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A comprehensive investigation into style momentum strategies in China

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Abstract
This study conducts a comprehensive investigation into style momentum strategies—the combination of price momentum strategies based on previous medium-term returns and style investing in terms of firm characteristics—in the China stock market over the period 1994 to 2017. Although we do not find style momentum profits over the first sub-period 1994 to 2006, strong evidence shows that style momentum strategies are profitable over the second sub-period 2007 to 2017, even after controlling for trading costs and various market and firm-specific risks. Importantly, the observed style momentum in the second sub-period is distinguished from price momentum and industry momentum but could be attributed to the improved institutional settings in recent years. Specifically, the fast growth of institutional investors since 2006, along with the introduction of margin trading and short sales in 2010, provides style switchers with more efficient investment vehicles to trade an entire style in the China stock market. Finally, we find that style profits exhibit momentum in a cyclical nature; in particular, style momentum profits are negatively related to market states, implying that it is likely for institutional investors to make profits by constructing style momentum strategies when stock market experiences a major decline.

Keywords Style momentum · Price momentum · Industry momentum · Market states · Institutional investors · China stock market

JEL Classification G11 · G14 · G15

1 Introduction

In the stock markets, when investors make portfolio allocation decisions, they generally categorize assets into broad classes across various firm characteristics, such as size measured by market capitalization of equity, value/growth measured

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by book-to-market ratio (B/M), and industry, and then decide how to allocate their funds across these asset classes. These asset classes are sometimes called *styles*, and the process that investors allocate their funds among styles is known as *style investing*. Barberis and Shleifer (2003) argue that style investing helps investors to optimally construct and simplify diversified portfolios, to effectively identify and manage sources of risk, as well as to easily measure and evaluate portfolio performance relative to specified style benchmarks, such as a growth or value index. Therefore, style investing is *"particularly attractive to institutional investors, such as pension plan sponsors, foundations, and endowments, who as fiduciaries must follow systematic rules of portfolio allocation"* (Barberis and Shleifer 2003; p. 162). Not surprisingly, with the interest in style investing grown over the years, most fund managers now tend to identify themselves as following a particular investment style, such as growth, value, small capitalization, high technology, and so on (see, Brookfield et al. 2015). Sharpe (1992) points out that investment style, rather than specific stock selection, determines over 90% of superior performance of mutual funds.

A growing body of empirical evidence demonstrates the existence of various profitable dynamic style-based investment strategies (see, e.g., Sharpe; 1992; Kao and Shumaker 1999; Levis and Liodakis 1999; Lucas et al. 2002; Brown and Goetzmann 2003; Wang 2005; Kumar 2009; Cheema and Nartea 2017; Brocas et al. 2019; among others). However, there is some lack of consensus on the underlying cause for such profits, that is, the reasons why some styles are more likely to generate superior performance than others are still open to debate. The market efficiency theory asserts that it is impossible to beat the market consistently as asset prices fully reflect all publicly available information. If the market is truly efficient, style portfolios should not be more profitable than other portfolios based on an arbitrary subset of stocks. Therefore, style investing might be fundamentally risky, and the profitability of style-based investment strategies would suggest either market inefficiency or the misspecification of asset pricing models.

Barberis and Shleifer (2003) develop the first theoretical model on style investing—a heterogeneous agent model including two types of investors, i.e., *style switchers* and *fundamental traders*. Specifically, style switchers allocate funds at the style level and the amount allocated to each style depends on the relative style performance, while fundamental traders generally trade against style switchers when prices deviate too far from fundamental values. Barberis and Shleifer (2003) provide a rich set of testable implications of style investing on stock valuation. Some of their propositions reflect previous empirical evidence, e.g., price momentum first documented by Jegadeesh and Titman (1993), while two propositions regarding style momentum—*Propositions 7 and 8*—have received much less attention in the literature. For example, *Proposition 7* predicts that style momentum strategies are more profitable than or at least as profitable as price momentum strategies given the presence of style switchers, while *Proposition 8* argues that the profitability of style momentum strategies is time-varying and state-dependent.

Although style momentum has begun to receive some attention in the USA and other developed markets (see, e.g., Lewellen 2002; Chen 2003; Chen and De

Bondt 2004; Wang 2005; Chao et al. 2012; Chan and Docherty 2016among others), return patterns of style portfolios are found very noisy and, in particular, little research in this area has focused on emerging markets. Examining the relationship between price momentum profits and information uncertainty, as proxied by firm size, firm age, volatility, volume turnover, and implied duration, Cheema and Nartea (2014) find that firms with greater information uncertainty do not necessarily generate higher momentum returns than those with lower information uncertainty in the China stock market. This study sheds fresh light on the profitability of style momentum strategies in the China stock market, with specific emphasis on the implications of Barberis and Shleifer's (2003) *Propositions 7 and 8*. Our particular attention to the China stock market is motivated by two additional considerations. First, the impact of China on world affairs has risen substantially in recent years and, from a financial market perspective, the China stock market, one of the largest and most important emerging markets in the world,[1] has become of great interest and importance to global investors. Specifically, the China Securities Regulatory Commission (CSRC) and the People's Bank of China (PBOC; the central bank of China) introduced the Qualified Foreign Institutional Investor (QFII) program in November 2002 as a provision for foreign long-term investment institutions to enter the China capital market (see more details on the QFII program in Subsection 2.1). Since then, more global institutional investors have been able to access this potential.

Second, and more importantly, institutional settings and trading practices in the China stock market are partially different from and independent of those in developed markets. In particular, in the early stage of its development, the dominance of individual investors, the existence of non-tradable shares (or the split share structure), and the prohibition of short selling have been widely criticized as an indicator of bureaucratic control and operating inefficiency (see, Sun and Tong 2003; Wang et al. 2008; Su and Bangassa 2011). However, the China stock market has undergone tremendous development in recent years, such as the fast growth of institutional investors since 2006, the launch of the China Financial Futures Exchange (CFFEX) in 2006, and the introduction of margin trading and short sales in 2010. These substantial changes in institutional settings make the China stock market an ideal arena to comparatively explore the nature and sources of style momentum profits in a *single* market context. Therefore, an investigation into style momentum strategies—the combination of price momentum strategies based on previous medium-term returns and style investing in terms of firm characteristics—in China is of particular relevance to institutional investors and policy makers in understanding stock return behavior in an important emerging market context.

Using a large sample of 2417 non-financial firms listed either on the SHSE or on the SZSE over the period January 1994 to December 2017, we first create

[1] There were 3,485 listed firms in the China stock market by the end of 2017, including 1,396 listed on the Shanghai Stock Exchange (SHSE) and 2,089 listed on the Shenzhen Stock Exchange (SZSE). The total market capitalizations of A- and B-shares were RMB 33.132trillion (USD 5.078trillion) in the SHSE and RMB 23.576trillion (USD 3.613trillion) in the SZSE by the end of 2017. The data are collected from *Shanghai Stock Exchange Fact Book* 2018 and *Shenzhen Stock Exchange Fact Book* 2017. USD 1 was approximately RMB 6.5247 on December 31st, 2017.

various style portfolios at the end of each year; each style portfolio comprises firms with similar size and B/M. Then, we rank these style portfolios based on their past F-month returns ($F=3$, 6, 9, or 12), so we are able to identify two extreme style portfolios, i.e., *winner* and *loser* style portfolios with the best and worst past performance, respectively. Finally, we construct various $F \times H$ style momentum strategies by simultaneously buying *winner* style portfolios and selling *loser* style portfolio; the arbitrage style portfolio will be held in the next H months ($H=3$, 6, 9, 12, or 24). The procedure is repeated every month until the end of our sample period. Therefore, style momentum profits are calculated as the differences of monthly average returns between *winner* and *loser* style portfolios. Our empirical investigation proceeds in the following three main parts.

In the first part of our empirical investigation, for comparison purposes, we divide the whole sample period to two sub-periods: the first sub-period January 1994 to December 2006 and the second sub-period January 2007 to December 2017. Although there is no evidence of significant style momentum profits shown in the first sub-period, a vast majority of style momentum strategies are profitable in the second sub-period. For example, the most successful 6×6 style momentum strategy generates a statistically significant monthly average return of 1.385% (t-stat$=3.03$), at the 1% level; also, a statistically significant monthly average return of 1.188% (t-stat$=2.18$), at the 5% level, for the 6×12 strategy. Importantly, these style momentum strategies in the second sub-period consistently outperform their contemporaneous price momentum strategies, in line with Barberis and Shleifer's (2003) *Proposition 7*; also, these style momentum strategies remain profitable after controlling for trading costs and various market and firm-specific risks. The significant style momentum profits found in the second sub-period rather than in the first sub-period could be attributed to the improved institutional settings of the China stock market in recent years, such as the fast growth of institutional investors and the removal of various institutional barriers, which allow style switchers to allocate capitals and manage risks in a more efficient way.

Moskowitz and Grinblatt (1999) report that industry momentum strategies that buy previous *winner* industry portfolios and meanwhile sell previous *loser* industry portfolios can generate significant returns in the medium-term horizons (see, also, Lewellen 2002; Nijman et al. 2004; Szakmary and Zhou 2015). Also, Su (2011, p. 4) finds *"significant abnormal profits for industry momentum strategies"* in the China stock market over the period 1994 to 2008, even after controlling for the lead-lag effect, the January effect, and price momentum. To rule out the concern that the observed style momentum in the second sub-period might be a phenomenon of industry momentum, we employ three alternative approaches in the second part of our empirical investigation to disentangle the two phenomena by (i) calculating industry-adjusted style momentum profits, (ii) using an independent two-way classification scheme, and (iii) running the Fama and MacBeth (1973) regressions. We find consistent evidence that industry-adjusted style momentum profits remain profitable in the second sub-period, confirming that style momentum is distinguished from industry momentum in the China stock market.

Barberis and Shleifer (2003), however, argue that prices can deviate substantially from their fundamental values as styles' popularity changes over time and consequently return patterns are hard to predict. Therefore, in the third part of our empirical investigation, we examine whether style profits exhibit momentum in a cyclical nature. An *Up* (*Down*) market state is defined when the past 1-year value-weighted market return on the SHSE and the SZSE A-share indices is non-negative (negative). We find style momentum profits are negatively related to market states, i.e., significantly positive style momentum profits following *Down* states and insignificant profits following *Up* states. For example, the 6×6 style momentum strategy generates an insignificant monthly average return of 0.598% (t-stat = 1.23) following *Up* states, but a significantly positive monthly average return of 2.166% (t-stat = 3.33), at the 1% level, following *Down* states. Our ordinary least squares (OLS) regressions further confirm the negative impact of market states on style momentum profits, supporting Barberis and Shleifer's (2003) *Proposition 8*. Our results imply that recent style return differentials are a crucial factor for predicting future style returns, which is particularly relevant to institutional investors.

To the best of our knowledge, this is one of the very first systematic and comprehensive studies that extend price momentum strategies to portfolio-based momentum strategies in style context in the China stock market, showing some important evidence that not only complements the existing financial literature, but has significant impacts on institutional investors and policy makers. First, we provide supportive evidence—the profitability of style momentum strategies is state-dependent and superior to that of price momentum strategies—for Barberis and Shleifer's (2003) two propositions regarding style momentum in an emerging market context. Second, from an investor's perspective, it is likely for institutional investors to make profits in the China stock market by constructing style momentum strategies especially when stock market experiences a major decline. Third, the fast development of institutional investors since 2006 plays an important role in resource allocation and price discovery in the China stock market; for example, the introduction of the QFII program is successful in providing style switchers with more efficient investment vehicles to trade an entire style in the China stock market.

The remainder of this paper is organized as follows. The next section presents institutional background, reviews related literature, and develops our main hypotheses. Section 3 describes sample selection and methodology, while Sects. 4 to 6 report our empirical results. The final section concludes this study.

2 Institutional background, related literature, and hypotheses development

2.1 The development of institutional investors in the China stock market

In the China stock market, institutional investors have undergone substantial changes in the past three decades. Specifically, at the first stage (1990 to 1997), institutional investors in the China stock market were of quite small scale. The first close-end fund (i.e., Zibo Township Enterprise Fund) was listed on the SHSE in August 1993. Since then, there had been around 70 close-end funds with asset values of over RMB 4billion in total trading in the two stock exchanges by the end of 1993, while these funds were gradually marginalized after 1996 (see, Sun et al. 2015).

At the second stage (1998 to 2005), a series of relevant policies were published by the governing bodies to promote the development of institutional investors. For example, *Interim Measures for the Administration of Securities Investment Funds* [No. 81, 1997] was promulgated by the State Council Securities Commission (SCSC) on November 14, 1997.[2] Accordingly, the first securities investment funds (i.e., Jingtai Fund and Kaiyuan Fund) were founded on March 23, 1998 and then went public on April 7, 1998. In November 2002, the QFII program was introduced to encourage foreign capitals to invest in China. In June 2004, the CSRC approved *Measures for the Administration of Securities Investment Fund Management Companies* [No. 22, 2004], which replaced the previous interim measures and became effective on October 1, 2004. The gradual improvement of the regulatory system for securities investment funds marks that institutional investors in the China stock market entered a normal development phase.

At the third stage (2006 to date), institutional investors in the China stock market enter a rapid growth phrase. Specifically, after the first three years of strict quota control, the approval of the number and annual investment quota of QFIIs has been accelerated with the release of *Measures on Administration of Domestic Securities Investments by Qualified Foreign Institutional Investors* [No. 36, 2006] on September 1, 2006. In December 2007, the CSRC announced the expansion of the QFII program from the initial investment quota of USD 10billion to USD 30billion, which was further expanded to USD 80billion in April 2012 and USD 150billion in July 2013.[3] The number and approved annual investment quota of QFIIs are quite small in the first few years, probably due to the influence of the 2008/09 global financial crisis. By the end of 2017, 258 international institutions had been granted the QFII licenses and approved with a total investment quota of USD 80.138billion (see "Appendix A"). The types of institutional investors have expanded dramatically from the exclusive close-end funds in its initial stage to a dozen of institutions, e.g., Public Offering Fund, QFII, Private Fund, Broker Asset Management, Broker Proprietary Trading, Insurance Company, Social Security Fund, Trust Company, Financial Company, Enterprise Annuity, and so on.

