Finance Research Letters 29 (2019) 206–215

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Residual momentum and the cross-section of stock returns: Chinese evidence

Qi Lin

School of Finance, Zhejiang University of Finance & Economics, 18 Xueyuan Street, Hangzhou 310018, China

A R T I C L E I N F O

Keywords:
Residual momentum
Conventional momentum
Asset pricing
Chinese market

JEL classification:
G12
G14,

A B S T R A C T

In this paper, I find that sorting stocks into portfolios based on their residual, as opposed to raw past returns, generates significant profits in the Chinese equity market and cannot be subsumed by the well-established factor models. Moreover, the residual momentum profits do not reverse in the long run (up to three years), supporting the investor underreaction hypothesis. Further analysis reveals that residual momentum is priced in the cross-section of stock returns whereas the Carhart (1997) momentum factor is found to be redundant for describing average stock returns.

1. Introduction

Momentum, a strategy that simultaneously buys winner stocks and shorts loser stocks, is one of the most persistent anomalies in finance. Although momentum profits have been widely documented in both U.S. and international equity markets (Jegadeesh and Titman, 1993; 2001; Griffin et al., 2003; Chui et al., 2010; Fama and French, 2012), the momentum strategy is ineffective in the Chinese market, where it fails to generate significant profits (Wang and Xu, 2004; Cheema and Nartea, 2014; Goyal and Wahal, 2015). The motivation for analyzing momentum patterns in the Chinese A-share market is inspired by the growing interest in momentum strategies alongside the gradual relaxation of capital controls and internationalization of the Chinese capital markets, which present both challenging and exciting opportunities for both domestic and international investors. Given the importance of the momentum anomaly in asset pricing literature and that the Chinese equity market is now the second largest equity market in the world, it is important to investigate whether there are other forms of momentum patterns in the cross-section of stock returns in the Chinese market.

In this paper, I evaluate the profitability of a momentum strategy based on residual stock returns instead of raw stock returns as in Jegadeesh and Titman (1993) for portfolio decisions, which remains an open question in the Chinese equity market. Residual stock returns are estimated each month for all eligible stocks trading in both the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) using 36-month rolling regressions of excess returns on three Fama and French (1993) factors. As noted by Blitz et al. (2011, 2017) and Chang et al. (2018), constructing the momentum strategy based on residual returns significantly reduces the volatility of the momentum strategy compared to constructing it on raw returns; this is because a substantial portion of the risk of conventional momentum returns can be attributed to the strategy's time-varying exposures to the Fama and French factors.[1]

Consistent with the prior literature, I find that the Jegadeesh and Titman (1993) conventional momentum strategy is unprofitable whereas the residual momentum strategy yields substantial profits in the Chinese equity market. Stocks in the highest residual momentum (winner) decile generate approximately 10.584% more annual returns compared to stocks in the lowest residual

E-mail address: qlin_sf@zufe.edu.cn.

[1] Throughout the paper, I refer to the momentum strategy of Jegadeesh and Titman (1993) as the conventional momentum strategy.

https://doi.org/10.1016/j.frl.2018.07.009
Received 18 May 2018; Received in revised form 1 July 2018; Accepted 21 July 2018
Available online 26 July 2018
1544-6123/

momentum (loser) decile. After controlling for the well-known market, size, book-to-market, momentum, profitability, and investment factors of Fama and French (1993, 2015) and Carhart (1997), I find the difference between the returns on the portfolios with the winner and loser (risk-adjusted returns/alphas) remains positive and highly significant. However, the raw and risk-adjusted returns for the conventional momentum strategy are tiny and indistinguishable from zero. Moreover, the success of the residual momentum strategy is largely attributed to its lower volatility, skewness, kurtosis, and smaller extreme returns in absolute values than those of the conventional momentum strategy, which in turn yields a much greater Sharpe ratio.

More importantly, the residual momentum profits do not display long-run reversal in returns (three months to three years after formation), suggesting an underreaction to stock returns. Similarly, given that their abnormal-return momentum does not reverse over long-term holding periods, Gutierrez and Prinsky (2007) argue that the abnormal-return momentum strategy supports the gradual-information-diffusion hypothesis, which is caused by investor underreaction to firm-specific information rather than to public information. In fact, the residual momentum strategy persists for at least two years on average, generating significant and robust risk-adjusted profits in the range of 300–800 basis points.

Next, I address one of the fundamental asset pricing questions that considers if residual momentum is an important factor in describing average returns in China. In other words, I investigate whether adding the residual momentum strategy to the investment opportunity set results in an attainable Sharpe ratio that significantly exceeds the ratio that can be achieved with the explanatory strategies consisting of already documented factors. For nested models, Barillas and Shanken (2017) argue that model comparison is equivalent to examining whether the excluded factors can be spanned by the remaining factors in the larger model, namely, simply running the factor spanning test of Fama and French (2015, 2016). I show that the residual momentum factor cannot be captured by any of the well-known factor models, even when the conventional momentum factor is included, whereas the conventional momentum factor is found to be redundant and thus does not add significantly to the investment opportunity set. To further compare the performance of both momentum factors in factor models, I conduct a Bayesian asset pricing test developed by Barillas and Shanken (2018), which computes model probabilities for the collection of all possible factor models that can be formed from a given set of factors. I find consistent evidence that the model with the highest posterior probability is the model that contains all non-momentum factors and the residual momentum factor instead of the conventional momentum factor. Further analysis reveals that the cumulative factor probabilities for the residual momentum factor are close to one, whereas the conventional momentum factor is ranked lowest, with a cumulative probability of only 39%. Taken together, my results indicate that substituting the conventional momentum factor with a residual momentum factor can substantially improve a model's pricing ability.

The remainder of this paper is organized as follows. Section 2 describes the data and variables. In Sections 3 and 4, I investigate the profitability of both conventional and residual strategies and the pricing performance of their corresponding factors. The last section concludes the paper.

