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Contrarian and momentum strategies in the China stock market: 1993–2000

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Abstract

Using data on "A" shares, accessible only to local investors in China, we find statistically significant abnormal profits for some short-horizon contrarian and intermediate-horizon momentum strategies. Further analysis indicates that: (1) overreaction to firm-specific information is the single most important source of short-term contrarian profits; (2) the intermediate-term momentum profits are not, however, distinct due to the dominance of overreaction effect; and (3) the negative cross-serial correlation contributes to momentum profits. The lead–lag structure in China is unique in that (i) lag firms follow lead firms in the opposite direction and (ii) large firms lead small firms in holding periods from 1 to 8 weeks, while small firms lead large firms in holding periods from 12 to 26 weeks. These findings are robust to bid–ask spread and nonsynchronous trading, time-varying market risk and firm-size effect.

JEL classification: G14; G15

Keywords: Momentum and contrarian profits and their sources; China stock market; Overreaction and underreaction; Firm-specific information; Common factor; Size-related lead–lag structure; Measurement error; Time-varying market risk

1. Introduction

An extensive body of finance literature documents that past stock returns can predict the future stock returns in short-, intermediate- and long-term horizons, although the predictability weakens over longer horizons. For example, Jegadeesh (1990) and Lehmann

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(1990) find return reversals in relatively short-term horizons (1 and 6 months, respectively). Jegadeesh and Titman (1993) document return continuations in intermediate horizons (3–12 months) where, on average, past winners continue to outperform past losers. DeBondt and Thaler (1985, 1987) report long-term (e.g., 3–5 years) price reversals where past long-term losers outperform past long-term winners. Given such time-series patterns in cross-sectional stock returns, one can formulate two portfolio-investment strategies: contrarian and momentum strategies. Under the contrarian strategy, past losers are bought and past winners are shorted or sold. Under the momentum strategy, past winners are bought and past losers are shorted or sold. Abnormal profits of these strategies are documented in the literature cited above.[1]

Abnormal profits of momentum and contrarian strategies are also documented in non-US equity markets. For example, Ahmet and Nusret (1999) find abnormal profits of long-term contrarian strategies in the stock markets of seven non-US industrialized countries. Chang et al. (1995) find abnormal profits of short-term contrarian strategies in the Japan stock market. Hameed and Ting (2000) find the same in the Malaysia stock market. Rouwenhorst (1998) finds momentum profits in 12 European equity markets. Rouwenhorst (1999) finds abnormal profits of momentum strategies in six (out of 20) emerging equity markets. Hameed and Yuanto (2000) find that a momentum strategy generates small but statistically significant profits in six Asian stock markets. Schiereck et al. (1999) find abnormal profits for intermediate-term momentum strategies, as well as short- and long-term contrarian strategies, in the Germany equity market.

Fama (1991) notes that the predictability of stock returns over time is among the most controversial issues on stock market efficiency. The controversy has led to various explanations on the possibility and the sources of abnormal profits of contrarian and momentum strategies. The explanations include one based on behavioral irrationality of investors and another based on stock market efficiency.

The most frequently cited explanation of the abnormal profits of contrarian strategies is the market's overreaction to firm-specific information and the subsequent correction. For example, Mun et al. (1999), as well as Bacmann and Dubois (1998), posit that an overreaction to firm-specific information is the primary reason behind the abnormal profits of short-term contrarian strategies. DeBondt and Thaler (1985) argue that investors' overreaction to recent past events can also lead to long-term contrarian profits. Lo and MacKinlay (1990) identify another potential source of contrarian profits that arise when large stocks react more quickly to information than small stocks. This source of contrarian profits is referred to as a lead–lag structure in stock returns because the returns of large stocks tend to lead the returns of small stocks. Jegadeesh and Titman (1995) and Boudoukh et al. (1994) argue, however, that the lead–lag structure arises from investors' delayed reaction to common factors. They show that the main source of contrarian profits is not the lead–lag structure but the overreaction

[1] In these studies, losers are those stocks whose returns are smaller than market index returns whereas winners are the stocks whose returns are larger than market index returns.

to firm-specific information. Another explanation for contrarian profits is that short-term (and long-term) contrarian profits can result from time-varying common factors. For example, Conrad and Kaul (1998) argue that even in frictionless markets, short-term stock returns can be negatively autocorrelated and negatively cross-correlated and that these negative serial correlations are consistent with time-varying common factors.[2]

According to behaviorists, momentum profits are due to market inefficiency and result from stock prices' irrational reactions to information and investors' herding behavior. For example, Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1997) develop models that are based on behavioral bias. In these models, the human cognitive bias leads investors either to underreact to information or to adopt positive-feedback strategies that result in delayed overreaction to information. The tendency to herd among investors (for example, among fund managers) is a well-documented fact, which helps explain the profits of intermediate-term momentum strategies (see, e.g., Grinblatt et al., 1995; Lakonishok et al., 1994).

The market-efficiency camp, on the other hand, argues that time-varying common factors and/or data mining lead to the existence of intermediate-term momentum profits. According to this explanation, the abnormal returns of momentum strategies are attributable to common factors that are not accounted for in, for example, CAPM or a three-factor model. As Jegadeesh and Titman (1993) point out, to the extent that high past returns are partly due to high expected returns, winner portfolios will contain high-risk stocks that would also generate higher expected returns in the future. Conrad and Kaul (1998) examine this possibility and conclude that momentum profits can be explained by the cross-sectional difference in individual stocks' expected returns. Chordia and Shivakumar (2000) also show that momentum profits can be driven by time-varying expected returns.

In this paper, we investigate various short-term contrarian and intermediate-term momentum strategies in the China stock market. Although the predictability of stock returns have been extensively investigated in emerging stock markets, China remains among the most important emerging markets awaiting such investigations.[3] Because China is one of the few countries whose stock markets are negatively correlated with the US stock market, China will become an increasingly important market to global investors. The lack of rigorous investigations on China stock returns is mainly due to both the short history of equity trading in China and the lack of material interests among global investors (who could invest only in the "B" shares mar-

[2] As reasons for long-term contrarian profits, the school of thought based on market efficiency also lists: mean-reverting expected market returns (see Chan, 1988; Ball and Kothari, 1989); firm-size effect (see Zarowin, 1990), and measurement error due to bid–ask bounce, nonsynchronous trading or illiquidity (see Park, 1995; Ball et al., 1995; Conrad et al., 1997).

[3] It has the largest population (1.2 billion) in the world. Its nominal GDP (US$1.02 trillion) is the second largest in Asia (after Japan), whereas its GDP growth rate of about 8% per annum is among the highest in the world. Its total trade is near US$0.5 trillion (about 60% of Japan's equivalent). See China Securities Regulatory Commission (2001).

ket).[4] The persistence of negative correlations between China and the United States (and other developed equity markets) should attract increasing attentions from global institutional investors. Hence, the investigation of momentum and contrarian strategies in the current China stock market is not only interesting to finance academics but also timely to investment professionals.

As stated in Hu (1999), the China stock market is very different from others, especially in terms of the extent of government regulations and the investor composition.[5] In China, financial data on listed companies (especially, small firms) are not of reliable quality (and, in the past, some were even fabricated) and the regulatory framework for the stock market is not fully developed.[6] One of the most interesting institutional features of the "A" shares market is the absolute dominance of individual investors, which has important implications on the profitability of contrarian and momentum strategies.[7] Most of these individual investors possess only rudimentary knowledge on stock investments and trade like noise traders who purely speculate in the stock market. For example, they select stocks mainly on historical price trends and trade mainly on market rumors. This practice is known in China as "stir-frying stocks." The consequence of "stir-frying stocks" is a stock market mania that leads to excessive speculation where stock prices are often pushed up several hundred percent and quickly corrected later on.[8]

[4] Currently, there are two stock exchanges: Shanghai and Shenzhen Stock Exchanges. Since their establishments in 1990, the respective exchange has seen sharp increases in listed companies and market capitalization. As of January 2001, there were about 1000 companies listed on the two exchanges with total capitalization of about US$590 billion. Starting 1991, both exchanges have two sections that are strictly segmented: namely, "A" share and "B" share sections. The "A" shares are denominated in the Chinese currency (1 RMB=1 Yuan=US$0.1208) and issued only to (and traded only by) domestic investors. On the other hand, the "B" shares are denominated in US or Hong Kong dollars and issued only to (and traded only by) foreign investors. The market capitalization of the local "A" shares (about 4048 billion RMB or US$581 billion) accounted for 98% of total market capitalization as of January 2001. The "A" shares had been much more actively traded than the "B" shares during our sample period of 1993–2000. Since February 2001, local investors are allowed to trade the "B" shares. But, under the current regulations on exchange control, local investors are strictly prohibited from converting their domestic currency to US or Hong Kong dollars for the purpose of "B" share investment.

