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Momentum, Reversals, and Investor Clientele

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Abstract

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Different share classes on the same firms provide a natural experiment to explore how investor clienteles affect momentum and short-term reversals. Domestic retail investors have a greater presence in Chinese A shares, and foreign institutions are relatively more prevalent in B shares. These differences result from currency conversion restrictions and mandated investment quotas. We find that only B shares exhibit momentum and earnings drift, and only A shares exhibit monthly reversals. Institutional ownership strengthens momentum in B shares. These patterns accord with a setting where short-term reversals (which represent inventory risk premia) prevail in a market dominated by noise traders, and momentum prevails in markets where noise traders are less prevalent relative to informed investors who underreact to fundamental signals. Overall, our findings confirm that clienteles matter in generating stock return predictability from past returns.

1 Introduction

A large and growing literature uncovers cross-sectional return predictability based on past price moves. There is extensive evidence for what is known as the momentum effect, which is the tendency of stocks that performed well in the previous six to 12 months to perform well in the next six to 12 months (Jegadeesh and Titman, 1993, Rouwenhorst, 1998). At shorter intervals, researchers find reversals. Specifically, stocks which outperform over weekly or monthly intervals tend to underperform over similar durations going forward (Jegadeesh, 1990). Understanding why financial markets exhibit such simple forms of predictability is important, and much research has been directed to this issue.

Considering momentum first, one class of explanations for this phenomenon is based on the idea that better-performing stocks tend to be riskier, and thus require higher future returns. Another class posits that momentum arises from investors' biases.[1] Empirical support for these alternative explanations is mixed. On the one hand, Sagi and Seasholes indicate that the momentum effect is stronger in firms with more real options and lower operating costs. Since firms that do well in the past have more real options, implying more risk and greater required returns, this supports the risk-reward hypothesis for momentum. On the other hand, Chan, Jegadeesh, and Lakonishok (1996) propose that momentum arises because some investors underreact to fundamentals. Note that the former category of explanations for momentum is focused on the characteristics of securities' cash flows, whereas the latter is focused on the biases of investors. This observation suggests that our understanding of momentum could be advanced if an empirical test held cash flows constant across securities, but varied the clientele of investors trading the securities.

Turning to explanations for short-term reversals, these tend to focus on liquidity-

[1]For example, Berk, Green and Naik (1999), Johnson (2002), and Cochrane, Longstaff, and Santa-Clara (2008) provide neoclassical models of momentum, and Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), and Luo, Subrahmanyam, and Titman (2021) build behavioral frameworks. Brennan, Chordia, and Subrahmanyam (1998) argue that the Sharpe ratios of momentum strategies are too large to be consistent with rational models.

related issues (Jegadeesh and Titman, 1995, Nagel, 2012, and Cheng et al., 2017). The idea is that such reversals arise because risk averse liquidity providers need inventory compensation to absorb the demands of noise traders. This rationale suggests an implication that also depends on investor clientele: Short-term reversals should be weaker (stronger) in settings where noise traders are less (more) active. Again, testing this implication can be facilitated in a setting where noise trading varies across securities with identical cash flows.

In this paper, we study momentum and short-term reversals by exploiting a natural experiment provided by Chinese A and B shares, which have the same cash flow and control rights but different clienteles. Our empirical tests are motivated by a combination of insights from the microstructure-based models of Grossman and Miller (1988), and Nagel (2012) that explain reversals, and the behavioral models of Hong and Stein (1999) and Luo, Subrahmanyam, and Titman (2021) that explain momentum. The former papers indicate that reversals arise because of inventory risk premia required to absorb noise trades, and the latter indicate that momentum arises because traders underreact to information signals. These arguments, taken together, suggest that markets in which noise traders dominate will exhibit short-term reversals, while those with a lower presence of noise traders relative to informed investors will exhibit momentum. We emphasize that our reasoning relies on the *relative* prevalence of noise traders in A vs. B shares, rather than fundamental differences between any particular type of investor (retail or institutional) in either of these markets.

Clientele differences across these shares tend to arise because of three exogenous features of the markets. The first is that currency restrictions preclude many domestic retail investors from investing in B shares. The second is that regulatory quotas preclude foreign institutions from holding A shares.[2] The third is that domestic institutions are prohibited from investing in B shares. The result of these institutional

[2]The annual cap on foreign exchange conversion by Chinese citizens was no more than $8,000 in 2005, and has been at $50,000 since 2007. Further, during our sample, foreign investment in A shares also is subject to a ceiling in dollar terms. See, for example, https://tinyurl.com/khnkf9fn and https://tinyurl.com/eavzep2c.

constraints is that domestic retail investors are largely confined to A shares, whereas foreign institutions are largely confined to B shares (indeed, *all* B share institutions are foreign). Since foreign institutions tend to be relatively sophisticated, whereas retail investors tend to be naïve, (Chan, Menkveld, and Yang, 2008, Barber et al. 2009), the clienteles of the two markets indicate a greater prevalence of noise traders in A shares, and a lower presence of noise traders in B shares.

As a consequence of these clientele differences, we expect short-term reversals to be more prevalent in A shares, and momentum to be more prevalent in B shares. Our empirical results support these hypotheses. Indeed, we document evidence of significant monthly reversals in the A share market, but insignificant reversals in the B share market, and evidence of significant momentum in the B share market but insignificant momentum in the A share market.

A deeper exploration of the A and B share return patterns provides additional support for our explanation. First, we show that weekly reversals (Lehmann, 1990) show the same pattern as monthly reversals: they are evident in A shares, but not in B shares. Supporting our argument that noise traders are more prevalent in A shares, we find that the daily returns of B shares tend to lead A shares, but not vice versa. Next, given the cost of short-selling, the market making hypothesis suggests greater reversals following positive returns, since market makers require greater compensation to absorb buy imbalances.[3] We indeed find that the A market reversals arise from positive, rather than negative, returns. We also find that A shares are substantially more volatile than B shares, which is consistent with the view that retail ownership and limited market making capacity magnify inventory premia in A shares relative to B shares, and thus result in greater price fluctuations in the former shares.

[3]Short selling in China faces severe institutional constraints. Even though shorting became possible for selected stocks in the A share market starting in March 2010, naked short selling is still not allowed and an "uptick" rule is applied. Furthermore, investors have to meet several requirements, such as minimum investment experience and net worth, before they can engage in short selling, so that shorting is quite costly. Indeed, the average monthly short interest ratio over the period from 2011 to 2018 does not exceed 0.03% (Liu, Luo, and Zhao, 2019, Figure 1). These observations all suggest frictions to market making in China.

Next, note that in our argument, momentum occurs because of active investors who underreact to fundamental information. We would expect that within the B shares, momentum should be stronger for stocks with higher institutional ownership, as these foreign institutions might more strongly represent active investors who underreact to fundamentals. We confirm this conjecture. This result, as well as the baseline momentum in B shares, survive other explanations for momentum proposed in the literature, including those based on real options. We also find that (only) B shares exhibit post-earnings drift, consistent with underreaction to fundamentals, and that such drift is stronger for shares with greater levels of institutional holdings. The B-share momentum findings also survive consideration of size, value, and liquidity.

The question naturally arises as to what this particular experiment offers that is of general interest to finance academics. While differences in risk preferences can influence the stochastic discount factors that determine required returns across markets, we believe we are the first to examine closely how variations in investor clienteles influence return predictability. We are able to conduct this exercise cleanly because of our unique setting of differing investor compositions across identical cash flow claims, and we show that our patterns are consistent with simple behavioral and microstructure-based arguments. We note that we are not the first to examine such "Siamese twin" stocks. For example, Schultz and Shive (2010) show that price differences in twin shares are economically meaningful, and are best explained by limits to arbitrage. Froot and Dabora (1999) find that the prices of twin shares co-move less with each other and more with the market on which they are traded most, and attribute this result to country-specific market sentiment. While these studies are of interest, their samples are limited, and therefore they do not explore the price patterns we examine in this paper.

Existing studies have recognized that the Chinese A and B shares are particularly interesting because they offer a broader cross-section of "twin" markets. For example, Chan, Menkveld, and Yang (2007, 2008) provide evidence that the price premium of A shares over B shares can be explained by the relative differences in information asymmetry across these share markets. Mei, Scheinkman, and Xiong (2009) argue that intense speculative trading in the A share market, and short-selling constraints that segment the markets (Shleifer and Vishny, 1997), lead to A share prices being higher than B share counterparts (see also Fong, Wong, and Yong, 2008). We abstract away from pricing differentials, and instead consider how key cross-sectional patterns such as momentum and short-term reversals differ across A and B shares.[4] Because we make a comparison between two markets where the firm fundamentals are identical but the shareholders are different, we are able to attribute the differences in predictability to clientele differences.

2 The Setting and Hypotheses

There are two stock exchanges in China; the Shanghai Exchange and the Shenzhen Exchange, which were established respectively on December 1990 and July 1991. Both exchanges allow the trading of two types of shares, A and B shares. These share types, issued on the same companies, are identical in terms of cash flow and voting rights, but the A shares are denominated in and require the local currency, while the B shares are denominated in and require an international currency. The B shares traded on the Shanghai Exchange are denominated in U.S. dollars and those traded on the Shenzhen Exchange are denominated in Hong Kong dollars.

[4] Hsu et al. (2018), Kang, Liu, and Ni (2002), Shi, Jiang, and Zhou (2015), Jansen, Swinkels, and Zhou (2021) study return anomalies in A shares, but do not contrast them with those in B shares. Naughton, Truong, and Veeraraghavan (2008) and Choudhry and Wu (2015) document momentum in Chinese domestic shares, using data from the Taiwan Economic Journal, and Guotai Junan Securities Co. Ltd (a private data supplier), respectively. Using the standard China Stock Market and Accounting Research (CSMAR) database, however, we do not find evidence of such A-share momentum during their sample period of 1995-2005. Our finding of no momentum in A shares is consistent with Gao, Guo, and Xiong (2021). In independent work, Cheema and Man (2017) also document momentum in Chinese B shares, but do not contrast reversals and momentum across A and B shares.

2.1 B Shares

The B share market was established to provide a channel for firms to raise foreign capital. Before February 2001, the A share and B share markets were completely segmented – domestic investors could only trade A shares and foreign investors could only trade B shares. Thereafter, the authorities allowed domestic retail investors (but not institutions) to trade B shares. Nonetheless, Figure 1, Panel A shows that the surge in the number of new individual investors in early 2001 was only temporary; this number fell to the pre-2001 level in the years after. The number shows just one similar spike in 2007. Indeed, domestic retail investors trade very little in the B share market (Chan, Menkveld, and Yang, 2008) for two reasons. First, strict foreign exchange controls restrict participation in the B share market.[5] Second, transactions in A shares are settled based on a "$T + 1$" settlement rule, while those in B shares are based on "$T + 3$." This difference in trading rules discourages short-term retail investors from trading B shares. In contrast, the number of new institutional investors in B shares increased substantially from 2002 to 2007 and stabilized at an average of around 2,000 new investors per year in the period from 2008 to 2014, as Panel B of Figure 1 demonstrates.[6]

2.2 A vs. B Shares

The A share market primarily consists of domestic investors. Foreign institutional investment in these shares was subject to quotas during our sample period. While this quota has increased over the years, ownership by foreign institutions in A shares has nonetheless remained at extremely low levels, with a mean holdings level of 0.2%

[5]These restrictions are frequently mentioned in the media as the reason for investors not being interested in the B share market. For example, the Financial Times in an article on Jan 9, 2013 titled "End of the road for China's 'B' market" stated the following: "In 2001, they changed the rules to allow domestic investors to buy in, prompting a doubling in the Shenzhen index within the space of a few weeks. But too few domestic investors held sufficient foreign currency to make the project sustainable and China now appears content to let the market fade away."

[6]Separate data on the number of individual and institutional investors are not available from China Securities Depository and Clearing Corporation Limited (CSDC) after 2014.

(See Table 1 of Liao, Du, and Sun, 2020). In untabulated results, we find that over the period 2008 to 2018, the average foreign institutional holdings in A shares were at about 0.25%, and never exceeded 1%. On the other hand, Figure 2 (from *FactSet*) shows that the average foreign institutional ownership of B shares rose gradually from about 1.5% in 2002 to 8% in 2007 and since then it stabilized at a lower level of around 5%.[7] Note that all institutions in B shares are foreign (domestic institutions cannot trade B shares), and many B share retail investors are also foreign. These B-share retail investors participate in a market other their own, and the domestic retail investors in the B market are required to have access to foreign currency. Due to all these features, we expect the clientele holding A shares to be relatively less sophisticated than that holding B shares.

In contrast, domestic retail investors dominate the A share market – for example, a recent report by Blair (2018) indicates that domestic retail investors account for about 85% of trading volume in A shares in 2015. The majority of these investors are under 40 and most do not have a college education (Shanghai Stock Exchange Annual Report 2015). A striking example of unsophisticated trading by Chinese individual investors is the warrants bubble documented by Xiong and Yu (2011), and Li, Subrahmanyam, and Yang (2021), who describe prices and trading within an episode between 2005 to 2008 in which a number of almost worthless put warrants traded frequently every day at highly inflated prices. Thus, owing to the dominance of domestic retail investors, we would expect more noise trading in A shares (Peress and Schmidt, 2020) relative to B shares.

2.3 Our Motivation

Existing literature suggests that the above-mentioned differences in clienteles can potentially generate differences in momentum and reversals in the A and B markets. For example, Nagel (2012) argues that returns reverse in the short-run because of tempo-

[7]From Kim, Pevzner, and Xin (2019, Table 1), this number is higher than the corresponding level of foreign institutional ownership in Hong Kong and Japan.

rary risk premia required to absorb imbalances in uninformed trades, and shows that such reversal profits are time-varying. This suggests a cross-market implication: Since noise trades are likely to be more prevalent in A shares due to the greater prevalence of domestic retail investors, this market might exhibit stronger reversals than B shares. Next, turning to momentum, in Hong and Stein(1999), and Luo, Subrahmanyam, and Titman (2021), momentum profits arise because active investors underreact to information signals. Since the B market should have a lower presence of noise traders relative to such informed investors, it may exhibit a lower tendency for reversals and stronger tendency to exhibit momentum. In Appendix A, we provide a simple model that rigorously integrates momentum and short-term reversals, and validates these observations.[8] Based on the model and the preceding arguments, we test the following hypotheses:

(H1) The inventory risk premia required to bear the noise trades of domestic retail investors leads to stronger reversals in the A market relative to the B market.

(H2) The lower prevalence of noise traders relative to quasi-rational informed investors in the B market leads to higher momentum in the B market relative to the A market.

After describing our data in the next section, we present the analysis that tests H1 and H2 in Section 4. We provide supporting evidence for our hypotheses in Section 5.

3 Data

Our sample initially includes all listed companies in China except those listed in the Growth Enterprise Market (ChiNext) and firms only issuing B shares. From this initial

[8] In our model, underreaction is necessary for momentum, but extremely large levels of underreaction cause reversals. The intuition is the following. Underreaction comes from underestimating the precision of an informative signal. With very low levels of this underestimation, there is little momentum, and reversals dominate. But with very high levels of this underestimation, the estimated risk of holding assets is extremely high, which also leads to reversals via increased risk premia. Thus, investors have to be "quasirational" (i.e., underreact moderately) for momentum to obtain.

sample we require firms to be listed for at least two years before they can be included in the data we analyze. Since our risk factors used for adjusting returns start in January 2000 and we need at least twenty-four monthly observations to estimate the factor loadings for the computation of risk-adjusted returns, our sample period begins in January 2002 and ends in December 2018.[9] We divide firms into two subsamples; the "Only A" sample includes 2,442 firms solely issuing A shares and the "AB" sample consists of 88 firms issuing both A and B shares.

