, volatility-scaled portfolios paint a different picture compared

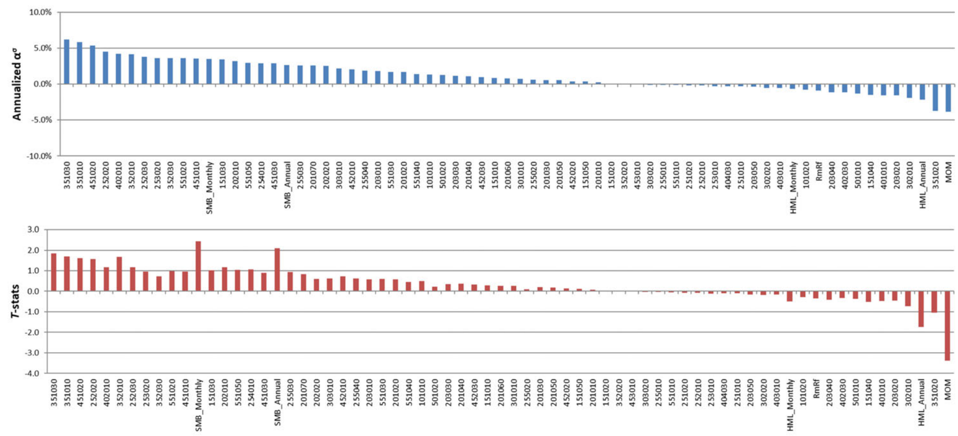

FIGURE 7 Spanning regressions of volatility-scaled portfolios on the original portfolios. We construct volatility-scaled portfolio f^{σ}_{t+1} as follows: $f^{\sigma}_{t+1} = \frac{\sigma_t}{k} f_{t+1}$, where f_{t+1} is the original portfolio. σ_t is the standard deviation estimated using daily observations of f_t. k is a constant such that f^{σ}_{t+1} and f_{t+1} have the same unconditional standard deviation. We then regress volatility-scaled portfolio f^{σ}_{t+1} on the original portfolio f_{t+1}: $f^{\sigma}_{t+1} = \alpha^{\sigma} + \beta^{\sigma} f_{t+1} + \varepsilon^{\sigma}_{t+1}$. For ease of presentation, annualized figures of α^{σ} and t-statistics are sorted by α^{σ}. The data are from January 1998 to December 2017. We mark each industry by its GICS level-3 code. We list the GICS-industry mapping in Appendix A

to volatility-managed portfolios. Scaling return series proportionally to lagged volatility appears to improve the investor's opportunity set.

Although the economic magnitudes of some intercepts in Figure 7 are large, they are generally not statistically significant due to low statistical power. We do not have enough power to reject the null of zero intercept for most of the spanning regressions. To increase the power of our test, we show how the investor's mean–variance frontier changes to the inclusion and exclusion of volatility-scaled portfolios in the next section.

2.3 | Investor's mean–variance opportunity set

The previous section provides univariate comparisons of volatility-scaled portfolios and the original portfolios. We have shown that volatility-scaled portfolios are often not spanned by the original portfolios, and the alphas from spanning tests are economically large. We further demonstrate the economic benefits of volatility-scaled portfolios through examining how the investor's opportunity set changes in a mean–variance setting. The ex post mean–variance frontier, formed with perfect knowledge of the average returns and the covariance matrix of the constituent assets, puts an upper bound on the largest possible investment opportunity set for the investor. Because volatility-scaled portfolios are not spanned by the original portfolios, it is likely by combining volatility-scaled portfolios with the original portfolios, we can expand the investor's ex post mean–variance frontier. We construct the ex post mean–variance frontiers for different sets of portfolios and show how those frontiers change when we include or exclude volatility-scaled portfolios.