2.2 Related literature and hypotheses

Jegadeesh and Titman (1993) first document price momentum, or the continuation of medium-term stock returns. That is, price momentum strategies, which simultaneously buy stocks that have performed well and sell stocks that have performed poorly in the past three to 12 months, are able to generate significantly positive returns in the subsequent three to 12 months. Schwert (2003) concludes that price momentum is a universal financial anomaly in markets worldwide and remains the only financial anomaly that has not faded since its discovery, posing a substantial

[2] The SCSC was established as national regulatory authority to regulate all activities in the China stock market on October 27, 1992, while it was dissolved and replaced by the CSRC in March 1998.

[3] On January 14, 2019, the total investment quota of the QFII program was doubled to USD 300billion; the investment quota limit was finally removed on September 10th, 2019.

challenge to the theory of market efficiency (see, also, Fama and French 1996; Swinkels 2004).[4] However, prior studies on the profitability of price momentum strategies in the China stock market provide some elements of conflicting results. For example, using a sample of 268 A-share firms over the period January 1995 to January 2000, Kang et al. (2002) find significantly positive value-weighted average weekly returns to 10 price momentum strategies with the ranking and holding periods ranging from 12 to 26 weeks, supporting the existence of price momentum over the medium-term horizons in the China stock market (see, also., Naughton et al. 2008; Cheema and Nartea 2014). Wang (2004), however, finds the non-profitability of price momentum strategies over a horizon of six months to two years over the period July 1994 to December 2000 (see, also., Chui et al. 2010; Wu 2011; Pan et al. 2013). These mixed results could be due to different sample periods, sample selections (e.g., coverage of the SHSE only or of both the SHSE and the SZSE; inclusion or exclusion of penny stocks and/or financials), and/or research designs (e.g., the varying ranking and holding periods; an interval between the ranking and holding periods or not; equal- or value-weighted style portfolios; monthly, weekly, or daily frequencies).

Chen and De Bondt (2004) extend price momentum strategies to portfolio-based momentum strategies in style context.[5] They examine style momentum strategies within the Standard & Poor's (S&P) 500 index over the period January 1976 to December 2000, using a simple trading rule based on past returns and firm characteristics. Specifically, Chen and De Bondt (2004) first categorize the constituents of the S&P 500 index into three classes along size, value/growth, and dividend yield, and then rank the obtained style portfolios by their past 3- to 12-month returns. They report that style momentum strategies that buy the best performing (*winner*) style portfolios and sell the worst performing (*loser*) style portfolios make significant profits in the following three to 12 months (see, also, Chen 2003; Wang and Wu 2011).

Barberis and Shleifer (2003) attribute style momentum profits to the presence of style switchers in the stock market; style switchers are able to allocate funds at the style level, and the amount allocated to each style depends on the relative style performance. A global study of Chao et al. (2012), however, documents that style momentum is not a universal phenomenon, as they find style momentum profits in the US and some stock markets, but not in others, in particular, not in some emerging markets. Therefore, if style momentum profits are truly due to the presence of style switchers, then it is hard to explain why style switchers

[4] Numerous studies confirm the existence of price momentum (see, e.g., Chan et al. 1996; Conrad and Kaul 1998; Rouwenhorst 1998, 1999; Chan et al. 2000; Grundy and Martin 2001; Jegadeesh and Titman 2001, 2002; Chordia and Shivakumar 2002; van Dijk and Huibers 2002; Hameed and Kusnadi 2002; Griffin et al. 2003; Doukas and McKnight 2005; Asness et al. 2013; among others).

[5] Price momentum strategies have been extended to portfolio-based momentum strategies in various contexts, such as industry (see, Moskowitz and Grinblatt; 1999; Nijman et al. 2004; Su 2011; Szakmary and Zhou 2015), trading volume (see, Lee and Swaminathan 2000; Naughton et al. 2008), analyst coverage (see, Hong et al. 2000; Muslu and Xue 2013), information uncertainty (see, Zhang 2006; Cheema and Nartea 2017), credit rating (see, Avramov et al. 2007), and so on.

are present in some markets, but absent in others. Froot and Teo (2008) argue that institutional barriers in some emerging markets, e.g., the immature of institutional investors, the short selling constrains, and/or the lack of financial derivatives vehicles, result in the absence of style switchers. Specifically, in the early stage of its development, the China stock market was widely criticized as an indicator of political control and operating inefficiency due to the lack of institutional investors, the dominant proportion of non-tradable state-owned shares, the ban on margin trading and short selling, and so on. However, the China stock market has experienced remarkable institutional developments in recent years, such as the fast growth of institutional investors since 2006, the launch of the financial futures exchange in 2006, and the introduction of margin trading and short sales in 2010, allowing style switchers to make portfolio allocation decisions at the style level in a more effective way. The China stock market thus provides an ideal arena to comparatively explore the profitability of style momentum strategies in two distinct institutional settings. Accordingly, we develop the following hypothesis:

Hypothesis 1 Style momentum strategies are more profitable after 2006 (i.e., during the sub-second period 2007 to 2017), probably due to the fast growth of institutional investors and the removal of institutional barriers in the China stock market.

Although style momentum is widely considered to be new empirical evidence against the theory of market efficiency, Lucas et al. (2002, p. 2) argue that the possible style rotation strategies are difficult to employ in practice, as *"the performance of value or size related investment styles is not stable over time"*, but partially a function of the economic environment. Barberis and Shleifer (2003) tend to capture any predictability in style returns; their *Proposition 8* allows fundamental traders to choose either to trade following the direction of style switchers or to trade against style switchers. Acting as arbitrageurs, fundamental traders generally trade against style switchers when prices deviate too far from fundamental values, thereby causing style momentum profits to be time-varying, rather than stable over time Chao et al. (2012). indicate that style momentum in general has state-dependent preferences in the global markets. Specifically, style momentum strategies generate significantly positive average returns following the *rising* markets and insignificantly negative average returns following the *declining* markets, which mirrors the impact of market states on price momentum profits (see, also, Chen and De Bondt 2004; Cooper et al. 2004). Accordingly, we develop the following hypothesis:

Hypothesis 2 Style momentum strategies are more profitable following market gains.

3 Data and methodology

3.1 Data and sample selection

Our sample consists of all available A-share firms listed either on the SHSE or on the SZSE over the period January 1994 to December 2017. We exclude financial firms in terms of the two-digit Industry Classification Benchmark (ICB) codes of 30 and 35 (see "Appendix B"), due to their highly regulated nature. As a result, the number of listed firms in our sample ranges from 195 at the end of 1994 to 2417 at the end of 2017. Our sample period starts from 1994 due to the limited number of listed firms in the first few years of the China stock market. A total of 87 delisted firms included in our sample help avoid the potential survivorship bias. Data on the stock price, size, and B/M of each listed firm are collected from the China Stock Market & Accounting Research (CSMAR) database. The monthly stock price is adjusted for stock splits, stock dividends, and rights offerings, while the year-end size is adjusted using the annual Consumer Price Index (CPI; 2017 = 100), released by the National Bureau of Statistics (NBS) of China.

3.2 Descriptive statistics on style portfolios

We create nine style portfolios at the end of each year, and each portfolio comprises firms with similar characteristics in terms of size and B/M, which are considered to be mutually exclusive and widely used in investment management community (see, Fama and French 1993; Froot and Teo 2008; Kumar 2009; Wahal and Yavuz 2013). Specifically, on December 31 of each year, all available firms are first divided into three size groups: big size group (*B*), medium size group (*M*), and small size group (*S*), according to whether the values of their firm size are included in the top 30, middle 40, or bottom 30 percentiles, respectively. Also, all firms are divided into three B/M groups: high B/M group (value; *H*), medium B/M group (*M*), and low B/M group (growth; *L*), according to whether the values of their B/M are included in the top 30, middle 40, or bottom 30 percentiles, respectively. So, nine style portfolios are constructed from the intersections of the three size groups and the three B/M groups: *BH* (big size + high B/M); *MH* (medium size + high B/M); *SH* (small size + high B/M); *BM* (big size + medium B/M); *MM* (medium size + medium B/M); *SM* (small size + medium B/M); *BL* (big size + low B/M); *ML* (medium size + low B/M); and *SL* (small size + low B/M).

Table 1 summarizes the average firm size and B/M in each style portfolio and the average percentile ranking of firms in each style portfolio relative to all firms listed in the SHSE and the SZSE, along with the number of firms in each style portfolio, at the end of each year from 1994 to 2017. For example, at the end of 2017, firms within *BL* (*SH*) portfolio have an average B/M of 0.148 (0.504) and an average size of RMB 31.77billion, or USD 4.87billion (RMB 3.59billion, or USD 0.55billion). In most years during the entire sample period, the typical big size (small size) firm in our sample is larger than 90% (20%) of all available listed firms, while the average

Table 1 The distribution of firm characteristics in each style portfolio

End of year	*BH*			*BM*			*BL*			*MH*			*MM*			*ML*			*SH*			*SM*			*SL*		
	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*
Panel A: Market capitalizations																											
End of 1994	8.29	0.96	10	3.55	0.87	15	12.79	0.98	10	1.68	0.59	20	1.66	0.59	20	1.28	0.43	10	0.87	0.18	5	0.99	0.28	10	0.98	0.27	5
End of 1995	8.19	0.98	15	3.58	0.91	27	3.43	0.90	30	1.11	0.53	18	0.95	0.44	15	1.13	0.54	9	0.54	0.10	9	0.64	0.22	6	0.68	0.25	3
End of 1996	11.68	0.98	45	6.67	0.95	60	8.53	0.96	15	1.94	0.58	20	1.53	0.45	30	1.62	0.47	35	1.00	0.20	10	0.94	0.16	5	0.89	0.13	15
End of 1997	10.77	0.96	30	12.06	0.97	54	8.66	0.94	54	2.42	0.55	66	2.12	0.48	54	2.48	0.57	24	1.03	0.11	12	1.14	0.16	24	1.19	0.18	18
End of 1998	8.31	0.95	70	8.53	0.95	77	8.87	0.96	63	2.91	0.61	49	2.52	0.52	70	2.24	0.44	35	1.65	0.24	21	1.55	0.20	49	1.52	0.20	28
End of 1999	8.81	0.93	63	7.10	0.89	60	8.96	0.93	45	3.22	0.54	77	3.16	0.53	101	3.19	0.53	59	1.82	0.20	38	1.77	0.18	78	1.61	0.13	69
End of 2000	13.42	0.93	81	11.00	0.89	74	12.03	0.92	46	5.27	0.54	78	5.19	0.54	101	5.03	0.50	85	3.28	0.20	45	3.21	0.18	92	2.78	0.10	68
End of 2001	10.32	0.93	103	9.49	0.91	67	7.93	0.87	57	4.05	0.55	100	3.90	0.53	147	3.88	0.52	78	2.54	0.20	33	2.49	0.18	99	2.23	0.12	100
End of 2002	11.74	0.95	98	8.91	0.93	95	7.04	0.88	63	3.13	0.55	125	3.00	0.52	136	3.04	0.53	83	1.74	0.13	30	1.86	0.18	100	1.73	0.13	103
End of 2003	15.31	0.96	127	8.26	0.90	89	8.13	0.90	55	2.66	0.57	112	2.44	0.53	157	2.32	0.50	94	1.30	0.17	26	1.34	0.19	106	1.16	0.13	114
End of 2004	7.54	0.92	97	13.14	0.97	118	6.47	0.90	79	1.98	0.55	126	1.92	0.54	149	1.90	0.54	92	1.00	0.19	54	0.99	0.18	95	0.86	0.12	101
End of 2005	5.95	0.91	95	10.98	0.96	115	7.30	0.93	93	1.48	0.55	134	1.50	0.55	175	1.43	0.52	93	0.78	0.20	70	0.76	0.18	95	0.67	0.14	99
End of 2006	14.29	0.93	90	17.26	0.95	116	13.59	0.93	96	2.20	0.54	136	2.19	0.54	162	2.25	0.55	99	0.99	0.18	69	1.00	0.19	109	0.88	0.14	94
End of 2007	31.04	0.90	98	52.11	0.94	120	36.38	0.92	98	5.8	0.53	143	5.96	0.54	173	5.81	0.53	107	2.48	0.17	69	2.55	0.18	113	2.39	0.16	102

Table 1 (continued)

End of year	*BH*			*BM*			*BL*			*MH*			*MM*			*ML*			*SH*			*SM*			*SL*		
	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*	Size	%	*N*
End of 2008	12.48	0.91	97	29.67	0.96	141	17.76	0.93	106	2.13	0.50	154	2.28	0.54	174	2.25	0.53	116	0.98	0.17	89	1.01	0.18	127	0.92	0.14	112
End of 2009	23.70	0.89	123	59.02	0.96	147	28.13	0.91	89	5.50	0.53	156	5.30	0.51	172	5.51	0.53	131	2.61	0.19	79	2.49	0.18	139	2.32	0.15	124
End of 2010	52.44	0.96	139	24.40	0.90	142	25.86	0.91	118	5.91	0.54	156	5.84	0.54	217	5.84	0.54	135	3.00	0.21	88	2.81	0.19	148	2.47	0.14	126
End of 2011	35.36	0.96	167	14.46	0.89	179	18.46	0.92	149	3.53	0.52	204	3.60	0.53	255	3.71	0.54	161	1.84	0.20	87	1.75	0.18	176	1.66	0.16	148
End of 2012	32.73	0.96	157	15.25	0.90	186	17.09	0.91	197	3.47	0.53	241	3.45	0.53	274	3.44	0.53	177	1.66	0.18	126	1.60	0.16	232	1.57	0.16	147
End of 2013	30.79	0.96	172	14.88	0.88	190	18.27	0.91	191	4.19	0.52	232	4.19	0.52	308	4.31	0.53	207	2.05	0.18	164	1.98	0.17	238	1.90	0.16	158
End of 2014	42.17	0.95	221	21.85	0.89	177	20.19	0.88	169	5.89	0.53	230	5.80	0.52	301	5.86	0.53	226	3.02	0.19	116	2.81	0.16	276	2.76	0.15	171
End of 2015	49.13	0.94	197	32.43	0.90	239	30.96	0.89	178	10.07	0.53	243	10.21	0.54	317	10.13	0.54	222	5.38	0.17	152	5.15	0.15	230	5.11	0.15	191
End of 2016	39.96	0.94	263	27.21	0.90	232	27.18	0.90	159	8.93	0.54	245	8.59	0.52	376	8.67	0.52	233	5.08	0.19	129	4.81	0.15	245	4.72	0.14	243
End of 2017	39.88	0.94	337	32.72	0.92	241	31.77	0.92	119	7.34	0.57	261	6.92	0.54	438	6.83	0.53	233	3.59	0.23	98	3.36	0.20	255	3.10	0.16	345