2. Data and variable definitions

2.1. Data

To construct my main sample, I use all A-share stocks that are publicly traded on both the SHSE and SZSE. Stock market data and accounting information come from the China Stock Market & Accounting Research (CSMAR) database. To ensure that I have a reasonable number of listed firms in the formation year, the annual accounting information sample period is between 1993 and 2016 and the market information sample period is from July 1994 to December 2017. Consistent with earlier studies, I exclude firms with the ST/PT status (short for special treatment and particular transfer, respectively) and firms with share price below 5 yuan at the portfolio formation month to reduce microstructure concerns. To minimize potential backfilling and survival biases, a firm must have appeared in the CSMAR database for at least two years before I begin calculating the accounting variables. To ensure that the firm-specific variables are in the investors' information set when the test portfolios are constructed, I follow the timing convention documented in prior literature. That is, the valid annual accounting variables for fiscal year ending in calendar year $t-1$ are matched with portfolios that are constructed at the end of June of year t. All annual variables are updated at the end of June each year. The total number of firms left after the above-mentioned sample selection criteria is on average 1403, which accounts for approximately 94% of total listed firms. Details on the number of listed firms over time are provided in Table A1.

2.2. Construction of momentum strategies

The conventional momentum strategy is constructed following the common approach of using prior 11-month returns from month $t-12$ through month $t-2$ and holding these portfolios for K month(s) in the empirical literature (see, e.g., Jegadeesh and Titman, 1993; 2001). To avoid the 1-month reversal in stock returns that may be related to liquidity or microstructure frictions, I skip the most recent month.

According to Blitz et al. (2011, 2017), the residual momentum strategy is constructed in three steps. First, residual returns are estimated each month from monthly rolling regressions of excess stock returns on three Fama and French (1993) factors from month $t-36$ to month $t-1$. Specifically, at the beginning of each month t, I run the following time-series regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{Mkt} \times Mkt_t + \beta_i^{SMB} \times SMB_t + \beta_i^{HML} \times HML_t + \varepsilon_{i,t}, \tag{1}$$

where $r_{f,\,t}$ is the risk-free rate and Mkt, SMB, and HML are the Fama and French (1993) factors. To improve the accuracy of the

Table 1
Performance of momentum strategies.
For each month, decile portfolios are formed by sorting individual stocks based on their past cumulative scaled residual returns and raw returns, where the winner (loser) decile contains stocks with the highest (lowest) cumulative returns during the prior 11 months. Conventional momentum is defined as the 12–2 month raw stock returns and residual momentum is the 12–2 months scaled residual returns estimated over past 36 months using the Fama and French (1993) three-factor model. The table presents the average excess returns (RET–RF) and risk-adjusted returns (alphas) for the decile portfolios and the zero-investment Winner–Loser decile portfolios formed on residual and conventional momentum separately. The factor models include the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the four-factor model augmenting the Fama and French (1993) three-factor model with a Carhart (1997) conventional momentum factor (C4), and the Fama and French (2015) five-factor model (FF5). Newey–West heteroscedasticity- and autocorrelation-robust *t*-statistics (with a lag of 12) are given in parentheses. The last seven rows present the summary statistics of profits for the residual and conventional momentum strategies, which include standard deviation, Sharpe ratio (information ratio), median, maximum, minimum, skewness, and kurtosis. The Sharpe ratio (SR) and the information ratio (IR) are annualized. The sample period is July 1997–December 2017.

Decile	Residual momentum					Conventional momentum				
	RET–RF	CAPM	FF3	C4	FF5	RET–RF	CAPM	FF3	C4	FF5
Loser	0.739	−0.088	−0.567	−0.550	−0.451	1.088	0.278	−0.219	−0.113	−0.053
	(0.934)	(−0.337)	(−3.833)	(−3.724)	(−3.470)	(1.423)	(0.866)	(−1.095)	(−0.726)	(−0.270)
2	0.925	0.112	−0.304	−0.311	−0.195	1.309	0.508	−0.131	−0.061	0.012
	(1.249)	(0.505)	(−2.431)	(−2.531)	(−1.639)	(1.623)	(1.817)	(−1.136)	(−0.715)	(0.107)
3	1.191	0.365	−0.020	−0.040	0.049	1.429	0.620	0.018	0.064	0.112
	(1.524)	(1.591)	(−0.175)	(−0.377)	(0.386)	(1.770)	(2.164)	(0.162)	(0.850)	(0.966)
4	1.214	0.411	−0.018	−0.029	0.053	1.419	0.611	−0.012	0.020	0.067
	(1.615)	(1.983)	(−0.177)	(−0.311)	(0.534)	(1.735)	(2.219)	(−0.149)	(0.348)	(0.828)
5	1.173	0.365	−0.047	−0.078	−0.020	1.473	0.673	0.093	0.099	0.136
	(1.479)	(2.179)	(−0.272)	(−0.522)	(−0.151)	(1.820)	(2.700)	(1.047)	(1.138)	(1.560)
6	1.246	0.442	0.058	0.030	0.099	1.492	0.687	0.134	0.128	0.156
	(1.624)	(2.607)	(0.489)	(0.307)	(1.052)	(1.875)	(2.839)	(2.312)	(2.218)	(2.530)
7	1.500	0.712	0.273	0.244	0.322	1.447	0.649	0.141	0.117	0.092
	(1.847)	(3.056)	(1.782)	(1.805)	(2.472)	(1.818)	(2.922)	(1.163)	(1.026)	(0.905)
8	1.480	0.691	0.240	0.210	0.239	1.257	0.443	−0.014	−0.070	−0.076
	(1.931)	(3.642)	(1.869)	(1.916)	(2.411)	(1.630)	(2.140)	(−0.103)	(−0.686)	(−0.609)
9	1.377	0.598	0.202	0.164	0.210	1.113	0.324	−0.020	−0.111	−0.127
	(1.867)	(2.901)	(1.427)	(1.306)	(1.741)	(1.472)	(1.723)	(−0.113)	(−0.980)	(−0.878)
Winner	1.622	0.854	0.444	0.426	0.481	1.114	0.342	0.151	0.010	−0.122
	(2.089)	(4.115)	(4.578)	(4.250)	(5.163)	(1.561)	(1.415)	(0.531)	(0.065)	(−0.572)
Winner–Loser	0.882	0.941	1.011	0.976	0.931	0.026	0.063	0.371	0.124	−0.068
	(4.491)	(4.811)	(5.476)	(4.974)	(5.066)	(0.071)	(0.170)	(0.930)	(0.729)	(−0.216)
Standard deviation	0.035					0.056				
SR(IR)	0.873	0.947	1.116	1.103	1.034	0.016	0.039	0.236	0.179	−0.046
Median(%)	0.970					−0.127				
Maximum(%)	14.420					20.700				
Minimum(%)	−9.654					−16.129				
Skewness	0.049					0.441				
Kurtosis	4.205					4.517				

estimation, I require that a stock have a complete return history over the 36-month rolling regression window to be included in the regression.[2] I then calculate the residual returns as:

$$\hat{\varepsilon}_{i,t} = r_{i,t} - r_{f,t} - \hat{\alpha}_i - \widehat{\beta}_i^{Mkt} \times Mkt_t - \widehat{\beta}_i^{SMB} \times SMB_t - \widehat{\beta}_i^{HML} \times HML_t. \tag{2}$$

Finally, I scale the residual returns with their volatilities as in Blitz et al. (2011) and then construct the residual momentum using the prior 11-month scaled residual returns from month $t - 12$ through month $t - 2$.

