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Factor momentum in the Chinese stock market[☆]

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ABSTRACT

Based on 10 commonly used factors, we construct a novel factor momentum strategy in the Chinese stock market, which earns an annualized return of 9.91 %, with a Sharpe ratio of 1.15. Factor momentum subsumes stock momentum, high-priced momentum, and industry momentum, digests its component factors and a variety of anomalies, and represents the momentum anomaly in China. Furthermore, mispricing correction helps explain factor momentum, which produces stronger returns during higher aggregate idiosyncratic volatility periods as well as among stocks with higher information asymmetry and short-sale constraints. Exposure to factor premiums and the manifestation of predictability determine factor momentum in China.

1. Introduction

Momentum is widely observed in financial markets such as stock (Jegadeesh and Titman, 1993, 2001), currency (Burnside et al., 2011; Menkhoff et al., 2012), option (Heston et al., 2021), and bond market (Sihvonen, 2021). Recently, factor momentum, where past winners earn higher returns than losers in long-short anomaly portfolio returns, has received much scholarly attention (Arnott et al., 2021; Avramov et al., 2017; Ehsani and Linnainmaa, 2022; Leippold and Yang, 2021; Zaremba and Shemer, 2018). However, no studies have thus far investigated factor momentum in China. Does factor momentum exist in China, where merely generates stock momentum? Do the unique features of the Chinese stock market affect its performance? Our paper expands factor momentum in China's stock market, investigates its explanatory power, and shows its economic sources.

We investigate factor momentum in China for three important reasons. First, China's stock market is the second-largest in the world, and its performance has a considerable influence on global capital markets (Allen et al., 2020). Second, the Chinese stock

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market lacks stock-level momentum (e.g., Pan et al., 2013; Gao et al., 2021). Chui et al. (2010) find that momentum is intriguingly absent in the Chinese market, in contrast to its' significantly present in the U.S. market. This difference between the world's two top equity markets attracts much attention from global investors. If China's stock market does indeed deliver significant factor momentum, it would supplement unique evidence on the momentum anomaly. Third, in contrast to other global markets, the Chinese stock market possesses unique features. As one of the important explanations for stock momentum, irrational behavior biases cause stock prices to deviate from their fundamental value (e.g., Daniel et al., 1998; Chui et al., 2010; Grinblatt and Han, 2005; George and Hwang, 2004). The Chinese market, with its high participation of retail investors and market frictions; could provide insights into the economic channels of momentum.

We first examine whether individual factors have time-series momentum (Moskowitz et al., 2012) in China. We use ten mainstream non-momentum factors from the asset pricing literature following Ehsani and Linnainmaa (2022): size (Banz, 1981), value (Rosenberg et al., 1985), profitability (Novy-Marx, 2013), investment (Titman et al., 2004), illiquidity (Amihud, 2002), the earnings-to-price ratio (Basu, 1983), accruals (Sloan, 1996), the cash flow-to-price ratio (Rosenberg et al., 1985), turnover (Datar et al., 1998), and betting against beta (Frazzini and Pedersen, 2014). The findings show that the individual time-series factor momentum strategy, which buys the factor with an above-zero return and sells it with negative performance over the prior year, earns significantly positive returns for most of the factors. Certain factor models, such as Fama and French's (2015) five-factor model (FF5) and Liu et al. (2019) Chinese three-factor model (CH3), cannot explain individual factor momentum.

Furthermore, we construct two aggregately factor momentum strategies. The first one is the time-series factor momentum approach (TSFM; Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2022), which longs factors with positive prior one-year returns and shorts those with negative returns, generating an annualized average return of 9.91 % ($t = 6.07$) and a Sharpe ratio of 1.15. The second strategy is the cross-sectional factor momentum strategy (CSFM; Avramov et al., 2017; Arnott et al., 2021), which buys factors with above-median returns relative to other factors over the prior year and shorts those with poor performance. The CSFM approach earns a 7.02 % ($t = 3.44$) average return per annum and a Sharpe ratio of 0.80. Both long-short strategies produce significant abnormal FF5 and CH3 alphas. Notably, we construct a conditional CH3 factor model that imposes Baker and Wurgler's (2006) investor sentiment into the model's coefficients to capture the time-varying components. The conditional CH3 model also generates significantly positive alphas of the factor momentum portfolios. Moreover, the long-leg portfolios generate significantly positive returns, while the short-legs produce insignificant returns. In addition, the TSFM strategy outperforms the CSFM because it purely focuses on the factor auto-correlations without being influenced by cross-serial covariances. Our findings suggest that factors persist and generate momentum in China.

Moreover, we investigate factor momentum's ability to digest stock anomalies, as it is aggregated from individual anomalies. The findings show that the TSFM portfolio has the additional explanatory ability for its component factors and, more generally, 50 fundamental-related anomalies in China than CH3, including value versus growth, profitability, investment, trading friction, and intangibles-related characteristics (e.g., Green et al., 2017; Gu et al., 2020; Hou et al., 2020). Over 80 % of the factors and anomalies produce lower abnormal alphas when adding TSFM as a control variable. The average absolute value of the TSFM augmented with the CH3 alpha is insignificant at 4.48 ($t = 1.36$), the slope of the TSFM is positively significant at a value of 0.39 ($t = 2.94$), and the regression R^2 is 46.34 %. Our results highlight the potential application value of factor momentum.

Due to the uniqueness of the insignificant stock momentum in the Chinese market, we investigate the relation between stock and factor momentum. The findings show that factor momentum subsumes the standard stock-level momentum, high-priced stock momentum (Du et al., 2022), and industry momentum and remains positively significant when adjusting for the momentum or reversal strategies. Factor momentum, which is the sum of the autocorrelations in the factors, represents the momentum anomaly in the Chinese stock market. Besides, we investigate whether factor momentum crashes with market states. We observe that factor momentum returns remain robust overall and have asymmetry following market declines. Our findings alleviate concerns that factor momentum strategies experience strings of negative returns, as momentum portfolios often do (Daniel and Moskowitz, 2016).

We proceed to analyze the economic mechanisms underlying factor momentum. First, we find that factor momentum arises from mispricing correction due to slow-moving arbitrage capital and limits to arbitrage. Factor returns form because of mispricing. Arbitragers who want to generate persistent factor returns trade gradually to correct this mispricing instead of aggressively eliminating all mispricing. According to Abreu and Brunnermeier (2002), there is delayed arbitrage because of the synchronization risk, the uncertainty about when peers of arbitragers take advantage of a common arbitrage opportunity. Then, during the high limits-to-arbitrage periods, arbitrageurs are more likely to take participation in trading due to market frictions (Li et al., 2022), resulting in higher returns of factor momentum. Our results demonstrate that factor momentum strengthens when there is high aggregate idiosyncratic volatility, low investor sentiment, high information asymmetry, and short-sale constraints, supporting the hypothesis that when limits to arbitrage exist, increased arbitrageur participation is associated with stronger factor momentum. Second, we decompose the factor momentum strategy into the factor timing and buy-and-hold portfolios (Leippold and Yang, 2021) and find that factor momentum is a manifestation of factor timing and exposure to factor premiums in China. Timing is important in the Chinese market, due to the high standard deviations of the factor returns, the large proportions of retail investors, and the variability of market states, compared to the findings of Leippold and Yang (2021) in the U.S. Third, our paper documents the impact of culture on factor momentum. Collectivistic culture markets' investors rely more on collective intelligence, leading to herding and intensification of the co-movement and auto-correlations between factors. Consequently, a collectivistic market like China lacks stock-level momentum (Chui et al., 2010) but generates significant factor momentum.

In the robustness checks, we first investigate how factor momentum performs after changing the formation and holding periods and find that it persists. Second, we construct factor momentum using an expanded 60-anomaly set and find that it is insensitive to the choice of anomaly set. Third, we examine factor momentum performance during two stock market crash periods in China and find that the results are similar to those of the full sample. Fourth, we find that factor momentum remains robust despite considering the price limit in China.[1]

Our paper contributes to studies of factor momentum in two main ways. First, we find that factor momentum is economically large and statistically significant in the Chinese stock market, despite the lack of stock-level momentum. Our robust results supplement the investigation that factor momentum is distinct from individual momentum and concur with previous findings on factor momentum and factor timing (Ehsani and Linnainmaa, 2022; Haddad et al., 2020; Leippold and Yang, 2021). Second, we provide a more comprehensive understanding of the linkages between time-series and cross-sectional studies than previous research has offered (Dong et al., 2022; Engelberg et al., 2021). We demonstrate that factor momentum can explain stock momentum, its component factors, and a large number of anomalies. Notably, we identify the potential channels through which factor momentum operates, such as the correction of mispricing. Zhang (2022) argues that limits-to-arbitrage help explain the carry factor momentum, as the currencies of the developed markets, countries with low capital account openness, and those with high idiosyncratic risk and currency volatility, experience higher factor momentum. Li et al. (2022) suggest that the level of arbitrageur participation and limits to arbitrage have an impact on the risk-based return momentum. Our paper is related to Zhang (2022) and Li et al. (2022) but extends the mispricing correction within the field of factor momentum. In addition, For the latter, our approach is the first to illustrate the cultural impact on the factor momentum, in the spirit of Chui et al. (2010).

Our study also expands the body of knowledge by providing novel evidence for China. First, we find that the highest return-generating strategy is related to one-year formation periods in China, whereas shorter formation periods perform better in most other global markets (Gupta and Kelly, 2019). This difference may stem from the high participation of short-horizon retail investors in China (Jones et al., 2020), which causes significant short-term reversals (Du et al., 2022) and attenuates factor momentum. Second, our results underscore the significant contribution of timing in China's stock market (Leippold et al., 2021; Tang et al., 2021), which differs from Leippold and Yang's (2021) findings in the U.S. The reason for this difference may be due to the larger variances of factor returns, the higher ratio of retail investors in the Chinese market who have more severe behavioral biases than institutional investors, and the collectivistic culture of the market that leads to herding. Third, the market structure of China, such as short-sale constraints, is essential in decomposing the returns of factor momentum.

The remainder of this paper is organized as follows. Section II describes the data. Section III presents the empirical results of factor momentum in the Chinese stock market, including its power in explaining anomalies. Section IV investigates the stock momentum and factor momentum. Section V describes the economic channels of factor momentum. Section VI presents the robustness tests. Section VII concludes.

2. Data

We obtain data from the China Stock Market & Accounting Research database from January 2001 to December 2019, including financial statement data and monthly and daily stock returns for all A-share stocks listed on the Shanghai and Shenzhen Stock Exchanges. To ensure the quality of the data, we exclude stocks with special and/or particular transfer status, as these tend to be under financial distress (Carpenter et al., 2021)).

We construct 10 characteristic-based non-momentum factor portfolios following Ehsani and Linnainmaa (2022) and Liu et al. (2019): size (Banz, 1981), value (Rosenberg et al., 1985), profitability (Novy-Marx, 2013), investment (Titman et al., 2004), illiquidity (Amihud, 2002), the earnings-to-price ratio (Basu, 1983), accruals (Sloan, 1996), the cash flow-to-price ratio (Rosenberg et al., 1985), turnover (Datar et al., 1998), and betting against beta (Frazzini and Pedersen, 2014).[2] These 10 non-momentum factors are the most commonly used in the global market. We calculate these factors following the original studies, with the annualized factor return defined as the difference between the average return in the top quintile and that in the bottom quintile.[3]

Panel A of Table 1 shows the significant variation in average annualized returns. For example, the earnings-to-price ratio is 14.33 % with a *t*-statistic of 4.78 in China. The standard deviations of the factors also vary significantly, ranging from 10.48 for accruals to 31.06 for betting against beta, indicating their high volatility. The average returns of the factors in China are higher than those in the United States (Liu et al., 2019), and the standard deviations.