End of year	*BH*			*BM*			*BL*			*MH*			*MM*			*ML*			*SH*			*SM*			*SL*		
	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*
Panel B: B/M																											
End of 1994	0.447	0.88	10	0.333	0.52	15	0.192	0.18	10	0.456	0.88	20	0.324	0.48	20	0.187	0.18	10	0.510	0.98	5	0.353	0.64	10	0.217	0.27	5
End of 1995	0.948	0.96	15	0.533	0.58	27	0.287	0.16	30	0.802	0.86	18	0.408	0.49	15	0.290	0.16	9	0.755	0.84	9	0.534	0.58	6	0.275	0.15	3

Table 1 (continued)

End of year	*BH*			*BM*			*BL*			*MH*			*MM*			*ML*			*SH*			*SM*			*SL*		
	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*
End of 1996	0.919	0.88	45	0.544	0.53	60	0.325	0.10	15	1.044	0.92	20	0.520	0.51	30	0.331	0.10	35	1.037	0.92	10	0.455	0.37	5	0.374	0.14	15
End of 1997	0.412	0.76	30	0.296	0.46	54	0.183	0.13	54	0.468	0.87	66	0.305	0.49	54	0.166	0.13	24	0.488	0.91	12	0.321	0.52	24	0.132	0.04	18
End of 1998	0.434	0.86	70	0.273	0.46	77	0.176	0.12	63	0.383	0.76	49	0.267	0.45	70	0.182	0.13	35	0.568	0.97	21	0.287	0.50	49	0.164	0.10	28
End of 1999	0.487	0.89	63	0.283	0.52	60	0.179	0.17	45	0.482	0.88	77	0.288	0.52	101	0.171	0.15	59	0.444	0.85	38	0.282	0.51	78	0.142	0.10	69
End of 2000	0.468	0.91	81	0.249	0.53	74	0.121	0.14	46	0.435	0.87	78	0.242	0.51	101	0.128	0.16	85	0.408	0.85	45	0.240	0.51	92	0.112	0.12	68
End of 2001	0.337	0.91	103	0.186	0.53	67	0.108	0.19	57	0.310	0.88	100	0.189	0.55	147	0.101	0.16	78	0.289	0.84	33	0.182	0.52	99	0.092	0.13	100
End of 2002	0.507	0.92	98	0.288	0.53	95	0.153	0.19	63	0.475	0.89	125	0.293	0.54	136	0.154	0.19	83	0.428	0.83	30	0.279	0.50	100	0.126	0.13	103
End of 2003	0.550	0.92	127	0.320	0.55	89	0.173	0.20	55	0.512	0.89	112	0.322	0.56	157	0.162	0.19	94	0.459	0.83	26	0.301	0.50	106	0.140	0.14	114
End of 2004	0.614	0.90	97	0.385	0.54	118	0.223	0.21	79	0.602	0.89	126	0.382	0.53	149	0.207	0.18	92	0.573	0.86	54	0.377	0.52	95	0.175	0.13	101
End of 2005	0.887	0.91	95	0.533	0.53	115	0.317	0.22	93	0.900	0.92	134	0.553	0.57	175	0.280	0.18	93	0.819	0.86	70	0.530	0.52	95	0.261	0.16	99
End of 2006	1.121	0.93	90	0.619	0.55	116	0.338	0.21	96	1.033	0.91	136	0.622	0.56	162	0.344	0.22	99	0.953	0.87	69	0.608	0.54	109	0.276	0.16	94
End of 2007	0.888	0.95	98	0.409	0.54	120	0.197	0.18	98	0.792	0.91	143	0.409	0.54	173	0.213	0.21	107	0.706	0.86	69	0.408	0.54	113	0.185	0.17	102
End of 2008	0.443	0.96	97	0.203	0.53	141	0.110	0.20	106	0.356	0.89	154	0.204	0.53	174	0.111	0.20	116	0.370	0.90	89	0.209	0.55	127	0.095	0.16	112
End of 2009	0.877	0.91	123	0.465	0.54	147	0.251	0.19	89	0.799	0.88	156	0.458	0.53	172	0.242	0.18	131	0.775	0.86	79	0.461	0.53	139	0.221	0.16	124

Table 1 (continued)

End of year	*BH*			*BM*			*BL*			*MH*			*MM*			*ML*			*SH*			*SM*			*SL*		
	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*	B/M	%	*N*
End of 2010	0.534	0.93	139	0.265	0.54	142	0.149	0.18	118	0.463	0.88	156	0.264	0.53	217	0.148	0.18	135	0.437	0.85	88	0.255	0.50	148	0.124	0.14	126
End of 2011	0.613	0.92	167	0.275	0.51	179	0.151	0.16	149	0.507	0.87	204	0.275	0.51	255	0.158	0.17	161	0.450	0.84	87	0.278	0.52	176	0.127	0.13	148
End of 2012	0.895	0.94	157	0.426	0.48	186	0.242	0.16	197	0.726	0.88	241	0.439	0.51	274	0.233	0.15	177	0.656	0.82	126	0.434	0.50	232	0.212	0.13	147
End of 2013	0.885	0.94	172	0.449	0.50	190	0.236	0.15	191	0.777	0.89	232	0.447	0.50	308	0.243	0.16	207	0.715	0.86	164	0.445	0.50	238	0.203	0.11	158
End of 2014	1.041	0.92	221	0.425	0.51	177	0.187	0.14	169	0.852	0.86	230	0.416	0.49	301	0.200	0.16	226	0.755	0.83	116	0.422	0.50	276	0.184	0.14	171
End of 2015	0.783	0.94	197	0.328	0.51	239	0.167	0.15	178	0.610	0.87	243	0.331	0.51	317	0.166	0.15	222	0.585	0.85	152	0.330	0.51	230	0.153	0.13	191
End of 2016	0.852	0.92	263	0.336	0.52	232	0.152	0.16	159	0.718	0.88	245	0.330	0.51	376	0.156	0.16	233	0.638	0.85	129	0.323	0.49	245	0.138	0.13	243
End of 2017	0.622	0.90	337	0.283	0.50	241	0.148	0.17	119	0.552	0.86	261	0.288	0.51	438	0.140	0.16	233	0.504	0.82	98	0.273	0.48	255	0.127	0.13	345

This table summarizes the number of firms (*N*) and distribution of firm characteristics (e.g., the average firm size in Panel A and B/M in Panel B) in each style portfolio, along with the average percentile ranking (%) of firms in each style portfolio relative to all firms listed in the SHSE and the SZSE, at the end of each year from 1994 to 2017. Nine style portfolios are created at the end of each year, and each portfolio comprises firms with similar characteristics in terms of size and B/M; the year-end size is presented in billions of RMB and adjusted using the annual CPI (2017 = 100). Specifically, on December 31 of each year, all available non-financial firms are first divided into three size groups: big size group (*B*), medium size group (*M*), and small size group (*S*), according to whether the values of their firm size are included in the top 30, middle 40, or bottom 30 percentiles, respectively. Also, all firms are divided into three B/M groups: high B/M group (value; *H*), medium B/M group (*M*), and low B/M group (growth; *L*), according to whether the values of their B/M are included in the top 30, middle 40, or bottom 30 percentiles, respectively. So, nine style portfolios are constructed from the intersections of the three size groups and the three B/M groups: *BH* (big size + high B/M); *MH* (medium size + high B/M); *SH* (small size + high B/M); *BM* (big size + medium B/M); *MM* (medium size + medium B/M); *SM* (small size + medium B/M); *BL* (big size + low B/M); *ML* (medium size + low B/M); and *SL* (small size + low B/M)

B/M of value (growth) firms in our sample is higher than 85% (15%) of all available listed firms.

3.3 Style momentum strategies

Starting in January 1995, we rank the nine style portfolios created at the end of 1994, based on their valued-weighted cumulative returns in previous F ranking months ($F=3$, 6, 9, or 12). We identify two extreme style portfolios that perform best (*winner* style portfolio) and worst (*loser* style portfolio). An $F \times H$ style momentum strategy simultaneously buys *winner* style portfolio and sells *loser* style portfolio according to their past F-month performance, and the arbitrage style portfolios are held in the subsequent H months ($H=3$, 6, 9, 12, or 24). We skip one month between the ranking and holding periods to avoid the potential market microstructure bias resulted from the bid-ask bounce and the lead-lag effect (see, Jegadeesh and Titman 2001; Chen and De Bondt 2004; Liu and Zhang 2008). We repeat this procedure every month until December 2017, allowing investment styles to vary over time. Frequent replications with overlapping test periods increase the power of the statistical tests, while autocorrelation of stock returns is inevitable because the holding period returns have a great deal of overlapping from month to month. Also, a majority of stocks contained in *winner* (*loser*) style portfolio tend to remain in *winner* (*loser*) style portfolio in the following months. Therefore, the t-statistics of style momentum profits (i.e., the differences of monthly returns between *winner* and *loser* style portfolios) are corrected for serial correlation and heteroskedasticity, according to the procedure of Newey and West (1987).

4 Are style momentum strategies profitable?

In this section, we first report the non-profitability of style momentum strategies over the whole sample period January 1994 to December 2017. However, when dividing the whole sample period into two sub-periods, i.e., the first sub-period January 1994 to December 2006 and the second sub-period January 2007 to December 2017, we find that a vast majority of style momentum strategies generate significantly positive returns in the second sub-period, though no such evidence shown in the first sub-period. In addition, the observed style momentum is not due to price momentum or industry momentum but has a positive relationship with the number and approved annual investment quota of QFIIs. Finally, we confirm that style momentum strategies remain profitable after controlling for trading costs and various time-varying market and firm-specific risks.

4.1 Style momentum profits over the whole sample period

Table 2 presents the value-weighted average monthly returns of *winner* style portfolios, *loser* style portfolios, and arbitrage style portfolios (*winner* style

Table 2 The value-weighted average monthly returns of style momentum portfolios in the whole sample period

$F=$		$H=3$	6	9	12	24
3	*Loser* style portfolio	0.466	0.503	0.443	0.414	0.353
	Winner style portfolio	0.713	0.760	0.673	0.642	0.535
	Arbitrage style portfolio (*winner–loser*)	0.247	0.257	0.230	0.228	0.182
		(0.88)	(0.96)	(0.84)	(0.78)	(0.52)
6	*Loser* style portfolio	0.489	0.506	0.455	0.413	0.361
	Winner style portfolio	0.833	0.865	0.804	0.732	0.583
	Arbitrage style portfolio (*winner–loser*)	0.344	0.359	0.349	0.319	0.222
		(1.26)	(1.37)	(1.11)	(0.90)	(0.77)
9	*Loser* style portfolio	0.469	0.523	0.437	0.394	0.383
	Winner style portfolio	0.792	0.844	0.743	0.696	0.598
	Arbitrage style portfolio (*winner–loser*)	0.323	0.321	0.306	0.302	0.215
		(1.09)	(1.18)	(0.93)	(0.86)	(0.75)
12	*Loser* style portfolio	0.421	0.464	0.399	0.375	0.350
	Winner style portfolio	0.705	0.751	0.670	0.617	0.546
	Arbitrage style portfolio (*winner–loser*)	0.284	0.287	0.271	0.242	0.196
		(1.05)	(1.14)	(0.82)	(0.80)	(0.71)

This table presents the value-weighted average monthly returns of *winner* style portfolios, *loser* style portfolios, and arbitrage style portfolios (*winner* style portfolio–*loser* style portfolio) for various style momentum strategies over the whole sample period January 1994 to December 2017. Specifically, starting in January 1995, we rank the nine style portfolios (i.e., *BH*, *MH*, *SH*, *BM*, *MM*, *SM*, *BL*, *ML*, and *SL*) created at the end of 1994, based on their valued-weighted cumulative returns in previous F ranking months ($F=3$, 6, 9, or 12). We construct arbitrage style portfolios based on two extreme style portfolios that perform best (*winner* style portfolio) and worst (*loser* style portfolio). An $F \times H$ style momentum strategy simultaneously buys *winner* style portfolio and sells *loser* style portfolio according to their past F-month performance, and the arbitrage style portfolios are held in the subsequent H months ($H=3$, 6, 9, 12, or 24). We skip one month between the ranking and holding periods to avoid the potential market microstructure bias resulted from the bid-ask bounce and the lead-lag effect. We repeat this procedure every month until December 2016. The t-statistics of the differences of monthly returns between *winner* and *loser* style portfolios presented in parentheses are corrected for serial correlation and heteroskedasticity, using the procedure of Newey and West (1987)

portfolio—*loser* style portfolio) for various style momentum strategies over the whole sample period January 1994 to December 2017.[6] On average, the average monthly returns of arbitrage style portfolios are all statistically insignificant, irrespective of the lengths of ranking and holding periods. For example, the 6×6 and 6×12 style momentum strategies generate statistically insignificant average monthly returns of 0.359% (t-stat $=1.37$) and 0.319% (t-stat $=0.90$), respectively.

[6] The value-weighted returns enable us to better capture economic significance of our results, while the equal-weighted returns are, on average, biased upward due to the bid-ask bounce (see, Lyon et al. 1999). Like Kang et al. (2002) and Su (2011), we exclude stock returns in the first month after initial public offerings (IPOs) due to the extremely high underpricing in the China stock market (see, Su and Brookfield 2013; Su 2018).

Given the long sample period of our study, it is likely that significant style momentum profits over some time periods are offset by their insignificant counterparts over other time periods; as a result, on average, style momentum strategies could not exhibit significant profits over the entire sample period 1994 to 2017. The next subsection comparatively examines the profitability of style momentum strategies in two sub-periods separately.