At the beginning of each month t, I split all stocks into deciles based on the values of the average stock return or scaled residual return over the prior 11-month from month $t - 12$ through month $t - 2$. Stocks with an average stock return or scaled residual return that ranked at the top 10% are defined as winners, and those ranked at the bottom 10% are defined as losers. In each month t, I hold the monthly decile portfolios for K month(s). A holding period longer than one month means that for a given decile in each month t there exist K subdeciles, each of which is carried from the previous $t - K$ months. I then take the simple average of the K subdecile returns. The long-short (winners minus losers) portfolios are updated at the beginning of the subsequent month. To facilitate the comparison of my results with those in the prior literature (e.g., Jegadeesh and Titman, 1993; Blitz et al., 2011; 2017), I use equal-weighting technique throughout the remainder of my paper.

[2] I also apply a rolling window size of five years or require a minimum of 24 valid observations to estimates residual returns following representative studies (Fama and French, 1992; Avramov and Chordia, 2006; Fama and French, 2016) and obtain robust results.

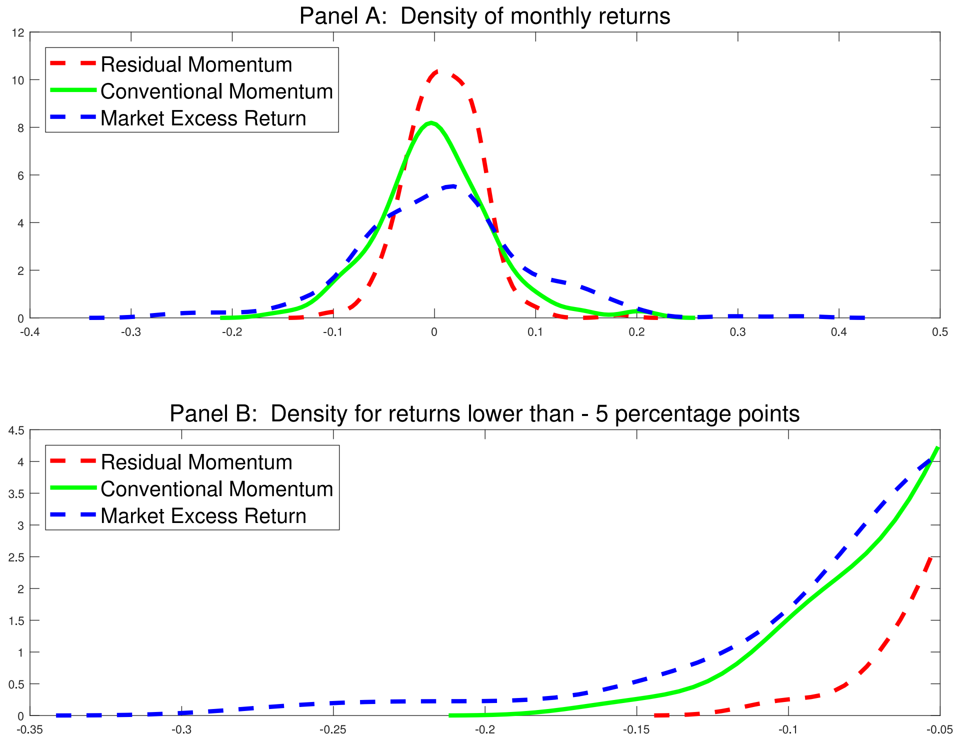

Fig. 1. The density of residual and conventional momenta along with the market portfolio.
Panel A depicts results of the density function of residual and conventional momenta along with the market portfolio, and Panel B depicts results of the density of these portfolios for returns lower than − 5 percentage points. Conventional momentum is defined as the 12–2 month raw stock returns and residual momentum is the 12–2 months scaled residual returns estimated over past 36 months using the Fama and French (1993) three-factor model. Portfolios are constructed using monthly holding periods. The sample period is July 1997–December 2017.

3. Strategy profitability

I begin my empirical analysis by investigating the performance of the conventional momentum and residual momentum strategies in China. Table 1 presents the average excess returns and risk-adjusted abnormal returns (alphas) on the equal-weighted portfolios, along with summary statistics.[3]

Consistent with the prior literature, the conventional momentum strategy cannot yield significant profits in the Chinese market. This is true regardless of whether one considers raw returns or risk-adjusted abnormal returns. The average return difference between the winner and loser is 0.026% per month, with a tiny Newey–West *t*-statistic of 0.071. The strategy continues to remain unprofitable after adjusted with factor models. The CAPM, FF3, C4, and FF5 alphas are 0.063%, 0.371%, 0.124%, and −0.068%, respectively, with Newey–West *t*-statistics less than one standard error from zero.

In contrast, the average excess return of the residual momentum portfolio increases monotonically from 0.739% to 1.622% per month when moving from the lowest to the highest past cumulative residual return decile. The average return difference between winner and loser deciles is 0.882% per month, with a Newey–West *t*-statistic of 4.491 and a Sharpe ratio of 0.873, which is much greater than that of the conventional momentum (0.016). This result indicates that stocks in the winner decile generate 10.584% higher annual returns than stocks in the loser decile. Another important gain of the residual momentum portfolio appears in the improvement in the higher-order moments. Isolating dynamic exposures to the Fama–French factors lowers the excess kurtosis from

[3] I employ four popular factor models, including the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), and the Fama and French (2015) five-factor model (FF5). Guo et al. (2017) and Lin (2017) show that FF5 substantially outperforms FF3 in capturing cross-sectional stock returns in the Chinese market. Note that the construction of the size factor, SMB, in Guo et al. (2017) is slightly different from mine, which closely follows Fama and French (2015). Instead, Guo et al. (2017) define SMB as the average of four stock portfolio returns ($SMB_{B/M}$, SMB_{OP}, SMB_{InvA}, and SMB_{InvB}), which are constructed by averaging the difference between three small and large B/M, OP, InvA, and InvB stock portfolio returns for each month, respectively. InvA is annual growth rate in total assets, and InvB is annual growth rate in book equity. In the factor spanning test of Fama and French (2015, 2016), I find that both the value factor, HML, and the profitability factor, RMW, in the five-factor model are important factors in capturing return patterns, whereas nothing is lost in the explanation of average returns if the investment factor, CMA, is excluded, which is consistent with the findings of Guo et al. (2017) and Lin (2017). However, the market factor, Mkt, is also found to be important for describing average returns, which is in line with Lin (2017) but inconsistent with Guo et al. (2017) who argue that Mkt is redundant in their sample. The results are presented in Table A2.