Panel B of Table 1 reports the Pearson correlations of the 10 non-momentum factors. Most factor pairs are correlated and below 0.50 in absolute value. These 10 factors thus contain distinct return behavior and represent large and well-diversified portfolios.

3. Factor momentum

3.1. Individual factor momentum

We first investigate whether each factor individually generates factor momentum. The time series momentum methodology is based on the idea of "portfolio timing" (Moskowitz et al., 2012). For each month, we long the factor with positive returns over the prior

[1] China's equity market imposes daily price limits of 10% on regular stocks.
[2] We do not include momentum-related factors because these are considered insignificant in the Chinese stock market.
[3] Online Appendix B provides the detailed construction of the ten factors.

Table 1
Descriptive Statistics.
Panel A reports the average annualized returns (in percentages), *t*-statistics (in square brackets), and standard deviations for the 10 non-momentum factors in China based on the literature. The factor return is defined as the high-quintile return minus the low-quintile return. Panel B reports the correlation matrix of the 10 non-momentum factors. The sample period runs from January 2002 to December 2019.

Panel A: Descriptive Statistics

Factor	Literature	Mean	STD
Size (SIZE)	Banz (1981)	10.02 [1.76]	24.86
Value (BM)	Rosenberg et al. (1985)	17.84 [4.27]	18.21
Profitability (GP)	Novy-Marx (2013)	12.48 [2.73]	19.95
Investment (CINVEST)	Titman et al. (2004)	8.91 [2.66]	14.61
Liquidity (ILL)	Amihud (2002)	9.70 [2.07]	20.44
Earnings to price ratio (EP)	Basu (1983)	14.33 [4.78]	13.05
Accruals (ACC)	Sloan (1996)	11.17 [4.65]	10.48
Cash-flow to price (CFP)	Rosenberg et al. (1985)	1.69 [0.46]	15.82
Turnover (TURN)	Datar et al. (1998)	12.38 [3.59]	15.04
Betting-against-beta (BAB)	Frazzini and Pedersen (2014)	11.43 [1.60]	31.06

Panel B: Correlation Matrix

	SIZE	BM	GP	CINVEST	ILL	EP	ACC	CFP	TURN	BAB
SIZE	1.00	0.43	–0.47	0.04	0.94	–0.67	–0.03	0.69	0.50	–0.08
BM		1.00	0.27	0.26	0.35	–0.31	0.50	0.57	0.36	0.13
GP			1.00	0.47	–0.54	0.63	0.43	–0.45	–0.43	0.40
CINVEST				1.00	0.01	0.04	–0.08	–0.25	–0.08	0.27
ILL					1.00	–0.64	–0.07	0.65	0.46	–0.09
EP						1.00	0.21	–0.66	–0.59	0.31
ACC							1.00	0.24	0.12	0.23
CFP									0.70	–0.22
TURN									1.00	–0.42
BAB										1.00

one-year period and short it if the prior one-year period return is negative. To capture the time-varying components of factor momentum, we also construct a conditional CH3 model (Cond-CH3) that incorporates investor sentiment into the model's β.[4] Table 2 reports the annualized average returns of the long-leg, short-leg, and long-short strategies; Sharpe ratios, abnormal alphas (FF5-α, CH3-α, and Cond-CH3-α) of the long-short portfolios; and corresponding *t*-statistics. The sample period runs from January 2002 to December 2019.

The individual factor momentum is ubiquitous. Table 2 shows that eight factors produce significantly positive factor momentum returns that cannot be explained by the FF5 model. For the significant average returns, the long-short strategy earns from 8.05 % (t = 2.19) for the turnover rate to 18.15 % (t = 4.15) for the book-to-market ratio per year. The annualized Sharpe ratio peaks at 0.97 for the book-to-market ratio, showing economically sizable benefits. Among the factors that generate significant raw returns, the CH3 factor model explains firm size and illiquidity, as it suits the Chinese stock market better than others. The Conditional CH3 factor model produces smaller alphas than CH3. Moreover, the long legs play an important role in generating factor momentum returns, as they lead to higher values and *t*-statistics.

To summarize, the individual factors demonstrate economically sizable time-series momentum. Hence, factors' recent performance can forecast their future returns (Moskowitz et al., 2012; Gupta and Kelly, 2019).

3.2. Time-series factor momentum and cross-sectional factor momentum strategies

We next investigate the performance of the TSFM and CSFM strategies as they consider the 10 non-momentum factors in combination. Gupta and Kelly (2019) adopt the TSFM strategy, while Avramov et al. (2017) and Arnott et al. (2021) mainly investigate the CSFM strategy. Table 3 reports the annualized average returns, standard deviations, Sharpe ratios, abnormal alphas (FF5-α, CH3-α, and Cond-CH3-α), and corresponding *t*-statistics for the TSFM and CSFM strategies.

The TSFM strategy is similar to individual factor momentum but integrates the individual signals into a single portfolio. In each month, the TSFM strategy longs factors with positive performance over the prior one-year period and shorts those with negative performance. Panel A of Table 3 shows that the TSFM is a beneficial factor investment strategy, as it earns an annualized average return of 9.91 % (t = 4.88), with a Sharpe ratio of 1.15. Furthermore, the TSFM strategy delivers significant abnormal alphas, equaling 9.59 % (t = 7.03), 7.76 % (t = 3.35), and 7.04 % (t = 3.21) for FF5-α, CH3-α, and Cond-CH3-α, respectively. The long- and short-legs generate 14.07 % (t = 5.96) and 3.37 % (t = 0.97) returns per year and have Sharpe ratios of 1.40 and 0.23, respectively. The factor models cannot explain the returns on the long legs, although they subsume the short-leg returns well.

The CSFM strategy takes positions based on the factors' recent performance compared with the cross-sectional performance of all

[4] The conditional CH3 factor model is: $FFM_t = \alpha + (1 + Sentiment_t)\beta_1 MKT_t + (1 + Sentiment_t)\beta_2 SIZE_t + (1 + Sentiment_t)\beta_3 BM_t + \varepsilon_t$, where $Sentiment_t$ is Baker and Wurgler (2006)'s investor sentiment with the Chinese data.

Table 2
Performance of Individual Factor Momentum.
This table reports the annualized average returns, Sharpe ratios (SR), abnormal alphas (FF5-α, CH3-α, and Cond-CH3-α), and corresponding *t*-statistics (in square brackets) for the individual factor momentum strategy (FM). For each month, we long the factor with positive returns over the prior one-year period and short it if the prior one-year period return is negative. We also report the average returns and *t*-statistics for the winner and loser portfolios. The portfolios are rebalanced monthly. The conditional CH3 model (Cond-CH3) imposes investor sentiment into the model's β. All the returns are reported in percentages. The sample period runs from January 2002 to December 2019.

	Winner	Loser	FM	SR	FF5-α	CH3-α	Cond-CH3-α
SIZE	21.36 [2.68]	−7.70 [−0.90]	15.99 [2.71]	0.63	8.51 [2.40]	3.83 [0.98]	3.56 [0.71]
BM	22.19 [4.49]	2.71 [0.35]	18.15 [4.15]	0.97	16.68 [4.92]	15.61 [3.17]	13.14 [3.04]
GP	14.18 [3.41]	3.84 [0.30]	10.60 [2.03]	0.58	11.04 [2.53]	12.91 [2.73]	10.25 [2.44]
CINVEST	−4.03 [−1.22]	−2.68 [−0.67]	−0.24 [−0.09]	−0.02	1.56 [0.41]	1.39 [0.34]	0.82 [0.20]
ILL	16.72 [2.84]	−3.97 [−0.47]	12.59 [2.60]	0.61	11.52 [2.70]	5.90 [1.33]	5.11 [1.12]
EP	13.66 [4.31]	24.17 [1.72]	10.45 [3.26]	0.76	12.68 [4.97]	−2.34 [−1.84]	−1.92 [−1.67]
ACC	11.24 [4.25]	14.91 [1.91]	9.43 [3.68]	0.86	11.76 [5.11]	8.52 [2.25]	8.25 [2.12]
CFP	11.19 [1.96]	−8.39 [−1.80]	9.90 [2.64]	0.62	6.96 [2.01]	9.29 [2.21]	8.54 [2.03]
TURN	12.98 [3.14]	11.18 [1.49]	8.05 [2.19]	0.51	5.70 [1.69]	11.32 [2.50]	10.44 [2.41]
BAB	14.00 [1.52]	4.53 [0.36]	7.65 [1.02]	0.24	9.40 [1.44]	9.84 [1.40]	7.21 [1.23]

Table 3
Performance of the TSFM and CSFM Strategies.
This table reports the annualized average returns, standard deviations, Sharpe ratios (SR), abnormal alphas (FF5-α, CH3-α, and Cond-CH3-α), and corresponding *t*-statistics (in square brackets) for the time-series factor momentum (TSFM) and cross-sectional factor momentum (CSFM) strategies using the 10 non-momentum factors. The TSFM strategy longs factors with positive returns over the prior year (winners) and shorts those with negative returns (losers). The CSFM strategy longs factors with above-median returns relative to other factors over the prior year (winners) and shorts those with below-median returns (losers). We rebalance all the strategies monthly. The conditional CH3 model (Cond-CH3) imposes the investor sentiment into the model's β. All the returns are reported in percentages. The sample period runs from January 2002 to December 2019.

	Mean	STD	SR	FF5-α	CH3-α	Cond-CH3-α
Panel A: Time-series factor momentum						
Full Sample	9.91 [4.88]	8.62	1.15	9.59 [7.03]	7.76 [3.35]	7.04 [3.21]
Winners	14.07 [5.96]	10.05	1.40	13.53 [8.55]	10.69 [4.07]	9.88 [3.75]
Losers	3.37 [0.97]	14.80	0.23	3.08 [1.27]	0.19 [0.06]	0.67 [0.42]
Panel B: Cross-sectional factor momentum						
Full Sample	7.02 [3.44]	8.78	0.80	7.20 [4.00]	6.10 [2.75]	5.72 [2.55]
Winners	16.95 [5.51]	13.04	1.30	16.00 [7.29]	13.59 [4.18]	11.24 [3.78]
Losers	2.91 [1.16]	10.64	0.27	2.60 [1.47]	1.40 [0.57]	1.17 [0.44]

factors. We long factors with above-median returns relative to other factors over the prior year and short those with below-median returns following Jegadeesh and Titman (1993). Panel B of Table 3 shows that the CSFM strategy produces 7.02 % ($t = 3.44$) average returns annually, with winners and losers generating 16.95 % ($t = 5.51$) and 2.91 % ($t = 1.16$) per annum, respectively. The Sharpe ratios reach 0.80, 1.30, and 0.27 for the full sample, long-legs, and short-legs, respectively. The FF5, CH3, and Cond-CH3 models produce significant abnormal returns for the full sample and long-legs but insignificant returns for the short-legs.

The TSFM and CSFM strategies share some commonalities. First, winner portfolios contribute more to overall returns than losers. Second, loser portfolios generate positive insignificant returns, which is similar to Ehsani and Linnainmaa's (2022) findings in the U.S. market. Third, the TSFM and CSFM strategies both produce higher Sharpe ratios than the individual strategies, thereby showing impressive economic benefits.

However, the two strategies are also different. The TSFM strategy generates higher returns and Sharpe ratios than the CSFM strategy. The standard deviations are also mostly lower for the TSFM strategy. These results are similar to those found in the United States (Ehsani and Linnainmaa, 2022) and globally (Gupta and Kelly, 2019). From a construction perspective, the TSFM method is a pure bet on the factor return autocorrelations, whereas the CSFM strategy is developed relative to a peer group and considers negative cross-serial covariance (Ehsani and Linnainmaa, 2022).