4.2 Style momentum profits in two sub-periods

Panel A of Table 3 shows that, in the first sub-period, the average monthly returns of arbitrage style portfolios are insignificantly positive, irrespective of the lengths of ranking and holding periods. However, Panel B shows that, in the second sub-period, 16 out of 20 style momentum strategies generate significantly positive returns, at least at the 5% level. For example, the most successful 6×6 style momentum strategy generates a significantly positive monthly return of 1.385% (t-stat = 3.03), at the 1% level; also, a significantly positive monthly return of 1.188% (t-stat = 2.18) for the 6×12 style momentum strategy, at the 5% level.

In Panel C of Table 3, the t-statistics for the difference of monthly returns to style momentum strategies between the two sub-periods are statistically significant, at least at the 5% level, supporting *Hypothesis 1*. A reasonable explanation of the non-profitability of style momentum strategies in the first sub-period could be due to the existence of institutional barriers to style switchers when the China stock market was at its early development stage, such as the immature of institutional investors, the short selling constrains, the lack of efficient financial derivative vehicles, and so on. Since 2006, institutional investors have experienced rapid growth and played a vital role in resource allocation and price discovery; in particular, the launch of the financial futures exchange in 2006 and the introduction of margin trading and short sales in 2010 provide style switchers with more efficient investment vehicles to trade an entire style in the China stock market.

To evaluate the performance of various arbitrage style portfolios in more detail, we report the percentage frequency of styles appearing in the *winner* and *loser* style portfolios, based on the past F-month ranking period returns (F = 3, 6, 9, or 12), in the second sub-period. Table 4 shows that style momentum strategies prefer to buy big size and/or growth stocks and to sell small size and/or value stocks. For example, based on the past 6-month ranking period returns, *loser* style portfolio includes 55.05% of small size stocks and 70.94% of value stocks, while *winner* style portfolio includes 68.33% of big size stocks and 78.27% of growth stocks. Table 4 shows qualitatively consistent frequency distribution of styles in *winner* and *loser*

Table 3 The value-weighted average monthly returns of style momentum profits and price momentum profits

$F=$		$H=3$	6	9	12	24
Panel A: Style momentum profits over the first sub-period January 1994 to December 2006						
3	*Loser* style portfolio	0.447	0.484	0.460	0.399	0.342
	Winner style portfolio	0.533	0.576	0.548	0.478	0.413
	Arbitrage style portfolio (*winner–loser*)	0.085	0.092	0.087	0.079	0.070
		(0.46)	(0.51)	(0.48)	(0.41)	(0.30)
6	*Loser* style portfolio	0.483	0.502	0.477	0.424	0.387
	Winner style portfolio	0.619	0.649	0.617	0.548	0.500
	Arbitrage style portfolio (*winner–loser*)	0.136	0.147	0.140	0.124	0.112
		(0.66)	(0.72)	(0.68)	(0.47)	(0.40)
9	*Loser* style portfolio	0.462	0.494	0.469	0.407	0.377
	Winner style portfolio	0.593	0.629	0.598	0.528	0.475
	Arbitrage style portfolio (*winner–loser*)	0.131	0.135	0.130	0.121	0.098
		(0.57)	(0.62)	(0.59)	(0.45)	(0.37)
12	*Loser* style portfolio	0.459	0.474	0.450	0.412	0.375
	Winner style portfolio	0.564	0.591	0.562	0.506	0.461
	Arbitrage style portfolio (*winner–loser*)	0.106	0.117	0.112	0.095	0.086
		(0.56)	(0.60)	(0.57)	(0.42)	(0.31)
Panel B: Style momentum profits over the second sub-period January 2007 to December 2017						
3	*Loser* style portfolio	0.458	0.494	0.461	0.406	0.345
	Winner style portfolio	1.544	1.636	1.539	1.394	1.278
	Arbitrage style portfolio (*winner–loser*)	1.086	1.142	1.078	0.988	0.933
		(2.53)**	(2.65)***	(2.44)**	(2.08)**	(1.76)*
6	*Loser* style portfolio	0.469	0.484	0.462	0.396	0.334
	Winner style portfolio	1.808	1.868	1.751	1.585	1.346
	Arbitrage style portfolio (*winner–loser*)	1.339	1.385	1.290	1.188	1.012
		(2.76)***	(3.03)***	(2.62)***	(2.18)**	(1.89)*
9	*Loser* style portfolio	0.451	0.522	0.446	0.375	0.338
	Winner style portfolio	1.713	1.826	1.692	1.502	1.359
	Arbitrage style portfolio (*winner–loser*)	1.263	1.303	1.246	1.127	1.021
		(2.57)***	(2.82)***	(2.40)**	(2.12)**	(1.79)*
12	*Loser* style portfolio	0.368	0.431	0.358	0.323	0.309
	Winner style portfolio	1.494	1.597	1.488	1.298	1.215
	Arbitrage style portfolio (*winner–loser*)	1.127	1.166	1.131	0.975	0.905
		(2.46)**	(2.59)***	(2.28)**	(2.01)**	(1.63)
Panel C: Test of differences of style momentum profits between the two sub-periods (t-diff of Panel A & Panel B)						
3		[2.78]***	[2.89]***	[2.65]***	[2.50]**	[2.38]**
6		[3.01]***	[3.24]***	[2.92]***	[2.74]***	[2.43]**
9		[2.84]***	[3.06]***	[2.69]***	[2.62]***	[2.39]**
12		[2.66]***	[2.76]***	[2.56]***	[2.38]**	[2.28]**
Panel D: Price momentum profits over the second sub-period January 2007 to December 2017						
3	*Loser* price portfolio	– 0.109	– 0.117	– 0.112	– 0.099	– 0.091
	Winner price portfolio	0.117	0.134	0.134	0.127	0.101
	Arbitrage price portfolio (*winner–loser*)	0.226	0.251	0.247	0.226	0.192
		(0.61)	(0.71)	(0.66)	(0.57)	(0.52)

Table 3 (continued)

F=		*H*=3	6	9	12	24
6	*Loser* price portfolio	– 0.101	– 0.106	– 0.129	– 0.135	– 0.124
	Winner price portfolio	0.144	0.158	0.138	0.116	0.099
	Arbitrage price portfolio (*winner* – *loser*)	0.245	0.264	0.268	0.250	0.223
		(0.66)	(0.84)	(0.80)	(0.70)	(0.48)
9	*Loser* price portfolio	– 0.123	– 0.107	– 0.138	– 0.140	– 0.135
	Winner price portfolio	0.112	0.138	0.115	0.096	0.092
	Arbitrage price portfolio (*winner–loser*)	0.234	0.245	0.254	0.236	0.227
		(0.59)	(0.64)	(0.53)	(0.50)	(0.44)
12	*Loser* price portfolio	– 0.112	– 0.101	– 0.111	– 0.112	– 0.104
	Winner price portfolio	0.120	0.139	0.136	0.113	0.103
	Arbitrage price portfolio (*winner–loser*)	0.232	0.240	0.248	0.225	0.207
		(0.60)	(0.54)	(0.52)	(0.45)	(0.41)
Panel E: Test of differences between price momentum profits and style momentum profits over the second sub-period January 2007 to December 2017 (*t*-diff of Panel B & Panel D)						
3		[3.42]***	[3.71]***	[3.30]***	[3.04]***	[2.61]***
6		[3.25]***	[3.53]***	[2.99]***	[2.92]***	[2.62]***
9		[3.11]***	[3.29]***	[2.97]***	[2.73]***	[2.50]**
12		[2.92]***	[3.10]***	[2.84]***	[2.54]**	[2.39]**

First, this table presents the value-weighted average monthly returns of *winner* style portfolios, *loser* style portfolios, and arbitrage style portfolios (*winner* style portfolio—*loser* style portfolio) for various style momentum strategies over the first sub-period January 1994 to December 2006 (in Panel A) and the second sub-period January 2006 to December 2017 (in Panel B). Specifically, in the first sub-period, starting in January 1995, we rank the nine style portfolios (i.e., *BH*, *MH*, *SH*, *BM*, *MM*, *SM*, *BL*, *ML*, and *SL*) created at the end of 1994, based on their valued-weighted cumulative returns in previous *F* ranking months (*F*=3, 6, 9, or 12). We construct arbitrage style portfolios based on two extreme style portfolios that perform best (*winner* style portfolio) and worst (*loser* style portfolio). An $F \times H$ style momentum strategy simultaneously buys *winner* style portfolio and sells *loser* style portfolio according to their past *F*-month performance, and the arbitrage style portfolios are held in the subsequent *H* months (*H*=3, 6, 9, 12, or 24). We skip one month between the ranking and holding periods to avoid the potential market microstructure bias resulted from the bid-ask bounce and the lead-lag effect. We repeat this procedure every month until December 2005. We use the similar procedure to construct various $F \times H$ style momentum strategies in the second sub-period. The *t*-statistics of the differences of monthly returns between *winner* and *loser* style portfolios presented in parentheses are corrected for serial correlation and heteroskedasticity, using the procedure of Newey and West (1987). Panel C of this table presents the *t*-statistics in brackets for the difference of average monthly returns of arbitrage style portfolios between the two sub-periods

In addition, we construct various price momentum strategies over the second sub-period January 2007 to December 2017, following the method of Jegadeesh and Titman (1993). Specifically, starting in January 2007, all stocks are ranked on the basis of their past *F*-month returns (*F*=3, 6, 9, or 12); stocks in the lowest past return decile are identified as *loser* price portfolio, and stocks in the highest return decile are identified as *winner* price portfolio. An $F \times H$ price momentum strategy simultaneously buys *winner* price portfolio and sells *loser* price portfolio according to their past *F*-month performance, and the arbitrage price portfolios are held in the subsequent *H* months (*H*=3, 6, 9, 12, or 24). We skip one month between the ranking and holding periods to avoid the potential market microstructure bias. We repeat this procedure every month until December 2017. We present the value-weighted average monthly returns of *winner* price portfolios, *loser* price portfolios, and arbitrage price portfolios (*winner* price portfolio–*loser* price portfolio) for various price momentum strategies over the second sub-period January 2007 to December 2017 (in Panel E). The *t*-statistics of the differences of monthly returns between *winner* and *loser* style portfolios presented in parentheses are corrected for serial correlation and heteroskedasticity, using the procedure of Newey and West (1987). Panel F presents the *t*-statistics in brackets for the difference of average monthly returns between arbitrage style portfolios and arbitrage price portfolios in the second sub-period

***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively

Table 4 The distribution of characteristics of *winner* and *loser* style portfolios

$F=$		*BH*	*BM*	*BL*	*MH*	*MM*	*ML*	*SH*	*SM*	*SL*	Value	Growth	Big	Small
3	Buy *winner* style portfolio	6.62	12.88	39.44	1.13	1.14	21.24	2.14	3.60	11.81	9.89	72.48	58.94	17.55
	Sell *loser* style portfolio	23.21	6.93	1.12	10.20	3.87	1.87	26.08	11.90	14.83	59.48	17.82	31.26	52.81
6	Buy *winner* style portfolio	1.40	14.12	52.81	0.29	1.49	19.07	2.07	2.36	6.39	3.77	78.27	68.33	10.82
	Sell *loser* style portfolio	23.00	2.75	0.13	17.38	1.08	0.62	30.56	14.13	10.37	70.94	11.12	25.88	55.05
9	Buy *winner* style portfolio	0.75	16.09	55.57	0.00	1.73	19.50	1.73	0.52	4.12	2.48	79.18	72.41	6.37
	Sell *loser* style portfolio	21.53	0.91	0.00	21.45	0.22	0.50	31.56	13.60	10.23	74.54	10.73	22.44	55.39
12	Buy *winner* style portfolio	1.48	15.50	57.34	0.00	1.02	19.37	1.54	0.52	3.23	3.01	79.94	74.31	5.29
	Sell *loser* style portfolio	22.00	0.27	0.00	21.34	0.00	0.00	31.96	15.30	9.14	75.30	9.14	22.26	56.39

This table reports the percentage frequency (%) of styles appearing in the *winner* and *loser* style portfolios based on the past F-month ranking period returns ($F=3$, 6, 9, or 12) over the second sub-period January 2007 to December 2017. Specifically, starting in January 2007, we rank the nine style portfolios (i.e., *BH*, *MH*, *SH*, *BM*, *MM*, *SM*, *BL*, *ML*, and *SL*) created at the end of 2006, based on their valued-weighted cumulative returns in previous F ranking months ($F=3$, 6, 9, or 12). We construct arbitrage style portfolios based on two extreme style portfolios that perform best (*winner* style portfolio) and worst (*loser* style portfolio). An $F\times H$ style momentum strategy simultaneously buys *winner* style portfolio and sells *loser* style portfolio according to their past F-month performance, and the arbitrage style portfolios are held in the subsequent H months ($H=3$, 6, 9, 12, or 24). We skip one month between the ranking and holding periods to avoid the potential market microstructure bias resulted from the bid-ask bounce and the lead-lag effect. We repeat this procedure every month until December 2017 portfolios based on the past 3-, 9-, and 12-month ranking period returns, indicating that style momentum does not cluster in a few stocks with certain styles.

4.3 Style momentum profits and price momentum

We also examine the profitability of various $F \times H$ price momentum strategies in the second sub-period, following the method of Jegadeesh and Titman (1993). Panel D of Table 3 shows no evidence of price momentum—none of price momentum strategies is profitable in the second period—consistent with prior Chinese studies (see, e.g., Wang 2004; Chui et al. 2010; Wu 2011; Pan et al. 2013). Panel E of Table 3 shows that that style momentum strategies consistently outperform their contemporaneous price momentum strategies, with significant *t*-statistics for the differences of monthly returns between the two momentum strategies, at the 1% level, supporting Barberis and Shleifer's (2003) *Proposition 7* and confirming that style momentum is distinguished from price momentum.

4.4 Style momentum profits and foreign institutional investors

We further examine the relationship between style momentum profits and foreign institutional investors in the second sub-period. Specifically, we regress the value-weighted monthly return of arbitrage style portfolios (R_{Style}) on two proxies for foreign institutional investors, i.e., the monthly number of QFIIs (*Number*) and the natural logarithm of approved monthly investment quota of QFIIs (*LnQuota*), separately.