[5] Other institutional features of China stock market are also documented in other studies (e.g., IPO study by Sun and Tong, 2000).

[6] Often, even the government statistics are of poor quality due to the difficult and time-consuming data gathering process involving many different layers of bureaucracy, huge population of over 50 ethnic groups with several thousand dialects, and 31 provinces scattered on the vast land area.

[7] There are several reasons behind the dominance of individual investors. Note that stocks and shares, the financial instruments in capitalist economic system, have been taboos in the socialist China until recently. China set up the two stock exchanges in early 1990s as an "experiment" for economic reform. Since the experiment is not officially over yet and, until recently, there has been uncertainty about the outcome of the experiment, the presence of institutional investors in China stock market has been very limited. Another reason behind the dominance of individual investors is that too much money chases too few stocks. The inadequate social security system in China has led to a personal savings rate that is among the highest in the world. Due to lack of their access to treasury securities or corporate bonds, individual investors have no choice but to resort to bank deposits, stocks or properties. However, the bank deposit rates in China are often kept below market rates (for the purpose of economic development) and, until recently, the government strictly regulated private ownership of properties. Hence, equity is the major wealth-building instrument favored by Chinese individual investors.

[8] During the period between December 1990 and December 1993, for example, the composite index of Shanghai Stock Exchange increased from 100 to 834. But, in the next 7 months, the index dropped to 334.

Based on the trading practices in China, one can argue that the stock market is mainly driven by market rumors and individual investors' sentiment (rather than information). When market rumors drive the stock prices, return reversals tend to be the dominant pattern in short horizons since false rumors tend to be short-lived. When market sentiment persists (due to individual investors' herding), return continuations can also be observed. Whether the herding among individual investors (rather than institutional investors) leads to abnormal momentum profits in intermediate horizons is also an interesting empirical question.

When stock prices are mainly driven by information, as in developed stock markets, stock prices of small firms may react to common factors with a lag or to diffuse information slowly because investors have less information on these small stocks. Then, the returns of large firms lead those of small firms, which will result in positive cross-serial correlations in stock returns. This size-related lead–lag structure would positively (negatively) contribute to contrarian (momentum) profits, although Lo and MacKinlay (1990) and Jegadeesh and Titman (1995) disagree on the magnitude of lead–lag effect in the US stock market.

In China, reliable information on listed companies (especially, on small firms) is not readily available. Hence, the stock prices are seldom driven by information. Instead, they are driven by rumors and investor sentiment, which can be easily manipulated by syndicate speculators. Since short selling is not allowed in China, the syndicate speculators may find it easier to manipulate the sentiment on small stocks due to relative lack of information. They may also find it more profitable to create bullish (rather than bearish) sentiment on small stocks. This is so because bullish stocks can attract all investors but bearish stocks concern only those who currently hold them. As a result, returns of small firms may lead those of large firms. Given this possibility, it is also interesting to examine the effect of size-related lead–lag structure in the China stock market.

The main objectives of this paper are threefold: firstly, we examine the profitability of various short-term contrarian and intermediate-term momentum strategies in the China stock market; secondly, we investigate the alternative sources of these abnormal profits; and, finally, we analyze the relative importance of the three major determinants of abnormal profits in the context of the Jegadeesh and Titman (1995) one-factor model.

We find statistically significant abnormal profits for some short-horizon contrarian and intermediate-horizon momentum strategies of various formation and holding periods. Our analysis indicates that overreaction to firm-specific information is the single most important determinant of short-term contrarian profits (and negative determinant of momentum profits). Intermediate-term momentum profits are relatively less distinct due to the dominance of the overreaction effect over the positive combined effect of the cross-sectional variation in individual mean returns and the lead–lag structure in stock returns. When the profitability of contrarian and momentum strategies is examined in terms of value-weighted returns (rather than equal-weighted returns), however, contrarian profits tend to decline whereas momentum profits tend to increase. In contrast to the evidence documented for the US market, the lead–lag structure in China increases (decreases) momentum (contrarian) profits. The different role results from the unique lead–lag structure that lag firms follow lead firms in the opposite direction and that large firms lead small firms in holding periods from 1 to 8 weeks, whereas small firms lead large firms in holding periods from 12 to 26 weeks.

The remainder of this paper is organized as follows. Section 2 describes data and the methodology employed for portfolio formation and investment strategies. Section 3 documents the profitability of various contrarian and momentum strategies. Section 4 examines the alternative sources of contrarian and momentum profits, namely, measurement error, time-varying market risk, overreaction to firm-specific information and lead–lag structure in stock returns. Section 5 analyzes the relative contribution of the three main determinants of contrarian and momentum profits, which are derived from the one-factor pricing model of Jegadeesh and Titman (1995). Section 6 concludes the study.

2. Data and methodology

2.1. Data and sample selection

Weekly stock prices covering the period of January 1993 to January 2000 were obtained from Datastream. The sample period excludes the first 2 years after the initial setup of the two exchanges in December 1990 because the year 1993 was the first year when a sizable number of "A" shares began trading. For implementation of intermediate-term momentum strategies, our sample includes the 268 firms that had been listed for at least 4 years prior to January 2000 and excludes those listed in or after 1995. In order to maximize the company-year observations, our sample-year also includes the years, 1993 and 1994. In all, our sample has 48 firms for year 1993, 163 firms for year 1994 and 268 firms for the respective years during 1995 and 2000.[9]

2.2. Portfolio formation

To test whether return reversal or return continuation exists, we use the testing methods employed in Lo and MacKinlay (1990) and Jegadeesh and Titman (1995). First, we rank the stock returns in the past F-week portfolio formation period in an ascending order. Based on the ranking, five equal-size quintile portfolios are formed. The quintile portfolio with the highest stock returns is the winner portfolio, whereas the quintile portfolio with the lowest return is the loser. Then, an equal-weighted average return for each quintile portfolio over the next H-week holding period, as well as the difference between returns of the loser and the winner portfolios during the H-week holding period, is calculated.[10] If average return of the winner portfolio in the H-week holding period is higher than that of the loser portfolio, then a return continuation is declared for the H-week holding period. If it is lower, then a return reversal is declared. The return reversal and continuation over the H-week horizon lead to H-horizon contrarian and momentum strategies, respectively. We consider eight different horizons (i.e., 1, 2, 4, 8, 12, 16, 20 and 26 weeks) for both

[9] Since new stocks frequently experience irregular returns around the times of their initial public offerings (see Sun and Tong, 2000), the returns of newly listed stocks in the first week after listing are excluded in the sample.

[10] The next H-week period is referred to as the H holding period. We use the term "holding" since short selling is equivalent to negative holding.

formation (F) and holding (H) periods. As there are eight periods for both formation (F) and holding (H) periods, we have 64 (8×8) different investment strategies.[11]

In order to avoid the bias that can arise from bid–ask spread, price pressure due to illiquid markets, and nonsynchronous data, we skip one trading day between portfolio formation and holding periods for all investment strategies (for similar treatment, see Chan et al., 1999; Lehmann, 1990). For the formation period, a week begins on Wednesday and ends on Tuesday (if the Tuesday is a nontrading day, then we use the next trading day). For the holding period, a week begins on Thursday and ends on Wednesday (if the Wednesday is a nontrading day, then we use the next trading day). To increase the power of our test, we implement the various "F-H" strategies every week such that, at any given week, the investor can hold "F-H" quintile portfolios that are formed according to abnormal stock returns in the current, as well as previous, $H-1$ weeks and will liquidate the "F-H" quintile portfolios formed in the previous H-weeks.[12]

3. Profitability of contrarian and momentum strategies

Table 1 reports equal-weighted average monthly returns of the loser, winner, and other quintile portfolios, as well as the difference between loser and winner portfolios, over various holding periods for the 64 strategies.[13] There are eight parts in Table 1, which differ by formation period, and each part has eight strategies with different holding periods. The first row in each part refers to the specific strategy. For example, Strategy 1-8 (that is, Strategy with $F=1$ and $H=8$) represents the strategy that stocks are ranked according to their previous 1-week returns and then held for the next 8 weeks. To examine whether contrarian or momentum profits exist, we calculate the holding period returns of winner and loser portfolios, which are normalized to monthly returns, and the difference between their normalized monthly returns. If the difference between the loser's return and winner's return is statistically significantly larger than zero, then there exists a contrarian profit. If it is negative, then there exists a momentum profit. Otherwise, neither profit exists.