Suppose we have N financial assets with excess return vector μ and variance–covariance matrix $\sum$. The mean–variance efficient portfolio weights for a target portfolio return r_0 is the solution to the following optimization problem

$$\min_{w} w^{T} \sum w$$

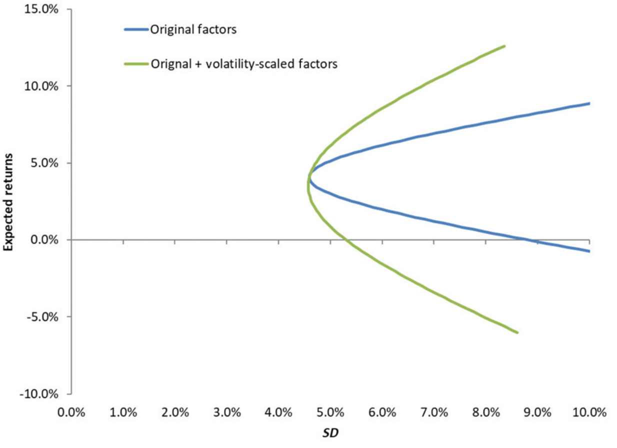

FIGURE 8 Ex post mean–variance frontiers for factor portfolios. We construct two ex post mean–variance frontiers for factor portfolios. The blue curve is the mean–variance frontier constructed from market (RmRf), size (SMB_Annual), value (HML_Annual), and momentum (MOM) factors (Carhart, 1997; Fama & French, 1992). The green curve is constructed from the same four factors plus the volatility-scaled versions of the factors. The data are from January 1998 to December 2017

$$s.t.\ \ \mu^T \sum \geq r_0,\ \ 1^T w = 1 \tag{9}$$

where 1^T is a conforming column of ones. The above problem was first proposed by Markowitz (1952, 1959) in his seminal papers on Modern Portfolio Theory. To construct the mean–variance efficient frontier, we solve this problem for different values of target portfolio return r_0, then plot the different r_0 against the portfolio standard deviation $\sqrt{w^T \sum w}$.

Figure 8 considers the ex post mean–variance frontier formed with the Fama and French (1992) factors and momentum (Carhart, 1997). We consider 100 different portfolio target returns r_0 and solve for the mean–variance efficient portfolio weights. The blue curve traces out the mean–variance frontier generated by the Fama and French (1992) factors (RmRf, SMB_Annual, and HML_Annual) and momentum (MOM). The green curve is the mean–variance frontier using a combination of the four factors and their volatility-scaled counterparts, for a total of eight portfolios. The mean–variance frontier including volatility-scaled factors appears to provide the investor with better choices. Compared to feasible portfolios on the blue frontier, the expanded green frontier allows for portfolios with lower volatility (given the same level of expected returns), higher expected returns (given the same level of volatility), or portfolios that have both lower volatility and higher expected returns. Portfolios between the upper halves of the green and blue frontiers can have higher Sharpe ratios than feasible portfolios on the blue frontier.

Figure 9 presents mean–variance frontiers formed using 63 industry portfolios (blue), or those 63 portfolios and their volatility-scaled counterparts (green). We observe a similar pattern for the two mean–variance frontiers as in Figure 8. When we combine volatility-scaled portfolios with the original industry portfolios, the mean–variance frontier moves up and to the left in the figure, expanding the investor's opportunity set to include portfolios with higher expected returns and lower volatility. For the investor, the ability to access volatility-scaled portfolios as part of the investment mix has the potential to improve his risk–return profile. The improvement in mean–variance frontier for industry portfolios is larger compared to the improvement for factor portfolios, reflecting our finding that lagged volatility is a better predictor of future returns for industry portfolios than for factors.

3 | DISCUSSION

3.1 | Potential explanations

We consider our empirical results on volatility-managed portfolios and volatility-scaled portfolios through the lens of asset pricing models. Moreira and Muir (2017) examine four models:

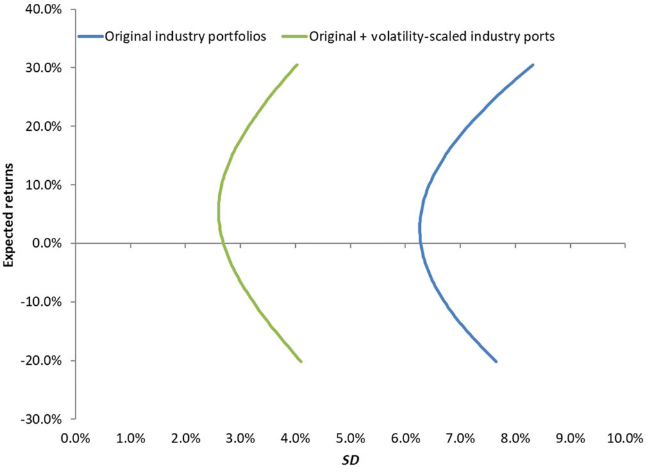

FIGURE 9 Ex post mean–variance frontiers for industry portfolios. We construct two ex post mean–variance frontiers for industry portfolios. The blue curve is the mean–variance frontier constructed from 63 industry portfolios. The green curve is constructed from the original 63 industry portfolios plus their volatility-scaled versions. The data are from January 1998 to December 2017

1. Campbell and Cochrane (1999): habit formation
2. Wachter (2013): disaster risk
3. Bansal and Yaron (2004) and Bansal, Kiku, and Yaron (2012): long-run risk
4. He and Krishnamurthy (2013): intermediary-based model

Through simulations, Moreira and Muir (2017) show that these models imply zero or negative intercepts in spanning regressions of volatility-managed portfolios onto the original portfolios. In particular, long-run risk and intermediary-based models show coefficients centered around zero, whereas habit formation and disaster risk models tend to show negative intercepts. Since Moreira and Muir (2017) find positive spanning regression intercepts for the aggregate U.S. market portfolio, they assert their empirical results pose a challenge to these leading asset pricing models.

Our results for the Chinese stock market stand in sharp contrast to those of Moreira and Muir (2017). We find negative alphas in spanning regressions of volatility-managed portfolios onto the original portfolios. In particular, the intercept is small and negative for the aggregate A-share stock market, consistent with the predictions from the four asset pricing models listed above.

Another possible channel to generate our empirical findings is that investors may become more risk-averse in times of high volatility. As such, those who can bear risks in these times are rewarded for having greater risk tolerance than the average investor. Volatility-scaled portfolios take on additional risk as portfolio exposure is increased during the most volatile times, and investors are rewarded for this additional risk. This channel is most plausible in a retail-dominated market, as retail investors tend to be more myopic compared to institutional investors, who may have longer investment horizons as well as greater capacity to bear short-term risk. The different institutional settings for the Chinese and U.S. stock markets may help explain the distinct portfolio management tools that are effective in each market. Further exploration in these directions is beyond the scope of our paper but could be fruitful for future research.

It may be difficult to establish short positions in the Chinese A-share market, and sometimes it is entirely infeasible to do so. We investigate the long and short legs of factor portfolios separately, and we do not find that the short leg is driving the positive relationship between returns and lagged volatility measures. In addition to the long-short factor portfolios, we also explore 63 industry portfolios in our analysis. The industry portfolios are long-only, and they are not affected by short-sale limitations in the A-share market. Since our results are consistent for long-short factors as well as long-only industry portfolios, they are unlikely to be driven by short-sale constraints.

3.2 | Intercept interpretation

We follow the theoretical framework of Moreira and Muir (2017) to illustrate the different interpretations of the spanning regression intercept associated with different portfolio management tools. Let r_t be the instantaneous risk-free rate. Suppose a portfolio's value R_t has conditional expected returns $r_t + \mu_t$ and volatility σ_t:

$$dR_t = (r_t + \mu_t)dt + \sigma_t dB_t \tag{10}$$

Then, Moreira and Muir's volatility-managed portfolio, R_t^{MM}, takes on the form

$$dR_t^{\mathrm{MM}} = r_t dt + \frac{c}{\sigma_t^2}(dR_t - r_t dt) \tag{11}$$

where c is the normalization constant from Equation (5). A spanning regression of excess returns of the volatility-managed portfolio R_t^{MM} onto the original portfolio R_t can be represented in continuous time as a regression of $dR_t^{\mathrm{MM}} - r_t dt$ on $dR_t - r_t dt$. The regression coefficient is

$$\beta_{\mathrm{MM}} = \frac{\mathrm{cov}\left(dR_t^{\mathrm{MM}} - r_t dt, dR_t - r_t dt\right)}{\mathrm{var}(dR_t - r_t dt)} = \frac{c}{E\left[\sigma_t^2\right]} \tag{12}$$