We find a positive relationship between style momentum profits and foreign institutional investors. For example, Table 5 shows a significantly positive coefficient of 0.037 (t-stat = 5.92) for *Number*, at the 1% level, for the 6×6 style momentum strategy; a significantly positive coefficient of 0.039 for *Number* (t-stat = 5.65), at the 1% level, for the 6×12 style momentum strategy. Similarly, we find significantly positive coefficients of 0.109 (t-stat = 2.51) and 0.097 (t-stat = 2.39) for *LnQuota*, at the 5% level, for the 6×6 and 6×12 style momentum strategies, respectively. Overall, our results confirm the importance of the fast growth of institutional investors; in particular, the introduction of the QFII program plays an important role in resource allocation and price discovery in the China stock market.

4.5 Can style momentum profits survive trading costs?

From a practical investment perspective, a natural question to ask is whether style momentum profits shown in the second sub-period remain statistically and economically significant after trading costs are taken into account. Several prior studies show that price momentum strategies are sensitive to trading costs; as a result, price momentum profits often disappear after adjusting for trading costs (see, e.g., Lesmond et al. 2004; Korajczyk and Sadka 2004). According to Chen (2003), in style momentum strategies, trading occurs for four main reasons: (i) a past *winner* or *loser* style portfolio no longer produces extreme performance; (ii) a firm migrates

Table 5 Style momentum profits and foreign institutional investors

$F=$		$H=3$		6		9		12		24	
3	*Intercept*	0.816	0.788	0.859	0.828	0.799	0.777	0.748	0.717	0.673	0.664
		(2.17)**	(2.09)**	(2.24)**	(2.18)**	(2.07)**	(2.01)**	(1.76)*	(1.72)*	(1.48)	(1.45)
	Number	0.036		0.034		0.031		0.037		0.035	
		(5.21)***		(5.02)***		(4.28)***		(5.36)***		(5.12)***	
	LnQuota		0.127		0.136		0.129		0.110		0.107
			(2.63)***		(2.95)***		(2.85)***		(2.56)***		(2.35)**
	Adj. R2	0.010	0.016	0.011	0.018	0.012	0.018	0.013	0.016	0.013	0.017
6	*Intercept*	1.141	1.105	1.198	1.145	1.132	1.114	0.968	0.952	0.852	0.834
		(2.32)**	(2.27)**	(2.50)**	(2.43)**	(2.16)**	(2.10)**	(1.84)*	(1.80)*	(1.62)	(1.56)
	Number	0.035		0.037		0.032		0.039		0.036	
		(5.88)***		(5.92)***		(5.82)***		(5.65)***		(5.61)***	
	LnQuota		0.125		0.109		0.117		0.097		0.096
			(2.66)***		(2.51)**		(2.30)**		(2.39)**		(2.43)**
	Adj. R2	0.009	0.017	0.010	0.017	0.010	0.016	0.009	0.017	0.009	0.019
9	*Intercept*	1.067	1.041	1.102	1.074	1.080	1.032	0.955	0.929	0.834	0.817
		(2.16)**	(2.12)**	(2.37)**	(2.32)**	(2.02)**	(1.98)**	(1.79)*	(1.75)*	(1.63)	(1.60)
	Number	0.030		0.034		0.033		0.035		0.034	
		(5.15)***		(5.66)***		(5.58)***		(5.71)***		(5.40)***	
	LnQuota		0.117		0.109		0.101		0.115		0.091
			(2.42)**		(2.46)**		(2.29)**		(2.18)**		(2.23)**
	Adj. R2	0.011	0.015	0.011	0.017	0.010	0.017	0.011	0.017	0.011	0.018
12	*Intercept*	0.920	0.903	0.950	0.935	0.931	0.907	0.794	0.781	0.735	0.725
		(2.08)**	(2.03)**	(2.14)**	(2.08)**	(1.86*	(1.83)*	(1.69)*	(1.66	(1.42)	(1.39)
	Number	0.027		0.028		0.027		0.023		0.023	
		(4.80)***		(4.82)***		(4.67)***		(4.77***		(4.33)***	
	LnQuota		0.127		0.142		0.138		0.129		0.124

Table 5 (continued)

$F=$	$H=3$		6		9		12		24	
		(2.36)**		(2.52)**		(2.32)**		(2.23)**		(2.14)**
Adj. R2	0.008	0.015	0.009	0.014	0.013	0.012	0.011	0.014	0.013	0.011

This table presents the time-series coefficients of the OLS regressions in the H-month holding period ($H=3$, 6, 9, 12, or 24), based on the past F-month ranking period returns ($F=3$, 6, 9, or 12), over the second sub-period January 2007 to December 2017. Specifically, we regress style momentum profits ($R_{Style,t}$) on two proxies for foreign institutional investors, i.e., the monthly number of QFIIs ($Number_t$) and the natural logarithm approved monthly investment quota of QFIIs ($LnQuota_t$), separately (see Appendix A). The t-statistics presented in adjusted using the procedure of Newey and West (1987)

***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively

between style portfolios; (iii) a firm joins or leaves the SHSE or the SZSE; and (iv) a firm performs differently from others within the same style portfolio and the style portfolio requires rebalancing. In this subsection, we examine whether our reported style momentum profits in the second sub-period can survive trading costs, though this may not be a very serious issue in our study as the returns of arbitrage style portfolios are calculated on a monthly basis.

For example, our 6×6 style momentum strategy requires an average turnover of 226.4% semiannually (the average turnovers for buying *winner* style portfolio and selling *loser* style portfolio are 235.2% and 217.6% semiannually, respectively). The break-even trading cost is therefore approximately 65.9 basis points (single-trip long or short transactions). Panel C of Table 3 shows that holding the 6×6 style momentum strategy for additional six months, i.e., the 6×12 style momentum strategy, does not reduce the average monthly return (see, also, Chen and De Bondt 2004). Thus, it is likely to reduce turnover to 113.2% annually, raising the break-even trading cost to 110.8 basis points.[7]

Keim and Madhavan (1998) categorize trading costs into explicit costs (e.g., brokerage commissions, trading fees, and taxes) and implicit costs (e.g., bid-ask spread and market impact of trading). The trading fees and taxes charged or collected by the SHSE and the SZSE include transaction levy (0.0487‰ for both buys and sells), regulatory levy (0.02‰ for both buys and sells), and stamp duty (1‰ only for sells).[8] Investors also need to pay commissions of no more than 0.3% to brokerage houses, though institutional investors have greater bargaining power and usually pay much lower commissions, e.g., less than 0.1% (see, van der Hart et al. 2003). Therefore, explicit costs in the China stock market are no more than 15 (25) basis points for buys (sells). Unlike explicit costs, which are typically visible accounting charges, implicit costs represent indirect trading costs that are difficult to measure. Domowitz et al. (2001) document that, although the composition of trading costs is varied across countries, explicit costs represent roughly two-third of the total trading costs, e.g., 62% for emerging markets, so the total trading costs will not be over 25 (40) basis points for buys (sells). From a cautious perspective, our estimate of the average trading costs of 50 basis points for buys and sells in the China stock market (see, also, Chen et al. 2015). Therefore, the break-even trading cost of 110.8 basis points appears to far exceed the actual trading costs in the China stock market.

4.6 Style momentum profits after controlling for market and firm-specific risks

Prior studies suggest that the profitability of price momentum strategies may simply be attributed to risk compensation (see, e.g., Conrad and Kaul 1998; Johnson 2002; Lewellen 2002). Specifically, Wang and Wu (2011) find that nearly all of style momentum profits could be explained by the Fama and French (1993) three-factor

[7] For the arbitrage style portfolio, the roundtrip break-even trading cost = style momentum profit / portfolio turnover (see more details in Berkowitz et al. 1988; Chen 2003).

[8] See details in the official websites of the SHSE (https://bit.ly/3fTWemQ) and the SZSE (https://bit.ly/2m9YsIn).

model. In this subsection, we proceed to explore whether the reported style momentum profits in the second sub-period will disappear after accounting for market and firm-specific risks. Like Wang (2004), Wang and Wu (2011), and Cheema and Nartea (2014), we estimate risk-adjusted returns of various arbitrage style portfolios using the Fama and French (1993) three-factor model:

$$R_{style,t} - r_{f,t} = \alpha + \beta_1 \left(Mkt_t - r_{f,t} \right) + s_i SMB_t + h_i HML_t + \varepsilon_t, \tag{1}$$

where $R_{style,t}$ represents the value-weighted monthly return of arbitrage style portfolio; $r_{f,t}$ represents the 3-month household deposit interest rate in China as a proxy for the risk free rate (see, also, Su 2015); Mkt_t represents the contemporaneous value-weighted monthly return on the SHSE and the SZSE A-share indices; SMB_t and HML_t represent the contemporaneous monthly returns on zero-investment factor-mimicking portfolios for size and B/M, respectively, collected from the CSMAR database.

Table 6 shows that beta values of various arbitrage style portfolios are all statistically insignificant, along with relatively small magnitude, indicating that little systematic risk associated with style momentum profits in the China stock market. In addition, the size and value factor loadings are insignificant and negative, suggesting that firm-specific risk factors are not relevant to style momentum profits in the China stock market. Therefore, it is not surprising that almost all estimated alphas are statistically significant, at least at the 10% level, in the second sub-period; also, these estimated alphas are quite close to the value-weighted average monthly returns to corresponding style momentum strategies as shown in Panel C of Table 3.[9] For example, for the 6×6 style momentum strategy, the estimated alpha of 1.268% (t-stat = 2.57) is significantly positive, at the 1% level; also, a significantly positive estimated alpha of 1.088% (t-stat = 1.97) for the 6×12 style momentum strategy, at the 5% level.

Overall, our time-series regression results suggest that the contemporaneous market, size, and value factors fail to account for style momentum profits in the China stock market, so we stick to the analysis of the profitability of style momentum strategies from the return perspective rather than on a risk-adjusted basis in the rest of this paper.

5 Is style momentum distinguished from industry momentum?

In this section, we examine whether the observed style momentum in the second sub-period is a phenomenon that can be distinguished from industry momentum. To remove any confounding effect associated with industry momentum, we employ three alternative approaches to disentangle the two phenomena: (i) the industry-adjusted style momentum profits, (ii) an independent two-way classification scheme,

[9] Also, Kang et al. (2002) report statistically significant price momentum profits after controlling for time-varying market risk.

Table 6 The risk-adjusted monthly returns of arbitrage style portfolios in the second sub-period

$F=$		$H=3$	6	9	12	24
3	*Alpha* (α)	0.939	1.044	0.971	0.904	0.844
		(2.31)**	(2.43)**	(2.23)**	(1.93)*	(1.67)*
	Mkt_t (β)	0.003	0.006	0.005	0.005	0.008
		(0.37)	(0.47)	(0.45)	(0.55)	(0.51)
	SMB_t	– 0.214	– 0.204	– 0.245	– 0.243	– 0.209
		(– 1.00)	(– 1.11)	(– 1.18)	(– 1.12)	(– 1.08)
	HML_t	– 0.229	– 0.215	– 0.279	– 0.258	– 0.222
		(– 1.32)	(– 1.17)	(– 1.17)	(– 1.22)	(– 1.05)
	Adj. R^2	0.058	0.067	0.061	0.062	0.057
6	*Alpha* (α)	1.198	1.268	1.217	1.088	0.886
		(2.51)**	(2.57)***	(2.37)**	(1.97)**	(1.73)*
	Mkt_t (β)	0.003	0.005	0.004	0.003	0.005
		(0.45)	(0.31)	(0.48)	(0.35)	(0.40)
	SMB_t	– 0.189	– 0.182	– 0.187	– 0.186	– 0.185
		(– 1.04)	(– 1.08)	(– 1.22)	(– 1.24)	(– 1.23)
	HML_t	– 0.215	– 0.219	– 0.211	– 0.213	– 0.191
		(– 1.25)	(– 1.17)	(–1.18)	(–1.11)	(–1.03)
	Adj. R^2	0.008	0.006	0.009	0.008	0.008
9	*Alpha* (α)	1.171	1.192	1.136	1.018	0.871
		(2.35)**	(2.48)**	(2.19)**	(1.92)*	(1.72)*
	Mkt_t (β)	0.004	0.004	0.003	0.004	0.006
		(0.51)	(0.40)	(0.49)	(0.50)	(0.43)
	SMB_t	–0.212	–0.237	–0.216	–0.233	–0.224
		(–1.32)	(–1.17)	(–1.41)	(–1.27)	(–1.16)
	HML_t	–0.209	–0.217	–0.237	–0.230	–0.238
		(–1.22)	(–1.34)	(–1.13)	(–1.08)	(–1.04)
	Adj. R^2	0.005	0.004	0.007	0.005	0.004
12	*Alpha* (α)	1.043	1.066	1.021	0.879	0.827
		(2.22)**	(2.36)**	(2.06)**	(1.86)*	(1.54)
	Mkt_t (β)	0.005	0.006	0.008	0.007	0.007
		(0.66)	(0.70)	(0.54)	(0.75)	(0.79)
	SMB_t	–0.174	–0.193	–0.177	–0.190	–0.183
		(–1.18)	(–1.36)	(–1.24)	(–1.48)	(–1.26)
	HML_t	–0.163	–0.161	–0.154	–0.153	–0.155
		(–1.23)	(–1.08)	(–1.17)	(–1.10)	(–1.03)
	Adj. R^2	0.004	0.005	0.007	0.005	0.004

This table presents the time-series coefficients of the OLS regressions in the H-month holding period ($H=3$, 6, 9, 12, or 24), based on the past F-month ranking period returns ($F=3$, 6, 9, or 12), over the second sub-period January 2007 to December 2017. Specifically, we regress style momentum profits (R_{Style}) in excess of the risk free rate (r_f) on market premium as well as on size and value factors. $R_{style,t}$ represents the value-weighted monthly return of arbitrage style portfolios; $r_{f,t}$ represents the 3-month household deposit interest rate in China as a proxy for the risk free rate; Mkt_t represents the contemporaneous value-weighted monthly return on the SHSE and the

Table 6 (continued) SZSE A-share indices; SMB_t and HML_t represent the contemporaneous monthly returns on zero-investment factor-mimicking portfolios for size and B/M, respectively, collected from the CSMAR database. The *t*-statistics presented in adjusted using the procedure of Newey and West (1987)

***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively

and (iii) the Fama and MacBeth (1973) regressions. Our results consistently show that style momentum is distinguished from industry momentum in China.