Our data on stock prices, returns, trading volume, total and tradable shares outstanding, as well as accounting data are from China Stock Market & Accounting Research, CSMAR. We measure all currency values in U.S. dollars. To deal with the data error problems commonly found in developing markets, we adopt the filtering procedures used in Chui, Titman, and Wei (2010). Specifically, to address issues surrounding companies with very small market capitalization (Hou, Xue, and Zhang, 2020), we exclude stocks below the fifth percentile of the market capitalization of tradable shares outstanding, and filter out suspicious stock returns by setting returns that are larger (less) than 100% (-95%) equal to 100% (-95%). As it turns out, our conclusions are not affected by these procedures.[10]

To calculate risk-adjusted returns, we use the Liu, Stambaugh, and Yuan (2019) three-factor model (CH-3). These factors include a market factor, a size factor based on market equity (small minus big, SMB), and a value factor that is based on the earnings-price ratio (value minus growth, VMG). Liu, Stambaugh, and Yuan (2019) show that their CH-3 factor model better explains Chinese return patterns than an adaptation of the Fama-French three factor model.

We measure the market capitalization of each type of share (A or B) in month t as the shares outstanding of the type times their respective end-of-month closing prices.

[9] Liu, Stambaugh, and Yuan (2019) start constructing their factor series in January 2000 because of two reasons. First, there was large variation in accounting standards before 1999 and hence it was difficult to compare accounting data across Chinese firms before 1999. Second, there were not enough firms to form portfolios before 1999.

[10] The monthly size breakpoints are determined using the entire A share market in the initial sample, i.e., not excluding firms listed less than 24 months but excluding those listed in ChiNext.

Firm size (SZ) in month t is the sum of the month-end market capitalizations of all share types for a firm. Return volatility ($Rvol$) of a share type in month t is computed as the standard deviation of daily returns during that month on a particular share class. To make the volatility measure more reliable, we require each share to have return and volume data for more than 60% of the days in the month (although removing this requirement does not affect our central findings). Appendix B provides detailed definitions of these variables as well as other variables used in this study.

Table 1 provides descriptive statistics for our sample. While the average return on A shares is lower than that on B shares in the AB sample, it is slightly higher than that on A shares in the Only A sample. As can be seen, the prices of A shares, relative to cash flows or book values, are, on average, higher than the B share counterparts in the AB sample (Mei, Scheinkan, and Xiong, 2009). The average market capitalization of A shares is larger than that of their corresponding B shares in the AB sample. Average monthly turnover in A shares (in either the Only A or the AB sample) is about three times larger than that in B shares. The median firm size in the AB sample is a bit larger than that in the Only A sample, suggesting that while firms issuing both A and B shares are not particularly large relative to the rest of the sample, they also are not very small firms.

4 Main Empirical Results

In this section we present our basic empirical findings. We first analyze momentum and monthly reversals across A and B shares using a portfolio approach. We then consider the evidence based on regressions.

4.1 Momentum

We estimate the momentum effect by constructing overlapping portfolios using the method of Jegadeesh and Titman (1993). Specifically, we examine a momentum strategy that forms portfolios based on past six-month returns, and holds these portfolios for six months. At the end of each month, stocks are allocated into three portfolios, low (bottom one-third) to high (top one-third) based on their returns over the past six months within each market. These portfolios are value-weighted, using the total market cap for each firm (summed across share classes) and are held for six months. If a stock has a missing return during the holding period, we replace it with the corresponding value-weighted market return. If the stock return is no longer available, we rebalance the portfolio at the end of the month. To minimize bid-ask bounce and thin trading effects, we follow Jegadeesh and Titman (1993) and skip a month between the ranking period and the holding period.

Since we form portfolios each month based on returns in a prior six-month period and hold the stocks for six months, we essentially hold six different portfolios each month. The return on a winner (loser) portfolio that we report for month t is the average of the returns on those high (low) portfolios formed in month $t-2$ to $t-7$. A momentum portfolio consists of taking a long (short) position in the winner (loser) portfolio. Accordingly, the return on a momentum portfolio, i.e. the momentum effect in month t, is the spread in returns between the winner and loser portfolios in that month. As our estimation period is January 2002 to December 2018 (see Section 3), the first return for the winner minus loser portfolio is the simple average of the returns in January 2002 on the six high minus low portfolios constructed based on past returns over the previous June-to-November period, the previous May-to-October period, and so on up to the previous January-to-June period.

Table 2 shows selected characteristics of the winner and loser portfolios. The winners are larger and have greater turnover than the losers, but both groups have similar book-to-market ratios. Our regression analysis in Section 4.3 controls for these and other cross-sectional characteristics. For now, in Table 3, we report the returns of momentum portfolios. Consistent with other studies (Chui, Titman, and Wei, 2010, Docherty and Hurst, 2018, and Griffin, Ji, and Martin, 2003), we find that stock returns in the A market do not exhibit momentum. As shown in Panel A of Table 3, over the entire sample period, the average momentum effect is 0.27% per month for A shares in the Only A sample, and it is statistically insignificant.

To investigate if the lack of momentum in the only A sample is due to a few large stocks that dominate the value-weighted portfolio, we sequentially remove the largest 0.5% to 10% of the A shares from the Only A sample each month and form momentum portfolios for each subsample. Panel A of Table 3 reveals that the point estimate of momentum profits decreases further after the largest A shares are removed from the sample. We also compute the returns on equal-weighted momentum portfolios of A shares in the Only A sample and find that the average momentum effect is 0.12% per month with a t-statistic of 0.57.

Panel B of Table 3 reports that the momentum effect in A shares within the AB sample is about 0.5% per month, which is larger than that within the Only A sample, but it is still statistically insignificant. In contrast, the momentum effect in the B share market is 1.15% per month, with a t-statistic of 3.33. The difference between the momentum effect across B and A shares in the AB sample is 0.63% per month and that between momentum in the B share and the Only A samples is 0.89% per month. These differences are statistically significant at the 5% level. Panel B also shows the average returns on equal-weighted momentum portfolios, which are uniformly lower than their value-weighted counterparts. The equal-weighted momentum effect for B shares is 0.82% per month with a t-statistic of 3.31 and that for their A share counterparts is 0.25% with a t-statistic of 0.90. The differences between the equal-weighted momentum effect in B and A shares are statistically significant at the 5% level for both the AB and the Only A subsamples.

In Table 3, we use six months as the interval for both the formation and holding periods as that is the period often used in the literature (see, for example, Hong, Lim, and Stein, 2000, and Avramov et al., 2007). However, the results we present in Table 3 are broadly robust to different momentum horizons. As an example, in Table IA.1 of the internet appendix, we present the results when momentum portfolios are formed based on returns over the past twelve months and held over the next six months. The findings are similar to those in Table 3.

Figure 3 Panel A reports the cumulative monthly returns on three value-weighted momentum portfolios: (1) A shares in the AB sample, *WL*$(A|AB)$; (2) B shares in the AB sample, *WL*$(B|AB)$; and (3) the Only A sample, *WL(Only A)*, from December 2001 to December 2018. On the right side of the figure, we present the final dollar value of each of the three portfolios, given a $1 investment in December 2001. *WL*$(B|AB)$ starts to outperform *WL*$(A|AB)$ and *WL(Only A)* in 2004. The final value of the B share momentum portfolio in December 2018 is about 3.6 to 5.5 times larger than that of the A share momentum portfolios. Panel B of Figure 3 shows similar patterns with the cumulative monthly returns for the three equal-weighted momentum portfolios.

4.2 Short-Term Reversals

In this section we examine the returns of short-term reversal strategies. As we show, reversals are stronger in the A market, which is consistent with our hypothesis in Section 2.3, which suggests that reversals arise when retail investors (noise traders) are more active.[11]

Specifically, we repeat the analysis from the previous subsection but set both the ranking and holding periods to one month rather than six months. Stocks are allocated into three portfolios, losers (bottom one-third) to winners (top one-third), based on their returns in the previous month (R_{t-1}). Value-weighted returns on these portfolios are then computed for month t. A reversal portfolio consists of a long position in the loser portfolio and short position in the winner portfolio. Hence, the short-horizon return reversal effect in month t refers to the difference in returns between the loser and winner portfolios in that month.

Table 4 displays the characteristics of these winner and loser portfolios. Winners tend to be larger and exhibit greater turnover than losers in all samples. Winners and losers have similar book-to-market ratios and return volatilities. We control for these

[11]Higher trading activity does not necessarily imply lower reversals from a theoretical standpoint. Indeed, in our model within Appendix A, it implies higher levels of noise trades, and hence greater inventory premia and stronger reversals.

characteristics in the regression analysis presented within Section 4.3 to follow. For now, Table 5 reports the average monthly returns on the reversal portfolios. Panel A reports that equal-weighted reversal profits in the Only A sample are at 1.2% and are strongly significant (t-statistic = 4.93). While the average return on the value-weighted portfolio is insignificant, this return becomes significant once we exclude just the largest 0.5% of the firms from the reversal portfolio. Specifically, in this case, the average value-weighted return on the reversal portfolio in this sample increases to 0.78% per month with a t-statistic of 2.57. The reversal effect in the Only A sample further increases when more large firms are excluded from the sample. After removing the largest 10% of the firms each month from the Only A sample, the average return on the reversal portfolio is 1.1% per month with a t-statistic of 4.68, which is very close to what we find for the equal-weighted reversal portfolio constructed with A shares in the Only A sample. These results indicate that all but the largest A shares exhibit a strong reversal effect.

Panel B of Table 5 shows that, for the AB sample, the equal-weighted reversal portfolio of A shares in the AB sample earns 1.38% per month with a t-statistic of 4.49. The return of the value-weighted reversal portfolio is insignificant, but this is again driven by a few large firms. Indeed, in untabulated results we find that if we just exclude the largest firm, the return increases to 0.77% per month, with a t-statistic of 2.16.

The average return on the value-weighted reversal portfolio of B shares is -0.51% per month with a t-statistic of -1.25. In contrast to the A market, the lack of significance in the B share sample is not because of a few large stocks. The equal-weighted reversal effect in B shares is also insignificant. The spread in the reversal effect between A and B shares in the AB sample is 1.1% per month with a t-statistic of 2.29. The difference in the reversal effect between A shares in the Only A sample and B shares is also statistically significant at the 5% level. The average monthly differentials in the equal-weighted reversal effect between B and A shares range from 1.59% to 1.77% and these spreads are statistically significant with t-statistics exceeding five (i.e. at the 1% level). Of course, with short-term reversals, bid-ask bounce is a potential issue. Jegadeesh (1990) checks for this by excluding the last trading day from the portfolio formation period. In Table IA.2 in the internet appendix we present our monthly reversal results after adopting Jegadeesh's (1990) method and find that our results are largely unaltered.Thus, the overall conclusion is that there is evidence of monthly reversals only in the A share market.

We now graphically depict the monthly reversal profits for A and B shares. Figure 4 (the analog of Figure 3) plots the cumulative monthly returns on the reversal portfolios formed on the A and B shares in the AB sample [*LW*$(A|AB)$ and *LW*$(B|AB)$, respectively], and on the Only A sample [*LW(Only A)*]. Given a $1 investment in December 2001, the equal-weighted *LW*$(A|AB)$ portfolio has the largest ending value of $13.70, while the *LW(Only A)* and *LW*$(B|AB)$ counterparts reach $10.20 and $0.40, respectively. These findings demonstrate that the differences in the economic magnitudes of the reversal effect across A and B shares are sizeable. The patterns for value-weighted portfolios are similar, though, as suggested by Table 5, the magnitudes are smaller. The overall analysis to this point thus accords with momentum in B shares, and short-term reversals in A shares.[12]

4.3 Regression Analysis of Past-Return-Based Trading Strategies

To examine how reversal, momentum, and other firm characteristics jointly determine the cross-section of stock returns in A and B shares, we use the Fama and MacBeth (1973) (FM) approach, and estimate the following regression in each month:

$$\begin{aligned} R^k_{jt} &= \alpha_t + \beta_{1t} R^k_{j,t-1} + \beta_{2t} R^k_{j,t-2,t-7} + \beta_{3t} LnBM_{jt-1} + \beta_{4t} LnSZ_{jt-1} \\ &+ \beta_{5t} LnIlliq^k_{j,t-1} + u^k_{jt}, \end{aligned} \tag{1}$$

where R^k_{jt} and $R^k_{j,t-1}$ are the returns on share k (k = A or B) of firm j in month t and month $t-1$, respectively, and $R^k_{j,t-2,t-7}$ is the past six-month return of share k of

[12]In unreported analysis we also examine the extent to which past six-month returns in the A (B) market predict future six-month returns in the B (A) market. We do in fact find one-way cross-predictability; stocks that outperform in the A market tend to outperform in the B market over the following six months. This is consistent with the notion that B-share investors underreact to the information conveyed by A share prices. We do not find evidence of cross-predictability in monthly reversals.

firm j that is computed from month $t-2$ to $t-7$. The regressions also include the natural logarithms of the book-to-market ratio ($LnBM_{jt-1}$) and market capitalization ($LnSZ_{jt-1}$) for firm j in month $t-1$, and the natural logarithm of the Amihud (2002) illiquidity measure ($LnIlliq^{k}_{jt-1}$) for share k of firm j in month $t-1$.

We also use the Brennan, Chordia, and Subrahmanyam (BCS) (1998) approach and estimate the regression described in Equation (1) using risk-adjusted rather than raw returns as the dependent variable. To estimate risk-adjusted returns, we apply the Liu, Stambaugh, and Yuan (2019) CH-3 model discussed in Section 3:

$$R_{jt} = \alpha_j + \beta_{Mkt,j} Mkt_t + \beta_{SMB,j} SMB_t + \beta_{VMG,j} VMG_t + e_{jt}, \tag{2}$$

where e_{jt} is the residual term.[13] The estimation period for Equation (2) covers a maximum of sixty months, with a requirement of at least twenty-four observations, prior to each month in our testing period. Specifically, since our factor series start in January 2000, the estimation period for the first month of the testing period (January 2002) has twenty-four months, the next month (February 2002) has twenty-five months, and so on till the sixty month period is reached; the interval for estimation is kept constant thereafter. We use these estimated betas ($\hat{\beta}_{Mkt,j}$, $\hat{\beta}_{SMB,j}$, and $\hat{\beta}_{VMG,j}$) to compute the risk-adjusted abnormal returns ($AdjR_{jt}$) for each stock. Specifically, the BCS-adjusted return, $AdjR_{jt}$, for stock j in month t during the testing period is calculated from the following equation:

$$AdjR_{jt} = R_{jt} - \hat{\beta}_{Mkt,j} Mkt_t - \hat{\beta}_{SMB,j} SMB_t - \hat{\beta}_{VMG,j} VMG_t. \tag{3}$$

Panel A of Table 6 reports the estimated coefficients from both sets of FM regressions. As we show, our results for momentum and reversals are consistent across the two types of regressions – we find evidence of reversals only in A shares and momentum is evident only in B shares. Panel B of Table 6 indicates that the differences in the estimated coefficients on the prior month return/past-six month return between B and

[13]We use the excess value-weighted A share market return as the market factor for A shares and use the excess value-weighted B share market return as the market factor for B shares. Our findings are similar if we use excess value-weighted A share market return to be the market factor for B shares.