Table 2
Performance of momentum strategies across subsampels.

For each month, decile portfolios are formed by sorting individual stocks based on their past cumulative scaled residual returns and raw returns, where the winner (loser) decile contains stocks with the highest (lowest) cumulative returns during the prior 11 months. Conventional momentum is defined as the 12–2 month raw stock returns and residual momentum is the 12–2 months scaled residual returns estimated over past 36 months using the Fama and French (1993) three-factor model. The table presents the average excess returns (RET–RF) and risk-adjusted returns (alphas) for the decile portfolios and the zero-investment Winner–Loser decile portfolios formed on residual and conventional momentum separately. The sample is divided into three periods: January 1997 to December 2006 (Panel A), January 2007 to December 2009 (Panel B), and January 2010 to December 2017 (Panel C). The factor models include the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the four-factor model augmenting the Fama and French (1993) three-factor model with a Carhart (1997) conventional momentum factor (C4), and the Fama and French (2015) five-factor model (FF5). Newey–West heteroscedasticity- and autocorrelation-robust *t*-statistics (with a lag of 12) are given in parentheses. The Sharpe ratio (SR) and the information ratio (IR) are annualized.

	Residual momentum					Conventional momentum				
	RET–RF	CAPM	FF3	C4	FF5	RET–RF	CAPM	FF3	C4	FF5
						Panel A: January 1997 to December 2006				
Winner–Loser	0.633	0.688	0.781	0.679	0.508	0.640	0.681	1.167	0.182	0.430
	(2.465)	(2.977)	(2.831)	(2.687)	(2.262)	(1.371)	(1.406)	(2.834)	(1.408)	(1.227)
Standard deviation	0.036					0.062				
SR(IR)	0.606	0.679	0.831	0.727	0.559	0.355	0.378	0.833	0.356	0.365
						Panel B: January 2007 to December 2009				
Winner–Loser	0.586	0.629	0.666	1.167	0.765	−0.991	−0.966	−0.982	0.292	−0.907
	(2.039)	(2.687)	(3.000)	(3.602)	(3.928)	(−1.166)	(−1.270)	(−1.281)	(0.699)	(−1.158)
Standard deviation	0.033					0.052				
SR(IR)	0.623	0.663	0.710	1.520	0.809	−0.657	−0.634	−0.639	0.461	−0.580
						Panel C: January 2010 to December 2017				
Winner–Loser	1.390	1.444	1.418	1.413	1.503	−0.224	−0.211	−0.535	−0.321	−0.649
	(3.953)	(3.834)	(4.806)	(4.914)	(5.335)	(−0.359)	(−0.326)	(−0.739)	(−1.093)	(−0.966)
Standard deviation	0.035					0.048				
SR(IR)	1.393	1.473	1.862	1.844	2.006	−0.161	−0.150	−0.391	−0.380	−0.480

4.517 to 4.205 and reduces the right skew from 0.441 to just 0.049 and the minimum from −16.129% to −9.654%. This reduction practically mitigates the crash risk of momentum (Barroso and Santa-Clara, 2015). Fig. 1 depicts the density function of two momenta. Consistently, conventional momentum has a long left tail, which is much reduced in the residual momentum. Moreover, controlling for the residual momentum strategy's exposure to the risk factors exacerbates the pricing errors of the spread portfolios. For example, the FF5 abnormal return is 0.931% per month, with a Newey–West *t*-statistic of 5.066. This evidence indicates that after controlling for the well-known market, size, book-to-market, investment, and profitability factors, the return difference between the winner and loser stocks remains positive and statistically significant.

To investigate the extent to which the performance of two momentum strategies may remain across different sample lengths, I further divide my sample period into three subsamples: January 1997 to December 2006, January 2007 to December 2009, and January 2010 to December 2017, which is presented in Table 2. Similar to the findings using the full sample in Table 1, the residual momentum strategy continues to yield significant raw and risk-adjusted abnormal returns (alphas) during the three subsample periods, indicating that the results are less likely due to the choice of sample length. In addition, the residual momentum strategy performs better in the last subsample, although its profitability remains in both expansionary and recessionary periods. In contrast, the conventional momentum strategy fails to generate significant profits in all subsample periods, in line with its poor full-sample performance documented in Table 1.

Fig. 2 presents similar, more nuanced results graphically. Panel A of Fig. 2 depicts the cumulative performances of conventional and residual momenta along with the market portfolio. As shown in Panel A, residual momentum generates more consistent returns than conventional momentum and is less likely to be affected by market crash, which may explain its significant abnormal returns generated during recessions. Panel B of Fig. 2, which depicts the two strategies' realized trailing three-year Sharpe ratios, shows that the residual momentum strategy performed consistently well over the entire sample, especially in the last six years. The conventional momentum strategy, in contrast, underperforms the residual momentum strategy in most periods, and it generates negative returns from 2009 to 2013 and in recent two years.[4]

Since the residual momentum strategy performs well over short-term holding periods, I am also interested in its long-term performance. If the profits of the residual momentum strategy are sourced from investor underreaction, the profits should exhibit

[4] I also show that constructing a momentum portfolio with residual returns successfully reduces drawdowns in my sample (unreported for brevity), with magnitudes and lengths less severe than those for conventional momentum.