Fig. 1 plots the cumulative returns associated with the winner and loser portfolios in Table 3 as well as the equal-weighted portfolio of the 10 non-momentum factors. The winner TSFM strategy earns 222 % from January 2002 to December 2019, and the winner CSFM strategy earns 205 %. In contrast, both loser strategies generate cumulative returns close to zero. The equal-weighted portfolio of the 10 non-momentum factors generates a lower cumulative return by the end of the sample period, which reinforces factor momentum strategies' economic benefits.

For robustness, we extend our anomaly set by adding 50 more anomalies, (i.e., 60 anomalies in total) to investigate the performance of the factor momentum strategies, which covers value versus growth, investment, profitability, trading friction, and intangibles, based on the categories of Hou et al. (2020). The Online Appendix B presents the construction of the 50 anomalies. Table 4 reports the results. We find that factor momentum constructed based on 60 anomalies also has high average returns, Sharpe ratios, and abnormal alphas, as Table 4 shows. Panel A reports the results for the TSFM strategy based on the 60 anomalies. The average return is 6.18 % ($t = 3.39$),

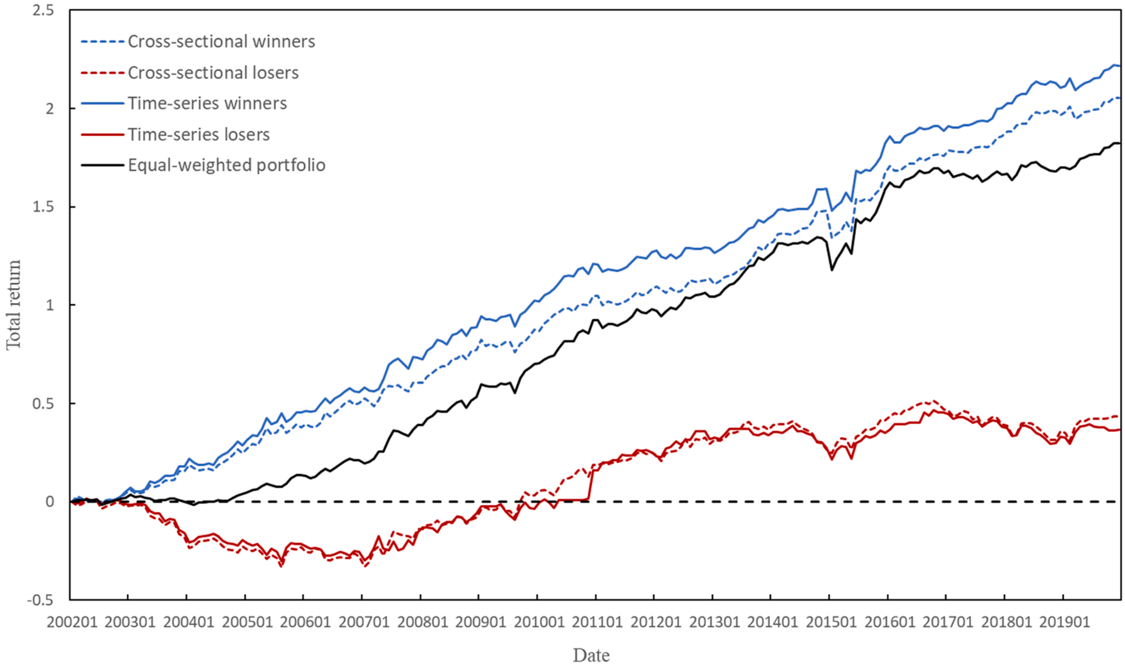

Fig. 1. Cumulative Returns
This figure plots the cumulative returns on factors divided into winners and losers based on their past performance and an equal-weighted portfolio of all 10 non-momentum factors from January 2002 to December 2019. Time-series winners and losers are factors with positive or negative returns over the past year. Cross-sectional winners and losers are factors that have above- or below-median returns over the prior year. The portfolios are rebalanced monthly, and each portfolio's standard deviation is standardized to equal that of the equal-weighted portfolio.

Table 4
Performance of the TSFM and CSFM Strategies with More Anomalies
This table reports the annualized average returns, standard deviations, Sharpe ratios (SR), abnormal alphas (FF5-α, CH3-α, and Cond-CH3-α), and corresponding *t*-statistics (in square brackets) for different combinations of 60 anomalies in China. The time-series factor momentum (TSFM) strategy longs factors with positive returns over the prior one-year period (winners) and shorts those with negative returns (losers). The cross-sectional factor momentum (CSFM) strategy longs factors with above-median returns relative to other factors over the prior year (winners) and shorts those with below-median returns (losers). We rebalance all the strategies monthly. The conditional CH3 model (Cond-CH3) imposes the investor sentiment into the model's β. All the returns are reported in percentages. The sample period runs from January 2002 to December 2019.

	Mean	STD	SR	FF5-α	CH3-α	Cond-CH3-α
Panel A: Time-series factor momentum						
Full Sample	6.18 [3.39]	7.73	0.80	6.96 [3.59]	4.92 [2.48]	4.89 [2.45]
Winners	7.10 [3.61]	8.35	0.85	7.92 [3.81]	5.04 [2.10]	4.97 [2.06]
Losers	−4.16 [−2.14]	8.24	−0.50	4.56 [2.24]	3.96 [1.77]	3.88 [1.97]
Panel B: Cross-sectional factor momentum						
Full Sample	5.81 [3.43]	7.19	0.81	6.36 [3.50]	4.56 [2.50]	4.51 [2.46]
Winners	8.71 [3.76]	9.83	0.89	9.60 [3.91]	6.00 [2.13]	5.88 [2.07]
Losers	−2.90 [−1.61]	7.65	−0.38	3.00 [1.53]	3.24 [1.62]	3.13 [1.55]

and the Sharpe ratio is 0.80. The abnormal alphas equal 6.96 % ($t = 3.59$), 4.92 % ($t = 2.48$), and 4.89 % ($t = 2.45$) for the FF5, CH3, and Cond-CH3 factor models. The CSFM strategy, reported in Panel B of Table 12, produces an average yearly return of 5.81 % ($t = 3.43$), a Sharpe ratio of 0.81, and positively significant abnormal alphas. In short, factor momentum is robust to the choice of the size of the anomaly set. Both the 10 factors and 60 anomalies yield substantial positive returns. However, for our main research focus, we adopt TSFM and CSFM with the 10 factors, as they generate higher profits compared to the 60 anomalies and are relatively more straightforward to construct (Ehsani and Linnainmaa, 2022; Li et al., 2022).

Overall, we find significant positive factor momentum in the Chinese stock market. The strategy earns higher returns in China than in the United States (Ehsani and Linnainmaa, 2022), but as the standard deviations of the returns are also larger, the Sharpe ratios of the two markets are similar.

3.3. Decomposing factor momentum profits

Following Lo and MacKinlay (1990), Lewellen (2002), and Ehsani and Linnainmaa (2022), we decompose the TSFM and CSFM strategies to clarify the sources of their profits. Here, we use the linear weight factor momentum strategy to run the Lo–MacKinlay decomposition (Ehsani and Linnainmaa, 2022).

For the TSFM strategy, the weight of factor f in month t is $w_t^f = r_{-t}^f$, where r_{-t}^f is factor f's past return over the formation period. According to Moskowitz et al. (2012), the expected return of the TSFM strategy can be written as

$$E\left[\pi_t^{TSFM}\right] = \frac{1}{F}E\left[\sum_{f=1}^{F} r_{-t}^f r_t^f\right] = \frac{1}{F}\sum_{f=1}^{F}\left[\mathrm{cov}\left(r_{-t}^f, r_t^f\right) + \left(\mu^f\right)^2\right], \tag{1}$$

where r_t^f is factor f's return in month t and μ^f is factor f's unconditional expected return. Eq. (1) suggests that the TSFM strategy can be decomposed into the factor return autocorrelations and mean squared returns.

As shown in Table 5, the TSFM strategy earns an annualized return of 17.83 % ($t = 4.06$). The factor returns autocorrelations generate an average return of 7.99 % ($t = 2.00$), and the mean-squared component delivers an average return of 9.84 % ($t = 4.15$) per annum. Hence, compared with Ehsani and Linnainmaa (2022), the mean-squared return contributes more in the Chinese stock market.

For the CSFM strategy, the weight of factor f in month t is $w_t^f = r_{-t}^f - \bar{r}_{-t}$, where $\bar{r}_{-t}$ is the cross-sectional mean of all the factors' returns over the formation period. The expected return of the CSFM strategy can be stated as

$$E\left[\pi_t^{CSFM}\right] = \frac{1}{F}E\left[\sum_{f=1}^{F}\left(r_{-t}^f - \bar{r}_{-t}\right) r_t^f\right] = \frac{1}{F}\sum_{f=1}^{F}\left[\mathrm{cov}\left(r_{-t}^f, r_t^f\right) - \mathrm{cov}\left(\bar{r}_{-t}, \bar{r}_t\right) + \left(\mu^f - \bar{\mu}\right)^2\right], \tag{2}$$

where $\bar{\mu}$ is the cross-sectional average of all the factors' unconditional expected returns. Eq. (2) shows that the profits of the CSFM strategy can be separated by the factor return autocovariance, negative cross-serial covariance, and cross-sectional variance of mean returns.

Table 5 shows that the CSFM strategy earns an average annualized return of 9.92 % with a t value of 2.68. The autocovariance contributes an average annualized return of 5.22 % ($t = 2.00$). The cross-serial covariance term is positive and therefore makes a negative contribution, which is −1.04 % per annum. The positive cross-serial covariance means that a positive return on one factor accompanies positive returns on the other factors. However, as the CSFM strategy bets on the relative performance of a factor, this decreases its performance. The mean-squared component delivers an average return of 3.66 % ($t = 3.24$) per annum.

Of the two strategies, the TSFM strategy, which is a pure bet on the factor return autocorrelations, outperforms the CSFM strategy (Ehsani and Linnainmaa, 2022). Therefore, we use the TSFM portfolio for our further analyses.

3.4. Digest stock anomalies

Factor momentum is aggregated from individual anomalies, which motivates us to explore whether the combined factor momentum strategy explains anomalies in this subsection.

First, we investigate whether factor momentum can explain its components (i.e., the 10 non-momentum factors) in China. We regress each of the factor's returns on the CH3 factors and CH3 factors augmented with factor momentum:

$$\mathrm{FACTORRET}_t = \alpha + \gamma \mathrm{CH3}_t + \varepsilon_t, \tag{3}$$

$$\mathrm{FACTORRET}_t = \alpha + \beta \mathrm{TSFM}_t + \gamma \mathrm{CH3}_t + \varepsilon_t, \tag{4}$$

where $\mathrm{FACTORRET}_t$ denotes each of the long-short spread portfolios of the 10 non-momentum factors at time t, TSFM_t is the return of

Table 5
Decomposition of Factor Momentum Profits
This table decomposes the profits of the time-series factor momentum (TSFM) and cross-sectional factor momentum (CSFM) profits using Eqs. (1) and (2). We report the annualized factor premiums in percentages and t-statistics in square brackets. When month t is sampled, we link month t with the factors' average returns from month $t-12$ to $t-1$ to compute the decomposition. The sample period runs from January 2002 to December 2019.

Decomposition	Mean	t-stat
Time-series factor momentum =	17.83	[4.06]
Autocovariances	7.99	[2.00]
+ Mean squared returns	9.84	[4.15]
Cross-sectional factor momentum =	9.92	[2.68]
Autocovariance	5.22	[2.00]
− Cross-serial covariances	1.04	[0.16]
+ Variance of mean returns	3.66	[3.24]

Table 6

Digesting Stock Anomalies

Panel A compares the performance of the Chinese three-factor models (CH3) and CH3 augmented with the time-series factor momentum (TSFM) strategy in digesting the monthly excess returns on the 10 non-momentum factors. Panel B expands the test by explaining 50 anomalies. Panel C reports the average absolute values of all the regressions. We report the alphas and adjusted R^2s (in percentages) for both models, loadings of the TSFM factor, and differences between the two alphas (Diff). We report the alphas in percentages per year and the *t*-statistics in square brackets. The sample period runs from January 2002 to December 2019.