The intercept of this regression, as Moreira and Muir (2017) show, can be written as

$$\alpha_{\mathrm{MM}} = E\left[dR_t^{\mathrm{MM}} - r_t dt\right]/dt - \beta_{\mathrm{MM}} E[dR_t - r_t dt]/dt = -\mathrm{cov}\left(\frac{\mu_t}{\sigma_t^2}, \sigma_t^2\right)\frac{c}{E\left[\sigma_t^2\right]} \tag{13}$$

Equation (13) shows that the spanning regression intercept α_{MM} measures how much the price of risk, $\frac{\mu_t}{\sigma_t^2}$, and variance σ_t^2 comove. Since the second term $\frac{c}{E\left[\sigma_t^2\right]}$ is positive and the covariance term is typically positive for the Chinese A-share stock market, α_{MM} is negative for the majority of our test portfolios.

What is the interpretation of the regression intercept if we use volatility rather than variance to scale the portfolio? The managed portfolio would take the form

$$dR_t^{v} = r_t dt + \frac{h}{\sigma_t}(dR_t - r_t dt) \tag{14}$$

for some constant h chosen such that R_t^{v} has the same unconditional volatility as R_t. A spanning regression of $dR_t^{v} - r_t dt$ on $dR_t - r_t dt$ would have the regression coefficient

$$\beta_{v} = \frac{\mathrm{cov}\left(dR_t^{v} - r_t dt, dR_t - r_t dt\right)}{\mathrm{var}(dR_t - r_t dt)} = \frac{h}{E[\sigma_t]} \tag{15}$$

The spanning regression intercept can be calculated as follows:

$$\alpha_{v} = -\mathrm{cov}\left(\frac{\mu_t}{\sigma_t}, \sigma_t\right)\frac{h}{E[\sigma_t]} \tag{16}$$

Equation (16) shows that if we use volatility to scale portfolios rather than variance, the spanning regression intercept measures the comovement between the Sharpe ratio $\frac{\mu_t}{\sigma_t}$ of the portfolio and its volatility.

What about volatility-scaled portfolios? In our proposed approach, portfolio exposure is increased when lagged volatility is high and decreased when lagged volatility is low. To construct such a portfolio, we form

$$dR_t^{vs} = r_t dt + \frac{\sigma_t}{k}(dR_t - r_t dt) \tag{17}$$

where k is the constant from Equation (7). A spanning regression of $dR_t^{vs} - r_t dt$ on $dR_t - r_t dt$ has the regression coefficient β_{vs}

$$\beta_{vs} = \frac{\operatorname{cov}\left(dR_t^{vs} - r_t dt, dR_t - r_t dt\right)}{\operatorname{var}(dR_t - r_t dt)} = \frac{E[\sigma_t]}{k} \tag{18}$$

The intercept is then

$$\alpha_{vs} = \frac{1}{k}\operatorname{cov}(\sigma_t, \mu_t) \tag{19}$$

Equation (19) shows that volatility-scaled portfolios exploit the covariance between volatility and expected returns. To the extent lagged volatility has positive predictive power for future expected returns, the covariance in Equation (19) is positive. Because k is a positive constant, the spanning regression intercept is also expected to be positive.

The regression coefficient δ of future returns on lagged volatility from Equation (3) is also a measure of cov (σ_t, μ_t). The sign of δ theoretically corresponds to the sign of α_{vs}. In the spanning regressions of volatility-scaled portfolios on the original portfolios, a positive α_{vs} reflect a positive covariance between lagged volatility and future returns, and these are typically the portfolios we observe to have positive δ. Portfolios with negative α_{vs} are typically also the ones with a negative predictive coefficient δ.