The difference between monthly returns of loser and winner portfolios (L–W) is reported in the second to last row for each part in Table 1. Some short-term contrarian and intermediate-horizon momentum profits are statistically significant. Statistically significant contrarian profits are available for 14 strategies whose formation periods are among 1, 2, 4, 8 and 12 weeks, whereas statistically significant momentum profits are available for 10 strategies whose formation periods are among 12, 16, 20 and 26 weeks.

For 1-H strategies (Part I), losers' returns are larger than winners' returns for most H holding periods. But, only the contrarian profit for 1-week holding period is statistically significant at 5% level. For 2-H strategies (Part II), only the contrarian profits for 8- and

[11] For more robustness, we consider more and longer periods for portfolio formation and holding than Jegadeesh and Titman (1995).

[12] Due to weekly overlapping implementation of the 64 strategies, the number of observations for various strategies ranges from 309 (for the case of 26-26 strategy) to 359 (for the case of 1-1 strategy).

[13] Here, the difference between returns of loser and winner portfolios remains the same regardless of whether the portfolio's returns are adjusted for market returns or not.

Table 1
Profitability of contrarian and momentum strategies based on equal-weighted returns

Part I: Portfolios formed based on previous 1-week returns and held over eight different horizons (1-H)

Quintile	1-1	1-2	1-4	1-8	1-12	1-16	1-20	1-26
Loser	0.014994	0.009470	0.005643	0.005019	0.005209	0.005170	0.004527	0.004802
2	0.010011	0.006037	0.004671	0.003710	0.004526	0.005067	0.004917	0.005733
3	0.005894	0.006486	0.006190	0.005157	0.006298	0.006336	0.006640	0.006787
4	0.001054	0.002686	0.003955	0.003642	0.004817	0.004728	0.005426	0.005941
Winner	−0.003610	0.001800	0.002019	0.001695	0.003384	0.003026	0.004121	0.004892
L−W	0.18600	0.007670	0.003624	0.003324	0.001835	0.002144	0.00416	−0.000090
t-value	2.44*	1.56	1.07	1.48	1.02	1.46	0.31	−0.08

Part II: Portfolios formed based on previous 2-week returns and held over eight different horizons (2-H)

Quintile	2-1	2-2	2-4	2-8	2-12	2-16	2-20	2-26
Loser	0.009364	0.001881	0.002538	0.004946	0.005467	0.005217	0.004386	0.004885
2	0.005678	0.005193	0.004726	0.005652	0.005854	0.005938	0.005672	0.006223
3	0.004196	0.004741	0.003798	0.003758	0.005327	0.005616	0.006140	0.006650
4	0.005062	0.005810	0.004465	0.003151	0.005175	0.005033	0.005950	0.006306
Winner	0.000244	0.004383	0.002873	0.000866	0.002528	0.002250	0.003585	0.004774
L−W	0.009120	−0.002498	−0.000335	0.004080	0.002939	0.002967	0.000801	0.000111
t-value	1.06	−0.48	−0.09	1.68**	1.62	1.93**	0.61	0.1

Part III: Portfolios formed based on previous 4-week returns and held over eight different horizons (4-H)

Quintile	4-1	4-2	4-4	4-8	4-12	4-16	4-20	4-26
Loser	0.007391	0.004172	0.004760	0.007371	0.007017	0.006315	0.005112	0.005289
2	0.004280	0.003803	0.004896	0.005753	0.006585	0.007453	0.006033	0.006737
3	0.003291	0.004106	0.004891	0.005069	0.006040	0.008029	0.006492	0.007044
4	0.002951	0.001493	0.002050	0.002246	0.005018	0.006949	0.005626	0.006322
Winner	0.000994	0.002013	−0.001136	−0.001309	0.002144	0.004038	0.003269	0.005278
L−W	0.006697	0.002160	0.005896	0.008680	0.004873	0.002977	0.001843	0.000011
t-value	0.77	0.41	1.67**	3.4*	1.91**	1.37	1.37	0.01

Part IV: Portfolios formed based on previous 8-week returns and held over eight different horizons (8-H)

Quintile	8-1	8-2	8-4	8-8	8-12	8-16	8-20	8-26
Loser	0.012106	0.009224	0.100621	0.009343	0.008310	0.007168	0.006342	0.005214
2	0.006833	0.007730	0.008064	0.007779	0.006725	0.006665	0.006937	0.007104
3	0.005269	0.005473	0.005930	0.005526	0.005177	0.006307	0.006958	0.007865
4	0.000556	0.000412	0.000737	0.002472	0.004053	0.005207	0.006420	0.007574
Winner	−0.003567	−0.002690	−0.001669	−0.000167	0.001769	0.003383	0.004773	0.006590
L−W	0.015673	0.011914	0.012290	0.009510	0.006541	0.003785	0.001569	−0.001376
t-value	2.09*	2.23*	2.98*	3.46*	3.06*	2.17*	1.1	−1.05

Part V: Portfolios formed based on previous 12-week returns and held over eight different horizons (12-H)

Quintile	12-1	12-2	12-4	12-8	12-12	12-16	12-20	12-26
Loser	0.012193	0.009348	0.009446	0.008093	0.006844	0.005845	0.004920	0.004681
2	0.102670	0.008787	0.007526	0.006061	0.006594	0.006832	0.007371	0.007731
3	0.008225	0.007394	0.006660	0.005707	0.006277	0.007162	0.007990	0.007858
4	0.003091	0.001186	0.001097	0.003215	0.005720	0.007253	0.008547	0.008618
Winner	0.001817	0.002938	0.000610	0.001477	0.003698	0.005133	0.006618	0.008208

Table 1 (*continued*)

Part V: Portfolios formed based on previous 12-week returns and held over eight different horizons (12-*H*)

Quintile	12-1	12-2	12-4	12-8	12-12	12-16	12-20	12-26
L–W	0.10376	0.006410	0.008836	0.006616	0.003146	0.000712	−0.001702	−0.003527
t-value	1.29	1.17	2.17*	2.35*	1.53	0.44	−1.19	−2.96*

Part VI: Portfolios formed based on previous 16-week returns and held over eight different horizons (16-*H*)

Quintile	16-1	16-2	16-4	16-8	16-12	16-16	16-20	16-26
Loser	0.011067	0.009453	0.007676	0.006921	0.006249	0.005670	0.004735	0.005299
2	0.004571	0.005553	0.005729	0.006047	0.006193	0.006970	0.007028	0.007205
3	0.003841	0.003251	0.004807	0.006159	0.007445	0.008006	0.008186	0.008291
4	−0.000651	0.000849	0.002484	0.004802	0.006868	0.008907	0.009601	0.009646
Winner	−0.000800	0.001227	0.002022	0.003605	0.005933	0.007235	0.008423	0.009287
L–W	0.011867	0.008226	0.005654	0.003316	0.000316	−0.001565	−0.003688	−0.003988
t-value	1.4	1.44	1.4	1.29	0.17	−0.98	−2.66*	−3.57*

Part VII: Portfolios formed based on previous 20-week returns and held over eight different horizons (20-*H*)

Quintile	20-1	20-2	20-4	20-8	20-12	20-16	20-20	20-26
Loser	0.011173	0.008900	0.008510	0.007442	0.006649	0.005679	0.005937	0.006104
2	0.006403	0.005651	0.006029	0.006162	0.006556	0.006357	0.006369	0.006772
3	0.004657	0.004646	0.005280	0.007054	0.008077	0.008530	0.008888	0.009256
4	0.005379	0.006836	0.007132	0.008454	0.010529	0.011120	0.011189	0.011356
Winner	0.004516	0.004743	0.004369	0.005795	0.007841	0.008937	0.009517	0.009608
L–W	0.006663	0.003957	0.004141	0.001653	−0.001192	−0.003258	−0.003579	−0.003504
t-value	0.87	0.72	1.08	0.68	−0.64	−2.07*	−2.79*	−3.15*

Part VIII: Portfolios formed based on previous 26-week returns and held over eight different horizons (26-*H*)

Quintile	26-1	26-2	26-4	26-8	26-12	26-16	26-20	26-26
Loser	0.011544	0.009343	0.009456	0.006136	0.006247	0.006221	0.005949	0.006056
2	0.006595	0.006606	0.007596	0.006319	0.005974	0.006699	0.007267	0.007020
3	0.005964	0.007641	0.008614	0.008787	0.009036	0.009500	0.009972	0.009673
4	0.009032	0.010286	0.011117	0.011715	0.012020	0.011967	0.012072	0.011552
Winner	0.005666	0.006724	0.006733	0.008204	0.009738	0.009865	0.009941	0.009536
L–W	0.005878	0.002619	0.002723	−0.002068	−0.003491	−0.003644	−0.003992	−0.003480
t-value	0.73	0.49	0.75	−0.85	−1.92**	−2.43*	−3.07*	−3.03*

The five quintile portfolios are formed according to stock returns in the past *F* weeks (formation period). Since eight formation periods are considered, there are eight parts in this table. The loser quintile refers to the quintile portfolio with the lowest stock returns in the formation period, whereas the winner quintile refers to the quintile portfolio with the highest stock returns in the *F* formation period. Then, an equal-weighted average return for each quintile portfolio in the next *H* weeks (holding period) and the difference between loser and winner quintile returns (L–W) over the *H* weeks are calculated. If the average return of winner portfolio over the *H* holding period is higher than that of loser portfolio, then a return continuation is observed for the *H* holding period. If it is lower, then a return reversal is observed. The return reversal and continuation over the *H* horizon lead to *H*-horizon contrarian and momentum strategies, respectively. Since eight holding periods are considered, each part has eight strategies and their profits. For example, 1–8 is the strategy that ranks stocks in five quintiles according to their previous 1-week returns and holds for 8 weeks (F=1 week and H=8 weeks). The *t*-value is provided for L–W.