	CH3 Regression		TSFM+CH3 Regression			Diff.
	CH3-α	R^2 (%)	TSFM+CH3-α	TSFM-β	R^2 (%)	
Panel A: Ten factors						
SIZE	0.84 [0.36]	89.67	0.96 [0.42]	0.23 [2.72]	90.25	0.12
BM	22.80 [4.75]	12.20	14.76 [3.55]	1.04 [6.13]	34.98	–8.04
GP	8.76 [2.42]	52.04	5.64 [1.64]	0.40 [2.86]	55.60	–3.12
CINVEST	0.48 [0.17]	11.01	0.36 [0.11]	0.02 [0.17]	11.03	–0.12
ILL	1.20 [0.68]	87.76	0.96 [0.52]	0.03 [0.47]	87.78	–0.24
EP	4.44 [2.12]	86.75	4.92 [2.34]	0.06 [0.79]	86.80	0.48
ACC	9.36 [2.54]	5.17	4.92 [1.50]	0.56 [5.03]	25.15	–4.44
CFP	4.32 [1.34]	52.10	0.96 [0.31]	0.43 [3.57]	57.20	–3.36
TURN	6.36 [1.86]	38.86	2.16 [0.65]	0.54 [5.26]	50.15	–4.20
BAB	0.72 [0.21]	60.06	0.96 [0.27]	0.03 [0.21]	60.07	0.24
Panel B: More Anomalies						
Value-versus-growth						
AM	19.44 [4.10]	12.86	11.40 [2.74]	1.05 [5.93]	35.36	–8.04
DA	6.00 [1.96]	41.06	1.56 [0.59]	0.57 [4.41]	50.28	–4.44
DER	14.76 [2.88]	6.60	5.88 [1.26]	1.14 [5.27]	29.83	–8.88
DLME	11.16 [2.99]	14.13	6.48 [1.86]	0.60 [3.74]	24.07	–4.68
LG	12.48 [4.60]	10.08	9.12 [3.53]	0.42 [4.04]	23.21	–3.36
SG	9.48 [2.78]	42.13	3.72 [1.21]	0.73 [5.50]	56.42	–5.76
SMI	4.32 [1.51]	2.20	1.92 [0.61]	0.30 [1.96]	7.15	–2.40
SP	14.76 [3.36]	23.69	7.08 [1.79]	1.00 [7.03]	47.44	–7.68
TG	6.00 [2.50]	8.71	2.88 [1.30]	0.40 [4.77]	23.09	–3.12
TOR	1.92 [0.90]	88.39	0.36 [0.18]	0.30 [2.88]	89.44	–1.56
Investment						
CAPXG	7.08 [3.00]	22.87	5.64 [2.29]	0.20 [2.33]	25.93	–1.44
IA	11.64 [3.45]	26.65	6.12 [1.87]	0.71 [5.08]	43.19	–5.52
IC	4.44 [1.69]	16.13	4.32 [1.67]	0.01 [0.09]	16.13	–0.12
IVC	7.68 [2.54]	14.68	3.60 [1.36]	0.52 [3.94]	28.92	–4.08
IVG	10.20 [3.60]	1.00	5.52 [2.03]	0.60 [4.32]	21.51	–4.68
Profitability						
CFOA	0.00 [0.01]	18.70	0.96 [0.30]	0.11 [0.93]	19.44	0.96
CHTX	0.84 [0.30]	70.49	0.36 [0.12]	0.16 [1.61]	71.19	–0.48
CTA	12.48 [2.98]	7.78	7.08 [1.91]	0.70 [4.48]	24.47	–5.40
CTO	5.76 [2.40]	33.93	5.52 [2.21]	0.03 [0.35]	33.99	–0.24
EPS	6.60 [2.57]	81.17	3.00 [1.26]	0.47 [5.65]	84.49	–3.60
EY	6.12 [2.71]	84.46	6.84 [3.15]	0.09 [1.08]	84.62	0.72
GM	9.24 [2.19]	18.04	2.28 [0.55]	0.90 [5.40]	40.22	–6.96
RNA	10.20 [4.04]	6.72	7.32 [3.07]	0.37 [5.02]	20.40	–2.88
ROA	12.48 [3.42]	54.76	6.00 [1.85]	0.84 [6.48]	67.55	–6.48
ROE	9.36 [2.84]	67.46	4.68 [1.58]	0.60 [5.17]	73.84	–4.68
ROIC	3.96 [1.50]	71.36	0.96 [0.43]	0.38 [4.78]	75.00	–3.00
SALEREV	0.36 [0.13]	76.69	0.24 [0.09]	0.08 [0.84]	76.80	–0.12
TBI	1.32 [0.56]	48.91	1.68 [0.73]	0.06 [0.69]	49.10	0.36
Z	4.20 [2.13]	84.02	3.00 [1.62]	0.17 [1.78]	84.65	–1.20
Trading friction						
BETA	5.16 [1.64]	74.33	5.04 [1.48]	0.01 [0.07]	74.33	–0.12
BETASQ	5.16 [1.64]	74.31	5.04 [1.48]	0.01 [0.08]	74.31	–0.12
BETA_DIM	0.48 [0.16]	43.40	1.08 [0.36]	0.08 [0.60]	43.60	0.60
BETA_DN	2.28 [0.70]	61.06	2.16 [0.58]	0.03 [0.18]	61.07	–0.12
BETA_FF	1.56 [0.50]	55.80	1.80 [0.54]	0.03 [0.22]	55.81	0.24
BETA_HS	3.48 [0.92]	58.05	3.36 [0.84]	0.03 [0.19]	58.06	–0.12
IVOL	5.76 [1.58]	27.76	3.48 [0.92]	0.29 [1.35]	29.66	–2.28
MAXRET	18.60 [3.37]	25.15	18.72 [3.24]	0.00 [0.03]	25.15	0.12
PRC	10.68 [2.16]	9.72	2.64 [0.56]	1.03 [4.63]	27.80	–8.04
PRCDEL	0.24 [0.10]	11.51	1.44 [0.57]	0.15 [1.31]	13.33	1.20
RETVOL	15.84 [3.59]	59.02	14.28 [3.08]	0.21 [1.48]	59.64	–1.56
RVOL	7.20 [2.64]	77.12	8.40 [3.23]	0.15 [1.68]	77.57	1.20
STD_RVOL	6.36 [1.38]	3.78	6.96 [1.42]	0.07 [0.30]	3.92	0.60
STD_TURN	7.32 [2.12]	38.14	3.00 [0.91]	0.55 [4.92]	48.56	–4.32

(*continued on next page*)

Table 6 (*continued*)

	CH3 Regression		TSFM+CH3 Regression			Diff.
	CH3-α	R^2 (%)	TSFM+CH3-α	TSFM-β	R^2 (%)	
VOLT	8.52 [2.19]	4.72	6.00 [1.52]	0.33 [2.39]	8.44	–2.52
ZEROTRADE	7.80 [2.22]	34.81	3.48 [1.02]	0.55 [5.02]	46.18	–4.32
Intangibles						
CFD	11.88 [3.00]	40.02	4.68 [1.33]	0.93 [5.96]	56.59	–7.20
CP	15.96 [3.16]	16.49	8.28 [1.85]	0.99 [4.88]	35.46	–7.68
CRG	2.28 [1.12]	29.76	1.92 [0.97]	0.03 [0.43]	29.87	–0.36
SC	6.24 [1.70]	20.04	1.32 [0.39]	0.64 [5.52]	37.02	–4.92
SI	5.88 [1.65]	22.57	3.36 [0.98]	0.33 [2.53]	27.06	–2.52
Panel C: Average Absolute Value						
Average	7.20 [2.06]	38.98	4.48 [1.36]	0.39 [2.94]	46.34	–2.72

the TSFM strategy, and $CH3_t$ is the CH3 model.

Panel A of Table 6 compares the performance of CH3 and CH3 augmented with the TSFM strategy to digest the excess returns on the 10 non-momentum factors, including the alphas and adjusted R^2s for both models, loadings of the TSFM strategy, and differences between the TSFM+CH3 and CH3 alphas.

We find that controlling for the TSFM decreases the abnormal alphas and corresponding *t*-statistics in seven of the 10 regressions. For example, the CH3 alpha for book-to-market equity is 22.80 % ($t = 4.75$), whereas its TSFM+CH3 alpha reduces to 14.76 % ($t = 3.55$). The loadings of the TSFM strategy are mostly positively significant. Furthermore, the R^2s increase in all 10 regressions. The results suggest the additional explanatory power of the TSFM strategy to subsume the factors compared with the CH3 factors.

Table 7
Stock Momentum and Factor Momentum
Panel A reports the annualized average returns, standard deviation, and annualized Sharpe ratios (SR) of the momentum strategies, i.e., stock momentum, high-priced stock momentum, industry momentum, and reversal, respectively. Stock momentum is calculated as the difference between the average value-weighted returns in the top quintiles and those in the bottom quintiles sorted by the stocks prior to the 12- to 2-month returns. High-priced stock momentum is the momentum in the highest 10 % price deciles; specifically, we independently sort stocks into deciles based on nominal prices and quintiles based on cumulative returns over the past 12 months. Industry momentum portfolio longs the top 20 % of industry portfolios that earn the largest returns in the prior k to 2 months and shorts the bottom 20 %. Reversal is constructed as the difference between the average value-weighted returns in the top quintiles and that in the bottom quintiles ranked by the stocks prior to one-month returns.
Panel B reports the results of regressing the return of the time-series factor momentum (TSFM) strategy on each of the four momentum strategies and FF5 separately:
$Ret_t^{TSFM} = \alpha + \beta Ret_t^M + \gamma FF5_t + \varepsilon_t,\ M \in \{MOMe, MOMe_{Prc}, MOMe_{Ind}, REV\}$.
Panel C reports the results of regressing each of the returns on the four momentum strategies on the return of the TSFM and FF5 separately:
$Ret_t^M = \alpha + \beta Ret_t^{TSFM} + \gamma FF5_t + \varepsilon_t,\ M \in \{MOMe, MOMe_{Prc}, MOMe_{Ind}, REV\}$.
The intercepts and returns are reported in percentages. We report the adjusted R^2s (in percentages). The *t*-statistics are reported in square brackets. The sample period runs from January 2002 to December 2019.

Panel A	MEAN	STD	SR
MOMe	6.00 [1.03]	24.71	0.24
$MOMe_{Prc}$	12.31 [2.59]	20.76	0.60
$MOMe_{Ind}$	9.03 [2.42]	15.40	0.59
REV	–13.46 [–2.40]	23.76	−0.57

Panel B	Intercept	Slope (Ret_t^M)	R^2 (%)
MOMe	5.73 [3.21]	0.20 [7.41]	40.34
$MOMe_{Prc}$	4.56 [2.05]	0.16 [6.31]	24.00
$MOMe_{Ind}$	6.83 [3.29]	0.32 [4.11]	22.79
REV	7.98 [3.80]	0.09 [2.58]	14.80

Panel C	Intercept	Slope (Ret_t^{TSFM})	R^2 (%)
MOMe	–4.29 [–0.80]	1.69 [8.59]	39.22
$MOMe_{Prc}$	1.20 [0.51]	1.00 [5.86]	20.30
$MOMe_{Ind}$	0.71 [0.29]	0.38 [4.25]	13.56
REV	–11.35 [–2.07]	0.64 [2.85]	20.81

Then, we expand the investigation by including 50 anomalies in the Chinese stock market, as discussed in Section III. A (i.e., 60 anomalies in total). We regress each of the anomaly's returns on the CH3 factors and factor momentum portfolio:

$$\text{ANOMALYRET}_t = \alpha + \gamma \text{CH3}_t + \varepsilon_t, \tag{5}$$

$$\text{ANOMALYRET}_t = \alpha + \beta \text{TSFM}_t + \gamma \text{CH3}_t + \varepsilon_t, \tag{6}$$

where ANOMALYRET_t denotes each of the long-short spread portfolios of the 50 anomalies at time t, TSFM_t is the return of the TSFM strategy of the 10 non-momentum factors, and CH3_t is the CH3 model.