A shares in each sub-sample are significantly positive. These findings are consistent with the results of the previous subsection.

In the traditional FM regression we find that the book-to-market, size, and illiquidity effects are positive and are statistically significant at the 1% level for A shares in the Only A sample. However, the coefficient of book-to-market becomes insignificant in the BCS version of the regression. The book-to-market and size effects are not statistically significant for A shares in the AB sample and none of these firm characteristics load significantly in either of regressions on the B shares.[14]

Liu, Stambaugh, and Yuan (2019) show that the smallest 30% of listed companies in China are frequently the targets of reverse mergers and hence have a shell premium, i.e., they earn higher returns. To explore if this shell premium contaminates our findings, we exclude the smallest 30% of firms in our sample and re-estimate the FM regressions using both raw and risk-adjusted returns. In line with Liu, Stambaugh, and Yuan (2019), the 30th size percentile is determined from firms in the entire A share market, including firms in the Growth Enterprise Market (ChiNext) as well as those listed for less than 2 years. Table IA.3 in the Internet Appendix indicates that the findings from this smaller sample are essentially the same as those reported in Table 6, indicating that our results are not driven by the shell premium.[15]

[14]We perform several robustness checks. First, we note that A shares are subject to seasoned equity offerings that can affect returns due to managerial market timing. We exclude firms which undertake SEOs. Next, following the policy decision which allowed domestic retail investors to participate in the B share market in February 2001, B share market values increased considerably. We exclude the year 2001 from our analysis. The split-share structure reform in 2005 involved shareholders of non-tradable shares compensating tradable shareholders in A shares. We regress the FM coefficients in Table 6 on a dummy variable which is unity from 2005 to 2007, the time span of the reform and examine the resulting intercepts. Finally, three firms moved from B share status to H (Hong Kong listing) share status during our sample period. These exercises leave our conclusions unchanged. Results are available on request.

[15]In results not reported for brevity, we also find that, consistent with Chen and Hong (2002), monthly B share returns are significantly and positively correlated with own past six-month returns, but the same is not true for A share monthly returns. Similarly, while monthly firm-specific residuals of A shares (after accounting for the factors of Liu, Stambaugh, and Yuan, 2019) exhibit statistically significant negative autocorrelation, those of B shares do not do so. Thus, the results from serial dependence match the cross-sectional evidence.

5 Additional Evidence

In this section, we provide further tests that shed light on our results, based on volatility, signed past returns, reaction to earnings surprises, and cross-sectional effects of institutional holdings in B shares.

5.1 Weekly Reversals

The tests of the previous section follow the extensive literature on empirical asset pricing, and use monthly returns. However, Lehmann (1990) shows the existence of weekly reversals in U.S. data, and these reversals are at least as strong as the monthly phenomena documented by Jegadeesh (1990). Accordingly, we now examine the extent to which the returns of A and B shares exhibit weekly reversals.

We form reversal portfolios in a manner analogous to Table 5 and Lehmann (1990). Specifically, we first compute returns from Wednesday to Tuesday on every week. We then sort stocks into reversal portfolios (extreme terciles) as in Table 5, and report he results in Table 7. As we see, the results are very similar to, and indeed, somewhat stronger, than those in Table 5. Specifically, we find strong evidence of reversals in both value- and equally-weighted portfolios in the Only A sample, with the smaller stocks exhibiting the strongest reversals. We find very similar results for the A shares that are in the AB sample, but most importantly, there is no reliable evidence of B share reversals. These results lend confidence to the conclusions from monthly reversals described in the previous section.

5.2 Lead-lag Relation Between A and B shares

We have asserted that the dominant clientele in B shares is more sophisticated than that in A shares. To investigate this assertion more fully, it is of interest to explore information flows between these markets. Accordingly, we examine the daily time-series lead-lag relation between these shares. We estimate the following regression for the AB sample:

$$\begin{aligned}
R^A_{j,CTO,d} &= \beta_{10} + \beta_{11} R^B_{j,OTC,d-1} + \beta_{12} R^A_{j,OTC,d-1} + \beta_{13} R^A_{j,CTO,d-1} \\
&+ \beta_{14} LnV^A_{j,d-1} + \beta_{15} LnV^B_{j,d-1} + e^A_{j,d}, \\
R^B_{j,CTO,d} &= \beta_{20} + \beta_{21} R^A_{j,OTC,d-1} + \beta_{22} R^B_{j,OTC,d-1} + \beta_{23} R^B_{j,CTO,d-1} \\
&+ \beta_{24} LnV^A_{j,d-1} + \beta_{25} LnV^B_{j,d-1} + e^B_{j,d},
\end{aligned}$$

where $R^k_{j,CTO,d}$ is the close-to-open return on the k ($k = \{A, B\}$ share of firm j on day d. Similarly, $R^k_{j,OTC,d-1}$ is the open-to-close return on the k share of firm j on day $d-1$. $LnV^k_{j,d-1}$ is the natural logarithm of the dollar trading volume on the k share of firm j on day $d-1$. We perform an estimation by firm using the seemingly-unrelated regression (SUR) approach to control for cross-sectional residual correlation across firms.

Results from this estimation appear in Table 8.[16] The results provide some evidence that the returns of the B shares lead the returns of A shares, but there is no evidence of A shares leading B shares. Specifically B share returns are useful in forecasting A share returns, but not vice versa. Indeed, the coefficient representing the lead from B to A is seventeen times higher than the one representing the lead from A to B, and only the former coefficient is significant. The difference in the two lead-lag coefficients is also statistically significant.

5.3 Return Volatilities of A vs. B shares

If retail noise trades are indeed more prevalent in A shares relative to B shares, then short-term return volatility should be higher in A shares, since inventory-induced

[16] See Chui and Kwok (1998) for a similar test, using an earlier sample period from 1993 to 1996. Our finding is consistent with those of Bae et al. (2012) at the weekly frequency. Chan, Menkveld, and Yang (2007) find that both A and B shares lead each other at an intraday frequency. Bae et al. attribute this to the notion that A shares respond fast to local domestic information at very short horizons whereas at longer horizons (daily or weekly), the foreign investors in B shares drive price discovery. We do not replicate the Chan, Menkveld, and Yang (2007) findings as we do not have intraday transactions data. However, we reiterate that our conditions for momentum and reversals do not preclude that some investors in A shares could be informed; we only require more noise trading in A shares (see Condition (A.5) in Appendix A).

fluctuations in response to retail liquidity demand should magnify price moves in these shares (e.g., Grossman and Miller, 1988, Foucault, Sraer, and Thesmar, 2011).[17]

To explore this issue, we calculate daily volatility as the square of the daily returns of A and B shares, and run daily FM-type regressions of this volatility measure on lagged volatility, return, turnover, a value/growth control (i.e., the book-to-market ratio), market capitalization, and the price level. The non-volatility controls (from Section 4.3) are all lagged by one day, and account for volatility persistence (Engle, 1982), the well-known volatility-volume relation (Karpoff, 1987), and the notion that small, growth, and low-priced stocks (Fama and French, 1993, Kumar, 2009) might be more volatile. We run the regression both excluding and including firms with only A shares, and include a dummy variable for A shares. To account for volatility persistence beyond the past day, we compute Newey-West t-statistics. The results appear in Panel A of Table 9. The A share dummy is strongly significant for both samples.

In Panel B, we provide the proportion of months in which the daily variance of A shares exceeds that of B shares. For both the Only A sample and the A shares in the AB sample, the proportion exceeds 85%, and is significantly different from the chance probability of 50%. We also provide the ratio of the average monthly A share variance to the correspondence average B share variance. The ratio is about 1.5 and significantly different from unity. These tests confirm that A shares are indeed more volatile than B shares.

5.4 Signed Returns and Monthly Reversals

If limited market making capacity indeed leads to reversals in A shares, we should see an asymmetric effect of positive, rather than negative, returns on reversals, since short-selling constraints (viz. Footnote 3) would prevent market makers from effectively absorbing buy imbalances. Accordingly, we investigate if positive returns are more

[17]There is also some work suggesting that retail investors supply liquidity (Kaniel, Saar, and Titman, 2008, Kelley and Tetlock, 2013, Barrot, Kaniel, and Saar, 2016, Peress and Schmidt, 2020). Chen, Lin, and Ma (2019), however, suggest otherwise. While both phenomena might be at play, our analysis accords with the latter.

likely to reverse than negative returns.

More specifically, we split past one-month returns into positive and negative components [i.e., $Pos\ R_{t-1} = \mathrm{Max}(R^A_{j,t-1}, 0)$ and $Neg\ R_{t-1} = \mathrm{Min}(R^A_{j,t-1}, 0)$, respectively, where $R^A_{j,t-1}$ is the previous month's return on the A share of firm j]. For convenience, we pool the A shares in the Only A and the AB sample. Table IA.4 of the internet appendix presents the results, which correspond to the specification in Table 6 Panel A, for both raw and risk-adjusted returns. The table shows that indeed, the effect of reversals arises primarily from positive, rather than negative returns. Specifically, positive returns reverse with an absolute t-statistic exceeding five, whereas negative returns are statistically insignificant. In untabulated results, we find that the long-short portfolio based on positive returns earns a monthly return of 1.2% per month with a t-statistic of 5.57, whereas the corresponding number for the negative-return counterpart is only 0.2% per month (t-statistic=0.83).

We also find from Table IA.4 that the coefficient of positive returns is very close in magnitude to the baseline effect for total returns in Table 7, suggesting that virtually all of the monthly reversals emanate from positive returns. Further, the last row of Table IA.4 shows that the differences in the monthly reversal coefficients across positive and negative returns are also significant. In sum, the results are consistent with the notion that absorbing buy orders often requires short positions, which are costly for market-making institutions. This allows reversals on positive returns to be more strongly evident than those on negative returns.

5.5 Post-Earnings Drift

Section 2.3 proposes that B market prices underreact to information. To examine this aspect further, we examine returns around earnings announcements for firms in our AB sample. Since momentum is present only in B shares, our primary aim is to test whether there is also earnings drift in B shares. For completeness, we also test for drift in A shares.

The details of our estimation procedure are as follows. We retrieve data on earnings and analyst forecasts from CSMAR over the 2002 to 2018 period. For the purposes of computing surprises, the forecast error of firm i in year t is computed as the difference between the announced earnings per share (eps_{it}) and the average of the most recent earnings forecasts by individual analysts (F_{it}). Consistent with other studies (e.g., Livnat and Mendenhall, 2006), we scale the earnings surprises by market prices. Thus, the standardized earnings surprise (*SUE*$_{it}$) of firm i in year t is calculated as $(eps_{it} - F_{it})/P_{it}$, where P_{it} is the average of the A and B share prices 21 days prior to the earnings announcement. Each earnings forecast is required to be made at least two days before the announcement date. Earnings forecasts (announcements) corresponding to a fiscal year that are made one year before (150 days after) the year-end are removed from the sample. To minimize data errors, we delete observations with realized or forecasted earnings greater than the share price at fiscal year-end. By construction, A and B shares of a firm in the AB sample have the same *SUE*. There are only five firms with observations on *SUE* for the year 2002, so that year is not included in our sample. We get similar results if we instead scale the raw surprise by the standard deviation of the analysts' forecasts.

The cumulative abnormal returns after the announcement are computed as the difference between the cumulative returns on the shares of the announcing firm and that of a size matching portfolio. We focus on a post-announcement window of 30 to 60 trading days because Bernard and Thomas (1989) find that most of the drift occurs over this period. In each year, we allocate firms in the AB sample into three portfolios, low (bottom one-third) to high (top one-third) according to their *SUE*. The cumulative abnormal return (*CAR*) on an *SUE*-sorted portfolio in a given year is the equally weighted average of the *CAR* of the firms in that portfolio in the same year.

In Panels A and B of Table 10, we examine post-earnings drift by respectively presenting the average cumulative returns of the *SUE*-sorted portfolios over the windows [1, 30] and [1, 60]. There is significant evidence of earnings drift in B shares. Specifically, the difference between *CAR*s across low and high *SUE* firms is statistically significant for B shares. Over the 30-day horizon, for B shares, the *CAR* differential is 3.4%, whereas it is almost 5% over the 60-day horizon. In contrast, for the A shares the corresponding differentials are only 0.02% and 2.05%, respectively. Further, the differences between the low-high *SUE* spreads for A and B shares are statistically significant. Overall, the evidence of post-earnings drift in B shares is consistent with our premise of underreaction by B-share investors to fundamental information.[18]

5.6 Institutional Investors and Momentum in B Shares

We now look more closely at the composition of investors across stocks within the B market, which is the one that exhibits momentum. Specifically, we look at cross-sectional differences in the holdings of foreign institutional investors in B shares. While the B market does consist of other investor types, foreign institutions are more likely to fall into the class of informed investors and less likely to be noise traders (see Chan, Menkveld, and Yang, 2008, Seasholes, 2004, and Grinblatt and Keloharju, 2000). We now test if higher levels of institutional holdings in B shares are associated with greater momentum in the cross-section.

Quarterly institutional ownership data are collected from *FactSet* at the end of March, June, September, and December each year. Institutional ownership is measured as the percentage of total shares held by all institutions. Ownership data for the end of March, June, and September in year y is matched to the monthly data from March to May/June to August/September to November in the same year. Ownership data in December in year y is matched to monthly data from December in year y to

[18]We also examine the extent to which stock returns underreact to earnings-related information, by replicating Table VII (p. 1702) of Chan, Jegadeesh, and Lakonishok (CJL) (2006) in our context. Specifically, in our Table 6 FM regression for B shares, we add the latest *SUE*, the abnormal return around a window three days immediately surrounding the most recent earnings announcement, and a six-month moving average of past changes in earnings forecasts (see p. 1685 of CJL). Because of data limitations that reduce the sample by more than 50%, and the addition of correlated regressors, the results of these unreported regressions lack statistical power. Nonetheless, we find that past changes in earnings forecasts positively predict returns in B shares, which is consistent with underreaction. No such relation is evident for A shares. Further, the B-share coefficient on momentum reduces by about 40% when these variables are included, which is consistent with CJL.

February in year $y+1$. Note that since domestic institutions cannot own B shares, all institutions owning B shares are foreign. After merging with our CSMAR data, we have institutional ownership data from 2001 to 2018 on 86 firms with B shares.