5.1 Industry-adjusted style momentum profits

In addition to creating various style portfolios in Subsection 3.2, we assign every firm to one of 16 super-sectors, according to four-digit ICB codes (see "Appendix B") and then adjust the value-weighted average monthly returns of arbitrage style portfolios by deducting the contemporaneous returns of their matching industry portfolios.

Table 7 shows that the industry-adjusted average monthly returns of arbitrage style portfolios are of similar magnitude to their unadjusted counterparts as shown in Panel B of Table 3. For example, the 6×6 style momentum strategy generates a significantly positive industry-adjusted monthly return of 1.267% (*t*-stat = 2.64), at the 1% level; also, a significantly positive industry-adjusted monthly return of 1.102% (*t*-stat = 2.16), at the 5% level, for the 6×12 style momentum strategy. Our results suggest that the observed style momentum profits are not affected by industry momentum.

5.2 An independent two-way classification scheme

To avoid the sorting-out-sorts problem criticized by Berk (2000), we further examine the interaction of style momentum and industry momentum on the basis of an independent two-way classification scheme (see, also, Chen and De Bondt 2004). Specifically, in every month from January 2006 to December 2017, nine style portfolios are formed based on the past *F*-month ranking period returns ($F=3$, 6, 9, or 12). The bottom three style portfolios are labeled $Style_1$ (*loser* style portfolios), while the top three style portfolios are labeled $Style_3$ (*winner* style portfolios); three style portfolios in the middle are labeled $Style_2$. Next, 16 industry portfolios are also ranked by their past *F*-month performance. The bottom five industry portfolios are labeled $Industry_1$ (*loser* industry portfolios), while the top five industry portfolios are labeled $Industry_3$ (*winner* industry portfolios); six industry portfolios in the middle are labeled $Industry_2$. Every firm in our sample is assigned to one of the nine *Industry-Style* portfolios.

Table 8 reports the value-weighted average monthly returns for each *Industry-Style* portfolio over the *H*-month holding periods ($H=3$, 6, 9, 12, or 24), based on the past *F*-month ranking period returns. For example, sorted by average returns

Table 7 The industry-adjusted value-weighted average monthly returns of style momentum portfolios over the second sub-period

$F=$		$H=3$	6	9	12	24
3	Industry-adjusted *loser* style portfolio	0.401	0.433	0.407	0.355	0.302
	Industry-adjusted *winner* style portfolio	1.391	1.436	1.366	1.257	1.130
	Arbitrage industry-adjusted style portfolio (*winner–loser*)	0.990	1.004	0.959	0.902	0.827
	t-stat	(2.19)**	(2.29)**	(2.13)**	(2.05)**	(1.62)
6	Industry-adjusted *loser* style portfolio	0.410	0.423	0.404	0.347	0.293
	Industry-adjusted *winner* style portfolio	1.663	1.690	1.697	1.449	1.134
	Arbitrage industry-adjusted style portfolio (*winner–loser*)	1.253	1.267	1.293	1.102	0.842
	t-stat	(2.45)**	(2.64)***	(2.24)**	(2.16)**	(1.75)*
9	Industry-adjusted *loser* style portfolio	0.394	0.457	0.390	0.329	0.322
	Industry-adjusted *winner* style portfolio	1.585	1.683	1.579	1.400	1.204
	Arbitrage industry-adjusted style portfolio (*winner–loser*)	1.191	1.226	1.189	1.072	0.882
	t-stat	(2.50)**	(2.57)***	(2.34)**	(2.01)**	(1.92)*
12	Industry-adjusted *loser* style portfolio	0.321	0.377	0.313	0.282	0.270
	Industry-adjusted *winner* style portfolio	1.370	1.474	1.337	1.143	1.065
	Arbitrage industry-adjusted style portfolio (*winner–loser*)	1.049	1.097	1.024	0.860	0.795
	t-stat	(2.39)**	(2.51)**	(2.25)**	(1.95)*	(1.61)

This table presents the industry-adjusted value-weighted average monthly returns of and arbitrage style portfolios (*winner* style portfolio–*loser* style portfolio) for various style momentum strategies over the second sub-period January 2007 to December 2017. Specifically, starting in January 2007, we rank the nine style portfolios (i.e., *BH*, *MH*, *SH*, *BM*, *MM*, *SM*, *BL*, *ML*, and *SL*) created at the end of 2006, based on their valued-weighted cumulative returns in previous F ranking months ($F=3$, 6, 9, or 12). We construct arbitrage style portfolios based on two extreme style portfolios that perform best (*winner* style portfolio) and worst (*loser* style portfolio). An $F \times H$ style momentum strategy simultaneously buys *winner* style portfolio and sells *loser* style portfolio according to their past F-month performance, and the arbitrage style portfolios are held in the subsequent H months ($H=3$, 6, 9, 12, or 24). We skip one month between the ranking and holding periods to avoid the potential market microstructure bias resulted from the bid-ask bounce and the lead-lag effect. We repeat this procedure every month until December 2005, allowing investment styles to vary over time. In addition to constructing various style portfolios, we assign every firm to one of 16 supersectors, according to four-digit ICB codes (see Appendix B) and then adjust the value-weighted average monthly returns of arbitrage style portfolios (*winner* style portfolio–*loser* style portfolio) by deducting the contemporaneous returns of their matching industry portfolios. The *t*-statistics of the differences of industry-adjusted monthly returns between *winner* and *loser* style portfolios presented in parentheses are corrected for serial correlation and heteroskedasticity, using the procedure of Newey and West (1987)

***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively

of industry portfolios in the past 6-month ranking period, the best past style portfolios continue to outperform the worst past style portfolios by between 0.877% and 1.247% per month. Table 8 shows consistent and even larger gap between the extreme style portfolios sorted by average returns of industry portfolios in the past 3-, 9-, and 12-month ranking periods. In summary, our results based on the

Table 8 The value-weighted average monthly returns of industry momentum portfolios that vary in style momentum in the second sub-period

$F=$		$H=3$	6	9	12	24
3	$Indstry_1$-$Style_1$	0.890	0.877	0.874	0.821	0.793
	$Indstry_1$-$Style_3$	2.076	2.106	2.116	1.987	1.709
	$Indstry_1$-$Style_3$–$Indstry_1$-$Style_1$	1.186	1.229	1.241	1.165	0.916
	t-stat	(2.40)**	(2.64)***	(2.24)**	(2.01)**	(1.91)*
	$Indstry_2$-$Style_1$	0.759	0.794	0.732	0.657	0.694
	$Indstry_2$-$Style_3$	1.906	1.995	1.897	1.714	1.657
	$Indstry_2$-$Style_3$–$Indstry_2$-$Style_1$	1.147	1.201	1.165	1.057	0.963
	t-stat	(2.49)**	(2.62)***	(2.31)**	(2.11)**	(1.98)**
	$Indstry_3$-$Style_1$	0.690	0.701	0.718	0.629	0.550
	$Indstry_3$-$Style_3$	1.853	1.896	1.807	1.591	1.424
	$Indstry_3$-$Style_3$–$Indstry_3$-$Style_1$	1.164	1.195	1.088	0.963	0.874
	t-stat	(2.40)**	(2.51)**	(2.28)**	(2.03)**	(1.94)*
6	$Indstry_1$-$Style_1$	0.895	0.879	0.881	0.830	0.800
	$Indstry_1$-$Style_3$	2.089	2.120	2.129	1.999	1.715
	$Indstry_1$-$Style_3$–$Indstry_1$-$Style_1$	1.195	1.240	1.247	1.169	0.916
	t-stat	(2.32)**	(2.56)***	(2.17)**	(1.99)**	(1.91)*
	$Indstry_2$-$Style_1$	0.762	0.795	0.738	0.663	0.700
	$Indstry_2$-$Style_3$	1.924	2.011	1.913	1.727	1.665
	$Indstry_2$-$Style_3$–$Indstry_2$-$Style_1$	1.161	1.216	1.175	1.064	0.966
	t-stat	(2.37)**	(2.53)**	(2.21)**	(2.03)**	(1.95)*
	$Indstry_3$-$Style_1$	0.692	0.702	0.723	0.635	0.556
	$Indstry_3$-$Style_3$	1.868	1.910	1.822	1.605	1.433
	$Indstry_3$-$Style_3$–$Indstry_3$-$Style_1$	1.177	1.208	1.099	0.970	0.877
	t-stat	(2.29)**	(2.42)**	(2.18)**	(1.94)*	(1.89)*
9	$Indstry_1$-$Style_1$	0.893	0.879	0.878	0.825	0.796
	$Indstry_1$-$Style_3$	2.083	2.112	2.123	1.994	1.712
	$Indstry_1$-$Style_3$–$Indstry_1$-$Style_1$	1.190	1.233	1.244	1.167	0.916
	t-stat	(2.36)**	(2.61)***	(2.20)**	(1.98)**	(1.91)*
	$Indstry_2$-$Style_1$	0.761	0.795	0.735	0.660	0.697
	$Indstry_2$-$Style_3$	1.915	2.003	1.905	1.721	1.662
	$Indstry_2$-$Style_3$–$Indstry_2$-$Style_1$	1.154	1.207	1.170	1.061	0.965
	t-stat	(2.44)**	(2.57)***	(2.26)**	(2.07)**	(1.96)**
	$Indstry_3$-$Style_1$	0.691	0.701	0.721	0.632	0.553
	$Indstry_3$-$Style_3$	1.861	1.902	1.814	1.597	1.429
	$Indstry_3$-$Style_3$–$Indstry_3$-$Style_1$	1.170	1.201	1.093	0.966	0.876
	t-stat	(2.35)**	(2.47)**	(2.24)**	(1.97)**	(1.93)*
12	$Indstry_1$-$Style_1$	0.896	0.878	0.884	0.833	0.803
	$Indstry_1$-$Style_3$	2.097	2.128	2.136	2.005	1.718
	$Indstry_1$-$Style_3$–$Indstry_1$-$Style_1$	1.201	1.250	1.252	1.172	0.915
	t-stat	(2.26)**	(2.50)**	(2.12)**	(1.93)*	(1.90)*
	$Indstry_2$-$Style_1$	0.763	0.795	0.740	0.665	0.702

Table 8 (continued)

$F=$		$H=3$	6	9	12	24
	$Indstry_2$-$Style_3$	1.933	2.021	1.921	1.734	1.669
	$Indstry_2$-$Style_3$–$Indstry_2$-$Style_1$	1.169	1.225	1.181	1.068	0.967
	t-stat	(2.30)**	(2.47)**	(2.15)**	(1.98)**	(1.94)*
	$Indstry_3$-$Style_1$	0.694	0.702	0.725	0.637	0.559
	$Indstry_3$-$Style_3$	1.878	1.920	1.831	1.612	1.437
	$Indstry_3$-$Style_3$–$Indstry_3$-$Style_1$	1.185	1.218	1.105	0.975	0.879
	t-stat	(2.22)**	(2.37)**	(2.12)**	(1.89)*	(1.86)*

This table presents the value-weighted average monthly returns for each *Industry-Style* portfolio in the H-month holding periods ($H=3$, 6, 9, 12, or 24), based on the past F-month ranking period returns ($F=3$, 6, 9, or 12), over the second sub-period January 2007 to December 2017. Specifically, the nine style portfolios (i.e., *BH*, *MH*, *SH*, *BM*, *MM*, *SM*, *BL*, *ML*, and *SL*) are ranked based on the past F-month ranking period returns ($F=3$, 6, 9, or 12). The bottom three style portfolios are labeled $Style_1$ (*loser* style portfolios), while the top three style portfolios are labeled $Style_3$ (*winner* style portfolios); three style portfolios in the middle are labeled $Style_2$. Next, 16 industry portfolios are also ranked by their past F-month performance. The bottom five industry portfolios are labeled $Industry_1$ (*loser* industry portfolios), while the top five industry portfolios are labeled $Industry_3$ (*winner* industry portfolios); six industry portfolios in the middle are labeled $Industry_2$. Every firm in our sample is assigned to one of the nine *Industry-Style* portfolios. The t-statistics of the value-weighted monthly returns of the *Industry-Style* portfolios presented in parentheses are corrected for serial correlation and heteroskedasticity, using the procedure of Newey and West (1987)

***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively

independent two-way classification scheme again confirm that style momentum profits are not affected by industry momentum in the China stock market.

5.3 The Fama and MacBeth (1973) regressions

Finally, we employ the Fama and MacBeth (1973) regressions to disentangle industry momentum and style momentum. Specifically, the monthly cross-sectional regressions are estimated from individual stock returns (R_i) on their contemporaneous returns of style portfolios (R_{Style}) and industry portfolios ($R_{Industry}$). The dependent variable of R_i represents the raw buy-and-hold returns of stock i in the H-month holding period ($H=3$, 6, 9, 12, or 24), based on the past F-month ranking period returns ($F=3$, 6, 9, or 12). The independent variables of R_{Style} and $R_{Industry}$, respectively, represent the average monthly returns of style portfolio and industry portfolio that stock i belongs to in the past F-month ranking periods.