3.3 | Volatility forecasts versus lagged volatility

Volatility-scaled portfolios are constructed by setting the portfolio exposure to be proportional to the previous month's volatility. For robustness, we consider an alternative portfolio construction using volatility forecasts rather than lagged volatility. We use a GARCH(1,1) (Bollerslev, 1986; Engle, 1982) model to produce monthly volatility forecast, then form volatility scaled portfolios f_{t+1}^{GARCH}:

$$f_{t+1}^{\text{GARCH}} = \frac{\sigma_{t+1}^{\text{GARCH}}}{\lambda} f_{t+1} \tag{20}$$

where $\sigma_{t+1}^{\text{GARCH}}$ is the one-step ahead GARCH forecast of monthly volatility, f_{t+1} is the original portfolio, and λ is a constant set such that f_{t+1}^{GARCH} and f_{t+1} have the same unconditional standard deviation. We then look at spanning regressions of f_{t+1}^{GARCH} on f_{t+1}.

$$f_{t+1}^{\text{GARCH}} = \alpha^{\text{GARCH}} + \beta^{\text{GARCH}} f_{t+1} + \varepsilon_{t+1}^{\text{GARCH}} \tag{21}$$

The intercepts and t-statistics are shown in Figure 10. The pattern in Figure 10 is similar to the one for volatility-scaled portfolios using lagged volatility in Figure 7: the majority of the regression coefficients are positive.

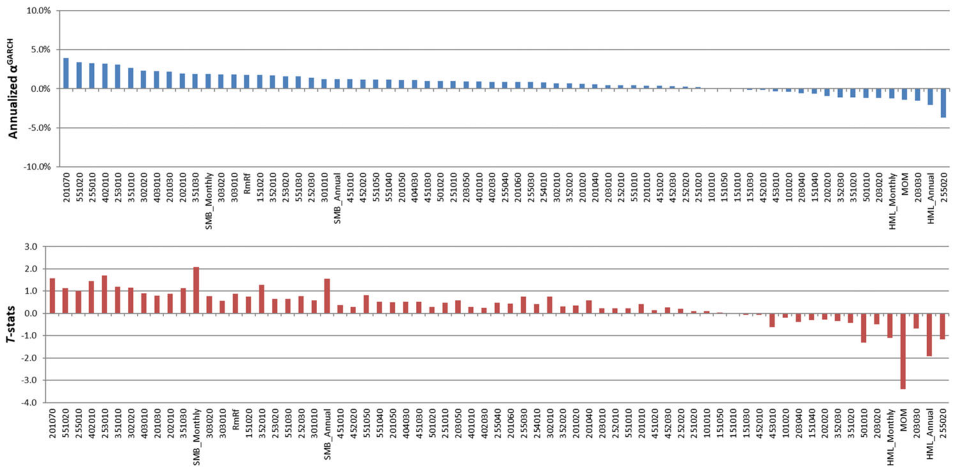

FIGURE 10 Spanning regressions of volatility-scaled portfolios using GARCH forecasts. We consider an alternative way of constructing volatility-scaled portfolios using GARCH volatility forecast rather than lagged volatility: $f_{t+1}^{GARCH} = \frac{\sigma_{t+1}^{GARCH}}{\lambda} f_{t+1}$, where f_{t+1}^{GARCH} is the volatility-scaled portfolio using GARCH forecasts. f_{t+1} is the original portfolio. σ_{t+1}^{GARCH} is the one-step ahead forecast of monthly volatility using a GARCH(1,1). λ is a constant such that f_{t+1}^{GARCH} and f_{t+1} have the same unconditional standard deviation. We then regress volatility-scaled portfolio f_{t+1}^{GARCH} on the original portfolio f_{t+1}: $f_{t+1}^{GARCH} = \alpha^{GARCH} + \beta^{GARCH} f_{t+1} + \varepsilon_{t+1}^{GARCH}$. For ease of presentation, annualized figures of α^{GARCH} and t-statistics are sorted by α^{GARCH}. The data are from January 1998 to December 2017. We mark each industry by its GICS level-3 code. We list the GICS-industry mapping in Appendix A

Specifically, 53 of 69 intercepts are positive; 16 are negative. Thirty-two intercepts are between 1 and 4%. Positive coefficients in spanning regressions indicate that the investor can form more attractive investments by combining the original portfolios and GARCH volatility-scaled portfolios. By using GARCH volatility forecasts to manage portfolio exposure, the investor can expand her investment opportunity set in much of the same way as using lagged volatility.