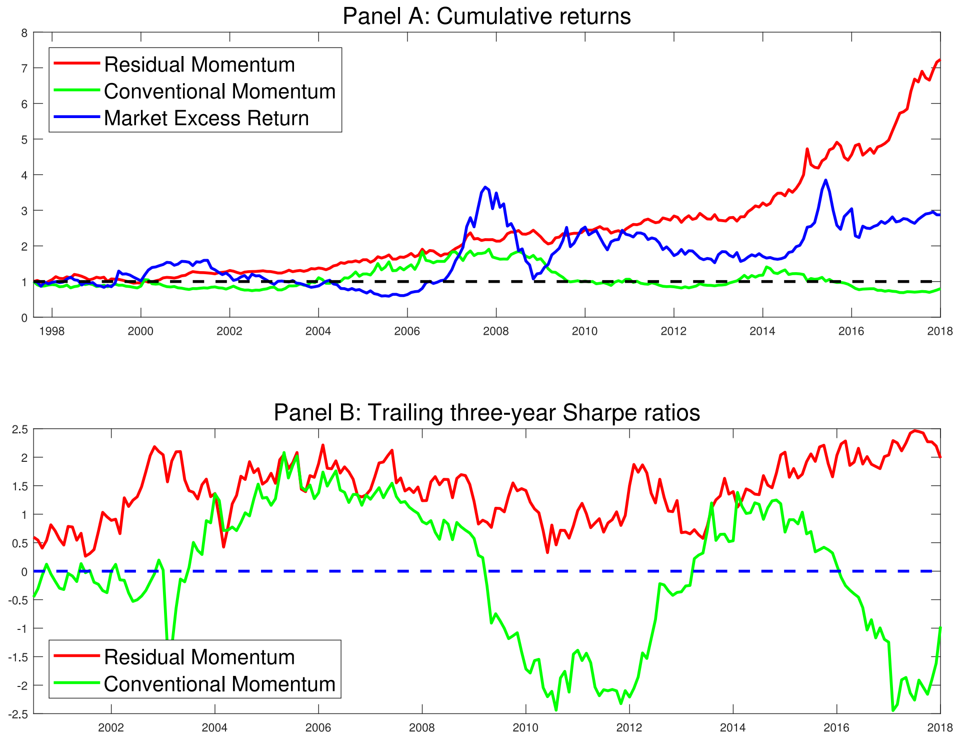

Fig. 2. Cumulative returns and three-year trailing Sharpe ratios on momentum strategies and market portfolios.
Panel A depicts results of cumulative returns of the zero-investment Winner–Loser decile portfolios formed on residual and conventional momentum along with the market portfolio. Conventional momentum is defined as the 12–2 month raw stock returns and residual momentum is the 12–2 months scaled residual returns estimated over past 36 months using the Fama and French (1993) three-factor model. Panel B depicts results of the Sharpe ratios of residual and conventional momentum strategies based on a three-year rolling window. Portfolios are constructed using monthly holding periods. The sample period is July 1997–December 2017 in Panel A and is July 2000–December 2017 in Panel B.

reversals in the long-run (Blitz et al., 2011; Da et al., 2014). In contrast, investor overreaction should generate continued returns (Blitz et al., 2011; 2017). Table 3 presents the results for the long-term performance to momentum strategies. The profits generated from the residual momentum strategy decrease over time. However, the strategy displays significant risk-adjusted profits at least up to 21 months and exhibits no reversals over the longer holding horizons, which is consistent with the investor underreaction hypothesis. In contrast, I find some evidence in China that profits with the conventional momentum strategy reverse in the long run, consistent with long-term return reversals that De Bondt and Thaler (1985) document.

Taken as a whole, my findings reveal that the failure of the conventional momentum in the Chinese market is primarily due to the time-varying exposures to the Fama and French (1993) factors. Momentum profits can be improved by ranking stocks on residual returns instead of raw returns. My results also indicate that the success of the residual momentum strategy in the Chinese market appears to be due to investor underreaction.[5]

4. Pricing performance

Having demonstrated the important role the residual return plays in predicting the cross-sectional stock returns, I proceed by generating a residual momentum factor and examining whether the ability of well-known factors can capture its factor premium. Following Fama and French (1993, 2015), at the end of each month, I independently sort all stocks into two size groups based on market capitalization, with the breakpoint dividing the two groups being the median market capitalization of stocks traded on both the SHSE and SZSE, and three groups based on the prior 11-month cumulative residual returns from month $t-12$ to $t-2$. The intersections of the two size groups and three residual momentum groups generate six portfolios. The residual momentum factor return, UMD^r, is taken as the difference between the simple average of the monthly value-weighted returns on the high 30% and low 30% prior residual return portfolios, which therefore captures returns associated with residual momentum while maintaining neutrality to market capitalization. For comparison, I also form the conventional momentum factor, UMD, using the same factor-forming technique.

[5] Comprehensively examine the sources of residual momentum profits in China can be an interesting topic in future research.

Table 3
Long-term profitability of momentum strategies.

The table presents the average excess returns (RET–RF) and risk-adjusted returns (alphas) along with the Sharpe ratios for the zero-investment Winner–Loser decile portfolios formed on residual and conventional momentum with holding periods (*K*) of the subsequent 3 to 36 months after portfolio formation separately. Conventional momentum is defined as the 12–2 month raw stock returns and residual momentum is the 12–2 months scaled residual returns estimated over past 36 months using the Fama and French (1993) three-factor model. The factor models include the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the four-factor model augmenting the Fama and French (1993) three-factor model with a Carhart (1997) conventional momentum factor (C4), and the Fama and French (2015) five-factor model (FF5). Newey–West heteroscedasticity- and autocorrelation-robust *t*-statistics (with a lag of 12) are given in parentheses. The Sharpe ratios are annualized.