Panel B of Table 6 reports that the TSFM strategy shows additional power in explaining the 50 anomalies. Accounting for the TSFM reduces the abnormal alphas and *t*-statistics in all the value versus growth group anomalies, all the investment-related anomalies, 11 of the 14 profitability-related characteristics, 10 of the 16 trading friction anomalies, and all the intangibles. In other words, 82 % of the anomalies produce lower abnormal alphas when controlling for the TSFM. Furthermore, 16 anomalies have insignificant TSFM+CH3 alphas despite producing significant CH3 alphas, while 62 % of the anomalies produce significantly positive TSFM coefficients. Adding the TSFM as a control variable increases the R^2s, representing the goodness of fit, of 47 regressions.

Additionally, we report the average absolute values of 60 anomalies. Controlling for the TSFM makes the significant 7.20 % intercept ($t = 2.06$) drop 2.72 percentage points to become insignificant at 4.48 % ($t = 1.36$). The beta loading of factor momentum is 0.39 ($t = 2.94$), and R^2 reaches 46.34 %. These average absolute values show that factor momentum helps explain anomalies.

Our results illustrate that the TSFM portfolio helps decompose the returns on its component factors and a higher number of anomalies. Only a few factors aligned explain nearly 82 % of the anomalies, which indicates the strong economic potential of factor momentum. Dong et al. (2022) use several shrinkage approaches to extract predictive signals from 100 anomalies and find that long-short anomaly portfolio returns are statistically and economically significant in forecasting market excess returns. Our findings also shed light on the economic linkages between time-series factors and cross-sectional anomalies.

4. Factor momentum vis-à-vis stock momentum

4.1. Regressions of factor momentum and stock momentum

Previous studies have discussed the relation between factor momentum and stock momentum. For example, Arnott et al. (2021) highlight that industry momentum comes from factor momentum. Leippold and Yang (2021) argue that stock momentum is a combination of factor momentum. In this subsection, we investigate the relation between factor momentum and stock momentum in China, in the spirit of Arnott et al. (2021), Ehsani and Linnainmaa (2022), and Leippold and Yang (2021).

The Chinese stock market lacks momentum on aggregate (e.g., Pan et al., 2013; Boubaker et al., 2021). We calculate stock-level momentum (MOMe) as the difference between the top quintile's average value-weighted return and the lowest quintile's, ranked by stocks' prior 12- to 2-month returns. Panel A of Table 7 shows that the stock-level momentum in China is insignificant, with an annualized return of 6.00 % and a *t*-statistic of 1.03, in line with the prior literature.

Many studies consider different subsamples and high-frequency data, finding intraday (overnight; Gao et al., 2021), idiosyncratic (Lin, 2022), industry (Boubaker et al., 2021), and down-market stock momentums (Cheema and Nartea, 2017) in China. Specifically, Du et al. (2022) show that momentum in high-priced stocks is significant and document that retail investors' noise trade attenuates momentum, for small retail investors in China are constrained to invest in high-priced stocks because of the minimum 100 unit of the number of shares. Following Du et al. (2022), we calculate the high-priced stock momentum strategy (MOMe_{Prc}). We sort stocks into deciles based on their previous month's nominal price. Independently, we sort stocks into quintiles based on their prior 12 months' cumulative returns. The high-priced momentum strategy longs in past winner stocks and shorts the past losers in the highest price decile. We rebalanced the portfolios monthly and report the equal-weighted monthly returns. Panel A of Table 7 reports a significant high-priced stock momentum in China. The annualized return equals 12.31 % ($t = 2.59$) with a Sharpe ratio of 0.60.[5]

We also test several types of individual stock momentum in China following Ehsani and Linnainmaa (2022): standard (Jegadeesh and Titman, 1993), industry-adjusted (Cohen and Polk, 1998), industry (Moskowitz and Grinblatt, 1999), intermediate (Novy-Marx, 2012), and Sharpe ratio momentums (Rachev et al., 2007). Of these, only the industry momentum approach is significant, consistent with Boubaker et al. (2021). In detail, we classify stocks into 90 industries based on the Guidelines for the Industry Classification of Listed Companies of the China Securities Regulatory Commission (CSRC). The industry momentum portfolio (MOMe_{Ind}) longs the top 20 % of industry portfolios that earn the largest returns in the prior 12 to 2 months and shorts the bottom 20 % (Asness et al., 2000; Leippold and Yang, 2021; Moskowitz and Grinblatt, 1999). We rebalance the portfolios monthly. The results of Panel A of Table 7 show that the Chinese stock market delivers positive industry momentum, with an average return of 9.03 % ($t = 2.42$) and a Sharpe ratio of 0.59 per annum.

Finally, we calculate the reversal factor (REV) as that ranked by the previous one-month returns. Reversal is significantly negative in China, generating a –13.46 % return per year with a *t* value of –2.40. The high participation of short-term trade retail investors (Jones et al., 2020) leads to significant short-term reversals (Du et al., 2022).

[5] We calculate the performance of momentum and time-series factor momentum across priced-based deciles and report the results in Online Appendix Table OA1. The results show that momentum is significant only in the top price decile and TSFM remains significant in nine decile groups.

To examine the ability of the four momentum (reversal) strategies to explain the factor momentum, we run the following regression:

$$\mathrm{RET}_t^{TSFM} = \alpha + \beta \mathrm{RET}_t^{\mathrm{M}} + \gamma \mathrm{FF5}_t + \varepsilon_t,\ M \in \{\mathrm{MOMe}, \mathrm{MOMe}_{\mathrm{Prc}}, \mathrm{MOMe}_{\mathrm{Ind}}, \mathrm{REV}\}, \tag{7}$$

where $\mathrm{RET}_t^{\mathrm{TSFM}}$ is the return of the TSFM strategy, RET_t^{M} is the return of each of the stock momentum strategies, $M \in \{\mathrm{MOMe}, \mathrm{MOMe}_{\mathrm{Prc}}, \mathrm{MOMe}_{\mathrm{Ind}}, \mathrm{REV}\}$, and $\mathrm{FF5}_t$ is the FF5 model. Panel B of Table 7 shows the results.

The findings suggest that the four momentum (reversal) strategies cannot subsume factor momentum returns, as shown in the intercepts. Factor momentum generates significant positive alphas of 5.73 % ($t = 3.21$), 4.56 % ($t = 2.05$), 6.83 % ($t = 3.29$), and 7.98 % ($t = 3.80$) after adjusting for $\mathrm{MOMe}, \mathrm{MOMe}_{\mathrm{Prc}}, \mathrm{MOMe}_{\mathrm{Ind}}$, and REV, respectively. The loadings on the momentum (reversal) portfolios are all positively significant, indicating that they partially explain the factor momentum. R^2 reaches the highest value of 40.34 % for the momentum portfolio.

Next, we investigate whether the TSFM strategy helps explain the returns of the four momentum (reversal) portfolios, with the following regression:

$$\mathrm{RET}_t^{M} = \alpha + \beta \mathrm{RET}_t^{\mathrm{TSFM}} + \gamma \mathrm{FF5}_t + \varepsilon_t,\ M \in \{\mathrm{MOMe}, \mathrm{MOMe}_{\mathrm{Prc}}, \mathrm{MOMe}_{\mathrm{Ind}}, \mathrm{REV}\}. \tag{8}$$

Panel C of Table 7 reports the results of Eq. (8). We find that the TSFM subsumes the return of the three stock momentum strategies, with an insignificant alpha of –4.29 % ($t = -0.80$), 1.20 % ($t = 0.51$), and 0.71 % ($t = 0.29$) of $\mathrm{MOMe}, \mathrm{MOMe}_{\mathrm{Prc}}$, and $\mathrm{MOMe}_{\mathrm{Ind}}$, respectively. However, the reversal portfolio remains negatively significant when controlling for factor momentum, with an abnormal alpha of –11.35 % ($t = -2.07$). The coefficients on the factor momentum are all positively significant.

In sum, we find that factor momentum subsumes momentum, high-priced momentum, and industry momentum in China. As Ehsani and Linnainmaa (2022) employ momentum-neutral factors and find that factor momentum exists in momentum-neutral factors, our findings indicate that factor momentum is distinct from stock momentum.

4.2. *Market timing of factor momentum and stock momentum*

Literature suggests that price momentum exhibits negative returns during market downturns, commonly referred to as momentum crashes (e.g., Daniel and Moskowitz, 2016; Dierkes and Krupski, 2022). We investigate whether market conditions affect the performance of factor momentum and stock momentum following Daniel and Moskowitz (2016) with the three regressions:

$$\mathrm{RET}_t^{K} = \alpha_0 + \beta_0 R_{m,t} + \varepsilon_t, \tag{9}$$

$$\mathrm{RET}_t^{K} = \left(\alpha_0 + \alpha_B I_{B,t-1}\right) + \left(\beta_0 + \beta_B I_{B,t-1}\right) R_{m,t} + \varepsilon_t, \tag{10}$$

$$\mathrm{RET}_t^{K} = \left(\alpha_0 + \alpha_B I_{B,t-1}\right) + \left(\beta_0 + I_{B,t-1}\left(\beta_B + I_{U,t}\beta_{B,U}\right)\right) R_{m,t} + \varepsilon_t, K \in TSFM, MOMe, \tag{11}$$

where RET_t^{TSFM} represents the returns of the time-series factor momentum, RET_t^{MOMe} is the zero-investment winner-minus-loser portfolio, which longs the top decile and shorts the bottom decile based on cumulative returns from $t-12$ to $t-2$-month, and $R_{m,t}$ is the value-weighted market excess returns in month t. The indicator $I_{B,t-1}$ denotes the bear market state, which equals one if the cumulative market return is negative over the past 24 months and zero otherwise, while $I_{U,t}$ stands for the bull market state, which is one if the excess market return is greater than the risk-free rate in month t and zero otherwise.

Panel A of Table 8 reports the results of TSFM for Eqs. (9)-(11) in columns (1)-(3), respectively. The findings indicate that the factor momentum returns are robust for the most part and exhibit asymmetry only after market downturns. Column (1) reports a negative estimated market beta of –0.031 with an insignificant t-statistic of –1.14, and an intercept of 0.87 ($t = 5.33$), indicating that the market return does not affect factor momentum. We then introduce a dummy variable for the bear market state and an interaction term in Eq. (10) to capture the differences in expected returns and market betas during bear markets. We observe a significant negative $\widehat{\beta}_B$ of –0.12 ($t = -2.27$), suggesting that factor momentum returns decrease following a bear market period. In column (3), we include a contemporaneous up-market indicator to examine factor momentum returns under up- and down-market conditions. The insignificant $\widehat{\beta}_{B,U}$ alleviates the concern that factor momentum is influenced when the market rebounds following a bear market, although stock momentum in the U.S. is affected (Daniel and Moskowitz, 2016). Nevertheless, Panel B of Table 8 presents the results of stock-level momentum, which shows that the returns of stock momentum exhibit asymmetry following bear markets.

Overall, our findings indicate that factor momentum returns are mostly robust and show asymmetries after downturn markets.