4 | CONCLUSION

In our paper, we investigate the risk–return trade-off for the Chinese A-share market. Whereas returns are negatively correlated to contemporaneous measures of volatility and change in volatility, returns are positively related to lagged volatility and change in volatility from the previous month. These results stand in contrast to the findings for the U.S. markets, where lagged volatility and current period returns do not have a clear positive relationship. Due to the positive relationship between return and lagged volatility, Moreira and Muir's (2017) volatility-managed portfolios do not work in China. These portfolios scale back exposure when volatility is high, and scale up exposure when volatility is low. This type of portfolio management does not account for the positive return predictability from lagged volatility. As a result, volatility-managed portfolios in the Chinese A-share stock market are spanned by the original portfolios: spanning regressions of volatility-managed portfolios on the original portfolios mostly show negative intercept estimates. Volatility-managed portfolios do not expand the investor's opportunity set relative to the original portfolios.

Motivated by the positive relationship between lagged volatility and returns, we propose volatility-scaled portfolios, which increase portfolio exposure when volatility is high and decrease exposure when volatility is low—just the opposite of volatility-managed portfolios. We find that volatility-scaled portfolios are not spanned by the original portfolios: spanning regressions show economically large intercepts up to 6% per year. Furthermore, we investigate the value creation of volatility-scaled portfolios to investors in a mean–variance framework. We construct mean–variance frontiers using the original portfolios and compare to frontiers constructed when we include volatility-scaled portfolios. Mean–variance frontiers that include volatility-scaled portfolios provide investors with a superior investment set, allowing for new feasible portfolios with higher Sharpe ratios. By combining the original portfolios with volatility-scaled portfolios, investors would achieve better risk–return trade-offs.

Our empirical findings are consistent with the predictions of several leading asset pricing models, including habit formation of Campbell and Cochrane (1999), disaster risk of Wachter (2013), long-run risk of Bansal and Yaron (2004), and the intermediary-based model of He and Krishnamurthy (2013). We also offer an intuitive explanation through the lens of retail investors, who may become highly risk averse when volatility is elevated. We demonstrate how our empirical results can be interpreted through the framework in Moreira and Muir (2017), and how a volatility-scaled portfolio differs from a volatility-managed portfolio. Lastly, we show our results are unchanged if we use GARCH volatility forecasts in volatility-scaled portfolios rather than lagged volatility.

While we present novel patterns of returns and volatility from China and we examine their portfolio management implications, we only provide suggestive explanations for our empirical findings. Additional empirical tests or quantitative models are needed to better understand the different performance of volatility-managed portfolios and volatility-scaled portfolios. These models would likely have to capture investor behavior and institutional details for the American and Chinese stock markets.

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ENDNOTES

[1] We also find a stronger positive risk–return relationship for the Shenzhen Stock Exchange than the Shanghai Stock Exchange. Results are available upon request.

[2] We start our sample in 1998 because the environment of the Chinese stock market before 1998 was quite different compared to that after 1998. Securities Law of the People's Republic of China was first tentatively introduced at the end of 1997 and then formally enacted in 1998. China Securities Regulatory Commission (CSRC) was not formally assigned as the regulator of the stock market until August 1997. Without a proper regulatory body prior to 1998, the behavior of market participants was more erratic, which was reflected in the tremendous levels of volatility experienced by the Chinese stock market. As such, the data before 1998 are somewhat less comparable to those after 1998.

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APPENDIX A

Global Industry Classification Standard (GICS) level-3 code and corresponding industries. (Effective September 1, 2016).