* Statistical significance at 5% level.

** Statistical significance at 10% level.

Table 2
Profitability of contrarian and momentum strategies based on value-weighted returns

Quintile	1-1	1-2	1-4	1-8	1-12	1-16	1-20	1-26
Loser	0.0045	0.0054	0.0039	0.0034	0.0048	0.0034	0.0054	0.0057
2	−0.0037	0.0026	0.0048	0.0033	0.0038	0.0035	0.0044	0.0034
3	−0.0017	0.0037	0.0027	0.0037	0.0034	0.0047	0.0055	0.0057
4	−0.0022	0.0012	0.0019	0.0025	0.0023	0.0039	0.0029	0.0039
Winner	−0.0009	0.0019	0.0028	0.0018	0.0030	0.0047	0.0047	0.0061
L − W	0.0054	0.0035	0.0011	0.0016	0.0018	−0.0012	0.0007	−0.0004
t-value	1.67**	1.34	0.96	0.34	0.24	−0.20	0.09	−0.17

Quintile	2-1	2-2	2-4	2-8	2-12	2-16	2-20	2-26
Loser	0.0078	0.0013	0.0029	0.0053	0.0065	0.0054	0.0059	0.0051
2	0.0065	0.0048	0.0061	0.0079	0.0058	0.0046	0.0050	0.0063
3	0.0053	0.0066	0.0062	0.0065	0.0057	0.0051	0.0069	0.0056
4	0.0050	0.0068	0.0054	0.0067	0.0042	0.0037	0.0047	0.0044
Winner	0.0013	0.0052	0.0064	0.0045	0.0048	0.0028	0.0038	0.0040
L − W	0.0065	−0.0039	−0.0035	0.0008	0.0017	0.0026	0.0021	0.0011
t-value	1.08	−0.53	0.26	1.24	1.59	1.69**	0.98	0.23

Quintile	4-1	4-2	4-4	4-8	4-12	4-16	4-20	4-26
Loser	0.0042	0.0059	0.0046	0.0065	0.0062	0.0070	0.0068	0.0064
2	0.0049	0.0046	0.0037	0.0047	0.0045	0.0099	0.0065	0.0069
3	0.0065	0.0044	0.0046	0.0050	0.0038	0.0055	0.0040	0.0070
4	0.0076	0.0041	0.0031	0.0028	0.0051	0.0069	0.0079	0.0054
Winner	0.0061	0.0047	0.0028	0.0031	0.0036	0.0065	0.0062	0.0059
L − W	−0.0019	0.0012	0.0018	0.0034	0.0026	0.0006	0.0006	0.0004
t-value	−0.62	0.23	1.54	1.68**	1.45	0.87	0.88	0.56

Quintile	8-1	8-2	8-4	8-8	8-12	8-16	8-20	8-26
Loser	0.0166	0.0103	0.0104	0.0085	0.0097	0.0096	0.0085	0.0066
2	0.0125	0.0088	0.0078	0.0065	0.0088	0.0086	0.0080	0.0048
3	0.0112	0.0092	0.0086	0.0065	0.0082	0.0078	0.0078	0.0053
4	0.0131	0.0087	0.0058	0.0042	0.0077	0.0066	0.0048	0.0079
Winner	0.0073	0.0054	0.0045	0.0035	0.0056	0.0052	0.0069	0.0060
L − W	0.0092	0.0048	0.0059	0.0050	0.0040	0.0043	0.0015	0.0005
t-value	1.69**	1.44	1.68**	1.93**	1.57	1.67**	1.23	0.66

Quintile	12-1	12-2	12-4	12-8	12-12	12-16	12-20	12-26
Loser	0.0099	0.0084	0.0081	0.0079	0.0064	0.0059	0.0031	0.0025
2	0.0103	0.0068	0.0052	0.0052	0.0070	0.0066	0.0058	0.0068
3	0.0067	0.0056	0.0054	0.0049	0.0059	0.0054	0.0079	0.0090
4	0.0050	0.0012	0.0005	0.0017	0.0035	0.0068	0.0064	0.0073
Winner	0.0039	0.0046	0.0021	0.0028	0.0034	0.0056	0.0068	0.0071
L − W	0.0060	0.0038	0.0060	0.0051	0.0030	0.0004	−0.0037	−0.0047
t-value	0.92	1.09	1.74**	1.84**	1.39	0.67	−1.60	−3.22*

Quintile	16-1	16-2	16-4	16-8	16-12	16-16	16-20	16-26
Loser	0.0063	0.0075	0.0056	0.0048	0.0034	0.0023	0.0017	0.0024
2	0.0059	0.0058	0.0066	0.0068	0.0059	0.0065	0.0069	0.0073

Table 2 (*continued*)

Quintile	16-1	16-2	16-4	16-8	16-12	16-16	16-20	16-26
3	0.0043	0.0074	0.0056	0.0060	0.0064	0.0077	0.0081	0.0092
4	0.0043	0.0039	0.0032	0.0063	0.0044	0.0032	0.0052	0.0068
Winner	0.0034	0.0035	0.0039	0.0036	0.0033	0.0041	0.0065	0.0079
L−W	0.0029	0.0040	0.0017	0.0012	0.0001	−0.0018	−0.0048	−0.0055
t-value	1.1	1.06	0.67	0.89	0.12	−1.58	−3.16*	−4.43*

Quintile	20-1	20-2	20-4	20-8	20-12	20-16	20-20	20-26
Loser	0.0070	0.0068	0.0059	0.0046	0.0051	0.0035	0.0019	0.0023
2	0.0058	0.0051	0.0047	0.0035	0.0046	0.0037	0.0057	0.0071
3	0.0033	0.0047	0.0056	0.0057	0.0046	0.0066	0.0085	0.0096
4	0.0057	0.0024	0.0044	0.0058	0.0068	0.0059	0.0064	0.0083
Winner	0.0055	0.0067	0.0049	0.0044	0.0062	0.0065	0.0070	0.0085
L−W	0.0015	0.0001	0.0010	0.0002	−0.0011	−0.0031	−0.0051	−0.0062
t-value	0.67	0.78	1.06	0.60	−1.29	−2.14*	−3.03*	−5.05*

Quintile	26-1	26-2	26-4	26-8	26-12	26-16	26-20	26-26
Loser	0.0046	0.0067	0.0056	0.0026	0.0027	0.0015	0.0029	0.0032
2	0.0056	0.0043	0.0058	0.0068	0.0058	0.0046	0.0058	0.0074
3	0.0049	0.0055	0.0058	0.0046	0.0058	0.0061	0.0075	0.0093
4	0.0058	0.0079	0.0064	0.0059	0.0068	0.0074	0.0085	0.0104
Winner	0.0039	0.0058	0.0055	0.0064	0.0074	0.0075	0.0096	0.0108
L−W	0.0006	0.0009	0.0002	−0.0038	−0.0047	−0.0060	−0.0067	−0.0076
t-value	0.85	0.92	0.67	−1.34	−2.17*	−4.13*	−5.69*	−6.75*

The five quintile portfolios are formed according to stock returns in the past F weeks (formation period). The loser quintile refers to the quintile portfolio with the lowest stock returns in the F formation period, whereas the winner quintile refers to the quintile portfolio with the highest stock returns in the F formation period. Then, the value-weighted average return for each quintile portfolio over the next H weeks (holding period) and the difference between loser and winner quintile returns (L−W) over the H weeks are calculated. The value-weighted average return of each quintile portfolio (over the H holding period) is computed as $r_P = \sum_i r_i V_i$, where r_i is the H holding period return of the ith stock, V_i is the ratio of the ith firm's average market value (over the entire sample period) to the total market value of the quintile portfolio. Since eight formation periods are considered, there are eight parts in this table. If the average return of winner portfolio in H holding period is higher than that of loser portfolio, then a return continuation is observed for the H holding period. If it is lower, then a return reversal is observed. The return reversal and continuation over the H horizon lead to H-horizon contrarian and momentum strategies, respectively. Since eight holding periods are considered, each part has eight strategies and their profits. For example, 1−8 is the strategy that ranks stocks in five quintiles according to their previous 1-week equal-weighted returns and holds for 8 weeks (F=1 week and H=8 weeks). The t-value is provided for L−W.