5. Economic channels of factor momentum

In this section, we aim to explore the economic mechanisms underlying factor momentum. First, we examine whether the mispricing correction brought by slow-moving arbitrage capital and limits-to-arbitrage is the source of factor momentum (Li et al., 2022). Instead of immediately eliminating all mispricing, arbitragers who seek to generate sustained factor returns attempt to correct the mispricing gradually through trading. Thus, during periods of high limits-to-arbitrage, arbitrageurs are more inclined to participate in trading to decrease synchronization risk (Abreu and Brunnermeier, 2002). We hypothesize that factor momentum is more pronounced during high limits-to-arbitrage periods. Besides, it takes time to make the price return to its fundamental value. Second, we decompose

Table 8
Market Timing Regression Results
Panels A and B of this table report the results of three monthly time-series regressions specifications of factor momentum and stock momentum, respectively. The dependent variable is the return on the TSFM for Panel A and the return on the winner-minus-loser stock momentum portfolio for Panel B. The independent variables include a constant (1); a dummy variable representing bear markets ($I_{B,t-1}$), which equals one if the market's cumulative past two-year return is negative; the excess market return (R_{mkt}); and an indicator for up-market ($I_{U,t}$), which equals one if R_{mkt} is positive. The sample period runs from January 2002 to December 2019.

Coefficient	Variable	Estimated Coefficients		
		(1)	(2)	(3)
Panel A Factor Momentum				
$\widehat{\alpha}_0$	1	0.87 [5.33]	0.80 [3.25]	0.80 [3.26]
$\widehat{\alpha}_B$	$I_{B,t-1}$		0.17 [0.51]	0.01 [1.41]
$\widehat{\beta}_0$	R_{mkt}	–0.03 [–1.14]	0.001 [0.03]	0.001 [0.03]
$\widehat{\beta}_B$	$I_{B,t-1} \cdot R_{mkt}$		**–0.12 [–2.27]**	–0.02 [–0.27]
$\widehat{\beta}_{B,U}$	$I_{B,t-1} \cdot I_{U,t} \cdot R_{mkt}$			–0.18 [–1.34]
Panel B Stock Momentum				
$\widehat{\alpha}_0$	1	0.67 [1.54]	–0.40 [–0.61]	–0.40 [–0.60]
$\widehat{\alpha}_B$	$I_{B,t-1}$		**0.02 [2.56]**	**0.03 [2.90]**
$\widehat{\beta}_0$	R_{mkt}	–0.03 [–0.57]	0.04 [0.65]	0.04 [0.66]
$\widehat{\beta}_B$	$I_{B,t-1} \cdot R_{mkt}$		**–0.28 [–2.55]**	–0.32 [–1.14]
$\widehat{\beta}_{B,U}$	$I_{B,t-1} \cdot I_{U,t} \cdot R_{mkt}$			–0.10 [–0.54]

the factor momentum strategy into buy-and-hold portfolios and factor time (Leippold and Yang, 2021) to analyze the contribution of each component. Third, we examine the impact of culture on factor momentum, as several studies have shown its influence on stock momentum (Chui et al., 2010).

5.1. Slowing-Moving mispricing correction

5.1.1. Aggregate idiosyncratic volatility

Frictions such as limited risk-bearing capacity and transaction costs cause arbitrageurs to respond slowly to mispricing, resulting in the persistence of asymmetric mispricing correction (Gârleanu and Pedersen, 2013, 2016; Dong et al., 2020; Dong et al., 2022). We suppose that factor momentum performs better during times of high aggregate idiosyncratic volatility (Li et al., 2022), as arbitrageurs are more likely to take advantage of high information asymmetry. Furthermore, high aggregate idiosyncratic volatility may cause large limits to arbitrage, leading to a scarcity of funds available for arbitrageurs and thus a long response time to correct mispricing.

Following Garcia et al. (2014) and Li et al. (2022), we calculate the monthly return dispersion to estimate aggregate idiosyncratic volatility, which is the cross-sectional standard deviation of daily stock returns. We calculate the average annualized returns of the factor momentum, winner, and loser portfolios during high and low return dispersion periods, following Stambaugh et al. (2012), according to whether they are above or below the mean of return dispersion, respectively.

Table 9 reports the results for the factor momentum strategies during periods of high and low aggregate idiosyncratic volatility.

Table 9
The Role of Idiosyncratic Volatility
Panels A and B report the annualized average returns and corresponding *t*-statistics (in square brackets) for the time-series factor momentum (TSFM) strategy, winners, and losers for stocks in low and high aggregate idiosyncratic volatility periods, respectively. The average monthly returns in low and high aggregate idiosyncratic volatility periods are estimates of α_L and α_H in the regression
$R_{i,t} = \alpha_H d_{H,t} + \alpha_L d_{L,t} + \epsilon_{i,t}$,
where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high- and low-aggregate idiosyncratic volatility periods. Panel C reports the difference in annualized average returns between the high and low idiosyncratic volatility periods. We calculate the monthly return dispersion to estimate aggregate idiosyncratic volatility, which is the cross-sectional standard deviation of daily stock returns. The high (low) aggregate idiosyncratic volatility period corresponds to the sample period with the above (below) mean return dispersion level. All the returns are reported in percentages. The sample period runs from January 2002 to December 2019.

	TSFM	Winners	Losers
Panel A: High aggregate idiosyncratic volatility			
Mean	4.74	9.03	9.61
t-stat	[2.02]	[3.09]	[2.24]
Panel B: Low aggregate idiosyncratic volatility			
Mean	2.14	0.93	–6.45
t-stat	[0.98]	[0.38]	[–1.81]
Panel C: Difference between high and low aggregate idiosyncratic volatility			
Return	2.60 [0.61]	8.10 [1.59]	16.06 [2.14]

Consistent with our conjecture, the factor momentum effect is stronger under high aggregate idiosyncratic volatility. The factor momentum strategy delivers an annualized return of 4.74 % ($t = 2.02$) during the high aggregate idiosyncratic volatility period compared with 2.14 % ($t = 0.98$) under low aggregate idiosyncratic volatility. The returns on the long- and short-legs reach higher values during high return dispersion periods (9.03 with 3.09 t-statistic and 9.61 with 2.24 t-statistic, respectively), whereas these values are lower (0.93 with 0.38 t-statistic and –6.45 with –1.81 t-statistic, respectively) during low return dispersion periods. In summary, the findings show stronger factor momentum during periods with increased aggregate idiosyncratic volatility.

5.1.2. Investor sentiment

Furthermore, we investigate the role of investor sentiment in factor momentum performance. According to Stambaugh et al. (2012), many anomalies generate high returns during high investor sentiment periods, and are particularly persistent in the presence of short-sale constraints because of mispricing. Factor momentum may be a different manifestation of the same mechanism, as it takes time to correct mispricing to the fundamental level due to short-sale constraints and slow-moving capital (Duffie, 2010). Thus, we presume that factor momentum is stronger during low investor sentiment periods than during high periods.

To test our hypothesis, we employ Baker and Wurgler's (2006) investor sentiment index in China and calculate the average annualized returns of the winner-minus-loser, winner, and loser portfolios during the high (above the mean) and low (below the mean) investor sentiment periods. Table 10 reports the results.

During the low investor sentiment period, the average underperforming factor earns a return of –2.97 % ($t = -0.88$), whereas factors with positive returns over the prior year earn a premium of 3.70 % ($t = 1.59$); this 4.10 % difference is significant with a t-statistic of 1.92. The average returns on the long-leg (5.94 % with 2.00 t-statistic) and short-leg (5.58 % with 1.26 t-statistic) are higher during the high investor sentiment period, but factor momentum strategy earns a lower benefit (2.64 % with 1.10 t-statistic). These findings are consistent with Stambaugh et al. (2012) study, which indicates that the average factor delivers high returns during high investor sentiment periods. However, the factor momentum strategy, as measured by the winner minus loser portfolio, generates lower returns during high sentiment periods. As it takes time for mispricing to develop, assets' values do not adjust immediately to the fundamental value due to limits to arbitrage. Factor momentum may therefore result from assets' values drifting back to their fundamental values.

5.1.3. Information asymmetry

The literature documents that information asymmetry influences cross-sectional stock momentum (Chen and Zhao, 2012; Gutierrez and Kelley, 2008). According to Zhang (2006), stocks with higher information uncertainty generate larger cross-sectional stock momentum because this intensifies the higher expected returns following good news and lower expected returns following bad news. Hence, we conjecture that information asymmetry impacts the factor momentum strategy.

Following Roll (1988), Jin and Myers (2006), and Boubaker et al. (2014), we exploit stock price nonsynchronicity (NONSYNC) as a measure of stock price informativeness. The higher NONSYNC is, the more informativeness and the less information asymmetry of stocks. We conjecture that stocks of higher (lower) factor momentum are less (more) informative and have a lower (higher) value of NONSYNC. To construct NONSYNC, we first run the following regression:

$$R_{i,t} = \alpha + \beta_1 R_{m,t} + \beta_2 R_{m,t-1} + \beta_3 R_{ind,t} + \beta_4 R_{ind,t-1} + \epsilon_{i,t} \tag{12}$$

where $R_{i,t}$ is the return on stock I on day t, R_m is the value-weighted market return, and R_{ind} is the value-weighted industry return. The regression is estimated for each firm i in a year. Then, we use the R_i^2 of the above regression to construct NONSYNC$_i$ in a given year.

Table 10
The Role of Investor Sentiment
Panels A and B report the annualized average returns and corresponding t-statistics (in square brackets) for the time-series factor momentum (TSFM) strategy, winners, and losers for stocks in low and high investor sentiment periods, respectively. We reconstruct Baker & Wurgler's (2006) investor sentiment index in the Chinese market. The average monthly returns in low and high sentiment periods are estimates of α_L and α_H in the regression
$R_{i,t} = \alpha_H d_{H,t} + \alpha_L d_{L,t} + \epsilon_{i,t}$,
where $d_{H,t}$and $d_{L,t}$ are dummy variables indicating high and low sentiment periods. Panel C reports the difference in annualized average returns between the high and low investor sentiment periods. The high (low) investor sentiment period corresponds to the sample period with the above (below) mean. All the returns are reported in percentages. The sample period runs from January 2002 to December 2019.

	TSFM	Winners	Losers
Panel A: High sentiment			
Mean	2.64	5.94	5.58
t-stat	[1.10]	[2.00]	[1.26]
Panel B: Low sentiment			
Mean	4.10	3.70	–2.97
t-stat	[1.92]	[1.59]	[–0.88]
Panel C: Difference between high and low sentiment			
Return	–1.46 [–0.33]	2.24 [0.44]	8.55 [1.14]

Following Morck et al. (2000), we logistically transform $1 - R_i^2$ to obtain an appropriate distribution, $\text{NONSYNC}_i = \ln\left(\frac{1-R_i^2}{R_i^2}\right)$.

We then sort the stocks into two groups using NONSYNC at the beginning of each year and calculate the performance of the TSFM strategy for each group. Panels A and B of Table 11 report the annualized average returns, Sharpe ratios, and *t*-statistics for the full sample and long-leg and short-leg portfolios for stocks that have low and high information asymmetry, respectively. Consistent with our conjecture, factor momentum performance is high among stocks with severe information asymmetry. The TSFM strategy delivers an annualized return of 7.46 % ($t = 2.99$) among stocks with high information asymmetry, while the return is 3.19 % with a *t*-statistic of 0.84 among stocks with low information asymmetry. Both winners and losers with high information asymmetry expand with higher absolute return values. The Sharpe ratios are also higher for stocks with high information asymmetry in the long-short, long-leg, and short-leg samples. To summarize, factor momentum is higher if information asymmetry is relatively high.

5.1.4. Short-Sale constraints

To assess whether factor momentum is sensitive to short-sale constraints, we consider the factor momentum return in short-selling stocks and stocks with short-sale constraints. Restrictions on short-selling in the Chinese stock market are severe. In March 2010, the CSRC introduced the securities margin trading program in which only certain brokerage companies can short-sale 90 stocks on a special list. The program was expanded to 1600 stocks in 2019. However, short-sale constraints are still binding in China. The literature shows that short-selling helps price discovery, which increases market efficiency (Leippold et al., 2021). Therefore, we consider the role of short-sale constraints in factor momentum using data on short-sale stocks obtained from the CSRC. We separate stocks into two subsamples: one that allows short selling and the other with short selling constraints. Then, in each group, we run the TSFM strategy and report the results in Table 12.