Industry		Industry	
101010	Energy Equipment & Services	302010	Beverages
101020	Oil, Gas & Consumable Fuels	302020	Food Products
151010	Chemicals	302030	Tobacco
151020	Construction Materials	303010	Household Products
151030	Containers & Packaging	303020	Personal Products
151040	Metals & Mining	351010	Health Care Equipment & Supplies
151050	Paper & Forest Products	351020	Health Care Providers & Services
201010	Aerospace & Defense	351030	Health Care Technology
201020	Building Products	352010	Biotechnology
201030	Construction & Engineering	352020	Pharmaceuticals
201040	Electrical Equipment	352030	Life Sciences Tools & Services
201050	Industrial Conglomerates	401010	Banks
201060	Machinery	401020	Thrifts & Mortgage Finance
201070	Trading Companies & Distributors	402010	Diversified Financial Services
202010	Commercial Services & Supplies	402020	Consumer Finance
202020	Professional Services	402030	Capital Markets
203010	Air Freight & Logistics	402040	Mortgage Real Estate Investment; Trusts (REITs)
203020	Airlines	403010	Insurance
203030	Marine	451010	Internet Software & Services
203040	Road & Rail	451020	IT Services
203050	Transportation Infrastructure	451030	Software
251010	Auto Components	452010	Communications Equipment
251020	Automobiles	452020	Technology Hardware, Storage & Peripherals
252010	Household Durables	452030	Electronic Equipment, Instruments & Components
252020	Leisure Products	453010	Semiconductors & Semiconductor Equipment
252030	Textiles, Apparel & Luxury Goods	501010	Diversified Telecommunication Services
253010	Hotels, Restaurants & Leisure	501020	Wireless Telecommunication Services
253020	Diversified Consumer Services	551010	Electric Utilities
254010	Media	551020	Gas Utilities
255010	Distributors	551030	Multi-Utilities
255020	Internet & Direct Marketing Retail	551040	Water Utilities
255030	Multiline Retail	551050	Independent Power and Renewable Electricity Producers
255040	Specialty Retail	601010	Equity Real Estate; Investment Trusts; (REITs)
301010	Food & Staples Retailing	601020	Real Estate Management & Development

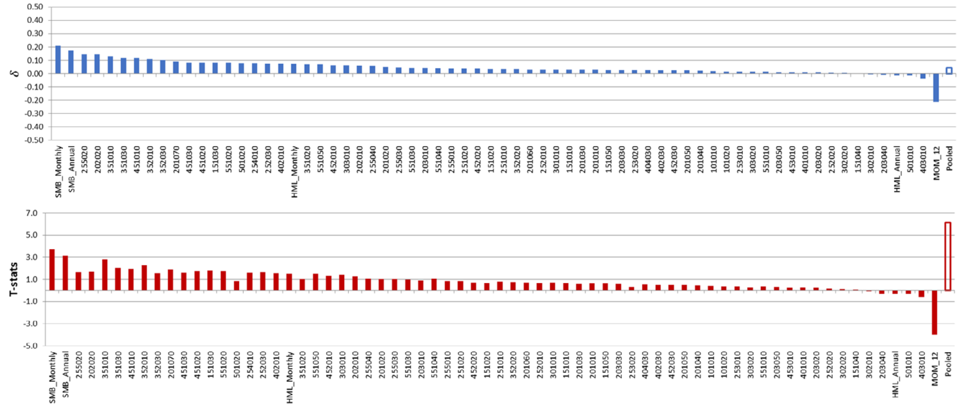
APPENDIX B

We reproduce Figures 4 and 5 excluding the bottom 30% of stocks by market capitalization.

We regress industry portfolio returns on portfolio volatility from the previous month.