* Statistical significance at 5% level.

** Statistical significance at 10% level.

16-week holding periods are statistically significant at 10% level. For 4-H strategies (Part III), contrarian profits for 4-, 8- and 12-week holding periods are statistically significant. For 8-H strategies (Part IV), most strategies except those with 20- and 26-week holding periods generate statistically significant contrarian profits. For 12-H strategies (Part V), contrarian profits for 4- and 8-week holding periods are statistically significant. But, the momentum profit for the 26-week period is also statistically significant. For 16-H, 20-H and 26-H strategies (Parts VI, VIII and VIII, respectively), none of the contrarian profits is statistically significant. Some of the 16-H momentum profits (for 20- and 26-week holding periods), the 20-H momentum profits (for 16-week and longer holding periods) and the 26-H momentum profits (for 12-week and longer holding periods) are statistically significant. The t-values for the momentum profits in Parts VI, VII and VIII are higher for those momentum profits over longer holding periods. Although 10 momentum strategies produce statistically significant profits, their magnitudes are much smaller than those of all but two contrarian strategies, suggesting relatively low economic importance of the momentum profits.

Many studies have examined the effect of firm size on the profitability of contrarian and momentum strategies. For example, Lo and MacKinlay (1990) find that the size-related lead–lag structure (where returns of large firms lead those of small firms) contributes to contrarian profits even when stock prices do not overreact to information. Jegadeesh and Titman (1995) find that the contrarian strategies applied to size-sorted portfolios do not generate significant abnormal returns. Hong et al. (2000) find that return continuation is stronger for small firms and it weakens as the firm size increases.

In order to examine the firm-size effect on contrarian and momentum profits, we also calculate the value-weighted returns for five quintile portfolios for the 64 strategies. The value-weighted average return of each quintile portfolio (over the H holding period) is computed as $r_P = \sum_i r_i V_i$, where r_i is the H holding-period return of the ith stock and V_i is the ratio of the ith firm's average market value (over the entire sample period) to the total market value of the quintile portfolio. The results are reported in Table 2.

Similar to the findings in Table 1 (the profitability based on equal-weighted returns), statistically significant contrarian profits are observed for strategies of 1-1 (Part I), 2-16 (Part II), 4-8 (Part III), 8-1, 8-4, 8-8 and 8-16 (Part IV) and 12-4 and 12-8 (Part V), whereas statistically significant momentum profits are observed for strategies of 12-26 (Part V), 16-20, 16-26 (Part VI), 20-16, 20-20 and 20-26 (Part VII) and 26-12, 26-16, 26-20 and 26-26 (Part VIII). However, both the statistical significance level for and the magnitude of contrarian profits decrease. Furthermore, the number of contrarian strategies with significant profits decreases from 14 to 9. The overall contrarian profit decline (in magnitude) is mainly due to large increases in winners' returns relative to changes in losers' returns over the holding periods.[14] On the other hand, both the statistical significance and the magnitude of momentum profits substantially increase, whereas the number of momentum strategies with significant profits remains at 10. The momentum-profit increase (in magnitude) is also mainly due to large increases in winners' returns relative to changes in losers' returns over the holding periods.[15]

[14] For example, in the 8-8 contrarian strategy, the winner's average return increases from −0.0016 to 0.0035, whereas the loser's average return changes from 0.0093 to 0.0085.

[15] The difference in findings is mainly due to the larger increases of the winner's value-weighted returns (in Table 2) relative to its equal-weighted returns (in Table 1) for all contrarian and momentum strategies of various holding periods. Note, however, that the winner's value-weighted returns can be larger than the winner's equal-weighted returns only if the equal-weighted return of small-firm winners are not larger than those of large-firm winners. It is not clear why, for both momentum and contrarian strategies, the equal-weighted returns of large-size winners are on average larger than those of small-size winners, whereas the equal-weighted returns of large-size losers are not materially different from those of small-size losers.

4. Alternative sources of contrarian and momentum profits

The contrarian and momentum profits observed in China may be due to: (1) measurement error; (2) time-varying market risk; (3) overreaction to firm-specific information; and (4) lead-lag structure in stock returns. The first subsection tests the robustness to measurement error. The second subsection tests the robustness to time-varying market risk. The final subsection reports on the own-serial and cross-serial correlations of five size-sorted quintile portfolios, which are the respective measures for stock prices' reactions to firm-specific information and common factors.

4.1. Robustness to measurement error

According to Lehmann (1990), Park (1995) and Conrad et al. (1997), short-term contrarian profits may be spurious if they are driven by bid–ask spread. When both bid and ask prices are used in computing portfolio returns, stocks wrongly appear to be winners or losers. Then, short-term contrarian profits are magnified. This is so because the initial transaction of selling winners (buying losers) is done at the bid (ask) price, and the corresponding transaction at the end of holding period is done at the ask (bid) price. Ignoring bid–ask spread may induce profits to short (long) positions. Lehmann (1990) controls for the bias due to bid–ask spread by skipping one trading day between portfolio formation and portfolio holding periods. As noted in Section 2, this conventional one-day skipping practice is adopted in this paper.

As a further check, we also skip 1 week and calculate the profits for all strategies. When we skip 1 week, the profit of the 1-1 contrarian strategy is not materially different from zero (−0.00082), suggesting that the 1-1 contrarian profit (0.0186 in Table 1) obtained from skipping 1 day may be spurious. However, for all other strategies, both skipping 1 week and skipping 1 day produce nearly identical results, suggesting that the measurement error is not serious. In the following analyses, we skip only 1 day for the purpose of controlling for the bid–ask spread bias.

4.2. Robustness to time-varying market risk

Chan (1988) proposes that common factors for winner and loser stocks are not constant over time. With time-varying common factors, he finds only small abnormal profits for contrarian strategies because losers tend to be riskier and winners tend to be less risky in the holding periods. He also finds that, when there are momentum profits, the correct strategy is to choose high-risk stocks as the winners and low-risk stocks as the losers. We use the following model (Chan, 1988) to investigate whether time-varying market risk plays an important role in explaining the contrarian and momentum profits:

$$r_{\mathrm{P}t} - r_{\mathrm{f}t} = \alpha + \beta(r_{\mathrm{M}t} - r_{\mathrm{f}t}) + \varepsilon_t, \qquad \mathrm{P}\in(\mathrm{W, L}), \tag{1}$$

$$r_{\mathrm{L}t} - r_{\mathrm{W}t} = \alpha^{\mathrm{c}} + \beta^{\mathrm{c}}(r_{\mathrm{M}t} - r_{\mathrm{f}t}) + \varepsilon_t, \tag{2}$$

$$r_{\mathrm{W}t} - r_{\mathrm{L}t} = \alpha^{\mathrm{m}} + \beta^{\mathrm{m}}(r_{\mathrm{M}t} - r_{\mathrm{f}t}) + \varepsilon_t, \tag{3}$$

where r_{Pt} is the portfolio return at time t, r_{ft} is the risk-free rate at time t, r_{Mt} is the market index return at time t, $r_{Mt}-r_{ft}$ is the market risk premium at time t, α and β are the respective intercept and slope (market risk) coefficients, r_{Lt} is loser's return at time t, r_{Wt} is winner's return at time t and the superscripts c and m refer to contrarian and momentum strategies, respectively.[16]

The winner and loser returns for five contrarian strategies (strategies 1-1, 2-8, 4-4, 8-8, 12-8) and three momentum strategies (16-20, 20-20 and 26-26) are tested by Eq. (1). Eq. (2) tests the effect of time-varying market risk on contrarian profits and Eq. (3) tests the same on momentum profits. The results are reported in Table 3.

Table 3 reports that the differences between betas of the winner and loser portfolios for all strategies are not statistically significant. The statistical insignificance of the beta difference between the loser and the winner indicates that the beta risk alone cannot explain the contrarian and momentum profits documented in Table 1.