To explore the relation between momentum and institutional investors in the B market we perform a cross-sectional FM regression that estimate the relationship between institutional ownership as well as other well-known firm characteristics and momentum. Specifically, we add a variable that interacts past returns with institutional ownership to our FM regressions. Because such ownership could proxy for firm size, we also add a size/past returns interaction variable. The FM regression we estimate is described as follows:

$$\begin{aligned} R_{jt}^{B} &= \alpha_t + \beta_{1t} R_{j,t-1}^{B} + \beta_{2t} R_{j,t-2,t-7}^{B} + \beta_{3t} R_{j,t-2,t-7}^{B} \times LIof_{j,t-1}^{B} \\ &+ \beta_{4t} R_{j,t-2,t-7}^{B} \times LnSZ_{j,t-1} + \beta_{5t} LIof_{j,t-1}^{B} + \beta_{6t} LnBM_{jt-1} \\ &+ \beta_{7t} LnSZ_{jt-1} + \beta_{8t} LnIlliq_{j,t-1}^{B} + u_{jt}^{B}, \end{aligned} \tag{4}$$

where R_{jt}^{B} and R_{jt-1}^{B} are, respectively, the return on the B shares of firm j in month t and month $t-1$, $R_{j,t-2,t-7}^{B}$ is the past six-month return on the B shares of firm j that is computed from month $t-2$ to $t-7$, and $LIof_{j,t-1}^{B}$ is a logistic transformation of the percentage institutional ownership (Iof) in the B shares of firm j in month $t-1$. The variable $LIof_{j,t-1}^{B} \times R_{j,t-2,t-7}^{B}$ denotes the interaction term between institutional ownership and the past six-month return in month $t-1$. The interaction term with firm size ($LnSZ_{j,t-1}$) is defined similarly. Both size and institutional holdings are included in the regression as separate variables. The other explanatory variables (book/market and illiquidity), are discussed in the context of Equation (1). As a robustness test, we also use the risk-adjusted returns based on the CH-3 risk factors as the dependent variable in Equation (4).

The results are reported in Table 11 (the B superscripts on the variables are omitted for brevity). Consistent with the Table 6 regressions, the estimated coefficient on the prior month's return is positive and loses significance after risk adjustment. This again confirms an absence of short-term reversals in B shares. Further, the coefficients of the other non-momentum control variables continue to be insignificant; in particular, institutional ownership does not predict returns when included by itself.[19] It is also notable that the coefficient of the variable that interacts size with past six-month return does not attain significance. However, we do find that the coefficient that interacts institutional ownership with past six-month return is positive and is statistically significant at the 1% level, both with and without risk adjustment.[20] We also note that the unconditional coefficient on momentum is not significant in either regression, which suggests that the momentum effect tends to be weak for shares without significant institutional ownership.

If institutions do underreact to information, then we should see stronger earnings drift in B shares with greater institutional holdings. Table IA.5 of the internet appendix explores this possibility. We split the AB sample into two groups by the median value of institutional holdings and then calculate the cumulative abnormal return $CAR(1, 30)$ separately for the two groups. We find that A shares continue to exhibit no evidence of drift, and the drift in B shares is principally evident in the B shares with high institutional holdings, thus confirming our conjecture.

At this point, it is worth commenting on the relation between institutional holdings and momentum for A shares. We desist from reporting a formal analysis for A share momentum by institutional ownership for three reasons. First, these shares do not exhibit unconditional momentum. Second, our holdings data are of low quality for these shares; thus, the average coverage for A shares in the only A (AB) sample in the pre-2008 period is only 4% (8%) (but improves to 76% thereafter). Third, the average

[19]Vayanos and Woolley (2013) and Lou (2012) propose important explanations for return predictability based on fund flows with inertia. While high quality fund flow data is hard to come by for A and B shares, the flow rationale does not directly imply earnings drift. Investors' naïve extrapolation from past outcomes (Greenwood and Shleifer, 2014), and the self-attribution bias (Daniel, Hirshleifer, and Subrahmanyam, 1998) also imply momentum. Note that return persistence from flows, extrapolation, and self-attribution bias should eventually reverse, but in unreported results, we do not find De Bondt and Thaler (1985)-type long-term reversals in Chinese A or B shares within our 2002-2018 sample . Of course, these findings do not preclude that some part of momentum in the U.S. may be driven by the preceding sources of momentum.

[20]To investigate the pervasiveness of momentum and its interaction with institutional holdings in the cross-section of B shares, we use robust regression with the weights suggested by Fair (1974) (see also Huber, 1973) in the first stage of the FM regressions. The results remain qualitatively unaltered.

foreign institutional ownership in A shares does not exceed 1% during our sample period. This potentially explains why in unreported regressions we find no relation between momentum and institutional ownership for A shares in the post-2007 sample.

In Table IA.6 of the internet appendix, we include additional terms interacting B-share momentum with book-to-market, illiquidity, and the A share price premium as of the previous month's end.[21] The A share premium variable is included because a high premium might represent misvaluation and thus attract institutions. We also include variables representing other explanations for momentum. Specifically, we include the information discreteness variable proposed by Da, Gurun, and Warachka (2014). Second, we include the 52-week high variable (representing the anchoring bias) of George and Hwang (2004). Finally, we also include the operating costs and revenue growth volatility variables proposed by Sagi and Seasholes (2007) as proxies for real options available to firms. We find that the 52-week high variable is significant, and the sign of its coefficient, as well as those of information discreteness and revenue growth volatility, conform to those in the original studies. Nonetheless, our conclusions on the interaction of momentum with institutional holdings remain unchanged relative to those from Table 9. Indeed, the interaction coefficient of institutional holdings with momentum increases after controlling for the above variables. Thus, the analysis in this section is consistent Section 2.3, which proposes that momentum arises from the underreaction of quasirational investors (such as institutions) to fundamental signals.

In terms of magnitude, note from Table 6 (last column), that the baseline risk-adjusted coefficient on momentum is about 0.02. Further, the time-series mean of the cross-sectional standard deviation for $LIof^B$ is 2.41, and the coefficient on $LIof^B_{j,t-1} \times R^B_{j,t-2,t-7}$ is 0.01. This implies that a one-standard-deviation change in $LIof^B$ has an impact of 0.01$\times$2.41 =0.02 on momentum, which is equal to the baseline coefficient. Hence, the impact of a one-standard-deviation move in institutional holdings on mo-

[21]We do not include the premium in other regressions as this would mean that the control variables would not be the same across the AB and Only A samples. Nonetheless, in unreported results we find that doing so makes no material difference to the central findings.

mentum is comparable to the unconditional momentum effect.[22]

6 Summary and Concluding Remarks

Momentum and short-term reversals provide perhaps the simplest form of predictability in financial markets, and thus play a special role in tests of the random walk hypothesis and market efficiency. We empirically isolate the role of investor clienteles in generating these return patterns. Based on earlier literature on momentum and reversals and a model that integrates these phenomena, we propose that the degree to which momentum and short-term reversals obtain depends on the prevalence of noise traders who demand immediacy relative to traders who underreact to fundamental signals.

For empirical testing, we use the natural experiment of A and B shares in China, which are claims on the same firms with differing clienteles. Specifically, due to mandated quotas, foreign institutions almost exclusively trade B shares and due to currency conversion restrictions, domestic retail investors mainly trade in A shares. The preceding observations indicate a greater prevalence of noise trading relative to informed trading in A shares, and the opposite clientele characteristics for B shares. These differences in clientele accord with our empirical findings of short-term (monthly and weekly) reversals exclusively in A shares and momentum exclusively in B shares. They also indicate that the absence of momentum from the entire A share market occurs because the premia required to absorb the noise trades in A shares offset the momentum that arises from the underreaction of informed investors.

Further evidence indicates that there is a lead from B to A shares, but not vice versa,

[22]In Section 2.2 we note that the quota on foreign institutional investing in A shares was raised several times throughout our sample period. We regress the time-series of A-share momentum profits on dummies for periods following the months where the quotas increased. We find that the dummies are insignificant, which probably reflects the observation (noted in Section 2.2) that foreign institutional holdings in A shares remained at 1% or below throughout our sample period in spite of quota increases. We conjecture that foreign institutions avoid A shares because of perceived regulatory risk, via a likelihood of forced liquidations if the quota were to get lowered instead of increased.

indicating that noise traders are more prevalent in A shares. A shares are significantly more volatile than B shares, which supports the view that accommodating the greater level of retail noise trades in A shares magnifies price fluctuations in these shares relative to the B counterparts. Consistent with the observation that institutions are more likely to represent active investors that underreact to fundamentals, momentum is stronger for B shares with greater (foreign) institutional ownership. Overall, our analysis confirms that clienteles play an important role in generating cross-sectional predictability of stock returns from past returns.

Although we do not rule out the possibility that pricing of cash flow risks (e.g., real options) plays a role in generating momentum, such an explanation is not obvious. For example, given that the domestic retail investors in A shares are likely more risk averse than foreign institutions (Haddad and Muir, 2021) and other relatively well-capitalized investors that prevail in B shares, we might expect an explanation based on cash flow risk pricing to generate more momentum in A shares. Instead, we find stronger momentum in the B market, particularly for those stocks held more by institutions, which prevails after controlling for real options proxies as well as other explanations for momentum. More generally, while stochastic discount factors (SDFs) across A and B markets should be different given market segmentation, what we show is that fluctuations in these SDFs are strongly related to investor clientele. Any neoclassical explanation of these fluctuations would not only need to accord with differing momentum and reversals across A and B shares, but also need to explain other evidence such as greater volatility in A shares, the lead from B returns to A returns but not vice versa, and stronger reversals after positive returns. Therefore, explanations of our results based on cash flow risk pricing appear to face daunting challenges.

In sum, our analysis suggests that differences in momentum across markets are not likely to be due to differences in the fundamental risks of the firms in these markets, but rather due to differences in their investor clientele. Based on this analysis, we conjecture that if investor clienteles become more global, and more similar across markets, that differences in momentum across the different markets will tend to narrow.

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Appendix A

This appendix provides a simple model that provides a rigorous framework for our hypotheses in Section 2.3. We propose a setting with unsophisticated noise trading and utility-maximizing risk averse investors who under-assess the precision of an information signal. The model yields two insights: First, noise trading can generate short-term reversals and can offset momentum, and second, for momentum to obtain, investors should "moderately" (i.e., not overly) under-assess signal precision. To clarify our intuition, we first consider the conditions a model with one round of trade. Subsequently, to fit the stylized facts of short-term reversals and longer-term momentum, we extend the setting to two rounds of trade, where both phenomena arise.

A.1 Momentum and Reversals

A risky asset pays off a random, zero mean amount of θ at Date 2. This security is traded at Date 1, in response to news and noise trader demands that arrive at this date. The asset can freely be exchanged for a risk-free asset whose gross return is normalized to unity. There also is an ex ante Date 0, on which there are no information signals or demand shocks.

The market consists of m identical investors, who each have negative exponential utility with risk aversion R, and noise traders. At Date 1, the former investors receive a public signal $I = \theta + \epsilon$.[23] We term the class of these investors S for convenience, because they trade on fundamental signals. Noise traders supply a quantity z (or, present a demand $-z$), which is unrelated to fundamentals. We term this class of traders N, for noise traders.

The random variables θ, ϵ, and z are mutually independent, and normally distributed with zero mean. We denote v_X to be the variance of a generic random variable

[23] Recent evidence suggests that the excess returns of momentum portfolios may arise from underreaction to systematic information, (e.g., Ehsani and Linnainmaa, 2021). Our model can capture this observation if we interpret θ as a payoff on a systematic factor and I as a signal about that payoff.

X. We assume that the S-traders underreact to the information signal I by underassessing the signal's quality. Thus, their assessment of v_ϵ is $v_c > v_\epsilon$. The reason for this underreaction is not crucial for our central arguments, but it can arise, for example, due to skepticism about outside information sources (Odean, 1998, Luo, Subrahmanyam, and Titman, 2021).

Each S-trader j chooses a demand y_j to maximize expected utility conditional on S. Given our setting, the objective of the trader is to maximize a standard mean-variance objective, so we have

$$y_j = \frac{\mu - P}{R\,v}, \tag{A.1}$$

where μ is the investor's conditional mean, $E(\theta|I)$, and v the conditional variance, $\mathrm{var}(\theta|I)$. In our setting, given normality, $\mu = \frac{v_\theta}{v_\theta + v_c}(\theta + \epsilon)$, and $v = \frac{v_\theta v_c}{v_\theta + v_c}$. The market clearing condition is $my_j = m\frac{\mu - P}{R\,v} = z$, implying that the equilibrium price is

$$P = \mu - \frac{R\,v}{m} z. \tag{A.2}$$

Substituting for μ and v into Equation (A.2), we have that

$$P = \frac{v_\theta}{v_c + v_\theta}(\theta + \epsilon) - \frac{R v_\theta v_c}{m(v_\theta + v_c)} z. \tag{A.3}$$

Thus, the price has an informational component (the first term on the right-hand side above), and a premium to absorb the noise trades (the second term).

Since the Date 0 price is not stochastic, it follows that the momentum/reversal in returns is given by[24]

$$\mathrm{cov}(\theta - P, P) = \frac{v_\theta^2(v_c - v_\epsilon)}{(v_c + v_\theta)^2} - \frac{R^2 v_c^2 v_\theta^2 v_z}{[m(v_c + v_\theta)]^2}. \tag{A.4}$$

[24]While we consider a single stock model (consistent with Hong and Stein, 1999), the expression in Equation (A.4) can be interpreted as the profitability of a cross-sectional trading strategy; see Luo, Subrahmanyam, and Titman (2021) or Chen and Hong (2002). Specifically, suppose that there are L homogeneous stocks, and let $r_{i,t}$ denote the return of stock i at time t. Further, denote the equal-weighted market return at time t as r_t. The momentum strategy can be implemented via a weight of $w_{i,t} = L^{-1}(r_{i,t-1} - r_{t-1})$ on stock i. Then $c \equiv \mathrm{cov}(r_{i,t}, r_{i,t-1})$ can be interpreted as a proxy for the right-hand side of Equation (A.4). In a market devoid of return cross-autodependence, the expected momentum profit is readily calculated as $E\left[\sum_{i=1}^{L} w_{i,t} r_{i,t}\right] = [(L-1)c]/L$ and asymptotes to c for large L. Indeed, average cross-autocorrelations are small in our data, and serial correlations match the cross-sectional patterns (viz. Footnote 15).

The S-traders play the dual role of absorbing the demands of retail investors and enabling the price to incorporate information about fundamentals. Equation (A.4) implies that $v_c > v_\epsilon$ is a necessary condition to obtain momentum. Further, if noise trading is vanishingly small ($v_z \to 0$), $v_c > v_\epsilon$ is also a sufficient condition for momentum.

With $v_z > 0$, letting $k = v_c/v_\epsilon$ be an index of underreaction, the right-hand side of Equation (A.4) is positive if and only if:

$$m^2(k-1) > k^2 R^2 v_\epsilon v_z. \tag{A.5}$$

Thus, while $k > 1$ is required for momentum to obtain, very high levels of k can cause reversals. This is because in this case, the signal noise variance is perceived to be so high that the informed investors charge a high premium for accommodating noise traders. Overall, k has to be at intermediate levels for momentum to obtain. This accords with the interpretation that S investors are "quasirational" (i.e., they underassess the signal's quality, but not overly so). This is a reasonable assumption for large institutions and more generally, for non-domestic investors, whom we think of as belonging to the class S in our empirical work.

Condition (A.5) also indicates that if the variance of N investors' noise trades is large ($v_z \gg 0$) or the risk-bearing capacity of the market (m/R) is low, the momentum effect is attenuated, and if m/R is sufficiently low, returns unambiguously exhibit reversals. This happens because in this case, the compensation for *de facto* market making dominates the effect of the signal I on the market price.