The factor momentum strategy produces higher long-short returns among stocks without short-sale constraints, reaching 6.78 % ($t = 3.87$) per annum, while stocks under short-selling constraints have an average return of 6.54 % ($t = 1.82$). The difference in the average return between the two subsamples is 0.24 percentage points, with an insignificant *t*-statistic of 0.20. Both the long- and short-legs of stocks without short-sale constraints generate higher returns than stocks with short-sale constraints. The Sharpe ratio is also higher among non-short-selling stocks (1.36) compared with 0.64 for short-selling stocks.

Miller (1977) documents that short-selling tends to temper the propensity for riskier stocks to be bid up to higher prices. In other words, when short-selling is hard to execute, such as in the Chinese stock market, stocks tend to be overvalued relative to their fundamentals. Hong and Stein (2003) argue that the removal of short-selling constraints can incorporate unrevealed negative information into stock prices in a timely manner. Our results are consistent with theirs; the factor momentum strategy earns lower returns on short-selling stocks, which are likely to be priced more rationally with fundamental information, than stocks with short-sale constraints. The analysis is also consistent with the results in Table 12, as non-short-selling stocks also suffer higher information asymmetry.

Overall, our findings suggest that the slow-moving mispricing correction and the higher participation of arbitrageurs during the high limits-to-arbitrage periods help explain the returns of factor momentum.

5.2. Factor timing and factor premiums

Factor momentum combines factor timing and factor premiums. In this subsection, we decompose the factor momentum strategy into the factor timing (FT) and buy-and-hold (BH) portfolios following Leippold and Yang (2021) to investigate which portfolio contributes more. Timing may improve investment performance and capture time-varying risk, especially in a market with high volatility, such as China (Leippold et al., 2021). Furthermore, exposure to factors also leads to a risk premium.

The factor timing portfolio isolates the advantages of factor timing from those of factor premiums. If previous returns have deviated from the prevailing average return, it takes the corresponding factor positions; it longs factors when their returns are above their

Table 11
The Role of Information Asymmetry
Panels A and B report the annualized average returns, Sharpe ratios (SR), and corresponding *t*-statistics (in square brackets) for the time-series factor momentum (TSFM) strategy, winners, and losers for stocks with low and high information asymmetry, respectively. Panel C reports the difference in annualized average returns between high and low information asymmetry stocks. We exploit stock price nonsynchronicity (NONSYNC) as a measure of stock price informativeness. The higher NONSYNC is, the less information asymmetry of stocks. The high (low) information asymmetry stocks correspond to the sample with the above (below) mean of NONSYNC. All the returns are reported in percentages. The sample period runs from January 2002 to December 2019.

	TSFM	Winners	Losers
Panel A: Low information asymmetry			
Mean	3.19 [0.84]	3.79 [1.03]	–2.98 [–0.61]
SR	0.35	1.17	–0.24
Panel B: High information asymmetry			
Mean	7.46 [2.99]	5.04 [1.37]	–7.05 [–1.80]
SR	1.20	1.68	0.76
Panel C: Difference between high and low information asymmetry			
Return	4.27 [1.26]	1.25 [0.27]	–4.07 [–0.95]

Table 12
The Role of Short-Sale Constraints
Panels A and B report the annualized average returns, Sharpe ratios (SR), and corresponding *t*-statistics (in square brackets) for the time-series factor momentum (TSFM) strategy, winners, and losers for stocks allowed to engage in short selling (Short) and stocks prohibited from engaging in short selling (Nonshort), respectively. Panel C reports the difference in annualized average returns between stocks allowed to engage in short selling and those that cannot. All the returns are reported in percentages. The sample period runs from January 2010 to December 2019.

	TSFM	Winners	Losers
Panel A: Short			
Mean	6.54 [1.82]	7.84 [2.36]	–4.48 [–0.90]
SR	0.64	1.17	–0.24
Panel B: Nonshort			
Mean	6.78 [3.87]	4.95 [2.13]	–8.52 [–3.40]
SR	1.36	1.68	0.76
Panel C: Difference between nonshort and short			
Return	0.24 [0.20]	–2.89 [–0.68]	–4.04 [–0.77]

prevailing mean and shorts factors when their returns are below the historical average:

$$\mathrm{RET}^{\mathrm{FT}}_{t+1} = \frac{1}{|\mathrm{I}_t|}\sum_{i\in I_t}\mathrm{SIGN}\left(F_{i,t}-\overline{F}_{i,t}\right)F_{i,t+1}, \tag{13}$$

where $\overline{F}_{i,t}$ is the historical average return on the i th factor estimated from all the data available until month t and $\mathrm{sign}(\cdot)$ is the sign function.

As Huang et al. (2020) demonstrate, the buy-and-hold portfolio benefits from factor premiums and avoids active timing. Specifically, this portfolio longs factors with a positive prior mean return and shorts factors that earned a negative historical mean return. The portfolios are rebalanced when the sign of the historical mean changes. Huang et al. (2020) show that mean returns, rather than predictability, are the key return-generating aspects of future market momentum returns:

$$\mathrm{RET}^{\mathrm{BH}}_{t+1} = \frac{1}{|\mathrm{I}_t|}\sum_{i\in I_t}\mathrm{SIGN}\left(\overline{F}_{i,t}\right)F_{i,t+1}. \tag{14}$$

After constructing the factor timing and buy-and-hold strategies, we first calculate their performance. Panel A of Table 13 reports their average returns, standard deviations, Sharpe ratios, and *t*-statistics, showing that both strategies generate significant positive returns. The factor timing strategy earns an average annualized return of 10.20 % with a *t*-statistic of 2.35, while the buy-and-hold strategy produces an average return of 13.56 % ($t = 3.73$) per annum, significant at the 1 % level. The Sharpe ratio of the factor timing portfolio is 0.55, which is below the 0.88 ratio of the buy-and-hold portfolio. The standard deviation of the factor timing portfolio is 18.55, which is less stable than that of the buy-and-hold strategy. These findings indicate that both strategies provide considerable returns and that pure factor premiums are strong in China. The analysis with the buy-and-hold strategy reaffirms our earlier results in Panel A of Table 1 that pure factor premiums are sizable in China.

Next, we investigate whether the factor timing and buy-and-hold portfolios help explain the return of the TSFM strategy. We run the following two regressions:

$$\mathrm{RET}^{\mathrm{TSFM}}_{t} = \alpha + \beta \mathrm{RET}^{K}_{t} + \varepsilon_t, \tag{15}$$

$$\mathrm{RET}^{K}_{t} = \alpha + \beta \mathrm{RET}^{\mathrm{TSFM}}_{t} + \varepsilon_t,\ \ K \in \{\mathrm{FT}, \mathrm{BH}\}, \tag{16}$$

where $\mathrm{RET}^{\mathrm{TSFM}}_{t}$ is the return of the TSFM strategy and RET^{K}_{t} is the return of the factor timing and buy-and-hold strategies, $K \in \{\mathrm{FT},\mathrm{BH}\}$, respectively.

Panel B of Table 13 reports the results of Eq. (15). The results show that both strategies partially explain factor momentum returns. From the intercepts, factor momentum produces statistically significant and economically large alphas after controlling for the factor timing and buy-and-hold strategies, equaling 6.48 % ($t = 4.76$) and 6.12 % ($t = 3.14$), respectively. Neither strategy can subsume factor momentum returns. The coefficient on the factor timing portfolio is significant at 0.34 ($t = 9.62$), while that on the buy-and-hold portfolio is 0.28 with a *t*-statistic of 5.25. The loading on the factor timing portfolio is higher and more significant than that on the buy-and-hold portfolio. The R^2 of the factor timing strategy is 51.40 %, implying its ability to explain the time variation in factor momentum. The buy-and-hold portfolio has lower explanatory power ($R^2 = 24.30$ %).

Panel C of Table 13 reports the results of Eq. (16) of regressing the factor timing and buy-and-hold portfolios on the TSFM signal. The results show that both intercepts are insignificant, with –5.04 % ($t = -1.49$) for the factor timing portfolio and 4.80 % ($t = 1.43$) for the buy-and-hold portfolio. The slopes of the TSFM are positively significant for both portfolios (1.53, $t = 12.54$ and 0.89, $t = 5.64$ for the factor timing and buy-and-hold portfolios, respectively). Therefore, the TSFM signal dominates both strategies.

Overall, we find that both active timing and buy-and-hold strategies are important for the factor momentum, in contrast to the findings of Leippold and Yang (2021) in the United States. Despite the nontrivial factor premiums, conditional timing also performs

Table 13
Factor Timing and Buy-and-Hold Strategies
Panel A reports the annualized average returns, standard deviations, and annualized Sharpe ratios (SR) of the factor timing and buy-and-hold strategies. The definitions of the two strategies are as follows:

$$Ret_{t+1}^{FT} = \frac{1}{|I_t|}\sum_{i \in I_t} sign(F_{i,t} - \overline{F}_{i,t})F_{i,t+1},$$

$$Ret_{t+1}^{BH} = \frac{1}{|I_t|}\sum_{i \in I_t} sign(\overline{F}_{i,t})F_{i,t+1}.$$

Panel B reports the results of regressing the return of the time-series factor momentum (TSFM) strategy on the factor timing and buy-and-hold portfolios separately:
$Ret_t^{TSFM} = \alpha + \beta Ret_t^K + \varepsilon_t,\ K \in \{FT, BH\}.$
Panel C reports the results of regressing each of the returns on the factor timing and buy-and-hold portfolios on the return of the TSFM strategy separately:
$Ret_t^K = \alpha + \beta Ret_t^{TSFM} + \varepsilon_t,\ K \in \{FT, BH\}.$
The intercepts are reported as percentages. The *t*-statistics are reported in square brackets. The sample period runs from January 2002 to December 2019.

Panel A			
	MEAN	STD	SR
FT	10.20 [2.35]	18.55	0.55
BH	13.56 [3.73]	15.41	0.88
Panel B			
	Intercept	Slope (Ret_t^K)	R^2 (%)
FT	6.48 [4.76]	0.34 [9.62]	51.40
BH	6.12 [3.14]	0.28 [5.25]	24.30
Panel C			
	Intercept	Slope (Ret_t^{TSFM})	R^2 (%)
FT	–5.04 [–1.49]	1.53 [12.54]	51.40
BH	4.80 [1.43]	0.89 [5.64]	24.30

well in the Chinese stock market (Tang et al., 2021). The higher volatility of factor returns, the larger proportion of retail investors in China who tend to have more behavioral biases, and the changeable market states may be the reason that timing is more important in China than in the U.S.

5.3. *Influence of culture on factor momentum*

Culture is an important factor that impacts investor behavior, stockholding and trading actions (Grinblatt and Keloharju, 2001), and stock price comovement (Eun et al., 2015). Kumar et al. (2011) posit that investors' religious affiliation, which is a part of a culture, can influence the construction of investment portfolios and stock returns. Chui et al. (2010) observe that cultural differences determine stock momentum returns. Specifically, markets with collectivistic cultures, like China, generate insignificant stock price momentum, while markets with individualistic cultures, like the U.S., exhibit significant price momentum. These findings inspire us to investigate the connection between culture and factor momentum.

Individuals in individualistic cultures tend to believe that their abilities are above average and are more confident in their own opinions. In contrast, people in collectivistic cultures rely more on mainstream opinions and display more herd-like behavior (Markus and Kitayama, 1991). This herding behavior might strengthen factor co-movements and, in turn, create portfolio-level momentum rather than stock-level momentum. Moreover, this behavior may increase the volatilities of factor-level returns. The Chinese stock market has a large proportion of retail investors who are more prone to herding than analyzing fundamental information. Our study reveals that factor momentum exists in a collectivistic market, the Chinese stock market. The results indicate that the relation between momentum profits and cultural differences is evident in the realm of factor momentum.