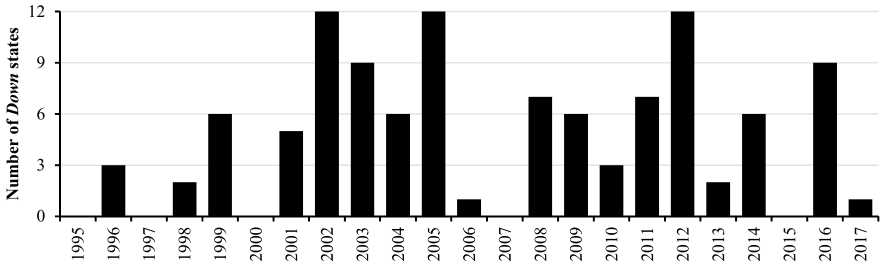
Table 9 reports the time-series coefficients of the Fama and MacBeth (1973) regressions in the H-month holding period, based on the past F-month ranking period returns, along with the t-statistics adjusted using the procedure of Newey and West (1987). Specifically, R_{Style} shows strong predictive power on R_i in the subsequent holding period up to 24 months, while this is not the case for $R_{Industry}$. For example, for the 6×6 style momentum strategy, R_{Style} has a significant coefficient of 0.185 (t-stat$=2.48$) at the 5% level, but $R_{Industry}$ has an insignificant coefficient of 0.367 (t-stat$=0.67$). Overall, our regression results

Table 9 The Fama and MacBeth (1973) regression results in the second sub-period

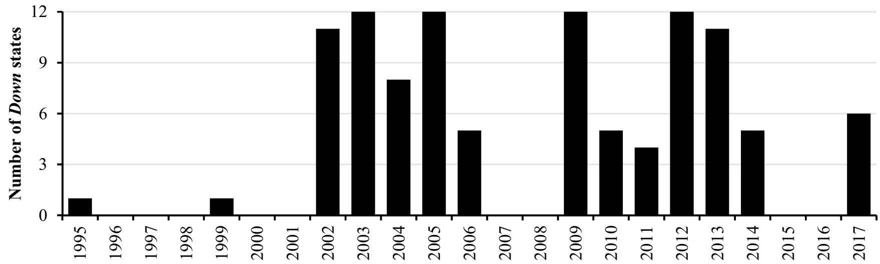
$F=$		$H=3$	6	9	12	24
3	*Intercept*	0.983	1.039	0.967	0.898	0.845
		(2.18)**	(2.29)**	(2.10)**	(1.80)*	(1.52)
	$R_{Industry}$	0.352	0.229	0.382	0.303	0.284
		(0.67)	(0.58)	(0.67)	(0.65)	(0.64)
	R_{Style}	0.159	0.178	0.161	0.174	0.147
		(2.29)**	(2.31)**	(2.26)**	(2.38)**	(2.08)**
	*Adj. R*2	0.101	0.097	0.102	0.098	0.099
6	*Intercept*	1.172	1.216	1.155	1.050	0.920
		(2.24)**	(2.49)**	(2.09)**	(1.88)*	(1.76)*
	$R_{Industry}$	0.396	0.367	0.356	0.310	0.298
		(0.78)	(0.67)	(0.60)	(0.57)	(0.44)
	R_{Style}	0.179	0.185	0.185	0.160	0.137
		(2.26)**	(2.48)**	(2.14)**	(1.79)*	(1.56)
	Adj. R^2	0.111	0.114	0.106	0.096	0.090
9	*Intercept*	1.144	1.188	1.129	1.025	0.898
		(2.21)**	(2.44)**	(2.07)**	(1.84)*	(1.73)*
	$R_{Industry}$	0.360	0.329	0.321	0.274	0.274
		(0.76)	(0.63)	(0.57)	(0.53)	(0.40)
	R_{Style}	0.163	0.169	0.169	0.145	0.124
		(2.18)**	(2.40)**	(2.07)**	(1.72)*	(1.49)
	Adj. R^2	0.103	0.107	0.098	0.089	0.082
12	*Intercept*	1.029	1.069	1.015	0.923	0.808
		(1.96)**	(2.17)**	(1.82)*	(1.63)	(1.53)
	$R_{Industry}$	0.369	0.346	0.331	0.297	0.287)
		(0.72)	(0.61)	(0.55)	(0.52)	(0.38)
	R_{Style}	0.161	0.166	0.167	0.142	0.122
		(2.13)**	(2.35)**	(2.02)**	(1.68)*	(1.45)
	Adj. R^2	0.094	0.095	0.090	0.081	0.076

This table presents the time-series coefficients of the Fama and MacBeth (1973) regressions in the H-month holding period ($H=3$, 6, 9, 12, or 24), based on the past F-month ranking period returns ($F=3$, 6, 9, or 12), over the second sub-period January 2007 to December 2017. Specifically, the monthly cross-sectional regressions are estimated from individual stock returns (R_i) on their contemporaneous returns of style portfolios (R_{Style}) and industry portfolios ($R_{Industry}$). The dependent variable of R_i represents the raw buy-and-hold returns of stock i in the H-month holding period, based on the past F-month ranking period returns. The independent variables of R_{Style} and $R_{Industry}$, respectively, represent the average monthly returns of style portfolio and industry portfolio that stock i belongs to in the past F-month ranking periods. The t-statistics presented in adjusted using the procedure of Newey and West (1987)

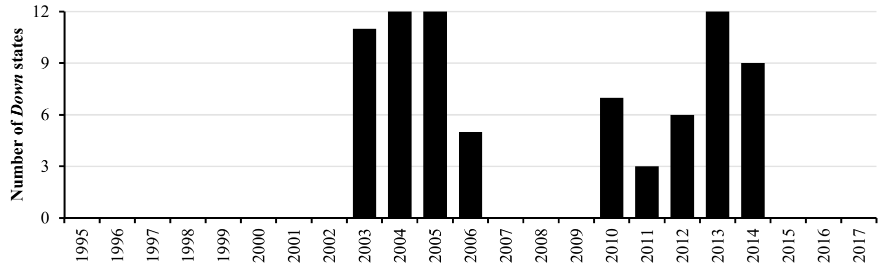
***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively



a The number of 1-year *Down* states through time



b The number of 2-year *Down* states through time



c The number of 3-year *Down* states through time

Fig. 1 The number of months within a given year for which the past k-year ($k=1$, 2, and 3) value-weighted SHSE and SZSE A-share indices is negative over the period 1995 to 2017

show that style momentum is the main determinant of stock future returns after counting for industry momentum.

5.4 Style momentum profits and market states

In this section, we identify that style portfolios exhibit momentum in a cyclical nature, e.g., statistically insignificant style momentum profits following *Up* states, but significantly positive style momentum profits following *Down* states.

5.5 Style momentum profits following Up and Down states

It has been well documented that price momentum is stronger during or after periods of low cross-sectional dispersion (see, Stivers and Sun 2010), economic expansions (see, Chordia and Shivakumar 2002), or positive market returns (see, Cooper et al. 2004; Asem and Tian 2010). In contrast, Cheema and Nartea (2017) find that the profitability of price momentum strategies exclusively follows *Down* rather than *Up* markets. Cooper et al. (2004, p. 1358) argue that *"longer horizons could capture greater differences in market states, but longer horizons also yield fewer observations of Down states"*. Figure 1 shows the number of *Down* months in each year over our entire sample period according to the lagged k-year ($k = 1$, 2, and 3) value-weighted SHSE and SZSE A-share indices. The number of *Down* states increases as the number of months defining market state decreases, in line with Cooper et al. (2004). In this study, we thus define an *Up* (*Down*) state when the past 1-year value-weighted return on the SHSE and SZSE A-share indices is non-negative (negative).[10]

Panel A of Table 10 shows that, following *Down* sates, the 6×6 and 6×12 style momentum strategies generate significantly positive monthly returns of 2.166% (t-stat = 3.33) and 1.839% (t-stat = 2.67), at the 1% level, respectively. In contrast, Panel B shows that, following *Up* states, the 6×6 and 6×12 style momentum strategies generate insignificantly positive monthly returns of 0.598% (t-stat = 1.23) and 0.533% (t-stat = 0.99), respectively. Furthermore, Panel C shows that the differences of style momentum profits between the *Up* and *Down* states are statistically significant at least at the 5% level. Our results suggest that style momentum might be predictable at some time periods and, in particular, market states have a negative impact on style momentum profits, in line with Chen and De Bondt (2004) and Cheema and Nartea (2017).

5.6 Market states as a continuous variable

We further examine the relationship between style momentum profits and market states using the lagged market return as a continuous variable. Like Cooper et al. (2004), we regress style momentum profits (R_{Style}) on the lagged market returns ($LagMkt$), the square of the lagged market returns ($LagMkt^2$), as well as the lagged returns on size and value factors:

$$R_{style,t} = \alpha + \beta_1 LagMkt_{t-1} + \beta_2 LagMkt_{t-1}^2 + s_i SMB_{t-1} + h_i HML_{t-1} + \varepsilon_t, \quad (2)$$

where $R_{style,t}$ represents the value-weighted monthly return of arbitrage style portfolios; $LagMkt_{t-1}$ represents the lagged 1-year value-weighted monthly return on the SHSE and the SZSE A-share indices; SMB_{t-1} and HML_{t-1} represent the

[10] We also replicate all analyses in Sect. 6 using the lagged 2- and 3-year market returns to define market states and find qualitatively similar results, which are not reported for the sake of brevity, but available on request.

Table 10 The average monthly returns of style momentum portfolios following *Up* and *Down* states in the second sub-period

F =		*H* = 3	6	9	12	24
Panel A: Following Down states						
3	*Loser* style portfolio	0.558	0.599	0.568	0.500	0.435
	Winner style portfolio	2.268	2.405	2.255	2.045	1.869
	Arbitrage style portfolio (*winner–loser*)	1.710	1.806	1.687	1.544	1.434
	t-stat	(2.79)***	(2.87)***	(2.70)***	(2.49)**	(2.22)**
6	*Loser* style portfolio	0.569	0.586	0.564	0.489	0.424
	Winner style portfolio	2.664	2.752	2.727	2.328	1.972
	Arbitrage style portfolio (*winner–loser*)	2.095	2.166	2.163	1.839	1.549
	t-stat	(3.04)***	(3.33)***	(2.88)***	(2.67)***	(2.32)**
9	*Loser* style portfolio	0.549	0.630	0.546	0.464	0.461
	Winner style portfolio	2.521	2.688	2.492	2.204	1.990
	Arbitrage style portfolio (*winner–loser*)	1.972	2.058	1.946	1.740	1.530
	t-stat	(2.85)***	(3.09)***	(2.67)***	(2.59)***	(2.26)**
12	*Loser* style portfolio	0.455	0.526	0.448	0.407	0.395
	Winner style portfolio	2.193	2.345	2.182	1.899	1.775
	Arbitrage style portfolio (*winner–loser*)	1.738	1.819	1.735	1.491	1.379
	t-stat	(2.72)***	(2.85)***	(2.53)**	(2.39)**	(2.20)**
Panel B: Following Up states						
3	*Loser* style portfolio	0.361	0.391	0.365	0.316	0.254
	Winner style portfolio	0.820	0.867	0.819	0.743	0.686
	Arbitrage style portfolio (*winner–loser*)	0.459	0.476	0.454	0.427	0.432
	t-stat	(1.04)	(1.06)	(1.01)	(0.93)	(0.80)
6	*Loser* style portfolio	0.373	0.385	0.364	0.308	0.245
	Winner style portfolio	0.952	0.984	0.976	0.841	0.721
	Arbitrage style portfolio (*winner–loser*)	0.578	0.598	0.612	0.533	0.476
	t-stat	(1.13)	(1.23)	(1.07)	(0.99)	(0.84)
9	*Loser* style portfolio	0.357	0.418	0.350	0.290	0.274
	Winner style portfolio	0.905	0.963	0.897	0.800	0.727
	Arbitrage style portfolio (*winner–loser*)	0.548	0.545	0.547	0.510	0.453
	t-stat	(1.07)	(1.15)	(1.00)	(0.97)	(0.82)
12	*Loser* style portfolio	0.284	0.340	0.272	0.243	0.223
	Winner style portfolio	0.795	0.847	0.795	0.697	0.655
	Arbitrage style portfolio (*winner–loser*)	0.511	0.507	0.523	0.455	0.431
	t-stat	(1.02)	(1.06)	(0.95)	(0.89)	(0.78)
Panel C: Test of difference of average monthly returns to style momentum strategies between Up and Down states						
3		[2.61]***	[2.71]***	[2.52]**	[2.32]**	[2.09]**
6		[2.84]***	[3.12]***	[2.69]***	[2.50]**	[2.19]**
9		[2.66]***	[2.90]***	[2.48]**	[2.41]**	[2.12]**
12		[2.54]**	[2.67]***	[2.36]**	[2.23]**	[2.08]**

Table 10 (continued)

This table presents the value-weighted average monthly returns of and arbitrage style portfolios (*winner* style portfolio–*loser* style portfolio) for various style momentum strategies following the *Up* (in Panel A) and *Down* (in Panel B) market states over the second sub-period January 2007 to December 2017. We define an *Up* (*Down*) state when the past 1-year value-weighted market return on the SHSE and SZSE A-share indices is non-negative (negative). Specifically, in the second sub-period, starting in January 2007, we rank the nine style portfolios (i.e., *BH*, *MH*, *SH*, *BM*, *MM*, *SM*, *BL*, *ML*, and *SL*) created at the end of 1994, based on their valued-weighted cumulative returns in previous *F* ranking months ($F=3$, 6, 9, or 12). We construct arbitrage style portfolios based on two extreme style portfolios that perform best (*winner* style portfolio) and worst (*loser* style portfolio). An $F \times H$ style momentum strategy simultaneously buys *winner* style portfolio and sells *loser* style portfolio according to their past *F*-month performance, and the arbitrage style portfolios are held in the subsequent *H* months ($H=3$, 6, 9, 12, or 24). We skip one month between the ranking and holding periods to avoid the potential market microstructure bias resulted from the bid-ask bounce and the lead-lag effect. We repeat this procedure every month until December 2017. The *t*-statistics of the differences of monthly returns between *winner* and *loser* style portfolios presented in parentheses are corrected for serial correlation and heteroskedasticity, using the procedure of Newey and West (1987). The *t*-statistics of the differences of monthly returns of arbitrage style portfolios following the *Up* and *Down* markets are reported in brackets. Panel C of this table presents the *t*-statistics in brackets for the difference of average monthly returns of arbitrage style portfolios between *Up* and *Down* states

***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively

lagged monthly returns on zero-investment factor-mimicking portfolios for size and value, respectively; ε_t represents the error term.

In Table 11, we find a significantly negative coefficient for *LagMkt* (coefficient = –0.326; *t*-stat = –2.07), at the 5% level, for the 6×6 style momentum strategy, suggesting a negative relationship between style momentum profits and the lagged market returns, though the negative relationship is not linear, as the monthly returns are also positively related to the square of lagged market returns, $LagMkt^2$ (coefficient = 5.310; *t*-stat = 2.66), at the 1% level. Overall, style momentum is not merely time-varying, but state-dependent, supporting Barberis and Shleifer's (2003) *Proposition 8*. In particular, the negative impact of market states on style momentum profits seems to be against our *Hypothesis 2*, but this has an important implication on institutional investors, that is, it is possible for them to make profits by constructing style momentum strategies when stock market experiences a major decline.