Also note from Equation (A.3) that the volatility of $\theta - P$ increases in the level of noise trading v_z. This is because higher v_z implies an increase in inventory risk premia. The result implies that markets with greater levels of noise trading should have higher return volatility. We mention two other points. First, the scale of trading volume in our model is driven by the variance of noise trading v_z, (since S investors simply take the opposite side of noise traders). Thus, in general, volume does not necessarily imply less reversals. In our model, it implies a greater scale of noise trading to be absorbed, which implies greater levels of reversals. Second, even when underreaction is present ($k > 1$), if retail noise trading is sufficiently high, it attenuates the level of momentum. Thus, while underreaction is necessary for momentum, it is not sufficient. Noise trading has to be at sufficiently low levels for momentum to obtain.

A.2 Momentum and Short-Term Reversals

We now extend the previous model to a case where there is trading at two dates. This allows us to consider short-term reversals and longer-term momentum within the same setting. Thus, we add a Date $1'$ which falls prior to Date 1 but after Date 0. We propose that at Date $1'$, a round of N traders with a supply quantity q arrive at the market, and exit the market at Date 1. The distribution of q is identical to that of the Date 1 noisy supply z, and q is independent of other random variables. The S-traders receive the signal S at Date $1'$, and are present in the market at both Dates $1'$ and 1.

Under the above setting, since the demands and beliefs of investors at Date 1 are the same as those in Section A.1, the Date 1 equilibrium price (P) continues to be given by Equation (A.3). We now solve for the equilibrium at the prior Date $1'$. Let $P_{1'}$ denote the Date $1'$ price. Further, let $E(P)$and $\text{var}(P)$ respectively denote the mean and variance of P conditional on the information set of the S-traders at Date $1'$ (which, in our case is simply the signal S). Using standard arguments (see the proof at the end of this appendix), each S-trader takes a position $y_{j'}$ at Date $1'$, where

$$y_{j'} = \frac{E(P) - P_{1'}}{R} \left[\{\text{var}(P)\}^{-1} + v^{-1} \right], \tag{A.6}$$

with $E(P) = \mu$ and $\text{var}(P) = m^{-2}R^2v^2v_z$ [from Equation (A.3)]. The market clearing condition at Date $1'$ is $my_{j'} = q$. Substituting for $y_{j'}$, we can solve for $P_{1'}$:

$$P_{1'} = \mu - \frac{R^3 v_c^2 v_\theta^2 v_z q}{m(v_c + v_\theta) \left[m^2(v_c + v_\theta) + R^2 v_c v_\theta v_z) \right]},$$

where $\mu = \frac{v_\theta}{v_\theta + v_c}(\theta + \epsilon)$ (from Section A.1).

Straightforward calculations yield the results that the covariances in pairs of contiguous returns are given by

$$\mathrm{cov}(\theta - P, P - P_{1'}) = -\frac{R^2 v_c^2 v_\theta^2 v_z}{m^2(v_c + v_\theta)^2} \tag{A.7}$$

and

$$\mathrm{cov}(P - P_{1'}, P_{1'}) = -\frac{R^6 v_c^4 v_\theta^4 v_z^3}{m^2(v_c + v_\theta)^2 \left[m^2(v_c + v_\theta) + R^2 v_c v_\theta v_z\right]^2}. \tag{A.8}$$

Both of the above expressions are negative as they represent compensation to the S-traders for absorbing retail demands at each date. Short-term reversals can then be viewed as an average of these covariances.

Turning now to momentum, in keeping with the observation that empirically, momentum returns are measured over horizons that are longer than those for monthly reversals, the time interval between Dates 1 and 0 can be viewed as the period over which past momentum returns are computed. Since the Date 1 equilibrium price does not change under the assumptions of this section, the expression representing the momentum effect remains unchanged from Equation (A.4) of the previous section.

Overall, Equations (A.7) and (A.8) indicate that markets where unsophisticated noise trading (v_z) is high should exhibit stronger reversals. Further, Equations (A.4) and (A.5) confirm that markets with a greater mass m of quasirational S investors should have a greater tendency to exhibit momentum. The hypotheses in Section 2.3 thus follow from the model.

Proof of Equation (A.6): The wealth of S-trader j is

$$W = y_j(\theta - P) + y_{j'}(P - P_{1'}).$$

Substituting for y_j from Equation (A.1), and, in turn, P from Equation (A.2), we have

$$W = \frac{Rvz^2}{m^2} - \frac{z(\mu + Rvy_{j'})}{m} - \frac{z\theta}{m} + y_{j'}(\mu - P_{1'}). \tag{A.9}$$

At Date 2, μ and P and, therefore, z [from Equation (A.2)] are known. The expected Date 2 utility, denoted by EU_2, is therefore

$$EU_2 = -E\left[\exp\left[-R\left\{\frac{Rvz^2}{m^2} - \frac{z(\mu + Rvy_{j'})}{m} - \frac{z\theta}{m} + y_{j'}(\mu - P_{1'})\right\}\middle|\mu, z\right]\right]. \tag{A.10}$$

The only random part on the right-hand side of Equation (A.10) is the third term $-z\theta/m$. Further, the conditional distribution of θ has a mean μ and a variance v. Finally, for any normal random variable $\nu \sim N(\mu_\nu, v_\nu)$, the moment generating function is given by

$$E\exp(t\nu) = \exp[t\mu_\nu + 0.5t^2 v_\nu].$$

Using these observations to integrate out the random variable θ from Equation (A.10), the derived Date 2 expected utility becomes

$$EU_2 = -E\left[-\exp\left\{-\frac{R^2vz^2}{2m^2} + \frac{R^2vy_{j'}z}{m} - Ry_{j'}(\mu - P_{1'})\right\}\Big|\mu, z\right]. \tag{A.11}$$

In the right-hand side of the above expression, the only variable that is random at Date 1 is z. Hence, we can write the expected Date 1 derived utility as

$$-[\sqrt{2\pi v_z}]^{-1}\int_{-\infty}^{\infty}\exp\left[-\frac{R^2z^2v}{2m^2} + \frac{R^2vy_{j'}z}{m} - Ry_{j'}(\mu - P_{1'}) - \frac{z^2}{2v_z}\right]dz. \tag{A.12}$$

The argument inside the exponential can be written as

$$-[0.5az^2 + bz + c], \tag{A.13}$$

where

$$a \equiv \frac{m^2 + R^2vv_z}{m^2v_z}, \tag{A.14}$$

$$b \equiv -\frac{R^2vy_{j'}}{m}, \tag{A.15}$$

$$c \equiv Ry_{j'}(\mu - P_{1'}). \tag{A.16}$$

To complete squares, let $u = \sqrt{a}z + b/\sqrt{a}$. Expression (A.13) becomes

$$-\frac{1}{2}u^2 + \frac{1}{2}\frac{b^2}{a} - c.$$

Note that the Jacobian of the transformation from z to u is $[\sqrt{a}]^{-1}$. In turn, Expression (A.12) can be written as

$$-[\sqrt{2\pi v_z a}]^{-1}\int_{-\infty}^{\infty}\exp\left[-\frac{1}{2}u^2 + \frac{1}{2}\frac{b^2}{a} - c\right]du,$$

which reduces to

$$-[\sqrt{v_z a}]^{-1}\exp\left[\frac{1}{2}\frac{b^2}{a}-c\right].$$

Substituting for a, b, and c from Equations (A.14), (A.15), and (A.16), respectively, and maximizing the resulting expression with respect to $y_{j'}$, we get Equation (A.6). $\|$

Appendix B
Variable definitions

A share premium (Prem): Calculated as $\left(\frac{P_A}{P_B} - 1\right) x\ 100\%$ where P_A is the end-of-month A share price and P_B is the corresponding end-of-month B share price.

Book-to-market ratio (BM): The *BM* for a firm from July of year *y* to June of year *y+1* is the ratio of its book value (*BE*) at fiscal year-end in year *y-1* to its firm size (*SZ*) in December of year *y-1*. *LnBM* is the natural logarithm of *BM*.

Close-to-open return: the close-to-open return (%) of a stock on day d is computed from its closing price on day d-1 and opening price on day d.

Cumulative abnormal return (CAR): The *CAR* around earnings announcements is computed as the difference between the cumulative returns on the shares of the announcing firm and that of a size matching portfolio over the window [s_1, s_2], over trading days s_1 and s_2 relative to the announcement date. Each share is matched with one of five value-weighted size-sorted portfolios formed at the end of June each year based on firm size (*SZ*). The *SZ's* of firms as of the end of June are used as the weights. These portfolios are updated annually. We exclude the announcing firm when we compute the returns on the matching portfolio of the announcing firm.

Daily return volatility (DRvol): Measured as the square of daily returns.

Daily dollar trading volume (V): the value of shares traded on a given day.

Dollar trading volume (Dval): The value of shares traded in a given month. It is expressed in US$ million.

Firm size (SZ): For firms in the Only A sample, firm size (market capitalization) is the size of tradable A shares outstanding in a given month. For firms in the AB sample, firm size is the sum of the size of tradable A shares outstanding and the size of tradable B shares outstanding in a given month. The size of tradable shares outstanding of share k (k = A or B) is the end-of-month price of share k times the tradable shares outstanding of share k. Firm size is expressed in US$ million.

Institutional ownership (Iof): We first sum the share ownership of investment companies, investment advisors, hedge funds, and venture capital in a given quarter to get share holdings of institutions. The *Iof* of share k is then the percentage of tradable shares outstanding of share k owned by an institution.

Logistic transformation of institutional ownership (LIof): LIof equals the natural logarithm of $\frac{Iof}{100-Iof}$, where *Iof* is expressed in percentage terms.

Monthly stock return (R_t): stock return (%) in month t.

Open-to-close return: the open-to-close return (%) of a stock on day d is computed from its opening and closing prices on day d.

Past 6-month return ($R_{t-2,t-7}$): Cumulative return (%) calculated from month t-2 to month t-7.

Return volatility (Rvol): The standard deviation of daily returns (%) in a given month.

Risk-adjusted return ($AdjR_{t-1}$): Stock returns (%) adjusted for the CH-3 factors in month t-1. While the excess value-weighted A share market return is used as the market factor for A shares, the excess value-weighted B share market return is used as the market factor for B shares.

Standardized earnings surprise (SUE): It is calculated as the earnings forecast error (earnings per share minus the average of the most recent analysts' forecasts) divided by the average of the prices of A and B shares on day −21 relative to the earnings announcement date.

Trading frequency: The number of days on which a stock is traded divided by the number of days the exchange is open in a given month. It is expressed in percentage terms.

Turnover (Tn): Number of *k (k*=A or B*)* shares traded divided by the tradable *k* shares outstanding in a given month. It is expressed in percentage terms.

Weekly return: the return (%) of a stock in week t is computed from its Wednesday closing price in week t-1 and its Tuesday closing price in week t.

Table 1
Descriptive statistics
The table displays descriptive statistics for price variables, share characteristics, and firm characteristics defined in Appendix B. The statistics are computed over the period from January 2001 to December 2018.

	Firm sample	Only A		AB			
	Share type	A		A		B	
	No. of firms	2442		88		88	
	Variable	Mean	Median	Mean	Median	Mean	Median
Price variables	Return (*R*, %)	0.802	1.133	0.987	1.075	1.520	1.362
	Volatility (*Rvol*, %)	2.674	2.701	2.695	2.739	2.238	2.255
	A share premium (%)	N.A.	N.A.	101.867	95.093	N.A.	N.A.
Share characteristics	Turnover (*Tn*, %)	43.281	40.665	38.156	37.761	12.131	11.278
	Dollar trading volume (*Dval*)	384.272	252.720	265.315	185.020	19.527	16.114
	Trading frequency (%)	97.160	97.564	96.719	97.452	97.285	98.126
	Market value of tradable shares outstanding (US $mill)	1518.490	553.970	805.511	500.405	200.449	132.889
Firm characteristics	Market value of all types of tradable shares (US $mill)	1518.490	553.970	1006.170	659.333	1006.170	659.333
	Book-to-market ratio (*BM*)	0.824	0.704	0.849	0.799	0.849	0.799

Table 2
Characteristics of the winner and loser portfolios of the momentum strategies
This table displays characteristics of the winner and loser portfolios for the momentum strategies in the A shares of the only A sample and the A and B shares in the AB sample. Means (medians) are computed over the ranking period, *i.e.* from June 2001 to October 2018.

Firm sample	Only A		AB			
Share type	A		A		B	
	Winner	Loser	Winner	Loser	Winner	Loser
Firm size (*SZ*)	1881.740	1221.150	1202.740	953.833	1223.330	959.974
	(513.235)	(422.557)	(514.080)	(430.787)	(512.984)	(402.586)
Book-to-market ratio (*BM*)	0.883	0.815	0.874	0.827	0.871	0.847
	(0.624)	(0.563)	(0.715)	(0.637)	(0.719)	(0.668)
Turnover (*Tn*)	50.696	36.473	45.273	32.838	13.148	8.766
	(34.652)	(24.664)	(29.433)	(21.977)	(8.493)	(5.881)
Volatility (*Rvol*)	2.907	2.569	2.894	2.587	2.307	2.165
	(2.696)	(2.306)	(2.716)	(2.342)	(2.057)	(1.958)

Table 3
Average returns on momentum portfolios
This table presents average returns (in percentages) on the momentum portfolios over the period from January 2002 to December 2018. In each month, shares in each sample are allocated into three portfolios based on their past six-month returns from high (top one-third) to low (bottom one-third). These value-weighted (equal-weighted) portfolios are held for six months. There is a one-month gap between the ranking period and the holding period. The winner (loser) portfolio in month t consists of the six high (low) portfolios formed in month t-2 to t-7. The reported return on a winner (loser) portfolio in month t is the average return on the six high (low) portfolios in that month. The momentum portfolio is formed by taking a long position in the winner portfolio and a short position in the loser portfolio. The return on the momentum portfolio (W – L) in month t is the difference in returns between the winner and loser portfolios in that month. Panel A shows the results from the Only A sample and Panel B displays the results from the AB sample. A|AB and B|AB represent A shares and B shares of the AB sample, respectively. Panel A also reports the average returns on value-weighted portfolios after excluding the largest x% of the firms each month from the Only A sample, x=0.5, 1, 5, and 10. We report t-statistics in parentheses.