K=	3	6	9	12	15	18	21	24	27	30	33	36
Panel A: Residual Momentum												
RET–RF	0.740	0.603	0.455	0.348	0.312	0.304	0.259	0.225	0.216	0.191	0.202	0.217
	(3.933)	(3.259)	(2.406)	(1.831)	(1.699)	(1.741)	(1.497)	(1.380)	(1.429)	(1.286)	(1.483)	(1.705)
CAPM	0.801	0.674	0.532	0.426	0.401	0.387	0.348	0.305	0.280	0.260	0.262	0.272
	(4.212)	(3.661)	(2.832)	(2.273)	(2.202)	(2.206)	(2.039)	(1.909)	(1.880)	(1.811)	(1.963)	(2.198)
FF3	0.840	0.695	0.538	0.426	0.396	0.398	0.370	0.327	0.312	0.297	0.294	0.287
	(4.705)	(3.919)	(3.201)	(2.598)	(2.439)	(2.503)	(2.384)	(2.255)	(2.350)	(2.336)	(2.496)	(2.684)
C4	0.784	0.637	0.484	0.379	0.360	0.361	0.333	0.294	0.277	0.259	0.274	0.267
	(4.381)	(3.786)	(3.103)	(2.508)	(2.423)	(2.477)	(2.315)	(2.167)	(2.221)	(2.167)	(2.510)	(2.646)
FF5	0.702	0.554	0.434	0.331	0.307	0.302	0.283	0.235	0.222	0.201	0.202	0.176
	(3.819)	(3.262)	(2.483)	(1.965)	(1.884)	(1.970)	(1.944)	(1.722)	(1.758)	(1.665)	(1.747)	(1.674)
Sharpe ratio	0.225	0.204	0.169	0.134	0.126	0.128	0.112	0.104	0.103	0.093	0.103	0.118
Panel B: Conventional Momentum												
RET–RF	0.163	0.035	−0.066	−0.114	−0.155	−0.176	−0.240	−0.308	−0.350	−0.385	−0.458	−0.433
	(0.515)	(0.118)	(−0.236)	(−0.455)	(−0.635)	(−0.747)	(−1.052)	(−1.384)	(−1.639)	(−1.893)	(−2.264)	(−2.306)
CAPM	0.195	0.067	−0.033	−0.084	−0.123	−0.148	−0.209	−0.276	−0.316	−0.350	−0.420	−0.397
	(0.613)	(0.222)	(−0.117)	(−0.329)	(−0.498)	(−0.632)	(−0.940)	(−1.317)	(−1.600)	(−1.879)	(−2.292)	(−2.349)
FF3	0.528	0.441	0.363	0.302	0.287	0.270	0.215	0.144	0.140	0.086	0.055	0.026
	(1.519)	(1.375)	(1.208)	(1.127)	(1.138)	(1.136)	(0.962)	(0.683)	(0.698)	(0.459)	(0.310)	(0.152)
C4	0.248	0.182	0.128	0.107	0.147	0.133	0.085	0.034	0.036	−0.016	0.005	−0.026
	(1.492)	(0.982)	(0.700)	(0.614)	(0.816)	(0.735)	(0.474)	(0.195)	(0.222)	(−0.102)	(0.030)	(−0.166)
FF5	0.079	0.054	−0.011	−0.063	−0.094	−0.106	−0.155	−0.225	−0.242	−0.273	−0.292	−0.315
	(0.291)	(0.205)	(−0.042)	(−0.288)	(−0.472)	(−0.574)	(−0.862)	(−1.309)	(−1.514)	(−1.795)	(−1.964)	(−2.224)
Sharpe ratio	0.030	0.007	−0.014	−0.026	−0.037	−0.043	−0.060	−0.080	−0.095	−0.110	−0.138	−0.137

Table 4
Momentum factors as test assets.

The table presents the average monthly returns, alphas, and adjusted R^2s of both the residual and conventional momentum factors. At the end of each month, I independently sort all stocks into two groups based on market capitalization (size) and three residual or conventional momentum groups using their 30th and 70th percentile values. The intersections of the two size groups and three momentum groups generate six portfolios. The value-weighted return of the residual or conventional momentum factor (UMD^r or UMD) is taken as the average return of the two value-weighted winner portfolios minus the average return of the two value-weighted loser portfolios. The factor models include the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the four-factor model augmenting the Fama and French (1993) three-factor model with a momentum factor (M4), the Fama and French (2015) five-factor model (FF5), and the six-factor model that augments the Fama and French (2015) five-factor model with a momentum factor (M6). The Carhart (1997) conventional momentum factor is used as a regressor in Panel A and the residual momentum factor is used as a regressor in Panel B. Newey–West heteroscedasticity- and autocorrelation-robust *t*-statistics (with a lag of 12) are given in parentheses.

	Panel A: Residual Momentum Factor (UMD^r)						Panel B: Conventional Momentum Factor (UMD)					
	Average Return	CAPM	FF3	M4	FF5	M6	Average Return	CAPM	FF3	M4	FF5	M6
Intercept	0.412	0.478	0.571	0.546	0.456	0.469	0.031	0.052	0.177	−0.021	−0.105	−0.238
	(2.727)	(3.063)	(4.427)	(4.221)	(3.706)	(4.055)	(0.130)	(0.219)	(0.627)	(−0.081)	(−0.432)	(−1.023)
Mkt		−0.088	−0.059	−0.055	−0.036	−0.038		−0.028	−0.031	−0.011	0.021	0.031
		(−2.770)	(−2.788)	(−2.760)	(−1.750)	(−1.769)		(−0.626)	(−0.688)	(−0.228)	(0.485)	(0.676)
SMB			−0.202	−0.188	−0.104	−0.126			−0.093	−0.023	0.171	0.202
			(−3.763)	(−3.480)	(−1.691)	(−1.969)			(−0.887)	(−0.252)	(1.768)	(2.028)
HML			0.354	0.395	0.359	0.378			−0.285	−0.407	−0.157	−0.261
			(5.064)	(5.795)	(5.007)	(5.511)			(−1.591)	(−2.513)	(−0.780)	(−1.445)
RMW					0.277	0.224					0.427	0.347
					(2.865)	(2.189)					(2.342)	(1.995)
CMA					0.163	0.175					−0.096	−0.143
					(1.324)	(1.512)					(−0.517)	(−0.829)
UMD/UMD^r				0.142		0.125				0.346		0.291
				(2.172)		(1.860)				(2.484)		(2.029)
Adj.R^2		6.287%	39.230%	41.977%	41.553%	43.437%		0.023%	3.782%	8.130%	11.418%	14.274%