We further test whether market states in terms of the lagged 1-year market volatility, measured by multiplying the daily volatility of the value-weighted SHSE and SZSE A-share indices by a square root of 243 (i.e., the average number of trading days per year in the second sub-period), have an impact on style momentum profits. Specifically, we regress style momentum profits (R_{Style}) on the lagged market returns (*LagMkt*), the lagged market volatilities (*LagVol*), as well as the lagged returns on size and value factors:

$$R_{style,t} = \alpha + \beta_1 LagMkt_{t-1} + \beta_2 LagVol_{t-1} + s_i SMB_{t-1} + h_i HML_{t-1} + \varepsilon_t. \quad (3)$$

where $Lagvol_{t-1}$ represents the lagged 1-year value-weighted market volatility on the SHSE and the SZSE A-share indices; other variables are as defined in Eq. (2); ε_t represents the error term.

Table 11 The state of the market as a continuous variable in the second sub-period

$F=$		$H=3$		6		9		12		24	
3	*Intercept*	0.928	0.923	0.975	0.967	0.916	0.911	0.843	0.799	0.797	0.757
		(2.12)**	(2.10)**	(2.21)**	(2.12)**	(2.04)**	(1.93)*	(1.73)*	(1.64)	(1.45)	(1.38)
	$LagMkt_{t-1}$	−0.276	−0.264	−0.309	−0.297	−0.280	−0.277	−0.302	−0.286	−0.225	−0.214
		(−1.89)*	(−1.78)*	(−1.98)**	(−1.89)*	(−1.90)*	(−1.78)*	(−1.61)	(−1.53)	(−1.71)*	(−1.62)
	$LagMkt^2_{t-1}$	5.032		5.047		5.346		5.234		5.172	
		(2.39)**		(2.48)**		(2.52)**		(2.32)**		(2.47)**	
	$LagVol_{t-1}$		0.149		0.156		0.152		0.141		0.139
			(1.72)*		(1.78)*		(1.71)*		(1.62)		(1.44)
	SMB_{t-1}	−1.037	−1.030	−0.797	−0.796	−0.971	−0.965	−0.942	−0.822	−0.974	−0.915
		(−1.54)	(−1.63)	(−1.47)	(−1.55)	(−1.63)	(−1.61)	(−1.53)	(−1.61)	(−1.58)	(−1.47)
	HML_{t-1}	−0.818	−0.814	−0.805	−0.799	−0.813	−0.808	−0.821	−0.778	−0.791	−0.752
		(−1.88)*	(−1.71)*	(−1.87)*	(−1.86)*	(−1.88)*	(−1.91)*	(−1.88)*	(−1.92)*	(−1.89)*	(−1.94)*
	Adj. R^2	0.118	0.112	0.116	0.109	0.119	0.112	0.115	0.108	0.120	0.113
6	*Intercept*	1.143	1.136	1.180	1.171	1.186	1.180	1.014	0.961	0.865	0.821
		(2.30)**	(2.25)**	(2.38)**	(2.31)**	(2.21)**	(2.02)**	(1.90)*	(1.80)*	(1.62)	(1.54)
	$LagMkt_{t-1}$	−0.291	−0.279	−0.326	−0.312	−0.294	−0.279	−0.318	−0.302	−0.239	−0.227
		(−1.98)**	(−1.83)*	(−2.07)**	(−1.80)*	(−1.99)**	(−1.88)*	(−1.71)*	(−1.62)	(−1.81)*	(−1.71)*
	$LagMkt^2_{t-1}$	5.417		5.310		5.577		5.213		5.561	
		(2.54)**		(2.66)***		(2.71)***		(2.45)**		(2.63)***	
	$LagVol_{t-1}$		0.151		0.163		0.159		0.140		0.136
			(1.79)*		(1.94)*		(1.85)*		(1.64)		(1.55)
	SMB_{t-1}	−1.099	−1.093	−0.865	−0.859	−1.041	−1.035	−1.016	−0.962	−1.044	−0.992
		(−1.87)*	(−1.78)*	(−1.72)*	(−1.67)*	(−1.77)*	(−1.66)*	(−1.86)*	(−1.76)*	(−1.82)*	(−1.73)*
	HML_{t-1}	−0.755	−0.751	−0.741	−0.735	−0.751	−0.747	−0.756	−0.716	−0.731	−0.694
		(−1.87)*	(−1.76)*	(−1.78)*	(−1.79)*	(−1.68)*	(−1.81)*	(−1.78)*	(−1.94)*	(−1.69)*	(−1.79)*
	Adj. R^2	0.107	0.101	0.109	0.103	0.107	0.101	0.108	0.102	0.111	0.105

Table 11 (continued)

$F=$		$H=3$		6		9		12		24	
9	*Intercept*	1.077	1.071	1.112	1.104	1.066	1.061	0.961	0.910	0.846	0.804
		(2.15)**	(2.04)**	(2.24)**	(2.12)**	(2.08)**	(2.00)**	(1.79)*	(1.70)*	(1.53)	(1.45)
	$LagMkt_{t-1}$	−0.300	−0.288	−0.335	−0.323	−0.303	−0.293	−0.327	−0.310	−0.246	−0.234
		(−1.96)**	(−1.87)*	(−1.98)**	(−1.89)*	(−1.90)*	(−1.88)*	(−1.61)	(−1.53)	(−1.71)*	(−1.62)
	$LagMkt^2_{t-1}$	5.279		5.234		5.439		5.137		5.423	
		(2.64)***		(2.77)***		(2.82)***		(2.54)**		(2.74)***	
	$LagVol_{t-1}$		0.143		0.148		0.139		0.130		0.126
			(1.69)*		(1.76)*		(1.68)*		(1.58)		(1.46)
	SMB_{t-1}	−1.221	−1.214	−0.961	−0.954	−1.156	−1.150	−1.128	−1.068	−1.159	−1.101
		(−1.77)*	(−1.86)*	(−1.91)*	(−1.90)*	(−1.93)*	(−1.92)*	(−1.86)*	(−1.95)*	(−1.81)*	(−1.91)*
	HML_{t-1}	−0.730	−0.726	−0.716	−0.711	−0.726	−0.722	−0.731	−0.693	−0.707	−0.671
		(−1.89)*	(−1.78)*	(−1.79)*	(−1.67)*	(−1.82)*	(−1.79)*	(−1.84)*	(−1.80)*	(−1.90)*	(−1.81)*
	Adj. R^2	0.104	0.098	0.103	0.097	0.105	0.099	0.102	0.096	0.107	0.100
12	*Intercept*	0.963	0.958	0.994	0.987	0.966	0.961	0.832	0.788	0.774	0.736
		(2.12)**	(2.01)**	(2.20)**	(2.08)**	(2.04)**	(1.93)*	(1.76)*	(1.67)*	(1.50)	(1.43)
	$LagMkt_{t-1}$	−0.289	−0.278	−0.324	−0.312	−0.293	−0.279	−0.316	−0.300	−0.238	−0.227
		(−1.89)*	(−1.78)*	(−1.99)**	(−1.86)*	(−1.80)*	(−1.69)*	(−1.61)	(−1.53)	(−1.71)*	(−1.62)
	$LagMkt^2_{t-1}$	5.196		5.171		5.348		5.078		5.334	
		(2.53)**		(2.65)***		(2.69)***		(2.45)**		(2.62)***	
	$LagVol_{t-1}$		0.128		0.139		0.131		0.125		0.120
			(1.67)*		(1.77)*		(1.69)*		(1.49)		(1.38)
	SMB_{t-1}	−1.141	−1.134	−0.902	−0.895	−1.082	−1.077	−1.056	−1.001	−1.085	−1.031
		(−1.94)*	(−1.89)*	(−1.79)*	(−1.68)*	(−1.84)*	(−1.73)*	(−1.93)*	(−1.83)*	(−1.89)*	(−1.80)*
	HML_{t-1}	−0.719	−0.715	−0.705	−0.700	−0.715	−0.711	−0.720	−0.682	−0.695	−0.661

Table 11 (continued)

$F=$	$H=3$		6		9		12		24	
	(−1.98)**	(−1.87)*	(−1.89)*	(−1.77)*	(−1.97)**	(−1.88)*	(−1.99)**	(−1.89)*	(−1.80)*	(−1.90)*
Adj. R^2	0.102	0.096	0.104	0.098	0.102	0.096	0.103	0.097	0.106	0.099

This table presents the time-series coefficients of the OLS regressions in the H-month holding period ($H=3$, 6, 9, 12, or 24), based on the past F-month ranking period returns ($F=3$, 6, 9, or 12), over the second sub-period January 2007 to December 2017. Specifically, we regress style momentum profits (R_{Style}) on the lagged market returns (*LagMkt*), the square of the lagged market returns ($LagMkt^2$), the lagged market volatilities (*LagVol*), as well as the lagged size and value factors. $R_{style,t}$ represents the value-weighted monthly return of arbitrage style portfolios; $Lagmkt_{t-1}$ represents the lagged 1-year value-weighted monthly return on the SHSE and the SZSE A-share indices; $LagVol_{t-1}$ represents the lagged 1-year value-weighted annual volatility on the SHSE and the SZSE A-share indices; SMB_{t-1} and HML_{t-1} represent the lagged monthly returns on zero-investment factor-mimicking portfolios for size and B/M, respectively, collected from the CSMAR database. The t-statistics presented in adjusted using the procedure of Newey and West (1987)

***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively

We find that, compared with the lagged market return, the lagged market volatility plays a relatively weak role in explaining style momentum profits. For example, Table 11 shows a significantly negative *LagVol* (coefficient = 0.163; t-stat = 1.94), at the 10% level, for the 6 × 6 style momentum strategy, but an insignificantly negative *LagVol* (coefficient = 0.140; t-stat = 1.64) for the 6 × 12 style momentum strategy.

6 Conclusions

In this study, we extend price momentum strategies to style momentum strategies—the combination of price momentum strategies based on previous medium-term returns and style investing in terms of firm characteristics (i.e., size and B/M). Specifically, we examine the profitability of style momentum strategies in the China stock market over the period 1994 to 2017. Although we do not find any evidence of style momentum profits over the first sub-period 1994 to 2006, style momentum strategies generate statistically and economically positive returns over the second sub-period 2007 to 2017. More importantly, the observed style momentum in the second sub-period is not due to price momentum or industry momentum; also, style momentum profits are large enough to cover trading costs, providing a violation of the efficient market hypothesis. In addition, we find that style profits exhibit momentum in a cyclical nature; for example, style momentum profits are negatively related to market states.

Overall, our results not only provide important evidence to supplement the existing financial literature in an emerging market context, but also imply that it is likely for institutional investors to make profits in the China stock market by using style momentum strategies, in particular, when stock market experiences a major decline. Furthermore, our results that style momentum profits are exclusively shown in the second sub-period could be attributed to the improved institutional setting in recent years, that is, the fast development of institutional investors since 2006, along with the introduction of margin trading and short selling in 2010, provides style switchers with more efficient investment vehicles to trade an entire style in the China stock market.

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Appendix A: The number and approved annual investment quota of QFIIs

	Approved annual investment quota (millions of USD)	Number
2004	50	1
2005	625	2
2006	400	2
2007	50	1
2008	350	3
2009	500	7
2010	900	6
2011	430	4
2012	8068	35
2013	6450	33
2014	14,850	44
2015	21,012	52
2016	15,338	51
2017	11,115	17
2004–2007	80,138	258

This appendix presents the number and approved annual investment quota of QFIIs, obtained from State Administration of Foreign Exchange (SAFE) of China (available at: https://bit.ly/3f7uifa).

Appendix B: Sample distribution by the industry sector

Industry	Super-sector	Sector	Number
10 technology	1010 technology	101,010 Software and Computer Services	139
		101,020 Technology Hardware and Equipment	170
15 telecommunications	1510 Telecommunications	151,020 Telecommunications Service Providers	8
20 health care	2010 health care	201,020 Medical Equipment and Services	38
		201,030 Pharmaceuticals, Biotechnology and Marijuana Producers	191
40 consumer discretionary	4010 automobiles and parts	401,010 Automobiles and Parts	140
	4020 consumer products and services	402,020 Household Goods and Home Construction	59
		402,030 Leisure Goods	43

Industry	Super-sector	Sector	Number
		402,040 Personal Goods	80
	4030 Media	403,010 Media	43
	4040 Retailers	404,010 Retailers	100
	4050 Travel and Leisure	405,010 Travel and Leisure	54
	4510 Food, Beverage and Tobacco	451,010 Beverages	39
		451,020 Food Producers	128
	4520 Personal Care, Drug and Grocery Stores	452,010 Personal Care, Drug and Grocery Stores	15
50 Industrials	5010 Construction and Materials	501,010 Construction and Materials	108
	5020 Industrial Goods and Services	502,010 Aerospace and Defence	14
		502,020 Electronic and Electrical Equipment	115
		502,030 General Industrials	45
		502,040 Industrial Engineering	162
		502,050 Industrial Support Services	61
		502,060 Industrial Transportation	80
55 Basic Materials	5510 Basic Resources	551,010 Industrial Materials	34
		551,020 Industrial Metals and Mining	127
		551,030 Precious Metals and Mining	52
	5520 Chemicals	552,010 Chemicals	226
60 Energy	6010 Energy	601,010 Oil, Gas and Coal	34
		601,020 Alternative Energy	28
65 Utilities	6510 Utilities	651,010 Electricity	60
		651,020 Gas, Water and Multi-utilities	24
Full sample			2417

This appendix presents the distribution of our sample in terms of the industry sector. Our sample consists of 2417 A-share firms listed either on the SHSE or on the SZSE over the period January 1994 to December 2017. We exclude all financial firms in terms of the two-digit ICB codes of 30 and 35. The structure and definitions are shown in Sect. 6 of *Industry Classification Benchmark* (Equity; version 3.1) as of July 1st, 2019 (see details available at https://bit.ly/2kSgMpi).

Appendix C: Annual market volatility in the second sub-period

Year	The number of trading days per year	Annual market volatility (%)
2007	242	34.39
2008	246	44.85
2009	244	30.07
2010	242	22.45
2011	244	18.65
2012	243	17.97
2013	238	18.13
2014	245	16.55
2015	244	37.95
2016	244	23.81
2017	244	9.24

This table presents annual market volatility in the China stock market over the second sub-period 2007 to 2017. The annual market volatility (%) is measured by multiplying the daily volatility of the value-weighted SHSE and SZSE A-share indices by a square root of 243 (i.e., the average number of trading days per year in the second sub-period).

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