Panel A: Only A sample

Value weighted	Winner (W)	2	Loser (L)	W – L
All firms	1.040 (1.75)	1.010 (1.65)	0.774 (1.19)	0.266 (1.00)
Excl. largest 0.5%	1.045 (1.69)	1.102 (1.72)	0.865 (1.29)	0.181 (0.73)
Excl. largest 1%	1.044 (1.66)	1.103 (1.69)	0.862 (1.27)	0.182 (0.75)
Excl. largest 5%	1.108 (1.69)	1.121 (1.68)	0.905 (1.30)	0.203 (0.92)
Excl. largest 10%	1.152 (1.72)	1.176 (1.72)	0.966 (1.37)	0.186 (0.90)
Equal weighted				
All firms	1.225 (1.84)	1.324 (1.92)	1.109 (1.56)	0.116 (0.57)

Panel B: AB sample

Value weighted	Winner (W)	2	Loser (L)	W – L
A shares	1.082 (1.71)	1.016 (1.62)	0.557 (0.83)	0.525 (1.47)
B shares	1.444 (2.28)	0.661 (1.09)	0.293 (0.46)	1.151 (3.33)
			B|AB minus A|AB	0.626 (2.05)
			B|AB minus Only A	0.885 (2.56)
Equal weighted	Winner (W)	2	Loser (L)	W – L
A shares	1.211 (1.84)	1.208 (1.82)	0.959 (1.34)	0.252 (0.90)
B shares	1.413 (2.11)	0.837 (1.26)	0.590 (0.86)	0.823 (3.31)
			B|AB minus A|AB	0.571 (2.72)
			B|AB minus Only A	0.707 (3.28)

Table 4
Characteristics of the winner and loser portfolios of the short-horizon return reversal strategies
This table displays the characteristics of the winner and loser portfolios of the short-horizon return reversal strategies in the A shares of the only A sample and the A and B shares in the AB sample. Means (medians) are computed over the ranking period, *i.e.* from December 2001 to November 2018.

Sample	Only A		AB			
Type	A		A		B	
Characteristics	Winner	Loser	Winner	Loser	Winner	Loser
Firm size (*SZ*)	1670.400	1429.470	1133.220	1038.530	1167.700	1064.480
	(498.043)	(463.301)	(504.186)	(459.009)	(501.695)	(451.967)
Book-to-market ratio (*BM*)	0.852	0.834	0.838	0.825	0.836	0.835
	(0.597)	(0.578)	(0.670)	(0.650)	(0.666)	(0.652)
Turnover (*TN*)	52.242	39.596	47.776	35.665	12.782	8.743
	(36.310)	(27.022)	(31.841)	(23.339)	(8.355)	(5.791)
Volatility (*Rvol*)	2.983	2.639	2.990	2.638	2.336	2.134
	(2.790)	(2.378)	(2.801)	(2.395)	(2.108)	(1.900)

Table 5
Average returns on short-horizon reversal portfolios
This table presents average monthly returns (in percentages) for portfolios sorted by monthly return in the prior month on loser (bottom one-third), middle two-thirds, and the winner (top one-third) stocks over the period from January 2002 to December 2018. The reversal portfolio is formed by taking a long position in the loser portfolio and a short position in the winner portfolio. The return on the reversal portfolio (L – W) in month *t* is the difference in returns between the loser and winner portfolios in that month. Panel A shows the results from the Only A sample and Panel B displays the results from the AB sample. A|AB and B|AB represent A shares and B shares of the AB sample, respectively. Panel A also reports the average returns on value-weighted portfolios after excluding the largest *x*% of the firms each month from the Only A sample where *x*=0.5, 1, 5, or 10. We report *t*-statistics in parentheses.

Panel A: Only A sample

Value weighted	Loser (L)	2	Winner (W)	L – W
All firms	1.265 (2.02)	1.147 (1.85)	0.832 (1.30)	0.433 (1.31)
Excl. largest 0.5%	1.466 (2.21)	1.255 (1.94)	0.982 (1.05)	0.784 (2.57)
Excl. largest 1%	1.480 (2.19)	1.255 (1.90)	0.640 (0.98)	0.840 (2.83)
Excl. largest 5%	1.582 (2.27)	1.292 (1.89)	0.610 (0.91)	0.972 (3.78)
Excl. largest 10%	1.696 (2.39)	1.346 (1.93)	0.561 (0.82)	1.135 (4.68)
Equal weighted				L – W
All firms	1.856 (2.57)	1.582 (2.25)	0.650 (0.95)	1.206 (4.93)

Panel B: AB sample

Value weighted	Loser (L)	2	Winner (W)	L – W
A shares	1.201 (1.75)	1.353 (2.13)	0.567 (0.87)	0.634 (1.49)
B shares	0.746 (1.14)	0.806 (1.32)	1.258 (1.93)	−0.512 (−1.25)
			A|AB minus B|AB	1.146 (2.29)
			Only A minus B|AB	0.945 (2.13)
Equal weighted	Loser (L)	2	Winner (W)	L – W
A shares	1.770 (2.38)	1.625 (2.37)	0.386 (0.58)	1.384 (4.49)
B shares	0.778 (1.11)	0.939 (1.40)	1.162 (1.69)	−0.384 (−1.25)
			A|AB minus B|AB	1.768 (5.88)
			Only A minus B|AB	1.590 (5.34)

Table 6

Momentum and reversals: Regression analysis by share type

Panel A reports average estimated coefficients and their *t*-statistics (in parentheses) obtained from monthly cross-sectional regressions. The estimation period is from January 2002 to December 2018. The dependent variable is the stock return in month *t* (R_t) or the risk-adjusted return in month *t* ($AdjR_t$). The independent variables are the prior month's stock return (R_{t-1}), the past six-month return ($R_{t-2,t-7}$), the natural logarithm of book-to-market ratio (*LnBM*), the natural logarithm of firm size (*LnSZ*), and the natural logarithm of Amihud illiquidity measure (*LnIlliq*) in month *t-1*. The risk-adjusted return of a stock is computed with respect to the CH-3 risk factors. While the excess value-weighted A share market return is used as the market factor for A shares, the excess value-weighted B share market return is used as the market factor for B shares. Panel B displays the differences in parameter estimates of the reversal variable (R_{t-1}) and the momentum variable ($R_{t-2,t-7}$) across samples. A|AB and B|AB represent A shares and B shares of the AB sample, respectively. We report *t*-statistics in parentheses. Definitions of these variables appear in Appendix B.

Panel A: Parameter estimates

Firm sample	Only A		AB		AB	
Share type	A		A		B	
	Raw Return	Risk-adjusted Return	Raw Return	Risk-adjusted Return	Raw Return	Risk-adjusted Return
Intercept	3.821	2.938	3.407	2.679	1.190	0.433
	(3.00)	(5.17)	(2.25)	(2.79)	(0.91)	(0.45)
R_{t-1}	−0.056	−0.071	−0.061	−0.074	0.033	0.015
	(−5.98)	(−7.25)	(−4.13)	(−4.87)	(2.22)	(0.94)
$R_{t-2,t-7}$	−0.000	−0.004	−0.000	−0.007	0.018	0.016
	(−0.01)	(−1.02)	(−0.03)	(−1.03)	(2.29)	(2.12)
$LnBM_{t-1}$	0.254	0.051	0.220	0.145	0.001	−0.047
	(3.09)	(0.72)	(1.54)	(1.02)	(0.00)	(−0.41)
$LnSZ_{t-1}$	0.513	0.417	0.240	0.175	−0.049	−0.024
	(2.91)	(3.57)	(1.02)	(0.91)	(−0.27)	(−0.14)
$LnIlliq_{t-1}$	0.909	0.863	0.630	0.629	0.043	0.154
	(6.95)	(7.22)	(3.53)	(3.54)	(0.36)	(1.37)

Panel B: Differences in parameter estimates

	Raw Return		Risk-adjusted Return	
	R_{t-1}	$R_{t-2,t-7}$	R_{t-1}	$R_{t-2,t-7}$
B|AB minus A|AB	0.094	0.018	0.089	0.023
	(6.03)	(2.93)	(5.16)	(3.46)
B|AB minus Only A	0.089	0.018	0.086	0.020
	(6.35)	(2.67)	(5.71)	(3.07)

Table 7
Average weekly returns on reversal portfolios
This table presents average weekly returns (in percentages) for portfolios sorted by weekly returns in the prior week on loser (bottom one-third), middle two-thirds, and the winner (top one-third) stocks over the period from January 2002 to December 2018. The return on a stock in week *t* is computed from its Wednesday closing price in week *t-1* and its Tuesday closing price in week *t*. The reversal portfolio is formed by taking a long position in the loser portfolio and a short position in the winner portfolio. The return on the reversal portfolio (L – W) in week *t* is the difference in returns between the loser and winner portfolios in that week. Panel A shows the results from the Only A sample and Panel B displays the results from the AB sample. A|AB and B|AB represent A shares and B shares of the AB sample, respectively. Panel A also reports the average returns on value-weighted portfolios after excluding the largest *x*% of the firms each week from the Only A sample where *x*=0.5, 1, 5, or 10. We report *t*-statistics in parentheses.

Panel A: Only A sample

Value weighted	Loser (L)	2	Winner (W)	L – W
All firms	0.192 (1.25)	0.099 (0.68)	−0.107 (−0.78)	0.299 (3.45)
Excl. largest 0.5%	0.189 (1.20)	0.094 (0.61)	−0.145 (−1.00)	0.334 (4.63)
Excl. largest 1%	0.191 (1.19)	0.087 (0.56)	−0.162 (−1.11)	0.353 (5.26)
Excl. largest 5%	0.188 (1.12)	0.102 (0.63)	−0.208 (−1.35)	0.396 (7.28)
Excl. largest 10%	0.197 (1.15)	0.120 (0.73)	−0.219 (−1.38)	0.416 (8.39)
Equal weighted				L – W
All firms	0.235 (1.37)	0.175 (1.06)	−0.202 (−1.29)	0.437 (8.54)

Panel B: AB sample

Value weighted	Loser (L)	2	Winner (W)	L – W
A shares	0.184 (1.10)	0.097 (0.62)	−0.172 (−1.10)	0.356 (3.75)
B shares	−0.028 (−0.18)	−0.075 (−0.53)	0.012 (0.08)	−0.040 (−0.48)
			A|AB minus B|AB	0.396 (4.14)
			Only A minus B|AB	0.339 (3.46)
Equal weighted	Loser (L)	2	Winner (W)	L – W
A shares	0.232 (1.35)	0.215 (1.31)	−0.243 (−1.52)	0.475 (6.45)
B shares	−0.061 (−0.39)	−0.075 (−0.53)	−0.069 (−0.48)	0.008 (0.14)
			A|AB minus B|AB	0.467 (7.05)
			Only A minus B|AB	0.429 (7.49)

Table 8
Lead-lag effect in daily returns between A and B shares
We use Seemingly Unrelated Regression to estimate the following system of equations by firm over the period from January 2002 to December 2018.

$$R^A_{j,CTO,d} = \beta_{10} + \beta_{11}R^B_{j,OTC,d-1} + \beta_{12}R^A_{j,OTC,d-1} + \beta_{13}R^A_{j,CTO,d-1} + \beta_{14}LnV^A_{j,d-1} + \beta_{15}LnV^B_{j,d-1} + \varepsilon^A_{j,d}$$

$$R^B_{j,CTO,d} = \beta_{20} + \beta_{21}R^A_{j,OTC,d-1} + \beta_{22}R^B_{j,OTC,d-1} + \beta_{23}R^B_{j,CTO,d-1} + \beta_{24}LnV^A_{j,d-1} + \beta_{25}LnV^B_{j,d-1} + \varepsilon^B_{j,d}$$

where $R^k_{j,CTO,d}$ is the close-to-open return (%) on the *k* (*k* = A or B) share of firm *j* on day *d* and it is the difference between the natural logarithm of the share's opening price on day *d* and its closing price on day *d*−*1*. Similarly, $R^k_{j,OTC,d-1}$ is the open-to-close return (%) on the *k* (*k* = A or B) share of firm *j* on day *d-1* and it is the difference between the natural logarithm of the share's closing price and opening price on day *d-1*. $LnV^k_{j,d-1}$ is the natural logarithm of the dollar trading volume on the *k* (*k* = A or B) share of firm *j* on day *d-1.* To be included in this test, we require each firm has at least 60 observations. There are 87 firms involved in this test. This table reports average estimated coefficients obtained from these daily cross-sectional regressions. We report *t*-statistics in parentheses.

Dependent Variable	Intercept	$R^B_{j,OTC,d-1}$	$R^A_{j,OTC,d-1}$	$R^B_{j,CTO,d-1}$	$R^A_{j,CTO,d-1}$	$LnV^A_{j,d-1}$	$LnV^B_{j,d-1}$
$R^A_{j,CTO,d}$	−0.045	0.073	0.031		0.115	−0.073	0.009
	(−4.39)	(23.37)	(10.32)		(14.36)	(−15.38)	(1.92)
$R^B_{j,CTO,d}$	−0.054	0.059	0.004	0.104		−0.012	0.069
	(−5.41)	(10.86)	(1.21)	(15.24)		(−2.41)	(12.03)
$\beta_{11} - \beta_{21}$		0.069 (12.03)					

Table 9
Daily return volatility
Panel A of this table reports the average estimated coefficients and their *t*-statistics (in parentheses) obtained from day-by-day cross-sectional regressions. The estimation period is from January 2002 to December 2018. The dependent variable is the natural logarithm of stock return volatility on day *s* ($LnDRVol_s$). The independent variables are a dummy variable for A shares (*AShare*), the natural logarithm of prior day's stock return volatility ($LnDRVol_{s-1}$), the prior day's stock return (R_{s-1}), the natural logarithm of turnover ratio ($LnTN_{s-1}$), the natural logarithm of the closing price ($LnPrc_{s-1}$), the natural logarithm of book-to-market ratio ($LnBM_{s-1}$), and the natural logarithm of firm size ($LnSZ_{s-1}$) in day $s-1$. Return volatility of a share in day *s* is measured as the square of return in day s (R_s^2). The dummy variable *AShare* takes a value of one for A shares, and it is zero otherwise. Newey-West (1994) heteroskedasticity and autocorrelation consistent estimates of standard errors are used to compute the *t*-statistics. We report *t*-statistics in parentheses. Panel B displays the proportion of months in which the average daily volatility of A shares is larger than that of B shares, together with *p*-values for whether the proportions are different from 50%, and the ratio of the average A share variance to that of B shares, with *p*-values for whether the ratios are different from unity.

Panel A: Fama-MacBeth regressions

	A∣AB & B∣AB combined sample		Only A & B∣AB combined sample	
Intercept	−0.246	−0.017	−0.246	0.362
	(−3.62)	(−0.09)	(−3.62)	(3.89)
AShare	0.638	0.187	0.656	0.076
	(18.18)	(6.60)	(17.52)	(2.42)
$LnRVol_{t-1}$		0.093		0.009
		(1.34)		(2.61)
R_{t-1}		0.003		0.009
		(0.23)		(3.42)
$LnTN_{t-1}$		0.286		0.347
		(35.58)		(34.38)
$LnPrc_{t-1}$		0.013		0.002
		(3.24)		(0.72)
$LnBM_{t-1}$		−0.101		−0.054
		(−13.58)		(−10.89)
$LnSZ_{t-1}$		−0.030		−0.037
		(−2.84)		(−3.67)
Adj R^2	0.01	0.10	0.01	0.06

Panel B: Proportion of months in which $DRVol_A$ > $DRVol_B$ and variance ratio ($DRVol_A$ / $DRVol_B$)

Sample combination	A∣AB & B∣AB	Only A & B∣AB
Proportion	0.877 (<0.001)	0.868 (<0.001)
Variance ratio	1.500 (<0.001)	1.480 (<0.001)

Table 10
Cumulative abnormal returns of portfolios sorted by earnings surprises for the AB sample
The standardized earnings surprise (SUE_{it}) of firm i in year t is calculated as $(eps_{it} - F_{it})/P_{it}$, where eps_{it}, and F_{it} are, respectively, the earnings per share and the average of the most recent forecasts on earnings per share from individual analysts for firm i in year t. Further, P_{it} is the average of the prices of A and B shares of firm i on day $d-21$ where d is the announcement day of the earnings of firm i in year t. The cumulative abnormal returns (CARs) after the announcement are computed as the difference between the cumulative returns on the shares of the announcing firm and that of a size matching portfolio over the window [1, s], $s = 30 \; or \; 60$, in trading days relative to the announcement date,

$$CAR[1, s]_{id} = \prod_{j=d+1}^{d+s}\left(1 + R_{ij}^{k}\right) - \prod_{j=d+1}^{d+s}\left(1 + R_{pj}^{k}\right) ,$$

where R_{ij}^{k} is the return on the k (k = A or B) share of firm i and R_{pj}^{k} is the value-weighted return of the matching size portfolio on day j and d is the earnings announcement date. All the shares in the matching portfolio of the announcing firm have the same size-rank as the announcing firm. We exclude the announcing firm when we compute the returns on the matching portfolio of the announcing firm. In each year, we allocate firms in the AB sample into three portfolios, low (bottom one-third) to high (top one-third) according to their SUEs. The cumulative abnormal return (CAR) on a SUE-sorted portfolio in a given year is the equally weighted average of the CAR of the firms in that portfolio in the same year. Panels A and B of this table respectively report the average cumulative returns of the SUE-sorted portfolios over the windows [1, 30] and [1, 60]. We provide t-statistics in parentheses. The sample period is 2003 to 2018.