$$f_t = \gamma + \delta\sigma_{t-1} + \varepsilon_t$$

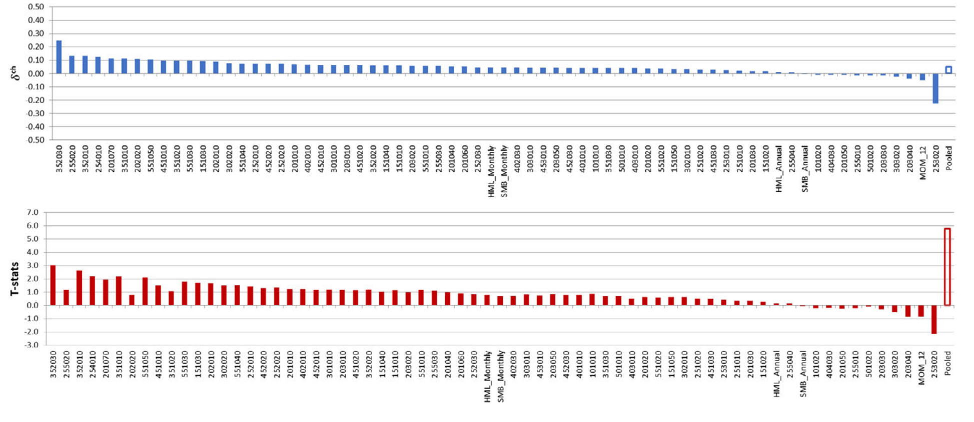
Forecasting coefficients δ and t-statistics are sorted from the largest to smallest δ. The rightmost (unshaded) bar shows the pooled regression coefficient including industry fixed effects. The t-statistic for the pooled regression is clustered by industry and by time. The data are from January 1998 to December 2017. We mark each industry by its GICS level-3 code. We list the GICS-industry mapping in Appendix A.



We also regress industry portfolio returns on the first difference in portfolio volatility from the previous month.

$$f_t = \gamma^{ch} + \delta^{ch}\Delta\sigma_{t-1} + \varepsilon_t^{ch}$$

Forecasting coefficients δ^{ch} and t-statistics are ordered from the largest to smallest δ^{ch}. The rightmost (unshaded) bar shows the pooled regression coefficient including industry fixed effects. The t-statistic for the pooled regression is clustered by industry and by time.



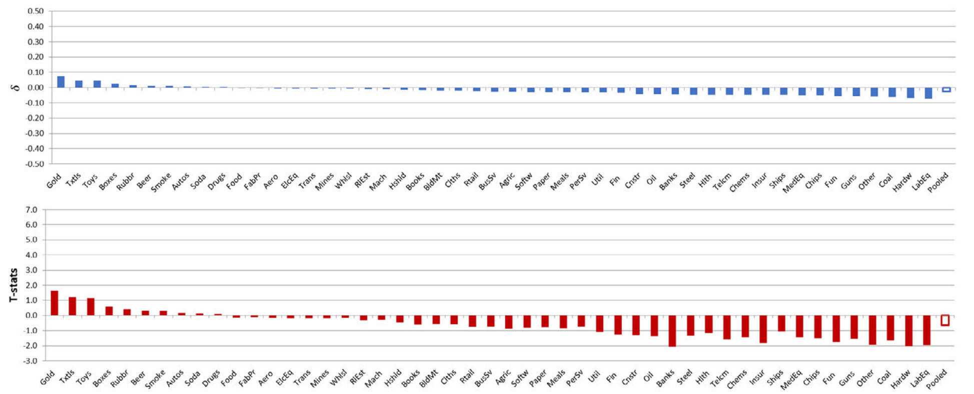
APPENDIX C

We reproduce Figures 4 and 5 using U.S. industry portfolios.

We regress industry portfolio returns on portfolio volatility from the previous month.

$$f_t = \gamma + \delta\sigma_{t-1} + \varepsilon_t$$

For ease of presentation, forecasting coefficients δ and t-statistics are sorted from the largest to smallest δ. The rightmost (unshaded) bar shows the pooled regression coefficient including industry fixed effects. The t-statistic for the pooled regression is clustered by industry and by time. The data are from January 1998 to December 2017. Following Ken French, 49 industries are defined according to the SIC codes.



We also regress industry portfolio returns on the first difference in portfolio volatility from the previous month.

$$f_t = \gamma^{ch} + \delta^{ch}\Delta\sigma_{t-1} + \varepsilon_t^{ch}$$

Forecasting coefficients δ^{ch} and t-statistics are ordered from the largest to smallest δ^{ch}. The rightmost (unshaded) bar shows the pooled regression coefficient including industry fixed effects. The t-statistic for the pooled regression is clustered by industry and by time.