4.3. Overreaction to firm-specific information and lead–lag structure in stock returns

It is well known that the overreaction to firm-specific information (which results in negative own-serial correlations) is the main source of contrarian profits. Lo and MacKinlay (1990) identify another potential source of contrarian profits that arises when some stocks react more quickly to information than others (namely, a size-related lead–lag structure in stock returns). They find a large positive cross-serial covariance between the returns of small stocks and lagged returns of large stocks (but, weak cross-autocorrelation between returns of larger stocks and lagged small stocks returns). They claim that, in general, the size-related lead–lag structure (that is, a positive cross serial covariance) rather than an overreaction to information (that is, a negative autocovariance) is the main source of contrarian profits in short horizons.

As noted earlier in Section 1, the China stock market is driven by rumors and investor sentiment, which can be easily manipulated by syndicate speculators. Syndicate speculators may find it easier to manipulate the sentiment on small stocks and more profitable to create bullish (rather than bearish) sentiment on small stocks. As a result, the returns of small firms may lead those of large firms. To shed some light on this conjecture, we examine the auto- and cross-serial correlation structure in stock returns of five size-sorted quintile portfolios for five contrarian and four momentum strategies and report them in Table 4.

Among 45 own-serial correlation coefficients (in the nine 5×5 matrices) reported in Panel A, only seven own-serial correlation coefficients are positive (but only three are statistically significant at 10%). The average magnitude of the seven positive own-serial coefficients is much smaller than the absolute average magnitude of the 38 negative own-serial coefficients, of which 19 are significant at 10%. The relative dominance of the negative own-serial coefficients indicates an overall negative own-serial correlation among individual stock returns. The negative own-serial correlations indicate an overreaction of

[16] As the portfolios are made up of stocks from both the Shanghai and Shenzhen exchanges, we use a simple arithmetic average of the two index returns as the proxy for market index return. The correlation coefficients among the market index return (r_{Mt}) and the two index returns are over 95%.

Table 3
Robustness to time-varying risk

	α	β	R^2
Strategy 1-1 (contrarian strategy)			
Winner	−0.002 (−1.79)	1.042 (53.48)	0.89
Loser	0.003 (2.04)	1.093 (50.28)	0.88
Loser–Winner	0.005 (2.43)	0.051 (1.46)	0.004
Strategy 2-8 (contrarian strategy)			
Winner	−0.006 (−2.65)	0.946 (49.67)	0.97
Loser	0.014 (3.79)	0.938 (48.28)	0.90
Loser–Winner	0.020 (4.01)	−0.008 (−0.14)	0.0002
Strategy 4-4 (contrarian strategy)			
Winner	−0.005 (−3.25)	0.927 (61.2)	0.91
Loser	0.006 (2.49)	0.916 (56.7)	0.93
Winner–Loser	0.011 (2.72)	−0.011 (1.48)	0.007
Strategy 8-8 (contrarian strategy)			
Winner	−0.007 (−2.27)	0.983 (55.32)	0.90
Loser	0.012 (3.27)	0.979 (46.36)	0.86
Loser–Winner	0.019 (3.46)	0.005 (−0.22)	0.0001
Strategy 12-8 (contrarian strategy)			
Winner	−0.005 (−2.96)	0.940 (45.34)	0.91
Loser	0.004 (3.45)	0.936 (36.40)	0.89
Loser–Winner	0.009 (3.09)	−0.004 (−0.23)	0.0004
Strategy 16-20 (momentum strategy)			
Winner	0.013 (2.95)	0.845 (45.9)	0.92
Loser	−0.001 (−0.23)	0.827 (49.6)	0.88
Winner–Loser	0.014 (1.74)	0.018 (1.45)	0.005
Strategy 20-20 (momentum strategy)			
Winner	0.015 (3.93)	0.893 (60.3)	0.92
Loser	−0.002 (−0.46)	0.854 (51.0)	0.89
Winner–Loser	0.017 (2.68)	0.039 (1.60)	0.007
Strategy 26-26 (momentum strategy)			
Winner	0.018 (4.67)	0.869 (69.3)	0.95
Loser	−0.001 (−0.57)	0.821 (54.8)	0.87
Winner–Loser	0.019 (3.76)	0.048 (1.62)	0.013

Eq. (1) is used to estimate the parameters for winner and loser portfolios for five contrarian strategies (strategies 1-1, 2-8, 4-4, 8-8 and 12-8) and three momentum strategies (strategies 16-20, 20-20 and 26-26). Eqs. (2) and (3) are used to estimate the parameters for the differences in loser and winner returns of contrarian and momentum strategies, respectively. If the parameter β for the differences in loser and winner returns is not statistically significant, then the respective profit is not due to time-varying market risk. The figures in the parentheses are the autocorrelation-consistent t-statistics.

stock prices to firm-specific information (and, hence, return reversal), which in turn suggests the profitability of contrarian strategies in short horizons.

Among 180 cross-serial correlation coefficients (in the nine 5×5 matrices), only 33 correlation coefficients are positive (10 in Matrix 1-1, 8 in Matrix 8-8 and 8 in Matrix 12-

Table 4
Own-serial and cross-serial correlations of size-sorted portfolio returns

Panel A

	S1	S2	S3	S4	S5
Matrix 1-1 (formation period = 1, holding period = 1)					
S1	0.0287	0.0335	0.0105	0.0225	−0.0124
S2	0.0236	0.0266	0.0076	0.0215	−0.0122
S3	0.0183	0.0252	0.0032	0.0241	−0.0095
S4	−0.0169	−0.0100	−0.0268	−0.0046	−0.0325
S5	−0.0128	0.0013	−0.0105	0.0133	−0.0041
Matrix 2-8 (formation period = 2, holding period = 8)					
S1	−0.0599	−0.0633	−0.0227	−0.0181	−0.0148
S2	−0.0841	−0.0851	−0.0378	−0.0195	−0.0081
S3	−0.1044	−0.1002	−0.0438	−0.0195	−0.0037
S4	−0.0934	−0.0830	−0.0182	0.0110	0.0324
S5	−0.0944	−0.0710	0.0033	0.0513	0.0819
Matrix 4-4 (formation period = 4, holding period = 4)					
S1	−0.0750	−0.0850	−0.0508	−0.0486	−0.0454
S2	−0.1042	−0.1103	−0.0693	−0.0549	−0.0396
S3	−0.1272	−0.1303	−0.0782	−0.0567	−0.0342
S4	−0.1116	−0.1100	−0.0509	−0.0223	0.0064
S5	−0.1204	−0.1022	−0.0344	0.0143	0.0666
Matrix 8-8 (formation period = 8, holding period = 8)					
S1	−0.1616	−0.1464	−0.0483	−0.0283	0.0114
S2	−0.1881	−0.1655	−0.0549	−0.0163	0.0332
S3	−0.2145	−0.1826	−0.0585	−0.0121	0.0388
S4	−0.1657	−0.1240	0.0070	0.0570	0.1083
S5	−0.1567	−0.0962	0.0367	0.1103	0.1500
Matrix 12-8 (formation period = 12, holding period = 8)					
S1	−0.1638	−0.1519	−0.0542	−0.0321	0.0092
S2	−0.1902	−0.1707	−0.0604	−0.0195	0.0315
S3	−0.2173	−0.1886	−0.0645	−0.0155	0.0371
S4	−0.1683	−0.1298	0.0014	0.0542	0.1074
S5	−0.1569	−0.0980	0.0347	0.1098	0.1504
Matrix 12-26 (formation period = 12, holding period = 26)					
S1	−0.2125	−0.2499	−0.1789	−0.2305	−0.2494
S2	−0.2212	−0.2597	−0.1668	−0.2113	−0.2310
S3	−0.2275	−0.2421	−0.1187	−0.1424	−0.1402
S4	−0.1513	−0.1542	−0.0246	−0.0465	−0.0539
S5	−0.1517	−0.1435	−0.0201	−0.0279	−0.0366
Matrix 16-20 (formation period = 16, holding period = 20)					
S1	−0.1646	−0.1991	−0.1440	−0.2018	−0.2495
S2	−0.1839	−0.2224	−0.1418	−0.1916	−0.2439
S3	−0.1756	−0.1865	−0.0789	−0.1088	−0.1366
S4	−0.0937	−0.0903	0.0218	−0.0020	−0.0393
S5	−0.0962	−0.0808	0.0240	0.0115	−0.0250

Table 4 (*continued*)