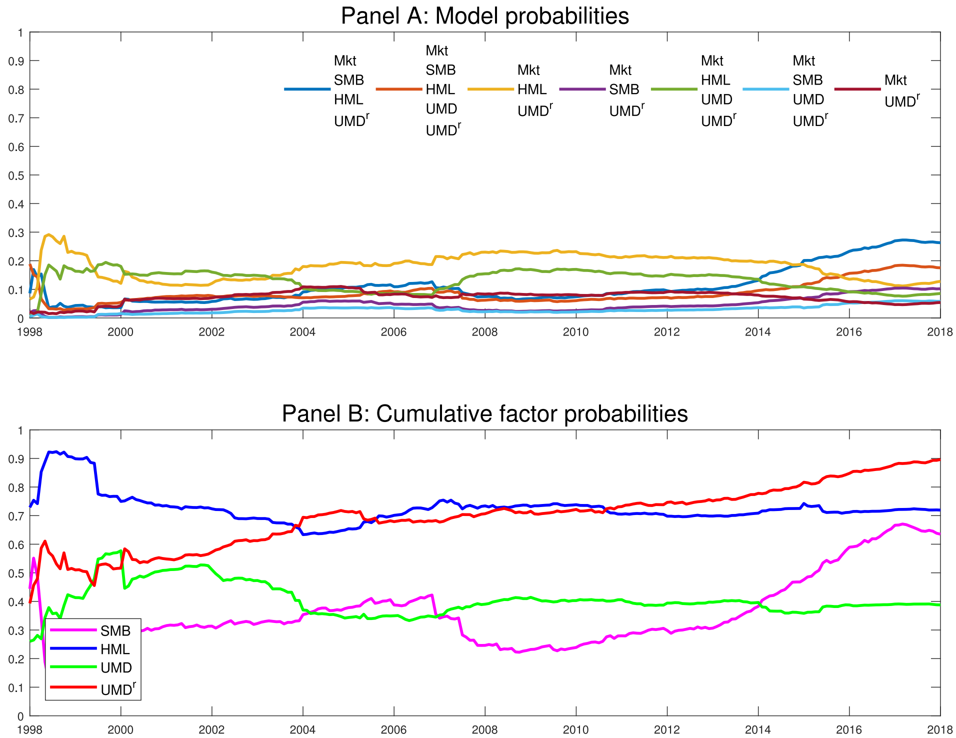

Fig. 3. Model probabilities and cumulative factor probabilities.
Panel A depicts the time series of posterior model probabilities for the seven factor models with highest probability (ranked at the end of the sample). Models are based on five factors: the three Fama and French (1993) factors (Mkt, SMB, and HML), the Carhart (1997) conventional momentum factor (UMD), and the residual momentum factor (UMD^r). Panel B depicts the time series of cumulative posterior probabilities for each of the four factors (exclude Mkt). Following Barillas and Shanken (2018), the prior is set so that $Sh_{\max} = 1.5 \times Sh(\text{Mkt})$, where $Sh(\text{Mkt})$ is the Sharpe ratio of the market factor. The sample period is December 1997–December 2017.

Barillas and Shanken (2017) argue that test assets are irrelevant for model comparison with traded factors when the squared Sharpe ratio metric is adopted, and they show that the Sharpe improvement metric for nested models can be simply conducted by testing the excluded factor restriction or running the factor spanning test of Fama and French (2015, 2016): whether the excluded factors can be spanned by the remaining factors in the larger model. Panel A of Table 4 shows that UMD^r generates an average monthly return of 0.412% with a Newey–West *t*-statistic of 2.727. I also estimate the alphas of UMD^r with respect to four different factor models. The alphas remain positive, ranging from 0.456% to 0.571% per month, and are statistically significant with Newey–West *t*-statistics ranging from 3.063 to 4.427, which indicates that UMD^r cannot be explained by the well-known risk factors. Panel B of Table 4 reveals that the intercepts in the regression of UMD on the factors of the Fama–French three-factor and five-factor models are indistinguishable from zero, consistent with the poor performance of the conventional momentum strategy documented above. This finding also indicates that adding UMD as a priced factor has no role in describing the cross-section of average returns in the model produced by combining the risk-free asset, market, size, value, profitability, and investment portfolios.

To further evaluate the UMD^r's pricing performance, I perform analysis as in Barillas and Shanken (2018) by implementing a Bayesian asset pricing test, which enables me to compare model probabilities for the collection of all possible factor models that can be formed from a given set of factors. To conserve space, I only repost results that consider the Fama–French three factors along with UMD and UMD^r, which is depicted in Fig. 3.[6] The model with the highest posterior probability is the four-factor model that augments the Fama and French (1993) three-factor model with UMD^r. I also find that the top seven models all include UMD^r, while only three models further include UMD. For cumulative factor probabilities, which are the sum of the posterior probabilities for models that include a particular factor, the probabilities for UMD^r are close to one, at approximately 90% (ranked at the end of the sample), followed by HML and SMB. UMD, however, is ranked lowest, with a cumulative probability of only 39%.

Taken together, the results in Table 4 and Fig. 3 demonstrate that augmenting UMD^r (instead of UMD) should improve a model's fit.

[6] In unreported tests, I further include RMW and CMA in the analysis and find that the six-factor model that augments the Fama and French (2015) five-factor model with UMD^r ranks at the top, followed by the five-factor model that includes the market factor, SMB, RMW, CMA, and UMD^r.

5. Conclusions

This paper investigates the role of residual momentum in the cross-sectional pricing of stock returns. Using a sample of all A-share stocks listed on the SHSE and SZSE over the sample period from July 1997 to December 2017, I find that the residual momentum strategy, as opposed to the conventional momentum strategy which fails to generate significant profits in the Chinese equity market, yields an annualized return of 10.584% and cannot be spanned by well-known factor models. My findings contribute to the literature on momentum strategies in China that although the conventional momentum is found unprofitable, hedging out the time-varying risk exposures can exhibit higher and more stable profitability. In addition, the residual momentum profits do not reverse in the long run, which implies that the profitability of the residual momentum strategy can be attributed to investor underreaction to information.

By conducting the factor spanning test of Fama and French (2015, 2016) and the Bayesian asset pricing test developed by Barillas and Shanken (2018), I further show that residual momentum is an important factor as it expands the efficient frontier comprising already established risk factors. However, the momentum factor is fully captured by its exposures to the factors included and ranks at the bottom based on factor cumulative probability, making it redundant for describing average returns in my sample. My analysis is of particular interest to both domestic and international investors given the rapid internationalization of the Chinese equity market and attractive characteristics of residual momentum, which presents an exciting opportunity for investors to outperform the market and generate superior risk-adjusted profits.

Acknowledgments

I am grateful to the editor, Narjess Boubakri, and an anonymous referee for valuable comments. I gratefully acknowledge fnancial support from the National Natural Science Foundation of China (Grant Numbers: 71703142 and 71471161) and the Key Program of the National Natural Science Foundation of China (Grant Number: 71631005).