Panel A: *CAR[1,30]*: 30-day cumulative returns post-announcement

	Low	2	High	High minus Low
A shares	0.433	0.069	0.457	0.024
	(0.37)	(0.07)	(0.49)	(0.02)
B shares	−0.061	0.559	3.327	3.388
	(−0.05)	(0.64)	(4.41)	(2.60)
			B minus A	3.364
				(3.25)

Panel B: *CAR[1,60]*: 60-day cumulative returns post-announcement

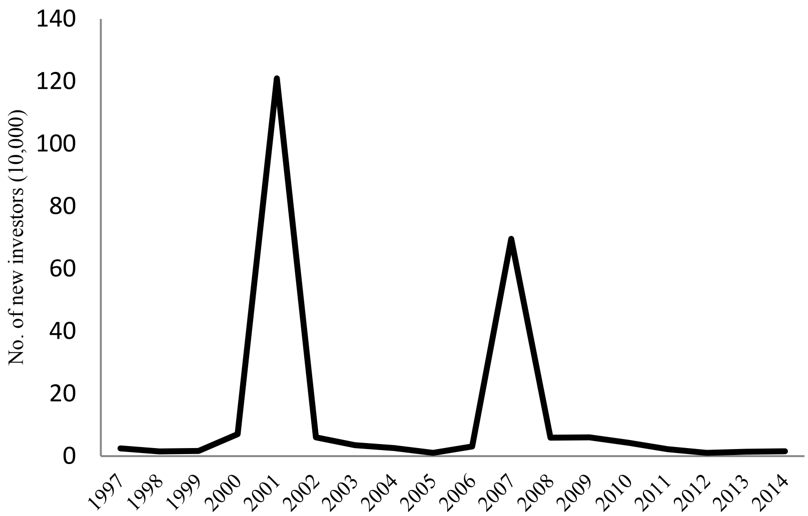
	Low	2	High	High minus Low
A shares	−1.792	−1.215	0.258	2.050
	(−2.02)	(−0.83)	(0.14)	(0.94)
B shares	−1.469	0.259	3.498	4.967
	(−1.28)	(0.19)	(1.88)	(2.35)
			B minus A	2.917
				(2.03)

Table 11
Institutional ownership, firm size, and momentum
This table reports average estimated coefficients and their *t*-statistics (in parentheses) obtained from monthly cross-sectional regressions for B shares that use Equation (4). The estimation period is from January 2002 to December 2018. The dependent variable is stock return in month t (R_t) or stock risk-adjusted return in month t ($AdjR_t$). The independent variables are the prior month's stock return (R_{t-1}), past six-month returns ($R_{t-2,t-7}$), the logistic transformation of B share institutional ownership in month $t-1$ ($LIof_{t-1}$), the interaction between $LIof_{t-1}$ and $R_{t-2,t-7}$, the interaction between the logarithm of firm size, $LnSZ_{t-1}$ and $R_{t-2,t-7}$, the logarithm of book-to-market ratio ($LnBM$), the natural logarithm of firm size ($LnSZ$), and the logarithm of Amihud illiquidity measure ($LnIlliq$) in month $t-1$. All variables except $LnSZ_{t-1}$ and $LnBM_{t-1}$ are measured for B shares, but the "B" superscript is omitted for convenience. The risk adjusted return of a stock is computed with respect to the CH-3 risk factors. Definitions of these variables appear in Appendix B.

	Raw Return	Risk-adjusted Return
Intercept	0.746	−0.002
	(0.46)	(−0.00)
R_{t-1}	0.037	0.012
	(2.24)	(0.67)
$R_{t-2,t-7}$	0.079	0.067
	(1.48)	(1.20)
$R_{t-2,t-7}$ x $LIof_{t-1}$	0.010	0.010
	(3.31)	(2.70)
$R_{t-2,t-7}$ x $LnSZ_{t-1}$	−0.001	0.000
	(−0.14)	(0.06)
$LIof_{t-1}$	0.093	0.112
	(1.22)	(1.14)
$LnSZ_{t-1}$	0.029	0.035
	(0.11)	(0.15)
$LnBM_{t-1}$	0.097	0.074
	(0.80)	(0.58)
$LnIlliq_{t-1}$	−0.060	0.005
	(−0.47)	(0.04)

Figure 1
Number of new investors in the B share market
Plotted are the annual increments in the number of investors and the number of institutional investors in the Chinese B share market over time.

Panel A: Number of new individual investors in the B share market



Panel B: Number of new institutional investors in the B share market

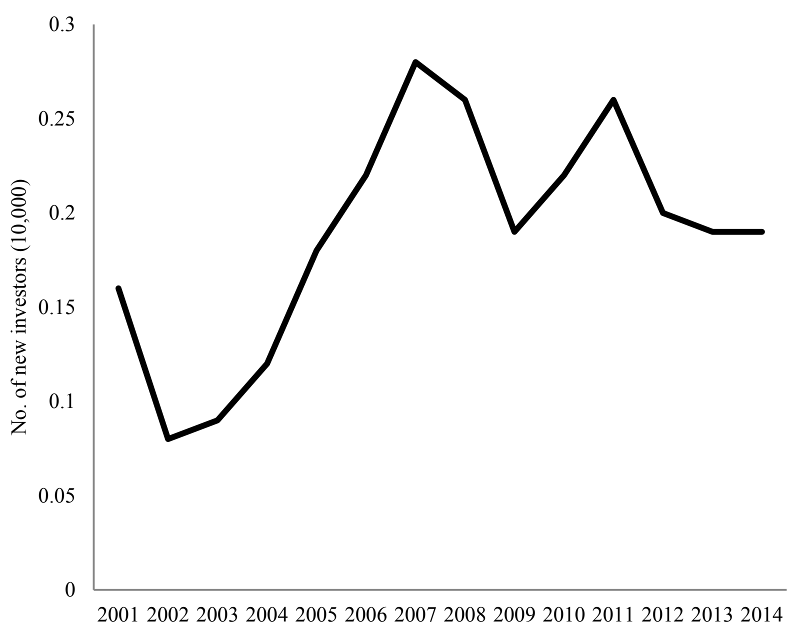


Figure 2
Foreign institutional ownership of B shares

Plotted is the average foreign institutional ownership per firm (in % of tradable shares outstanding) of B shares in the AB sample over the period January 2001 to December 2018.

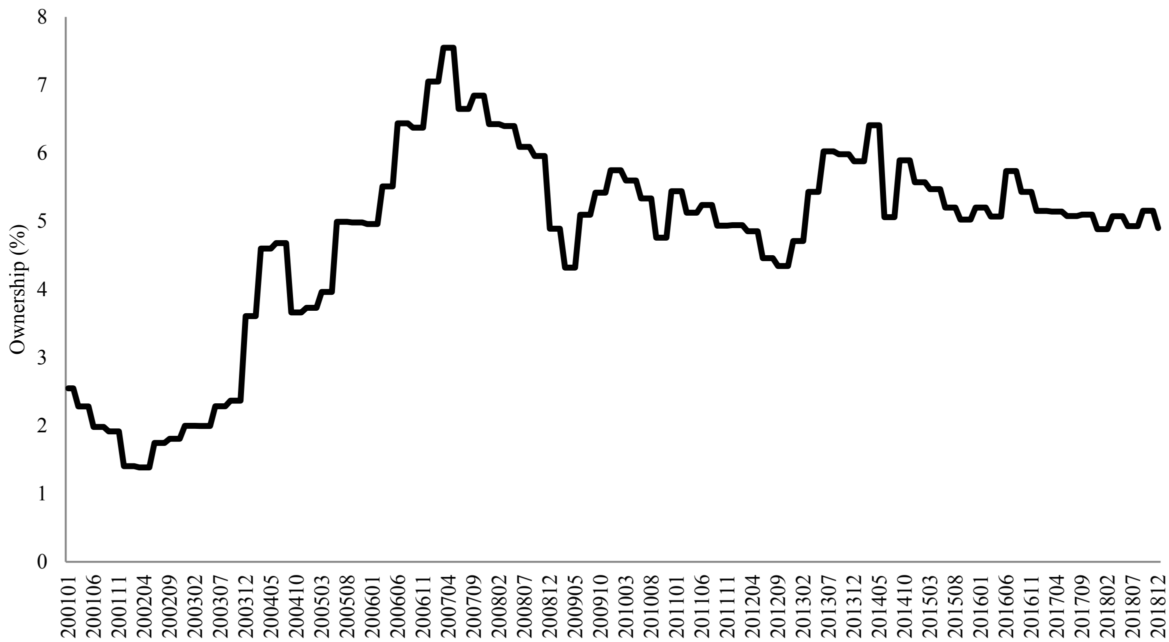
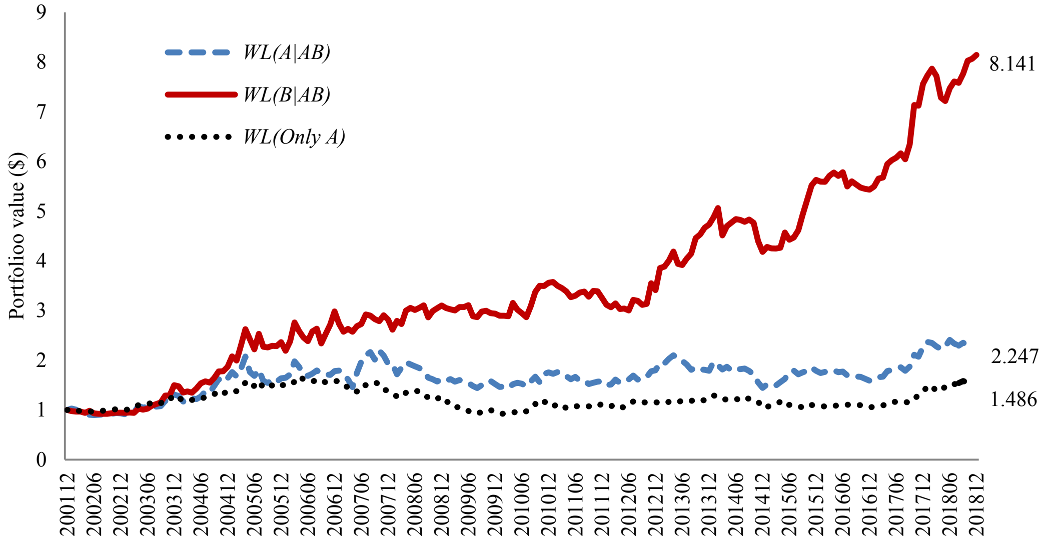


Figure 3
Cumulative monthly returns to momentum strategies
Plotted are the cumulative returns on three momentum portfolios: (1) A shares in the AB sample, *WL(A|AB)*; (2) B shares in the AB sample, *WL(B|AB)*; and (3) A shares in the Only A sample, *WL(Only A),* over the period from December 2001 to December 2018. Figure 3A shows value-weighted portfolio returns and Figure 3B displays equal-weighted portfolio returns. To the right of the plot we show the final dollar values of each of the three portfolios, given a $1 investment in December 2001.

Panel A: Value weights



Panel B: Equal weights

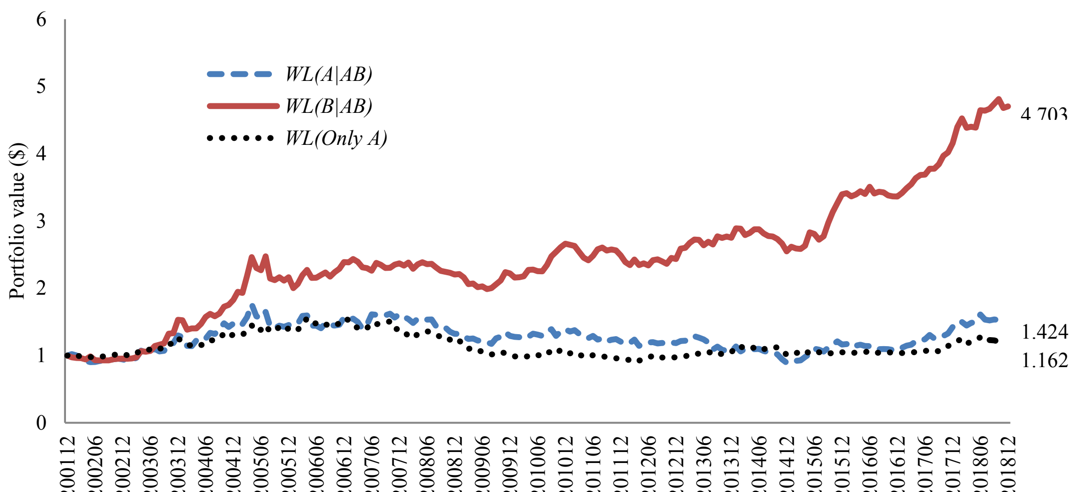
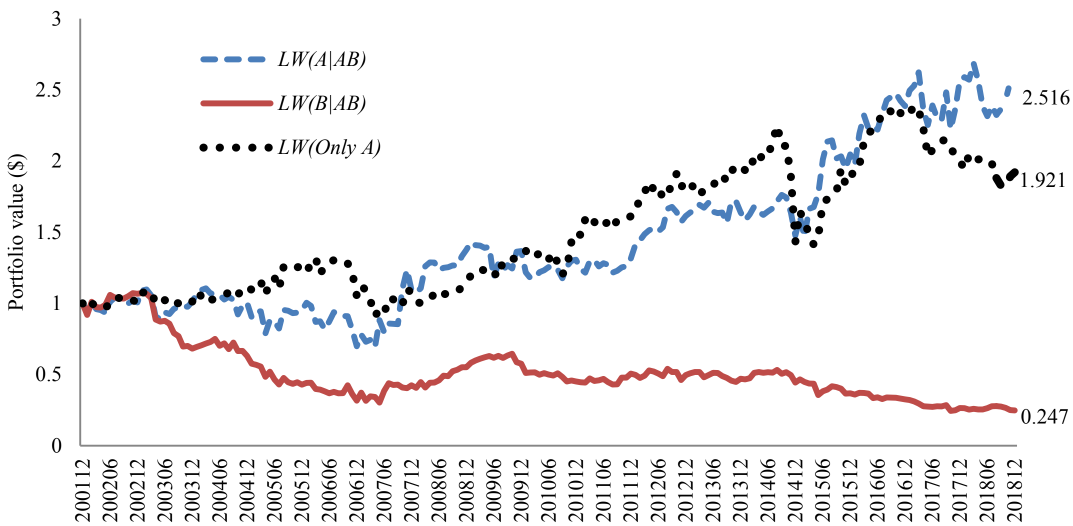