Panel A

	S1	S2	S3	S4	S5
Matrix 20-20 (formation period = 20, holding period = 20)					
S1	−0.1619	−0.2188	−0.1681	−0.2511	−0.3159
S2	−0.1700	−0.2300	−0.1524	−0.2273	−0.2944
S3	−0.1645	−0.1913	−0.0831	−0.1301	−0.1625
S4	−0.0751	−0.0897	0.0241	−0.0163	−0.0571
S5	−0.0751	−0.0795	0.0276	−0.0011	−0.0358
Matrix 26-26 (formation period = 26, holding period = 26)					
S1	−0.2563	−0.3465	−0.2877	−0.3726	−0.4281
S2	−0.2410	−0.3285	−0.2264	−0.3070	−0.3449
S3	−0.2426	−0.2898	−0.1574	−0.1961	−0.1838
S4	−0.1396	−0.1812	−0.0310	−0.0756	−0.0725
S5	−0.1016	−0.1352	0.0052	−0.0331	−0.0138

Panel B

Contrarian strategies	1-1	2-8	4-4	8-8	12-8
S1–S1	0.0287	−0.0599	−0.0750	−0.1616	−0.1638
S5–S5	−0.0041	0.0819	0.0666	0.1500	0.1504
S1–S5	−0.0124	−0.0148	−0.0454	0.0144	0.0092
S5–S1	−0.0128	−0.0944	−0.1204	−0.1567	−0.1569
Momentum strategies	12-26	16-20	20-20	26-26	
S1–S1	−0.2125	−0.1646	−0.1619	−0.2563	
S5–S5	−0.0366	−0.0250	−0.0358	−0.0138	
S1–S5	−0.2494	−0.2495	−0.3159	−0.4281	
S5–S1	−0.1517	−0.0962	−0.0751	−0.1016	

Panel A reports nine autocorrelation matrices for holding period returns of size-sorted quintile portfolios corresponding to nine strategies: five contrarian strategies (i.e., 1-1, 2-8, 4-4, 8-8 and 12-8 formation-holding periods) and four momentum strategies (i.e., 12-26, 16-20, 20-20 and 26-26 formation holding periods). The size-sorted quintile portfolios are S1 (the smallest), S2, S3, S4 and S5 (the largest) in an ascending order of firm size measured by market capitalization at the initial portfolio formation time. Matrix *F-H* (for *F* formation and *H* holding periods) provides the 1-week lag own- and cross-serial correlations between holding period returns of size-sorted quintile portfolios. The diagonal elements in each Matrix *F-H* are the 1-week lag own-serial correlations of quintile portfolios' returns over the *H* holding period. The below-diagonal elements are the cross-serial correlations between the 1-week lagged holding-period returns of larger quintile portfolios and the holding-period returns of smaller quintile portfolios, whereas the above-diagonal elements are the cross-serial correlations between the 1-week lagged holding period returns of smaller quintile portfolios and the holding period returns of larger quintile portfolios. For example, the below-diagonal element E_{43} (−0.0182) in Matrix 2-8 refers to the cross-serial correlation between the 1-week lagged holding period returns of S4 quintile portfolio and the holding period returns of S3 quintile portfolio, whereas the above-diagonal element E_{34} (−0.0378) in Matrix 2-8 refers to the cross-serial correlation between the 1-week lagged holding period returns of S3 quintile portfolio and the holding period returns of S4 quintile portfolio element. Since the number of observations (*T*) for this table ranges from 309 (for the case of 26-26 strategy) to 359 (for the case of 1-1 strategy) due to weekly overlapping implementation of the nine strategies, the asymptotic standard errors ($T^{-0.5}$) for own- and cross-serial correlations under an i.i.d. null hypothesis range from 0.0528 to 0.0569. Panel B reports auto- and cross-autocorrelations of returns of the smallest- and the largest-size portfolios for the contrarian and momentum strategies. The rows of S1–S1 and S5–S5 report the autocorrelations for the returns of small stock (S1) and large stock (S5) portfolios. The rows of S1–S5 report the cross autocorrelation between the returns of large stock portfolio (S5) and lagged returns of small stock portfolio (S1). Similarly, the rows of S5–S1 report the cross autocorrelation between the returns of small stock portfolio (S1) and lagged returns of large stock portfolio (S5).

8) but only two are significant at 10%. The average magnitude of the 33 positive cross-serial coefficients is not materially different from the absolute average magnitude of the 147 negative cross-serial coefficients, of which 82 are significant at 10%. The relative dominance of negative cross-serial coefficients indicates an overall negative cross-serial correlation among individual stock returns. The negative cross-serial correlations (for all but Matrix 1-1) suggest that lag stocks follow lead stocks in the opposite direction. In other words, as the lead stocks produce positive returns, the lag stocks follow with negative returns. Note that the lead–lag status is determined in terms of relative absolute magnitude in cross-serial correlations. Hence, we can see that, although the lead–lag structure is not determinable for the 1-1 contrarian strategy, large firms lead small firms in short-term holding horizons of the 2-8, 4-4, 8-8 and 12-8 contrarian strategies, whereas small stocks lead large stocks in intermediate holding horizons of the 12-8, 12-26, 16-20, 20-20 and 26-26 momentum strategies.

Panel B summarizes the own-serial and cross-serial correlations of stock returns for the largest and the smallest firm-size portfolios according to contrarian strategies and momentum strategies. The own-serial correlations of small stock returns for all but 1-1 strategy are negative. The own-serial correlations of returns of large stock returns are mixed in their signs and much smaller in magnitude. The cross autocorrelations between returns of small stocks and lagged returns of large stocks (see the S5–S1 row) are negative for all strategies. For contrarian strategies, they are larger in relative magnitude than the cross-serial correlations between returns of large stocks and lagged returns of small stocks (see the S1–S5 row for contrarian strategies). For momentum strategies, the opposite holds. These relative magnitudes are consistent with earlier interpretation that large stocks lead small stocks in holding periods from 1 to 8 weeks and the opposite holds in holding periods from 12 to 26 weeks.

The negative cross-serial correlations indicate that, unlike the US stock market, the size-related lead–lag structure will contribute to momentum (rather than contrarian) profits. Furthermore, the lead–lag structure in China also indicates that small stocks lead large stocks negatively in relatively long holding periods (beyond 8 weeks). Hence, momentum profits tend to be reinforced by the unique lead–lag structure in China, an implication quite the opposite of that documented in Lo and MacKinlay (1990) for the US market.

One possible reason for the different role of the lead–lag structure in China lies in the distinct characteristics of the China stock market, which are described in Section 1. Since short selling is not allowed in China, the syndicate speculators may find it more profitable to create bullish (rather than bearish) sentiment on small stocks. This is so because bullish stocks can attract any investors but bearish stocks concern only those who currently hold the stocks. As a result, returns of small firms may lead those of large firms. The simultaneous presence of negative own-serial and cross-serial correlations in stock returns also suggests that the bearish sentiment on some stocks should have been triggered by the bullish sentiment on others and vice versa.[17] If this is the case, the emergence and

[17] The reason is that most investors are chasing bullish stocks and, at the same time, selling bearish stocks. In China, the settlement for "A" shares transactions is done on T+1 basis. This means that contra trades are effectively prohibited. Since margin trading is not allowed, investors with cash constraints must sell their current holding to make new purchases.

submergence of investor sentiment that led to return reversals on some stocks in short horizons can also lead to return continuations on other stocks in relatively longer horizons.

5. Jegadeesh and Titman (1995) decomposition of contrarian and momentum profits

Lo and MacKinlay (1990) posit that the lead-lag structure is an important source for contrarian profits, whereas Jegadeesh and Titman (1995) document that the lead–lag structure is not an important source of momentum profits in the US market. The finding in this paper indicates that the lead–lag structure in China may be an important source of momentum profits, but not of contrarian profits. To further investigate the stock prices' reactions to firm-specific information and common factors, we measure the relative contribution of the three main sources derived in the context of the one-factor pricing model (Jegadeesh and Titman, 1995):

$$r_{i,t} = \mu_i + b^t_{0,i} f_t + b^t_{1,i} f_{t-1} + e_{i,t} \tag{4}$$

where μ_i is the unconditional expected return of stock i, f_t is the unexpected common-factor realization at time t [proxied by the demeaned market index return obtained from Eq. (1)], $b_{0,i}$ and $b_{1,i}$ are the ith stock's contemporaneous and lagged betas, respectively.[18]

If the one-factor model generates stock returns and if every stock is weighted by its own return in excess of average market return in the past F-week horizon, then the expected contrarian and momentum profits can be decomposed as follows:

$$E(\pi^{c}) = -E\left(\frac{1}{N}\sum_{i=1}^{N} (r_{i,t-1} - \bar{r}_{t-1}) r_{i,t}\right) = -\sigma^2_{\mu} - \Omega - \delta\sigma^2_f, \tag{5}$$

$$E(\pi^{m}) = E\left(\frac{1}{N}\sum_{i=1}^{N} (r_{i,t-1} - \bar{r}_{t-1}) r_{i,t}\right) = \sigma^2_{\mu} + \Omega + \delta\sigma^2_f, \tag{6}$$

where

$$\sigma^2_{\mu} = \frac{1}{N}\sum_{i=1}^{N} (\mu_i - \bar{\mu})^2, \tag{7}$$

$$\Omega = \frac{1}{N}\sum_{i=1}^{N} \operatorname{cov}(e_{i,t}, e_{i,t-1}), \tag{8}$$

$$\delta = \frac{1}{N}\sum_{i=1}^{N} (b_{0,i} - \bar{b}_0)(b_{1,i} - \bar{b}_1), \quad \delta \equiv E(\delta), \tag{9}$$

where $\bar{b}_0$ and $\bar{b}_1$ are the cross-sectional averages of $b_{0,t}$ and $b_{1,t}$.