Appendix A

Table A1

Number of firms: 1993–2016. The table presents the number of listed firms (Total N.), firms with the ST/PT status (ST/PT), firms that have appeared in the CSMAR database less than two years (< 2Y), and firms that are used for portfolio construction (N.) each year over the period 1993–2016. The percentage of firms with the ST/PT status (ST/PT(%)) and firms that are used for portfolio construction (N.(%)) are also presented in the last two columns.

Year	Total N.	ST/PT	< 2Y	N.	ST/PT(%)	N.(%)
1993	181	17	0	164	9.39	90.61
1994	292	25	0	267	8.56	91.44
1995	316	29	0	287	9.18	90.82
1996	522	52	0	470	9.96	90.04
1997	724	66	0	658	9.12	90.88
1998	829	71	0	758	8.56	91.44
1999	927	79	0	848	8.52	91.48
2000	1062	88	0	974	8.29	91.71
2001	1143	87	0	1056	7.61	92.39
2002	1205	81	0	1124	6.72	93.28
2003	1267	81	0	1186	6.39	93.61
2004	1356	74	0	1282	5.46	94.54
2005	1352	63	0	1289	4.66	95.34
2006	1435	63	0	1372	4.39	95.61
2007	1549	64	0	1485	4.13	95.87
2008	1603	64	0	1539	3.99	96.01
2009	1752	67	0	1685	3.82	96.18
2010	2107	71	0	2036	3.37	96.63
2011	2341	72	0	2269	3.08	96.92
2012	2470	70	0	2400	2.83	97.17
2013	2515	70	0	2445	2.78	97.22
2014	2632	69	0	2563	2.62	97.38
2015	2823	68	0	2755	2.41	97.59
2016	3118	68	298	2752	2.18	88.26
All	35,521	1559	298	33,664		
Mean	1480	65	12	1403	5.75	93.85

Table A2
The factor spanning test: July 1997–December 2017.

The table presents regression results using four factors in regressions to explain average returns on the fifth. Mkt is the value-weighted monthly return on all A-share stocks listed on SHSE and SZSE in excess of the monthly deposit interest rate calculated using the one-year deposit interest rate; SMB (small minus big) is the size factor, which is the average of three stock portfolio returns constructed by averaging the difference between three small and large B/M, OP, and Inv stock portfolio returns for each month, respectively; HML (high minus low B/M) is the value factor; RMW (robust minus weak OP) is the profitability factor; and CMA (conservative minus aggressive Inv) is the investment factor. Newey–West heteroscedasticity- and autocorrelation-robust *t*-statistics (with a lag of 12) are given in parentheses.

	Intercept	Mkt	SMB	HML	RMW	CMA	$Adj.R^2$
Mkt	1.513		−0.731	−0.410	−1.891	−0.800	19.704%
	(2.121)		(−2.465)	(−0.940)	(−4.658)	(−1.369)	
SMB	1.033	−0.105		−0.523	−1.059	−0.189	61.987%
	(4.975)	(−2.855)		(−4.232)	(−6.544)	(−1.049)	
HML	0.486	−0.043	−0.383		−0.085	0.384	28.906%
	(3.698)	(−0.877)	(−4.699)		(−0.485)	(2.253)	
RMW	0.450	−0.094	−0.368	−0.040		−0.708	75.138%
	(4.585)	(−4.898)	(−6.625)	(−0.513)		(−8.070)	
CMA	0.121	−0.032	−0.052	0.144	−0.559		54.813%
	(1.322)	(−1.446)	(−0.945)	(2.112)	(−12.017)		

References

Avramov, D., Chordia, T., 2006. Asset pricing models and financial market anomalies. Rev. Financ. Stud. 19, 1001–1040.
Barillas, F., Shanken, J., 2017. Which alpha? Rev. Financ. Stud. 30, 1316–1338.
Barillas, F., Shanken, J., 2018. Comparing asset pricing models. J. Finance 73, 715–754.
Barroso, P., Santa-Clara, P., 2015. Momentum has its moments. J. Financial Econ. 116, 111–120.
Blitz, D., Hanauer, M.X., Vidojevic, M., 2017. The idiosyncratic momentum anomaly. SSRN Working Paper No. 2947044.
Blitz, D., Huij, J., Martens, M., 2011. Residual momentum. J. Emp. Finance 18, 506–521.
Carhart, M.M., 1997. On persistence in mutual fund performance. J. finance 52, 57–82.
Chang, R.P., Ko, K.C., Nakano, S., Rhee, S.G., 2018. Residual momentum in Japan. J. Emp. Finance 45, 283–299.
Cheema, M.A., Nartea, G.V., 2014. Momentum returns and information uncertainty: Evidence from china. Pacific-Basin Finance J. 30, 173–188.
Chui, A.C., Titman, S., Wei, K.J., 2010. Individualism and momentum around the world. J. Finance 65, 361–392.
Da, Z., Gurun, U.G., Warachka, M., 2014. Frog in the pan: Continuous information and momentum. Rev. Financ. Stud. 27, 2171–2218.
De Bondt, W.F., Thaler, R., 1985. Does the stock market overreact? J. Finance 40, 793–805.
Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Finance 47, 427–465.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financial Econ. 33, 3–56.
Fama, E.F., French, K.R., 2012. Size, value, and momentum in international stock returns. J. Financial Econ. 105, 457–472.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financial Econ. 116, 1–22.
Fama, E.F., French, K.R., 2016. Dissecting anomalies with a five-factor model. Rev. Financ. Stud. 29, 69–103.
Goyal, A., Wahal, S., 2015. Is momentum an echo? J. Financ. Quant. Anal. 50, 1237–1267.
Griffin, J.M., Ji, X., Martin, J.S., 2003. Momentum investing and business cycle risk: Evidence from pole to pole. J. Finance 58, 2515–2547.
Guo, B., Zhang, W., Zhang, Y., Zhang, H., 2017. The five-factor asset pricing model tests for the chinese stock market. Pacific-Basin Finance J. 43, 84–106.
Gutierrez, R.C., Prinsky, C.A., 2007. Momentum, reversal, and the trading behaviors of institutions. J. Financ. Markets 10, 48–75.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. J. Finance 48, 65–91.
Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. J. Finance 56, 699–720.
Lin, Q., 2017. Noisy prices and the Fama–French five-factor asset pricing model in china. Emerging Markets Review 31, 141–163.
Wang, F., Xu, Y., 2004. What determines chinese stock returns? Financial Analysts J. 60, 65–77.