To generally examine the influence of culture on factor momentum, we construct a time-series factor momentum strategy by extracting principal component (PC) factors from the extensive set of 142 non-momentum factors proposed by Jensen et al. (2023).[6] The formation period spans 12 months, with holding periods of 1-, 3-, 6-, and 12-months. We calculate the average annualized returns and Sharpe ratios of this TSFM-PC strategy across multiple markets, including China (CHN), Japan (JPN), Israel (IRS), Germany (DEU), Sweden (SWE), Norway (NOR), France (FRA), Denmark (DNK), Italy (ITA), the Netherlands (NLD), the United Kingdom (GBR), Australia (AUS), and the United States (USA). This PC-based TSFM encompasses a wide range of factors and helps address performance disparities of various anomalies in different markets (Kozak et al., 2020; Ehsani and Linnainmaa, 2022). The culture index is proposed by Eun et al. (2015), with smaller values signifying a collectivistic culture, and larger values denoting individualism. The results are reported in Table OA2 and Figure OA1 in Online Appendix A.

[6] These data sets are available at https://jkpfactors.com/.

Panel B of Table OA2 shows that the TSFM-PC strategy generates significant positive returns across all markets with a 1-month holding period, affirming the robustness of factor momentum (Gupta and Kelly, 2019). The persistence of TSFM-PC is also pronounced. Only four markets display insignificant returns during longer holding periods. In Panel C of Table OA2, we find that the Sharpe ratios of TSFM-PC tend to be slightly higher in collectivistic markets compared to individualism-oriented markets. Besides, Figure OA1 illustrates a U-shaped curve for the relationship between TSFM-PC Sharpe ratios and the culture index, indicating that extreme cultural values may exert a more pronounced influence on factor momentum.

In short, the factor momentum strategy exhibits robust and significant performance "everywhere" (Gupta and Kelly, 2019). The strong and significant factor momentum is evident in both collectivistic and individualism-oriented markets, but the underlying economic mechanisms driving individualism-factor momentum and collectivistic-factor momentum may differ, and it is worth further investigation.

6. Robustness check

6.1. Different formation and holding periods

We perform our first robustness test with alternative formation and holding periods of the TSFM strategy. Specifically, we form the TSFM signal using look-back windows of one month ("1–1″), one quarter ("1–3″), two quarters ("1–6″), three quarters ("1–9″), four quarters ("1–12″), three years ("1–36″), and five years ("1–60″). We also hold the strategies for these periods. Panels A and B of Table 14 report the average annualized returns and Sharpe ratios of the long-short factor momentum portfolios based on different combinations of portfolio formation and holding periods.

Table 14 shows that the factor momentum returns are persistent. We find that 41 of the 49 alternative formation and holding period strategies generate significantly positive average returns, 35 strategies are significantly above the 5 % level, 34 strategies have an annualized return of 5 % or above, and 29 strategies produce an annualized Sharpe ratio above 0.6. The findings show the TSFM strategy's robustness and profitability.

Notably, when we use the one-month formation and holding windows, the factor momentum portfolio is also positively significant and generates an annualized return of 5.07 % with a t-statistic of 2.22 and a Sharpe ratio of 0.52. The results highlight that, different from the stock reversal shown in Section III. D, past factor returns still predict stronger future returns, even in the short term (Falck et al., 2022).

Additionally, when the formation period increases from one month to one year, the returns increase in China, whereas short-formation periods perform better in global markets (Gupta and Kelly, 2019). First, the Chinese stock market has a large proportion of retail investors (Jones et al., 2020), who have shorter average holding periods, exhibit greater turnover, cause short-term reversals, and attenuate momentum (Du et al., 2022). Second, the explanatory power of the significant reversal portfolio on the factor momentum strategy, reported in Section IV. A, may decrease the performance of factor momentum in China.

Overall, factor momentum is a profitable investment strategy in China, and investors may benefit from factor return autocorrelations.

6.2. Stock market crashes

The Chinese stock market was affected by the 2008 global financial crisis and the 2015 stock crash. In 2015, the Chinese stock market experienced a tremendous rise followed by a sharp drop (Liu et al., 2016). To investigate whether factor momentum exists during these two crash periods, we construct factor momentum strategies from July 2008 to December 2010 and from July 2015 to December 2017.

Table 15 shows that conditional factor momentum continues to exist and remains robust for both crash periods. Specifically, the TSFM strategy has an average return of 9.21 % ($t = 2.37$), and the CSFM strategy has an average return of 7.47 % ($t = 2.94$), similar to the main results in Table 3. The long legs contribute more to the factor momentum performance. The Sharpe ratios reach 0.93 and 1.08 for the TSFM and CSFM strategies, respectively. The factor models cannot explain the full-sample or long-leg portfolios for the conditional strategies. Overall, our findings suggest that factor momentum performs well during stock market crash periods, which is different from traditional momentum.

6.3. Price limit

China's stock market restricts daily price movements for regular stocks to a maximum of 10 %, leading to concerns about whether this regulation affects the efficacy of the factor momentum strategy. To address this issue, we remove the stocks that surpass the limit line (i.e., those that exceed 9.8 % or fall below –9.8 %) for more than 10 trading days per month. Subsequently, we construct time-series factor momentum portfolios from January 2002 to December 2019, and present the findings in Table 16. Notably, the TSFM portfolio yields an annualized return of 9.16 % ($t = 4.28$) and a Sharpe ratio of 1.01, which are similar to the full sample analysis. Therefore, we conclude that stocks triggering the price limit line merely influence the overall profits of factor momentum.[7]

[7] We also test the effect of price limit on stock momentum and find that after deleting the stocks that trigger the price limit line, the performance of stock momentum in China increases. Its Sharpe ratio reaches 0.41.

Table 14
Different Holding and Formation Periods
Panels A and B report the annualized average returns and *t*-statistics (in square brackets) as well as the annualized Sharpe ratios of the alternative holding and formation periods of the time-series factor momentum strategy of the 10 non-momentum factors in China, respectively. Specifically, the factor momentum signals are constructed based on the average return in the prior *k* months and held for *h* months with $k, h = 1, 3, 6, 9, 12, 36$, and 60, without dropping the most recent month. We bold all the positively significant returns. All returns are reported in percentage. The sample period runs from January 2002 to December 2019.

Holding/Formation	1	3	6	9	12	36	60
Panel A: Mean Return							
1	**5.07** [2.22]	**5.74** [2.47]	**4.26** [1.79]	**6.85** [3.42]	**9.91** [4.88]	**8.61** [4.14]	**6.92** [3.60]
3	3.18 [1.35]	**4.91** [2.12]	**3.91** [1.72]	**7.47** [3.54]	**7.64** [3.55]	**8.98** [4.28]	**6.34** [3.34]
6	–0.12 [–0.05]	3.16 [1.36]	**5.69** [2.48]	**6.02** [2.78]	**6.83** [3.26]	**6.74** [3.21]	**5.85** [2.96]
9	1.11 [0.51]	**5.54** [2.71]	**5.90** [2.89]	**9.26** [4.69]	**8.22** [4.03]	**9.19** [4.82]	**5.81** [3.09]
12	3.50 [1.49]	**4.77** [2.24]	**5.84** [2.66]	**6.59** [3.27]	**7.49** [3.55]	**7.35** [3.29]	**6.24** [2.91]
36	**4.01** [1.75]	**6.80** [3.04]	**5.84** [2.48]	**7.70** [3.45]	**8.51** [3.63]	**8.29** [3.77]	**6.03** [2.70]
60	–6.87 [–2.56]	–0.76 [–0.30]	2.30 [0.80]	**4.78** [1.67]	**5.15** [1.77]	**4.61** [1.84]	**5.20** [2.17]
Panel B: Sharpe Ratio							
1	0.52	0.58	0.42	0.80	1.15	0.97	0.85
3	0.32	0.50	0.41	0.83	0.83	1.00	0.79
6	−0.01	0.32	0.58	0.65	0.77	0.75	0.70
9	0.12	0.64	0.68	1.10	0.95	1.13	0.73
12	0.35	0.53	0.63	0.77	0.83	0.77	0.68
36	0.43	0.75	0.61	0.85	0.89	0.92	0.66
60	–0.67	–0.08	0.21	0.44	0.46	0.48	0.57

Table 15
Performance of the TSFM and CSFM Strategies in Stock Market Crash Periods
This table reports the annualized average returns, standard deviations, Sharpe ratios (SR), abnormal alphas (FF5-α, CH3-α, and Cond-CH3-α), and corresponding *t*-statistics (in square brackets) for time-series and cross-sectional factor momentum, winners, and losers with the 10 non-momentum factors in China's two market crash periods. The conditional CH3 model (Cond-CH3) imposes the investor sentiment into the model's β. All returns are reported in percentage. The sample periods run from July 2008 to December 2010 and from July 2015 to December 2017.

	Mean	STD	SR	FF5-α	CH3-α	Cond-CH3-α
Panel A: Time-series factor momentum						
Full Sample	9.21 [2.37]	9.90	0.93	9.84 [2.43]	8.64 [1.86]	8.51 [1.84]
Winners	19.49 [5.06]	11.53	1.69	14.40 [5.71]	8.76 [2.38]	8.62 [2.33]
Losers	12.54 [1.97]	16.50	0.76	8.16 [1.52]	3.00 [0.56]	3.02 [0.55]
Panel B: Cross-sectional factor momentum						
Full Sample	7.47 [2.94]	6.92	1.08	6.48 [2.36]	5.04 [1.88]	4.96 [1.82]
Winners	24.26 [5.05]	14.79	1.64	17.76 [4.73]	11.76 [2.68]	11.60 [2.63]
Losers	9.31 [2.25]	10.95	0.85	4.68 [1.63]	1.56 [0.40]	1.42 [0.38]

Table 16
Performance of the TSFM Considering Price Limit
This table reports the annualized average returns, standard deviations, Sharpe ratios (SR), and corresponding *t*-statistics (in square brackets) for time-series factor momentum, winners, and losers with the 10 non-momentum factors considering the price limitation. Specifically, we delete the stocks that trigger the limit line (above 9.8 % or below –9.8 %) more than 10 trading days in a month. All returns are reported in percentage. The sample period runs from January 2002 to December 2019.

	Mean	STD	SR
Full Sample	9.16 [4.28]	9.09	1.01
Winners	9.06 [4.10]	9.39	0.96
Losers	–8.94 [–3.37]	11.25	–0.79

7. Conclusion

Factor momentum strategies are valuable, beneficial, and robust in the Chinese stock market. By employing 10 commonly used non-momentum factors, we demonstrate that both the TSFM and CSFM strategies generate positively significant returns and high Sharpe ratios. The TSFM strategy outperforms the CSFM strategy, as the former purely bets on the factor return autocorrelations.

We document the strong power of factor momentum in subsuming stock momentum, high-priced stock momentum, and industry momentum, along with digesting its constituent factors as well as various categories of anomalies. Stock-level momentum and reversal strategies cannot absorb factor momentum. Furthermore, we examine the economic channels of factor momentum. We find that factor momentum generates higher returns during periods of higher aggregate idiosyncratic volatility and lower investor sentiment as well as among stocks with higher information asymmetry and short-sale constraints, consistent with increased arbitrageur participation in correcting mispricing under these scenarios. Moreover, we observe that factor timing and factor premiums both contribute to factor momentum returns. In addition, the collectivistic culture, that leading to herding behavior, may contribute to the factor momentum.

This study thus answers the question of whether factor momentum is statistically and economically significant in a market that lacks stock-level momentum, such as the Chinese stock market. The explanatory power and economic grounds of factor momentum in China provide important implications for the global market.

Author statement

All authors have equal contribution.

Supplementary materials

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