[18] For more detailed assumptions on this model and their implications, see Jegadeesh and Titman (1995).

The expected contrarian profits (Eq. (5)) and momentum profits (Eq. (6)) have three components. The first component (σ_μ^2) is the cross-sectional variance of expected returns. To the extent that stocks with higher expected returns experience higher-than-average returns during both portfolio formation and holding periods, this component will reduce contrarian profits but increase momentum profits. The second component Ω is the cross-sectional average serial covariance of idiosyncratic component of individual stock returns. It is determined by stock-price reactions to firm-specific information (or by investor sentiment on the particular stocks). If stock prices overreact to firm-specific information and correct the overreaction in the following period (or if the sentiment on these stocks changes direction), the own-serial covariance will be negative. Hence, it will increase the contrarian profits but decrease the momentum profits.[19] The last component $\delta\sigma_f^2$ is the lead–lag structure. If $\delta<0$ (i.e., the cross-serial covariance between contemporaneous and lagged betas is negative), then the lead–lag structure contributes positively to contrarian profits and negatively to momentum profits. The reverse holds if $\delta>0$.[20]

Table 5 reports the regression estimates of the three major determinants for eight selected strategies: namely, 1-1, 2-8, 4-4, 8-8 and 12-8 contrarian strategies and 16-20, 20-20 and 26-26 momentum strategies.[21] Among the three components, the second component (the average cross-sectional autocovariance of the idiosyncratic component in stock returns) is the most important determinant for all strategies. It is also negative for all strategies. In the case of contrarian profits, it is the only component that contributes positively to the profits. In the case of momentum profits, it is the dominant component that outweighs the positive contributions of the other two components. The relative dominance of the second component (the overreaction term) indicates that stocks in China heavily overreact to firm-specific information, which is consistent with the documented fact that stocks prices are often pushed too high or too low by rumors but then they are quickly corrected later on (when short-lived rumors are cleared).

The first component (the cross-sectional variance of expected returns) increases with the holding period. Hence, it becomes the most importance source of momentum profits. Since the cross-sectional variance of expected return arises from the fact that higher expected returns experience higher-than-average returns during both portfolio formation and holding periods, it can serve as an additional risk factor that is not captured by contemporaneous and lagged betas in the one-factor model of Jegadeesh and Titman (1995). The third component (the lead–lag structure) is positive for all strategies. This

[19] If stock prices under-react to firm-specific information (or if noise trading cancels each other and no sentiment has been created), the own-serial covariance will be positive. In this case, it will contribute to the momentum profits.

[20] It can be shown that the profit implications of both Lo and MacKinlay's lead–lag structure (captured by positive cross-serial correlation in stock returns) and Jegadeesh and Titman's lead–lag structure (captured by negative cross-serial covariance between contemporaneous and lagged betas) are mutually consistent.

[21] The time period between t and $t-1$ is the portfolio holding period. Although data covers a period of only 8 years, we employ the method of overlapping implementation of the strategies. Hence, sufficient number of observations is secured for the estimation of regression coefficients. For example, for each stock in 16-20 strategy, we compute the parameter estimates for μ_i, $b_{0,i}$,$b_{1,i}$ and $\text{cov}(e_{i,t}, e_{i,t-1})$ 20 times before we compute the respective averages.

Table 5
Regression estimates for the three components of contrarian and momentum profits

Expected profit of the contrarian strategy $= -\sigma_{\mu}^2 - \Omega - \sigma_f^2\delta$			
F-H Strategy	σ_{μ}^2	Ω	$\sigma_f^2\delta$
1-1 (contrarian)	0.000004 (−0.03)	−0.000159 (1.10)	0.000010 (−0.07)
2-8 (contrarian)	0.000059 (−0.48)	−0.000250 (2.03)	0.000068 (−0.55)
4-4 (contrarian)	0.000179 (−0.23)	−0.001046 (1.35)	0.000092 (−0.12)
8-8 (contrarian)	0.000255 (−0.19)	−0.001780 (1.30)	0.000153 (−0.11)
12-8 (contrarian)	0.001529 (−0.86)	−0.005890 (3.33)	0.002590 (−1.46)
Expected profit of the momentum strategy $= \sigma_{\mu}^2 + \Omega + \sigma_f^2\delta$			
6-20 (momentum)	0.001928 (2.03)	−0.004600 (−4.85)	0.001723 (1.82)
20-20 (momentum)	0.002200 (2.13)	−0.005000 (−4.84)	0.001768 (1.71)
26-26 (momentum)	0.002400 (3.21)	−0.005000 (−6.68)	0.001852 (2.48)

This table provides the estimates of the three main sources of the momentum and contrarian profits. The expected profits are decomposed using the one-factor model in Jegadeesh and Titman (1995). In estimating the parameters, μ_i, $b_{0,i}$ and $b_{1,i}$, we use the demeaned market index return ($r_{M,t}$) in Eq. (1) as the proxy for common factor f_t. Given the regression estimates for the three components, the expected profits for contrarian and momentum strategies are computed as: "$-\sigma_{\mu}^2 - \Omega - \sigma_f^2\delta$" and "$\sigma_{\mu}^2 + \Omega + \sigma_f^2\delta$," respectively. The numbers in the parentheses are the relative contribution of respective component to the expected profits of contrarian and momentum strategies. *Notes:* (1) $\sigma_{\mu}^2 = \frac{1}{N}\sum_{i=1}^{N}(\mu_i - \bar{\mu})^2$ is the variance of μ_i, unconditional expected return of stock. It decreases (increases) contrarian (momentum) profits. (2) $\Omega = \frac{1}{N}\sum_{i=1}^{N}\mathrm{cov}(e_{i,t},\ e_{i,t-1})$ is the cross-sectional average of autocovariance of the error terms, a proxy for overreaction to firm-specific information. If it is negative (positive), it increases (decreases) contrarian profits. (3) $\sigma_f^2\delta = \left(\frac{1}{T}\sum_{t=1}^{T}(f_t - \bar{f})^2\right)\left(\frac{1}{N}\sum_{i=1}^{N}(b_{0,i} - \bar{b}_0)(b_{1,i} - \bar{b}_1)\right)$ is the cross-sectional variance of common factor's unexpected realization times the cross-sectional average of individual stock's cross-serial covariance of contemporaneous and lagged sensitivities to common factor realization. It is a proxy for the lead–lag structure of Jegadeesh and Titman (1995). If δ is positive, lead–lag structure increases (decreases) momentum (contrarian) profits and vice versa.

unique lead–lag structure in China provides additional source of momentum profits (not of contrarian profits).

6. Summary and conclusions

In this paper, we examine the stock-return behavior in the China stock market. We find statistically significant short-term contrarian and intermediate-term momentum profits. In the case of equal-weighted portfolio strategies, the momentum profits are less distinct. The more distinct contrarian profits are due to the dominance of stock prices' overreactions to firm-specific information. The excessive overreaction is due to the followings: the dominance of individual investors in stock market; the lack of reliable information on firms (especially, small firms), which lead individual investors to rely on market rumors and past price trends; the presence of syndicate speculators who favor to create bullish sentiment on small stocks.

In the case of value-weighted portfolio strategies, the momentum profits become more distinct. This becomes so as a result of the unique lead-lag structure in China. It is unique in that the lead stocks lead the lag stocks negatively and that large firms lead small firms in short horizons, whereas small firms lead large firms in relatively longer horizons.

The super-speculative environment in China (referred to as "stir-frying stocks") results from lack of reliable information on firms, the absolute dominance of individual investors who tend herd among themselves, the rampant market manipulation by syndicate speculators, and the lack of alternative means for building personal wealth. To conclude, the profitability of contrarian strategies (and, to a less extent, momentum strategies) will dissipate as the market becomes mature and more transparent in the future.

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