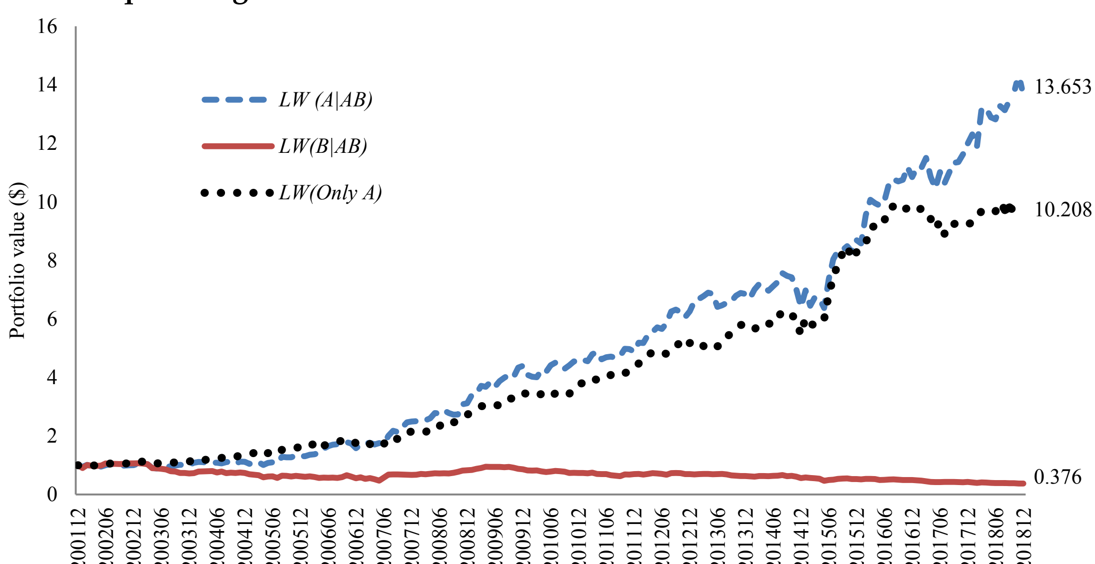
Figure 4
Cumulative monthly returns to reversal strategies

Plotted are the cumulative returns on three short-horizon return reversal portfolios: (1) A shares in the AB sample, *LW(A|AB)*; (2) B shares in the AB sample, *LW(B|AB)*; and (3) A shares in the Only A sample, *LW(Only A)*, over the period from December 2001 to December 2018. Figure 4A shows value-weighted portfolio returns and Figure 4B displays equal-weighted portfolio returns. To the right of the plot we show the final dollar values of each of the three portfolios, given a $1 investment in December 2001

Panel A: Value weights



Panel B: Equal weights



Internet Appendix for "Momentum, Reversals, and Investor Clientele"

Table IA.1

Table 3 equivalent: Momentum profits when past returns are measured over the period from *t*-13 to *t*-2 and portfolios are held for the period from *t* to *t*+6.

Panel A: Only A sample

	Winner (W)	2	Loser (L)	W − L
Value weighted	0.881 (1.47)	1.070 (1.75)	0.906 (1.39)	−0.025 (−0.08)
Equal weighted	1.096 (1.65)	1.312 (1.90)	1.274 (1.79)	−0.178 (−0.76)

Panel B: AB sample

Value weighted	Winner (W)	2	Loser (L)	W − L
A shares	0.891 (1.40)	1.034 (1.59)	0.888 (1.31)	0.003 (0.01)
B shares	1.166 (1.88)	0.696 (1.10)	0.441 (0.69)	0.725 (1.98)
			B|AB minus A|AB	0.722 (2.07)
			B|AB minus Only A	0.750 (2.12)
Equal weighted	**Winner (W)**	**2**	**Loser (L)**	**W − L**
A shares	1.008 (1.57)	1.170 (1.72)	1.209 (1.69)	−0.201 (−0.63)
B shares	1.240 (1.91)	0.887 (1.30)	0.696 (1.02)	0.544 (1.98)
			B|AB minus A|AB	0.745 (2.90)
			B|AB minus Only A	0.722 (2.93)

Table IA.2

Table 5 equivalent: Average returns on short-horizon reversal portfolios when R_{t-1} is measured excluding the last trading day in month *t*-1

Panel A: Only A sample

Value weighted	Loser (L)	2	Winner (W)	L – W
All firms	1.296 (2.08)	1.162 (1.85)	0.789 (1.24)	0.507 (1.56)
Excl. largest 0.5%	1.454 (2.22)	1.258 (1.93)	0.671 (1.03)	0.783 (2.57)
Excl. largest 1%	1.461 (2.19)	1.225 (1.86)	0.656 (1.00)	0.805 (2.73)
Excl. largest 5%	1.545 (2.25)	1.270 (1.86)	0.589 (0.88)	0.956 (3.69)
Excl. largest 10%	1.632 (2.33)	1.322 (1.91)	0.557 (0.81)	1.075 (4.47)
Equal weighted				
All firms	1.811 (2.53)	1.570 (2.23)	0.658 (0.96)	1.153 (4.83)

Panel B: AB sample

Value weighted	Loser (L)	2	Winner (W)	L – W
A shares	1.398 (2.07)	0.887 (1.40)	0.752 (1.14)	0.646 (1.48)
B shares	0.605 (0.94)	0.806 (1.29)	1.304 (1.98)	−0.699 (−1.68)
			A|AB minus B|AB	1.345 (2.86)
			Only A minus B|AB	1.206 (2.80)
Equal weighted	Loser (L)	2	Winner (W)	L – W
A shares	1.794 (2.42)	1.455 (2.10)	0.446 (0.68)	1.348 (4.26)
B shares	0.740 (1.07)	0.843 (1.24)	1.203 (1.75)	−0.463 (−1.48)
			A|AB minus B|AB	1.811 (5.91)
			Only A minus B|AB	1.616 (5.55)

Table IA.3

Table 6 equivalent: Regression analysis by share type, excluding the smallest 30% of firms

We remove the smallest 30% of firms each month from our sample. The size break points are determined from the monthly market capitalization of tradable A shares of firms in our sample.

Panel A: Parameter estimates

Firm sample	Only A		AB		AB	
Share type	A		A		B	
	Raw Return	Risk-adjusted Return	Raw Return	Risk-adjusted Return	Raw Return	Risk-adjusted Return
Intercept	3.787	1.165	3.572	1.542	2.057	0.874
	(3.01)	(2.28)	(2.20)	(1.59)	(1.48)	(0.80)
R_{t-1}	−0.049	−0.061	−0.051	−0.062	0.036	0.022
	(−5.10)	(−5.95)	(−3.37)	(−4.06)	(2.27)	(1.32)
$R_{t-2,t-7}$	0.003	−0.003	0.003	−0.004	0.023	0.020
	(0.69)	(−0.66)	(0.42)	(−0.52)	(2.86)	(2.50)
$LnBM_{t-1}$	0.247	0.100	0.330	0.349	0.084	0.135
	(2.49)	(1.21)	(2.02)	(2.16)	(0.65)	(1.10)
$LnSZ_{t-1}$	0.421	0.596	0.120	0.380	−0.155	−0.100
	(2.31)	(4.90)	(0.46)	(1.85)	(−0.80)	(−0.53)
$LnIlliq_{t-1}$	0.810	0.773	0.519	0.662	0.050	0.102
	(5.80)	(6.19)	(2.73)	(3.49)	(0.41)	(0.85)

Panel B Difference in parameter estimates

	Raw Return		Risk-adjusted Return	
	R_{t-1}	$R_{t-2,t-13}$	R_{t-1}	$R_{t-2,t-13}$
B|AB minus A|AB	0.087	0.020	0.084	0.024
	(5.21)	(3.00)	(4.51)	(3.31)
B|AB minus Only A	0.085	0.020	0.083	0.023
	(5.58)	(2.80)	(4.97)	(3.10)

Table IA.4

Table 6 equivalent: Regression analysis using signed one-month lagged returns for A shares

We replace R_{t-1} by Max (R_{t-1}, 0) and Min (R_{t-1}, 0)). R_{t-1} is measured excluding the last trading day in month *t*-1. *Pos* R_{t-1} = Max (R_{t-1}, 0) and *Neg* R_{t-1} = Min (R_{t-1}, 0).

Firm sample	Only A & A|AB	
Share type	A	
	Raw Return	Risk-adjusted Return
Intercept	3.905	2.922
	(3.09)	(5.24)
Pos R_{t-1}	−0.058	−0.074
	(−5.54)	(−6.59)
Neg R_{t-1}	0.024	0.001
	(0.85)	(0.02)
$R_{t-2,t-7}$	0.001	−0.004
	(0.17)	(−0.87)
$LnBM_{t-1}$	0.233	0.030
	(2.86)	(0.43)
$LnSZ_{t-1}$	0.416	0.342
	(2.53)	(3.22)
$LnIlliq_{t-1}$	0.815	0.775
	(6.64)	(6.78)
Pos R_{t-1} minus *Neg* R_{t-1}	−0.082	−0.075
	(−2.84)	(−2.53)

Table IA.5

Table 8 equivalent: Cumulative abnormal returns of portfolios sorted by foreign institutional ownership and earnings surprises for the AB sample

In each year, we allocate firms in the AB sample to two groups, low (bottom one-half) to high (top one-half) according to their foreign institutional ownership of B shares (*Iof*) in the month prior to their last earnings announcement date. Firms in each *Iof*-sort group are further divided into three groups, low (bottom one-third) to high (top one-third) according to their *SUE*s. As a result, there are six *Iof-SUE*-sorted portfolios. Each portfolio is required to have at least five firms in each year. The cumulative abnormal return (*CAR[1,30]*) on a *Iof-SUE*-sorted portfolio in a given year is the equally weighted average of the cumulative abnormal return over the 30 days after the earnings announcement for the firms in that portfolio. We provide *t*-statistics in parentheses. The statistics are calculated over the period 2007 to 2018.

Foreign institutional ownership of B shares: Low				
SUE	Low	2	High	High minus Low
A shares	1.695	0.436	0.474	–1.221
	(0.68)	(0.47)	(0.49)	(–0.54)
B shares	2.436	2.570	2.530	0.094
	(0.80)	(1.57)	(1.83)	(0.04)
			B minus A	1.315
				(0.95)
Foreign institutional ownership of B shares: High				
SUE	Low	2	High	High minus Low
A shares	–3.322	0.992	–1.396	1.926
	(–2.38)	(0.62)	(–0.80)	(1.57)
B shares	−3.800	0.807	1.478	5.278
	(−2.51)	(0.35)	(0.92)	(4.97)
			B minus A	3.352
				(2.08)
High-*Iof* minus Low-*Iof* *SUE* spreads				
			A shares	3.147 (1.14)
			B shares	5.184 (1.99)

Table IA.6

Table 9 equivalent: Additional interactive terms for momentum

This table reports average estimated coefficients and their *t*-statistics (in parentheses) obtained from monthly cross-sectional regressions for B shares. The estimation period is from January 2002 to December 2018. The dependent variable is stock return in month *t* (R_t) or stock risk-adjusted return in month *t* ($AdjR_t$). The independent variables are the prior month's stock return (R_{t-1}), past six-month returns ($R_{t-2,t-7}$), the interaction of the logistic transformation of B share institutional ownership between $LIof_{t-1}$ and $R_{t-2,t-7}$, the interaction between the logarithm of firm size, $LnSZ_{t-1}$ and $R_{t-2,t-7}$, the interaction between the logarithm of information discreteness, $LnID_{t-2,t-7}$ and $R_{t-2,t-7}$, the interaction between the logarithm of revenue growth volatility, $LnVRevgw_{t-1}$ and $R_{t-2,t-7}$, the interaction between the logarithm of operating costs-to-revenue ratio, $LnCost\_Rev_{t-1}$ and $R_{t-2,t-7}$, the interaction between the logarithm of the 52-week high ratio, $LnFH_{t-1}$ and $R_{t-2,t-7}$, the logistic transformation of B share institutional ownership in month *t-1* ($LIof_{t-1}$), the natural logarithm of firm size in month *t-1* ($LnSZ_{t-1}$), information discreteness in month *t-2* ($ID_{t-2,t-7}$), the natural logarithm of revenue growth volatility ($LnVRevgw_{t-1}$), the natural logarithm of operating costs-to-revenue ratio ($LnCost\_Rev_{t-1}$), the natural logarithm of the 52-week high ratio ($LnFH_{t-1}$), the logarithm of book-to-market ratio ($LnBM_{t-1}$), and the logarithm of Amihud illiquidity measure ($LnIlliq_{t-1}$) in month *t-1.* $ID_{t-2,t-7}$ is defined as $sgn(R_{t-2,t-7}) \times [\%neg - \%pos]$, where $sgn(R_{t-2,t-7})$ is the sign of the past 6-month return, and %neg − *%pos* is the percentage of negative daily returns minus the percentage of positive daily returns form month *t-2* to month *t-7*. $Costs\_Rev_q$ for a firm in quarter *q* is computed as operating costs divided by operating revenue. $Costs\_Rev_q$ in quarter *q* is assigned to the months in quarter *q+1*. Operating revenue growth for a firm in quarter q is computed as $Revgw_q = \frac{Revenue_q - Revenue_{q-4}}{Revenue_{q-4}}$. $VRevgw_q$ for quarter *q* is calculated as the standard deviation of $Revgw_q$ to $Revgw_{q-9}$. We require at least five observations between quarter *q* and quarter *q-9*. $VRevgw_q$ in quarter *q* is assigned to the months in quarter *q+1*. For $Costs\_Rev_{q,}$ and $VRevgw_{qI,}$ *Ln* represents the natural logarithm and the subscript *t-1* represents that they are measured as the values in the month before the dependent variable is measured. Other variables are defined in Appendix B. The risk adjusted return of a stock is computed with respect to the CH-3 risk factors.

Table IA.6, continued

	Raw Return	Risk-adjusted Return
Intercept	−2.140	−4.099
	(−0.86)	(−1.48)
R_{t-1}	0.023	0.001
	(1.35)	(0.03)
$R_{t-2,t-7}$	0.178	0.118
	(1.96)	(1.13)
$R_{t-2,t-7}$ x $LIof_{t-1}$	0.016	0.016
	(4.06)	(3.62)
$R_{t-2,t-7}$ x $LnSZ_{t-1}$	−0.015	−0.007
	(−0.97)	(−0.40)
$R_{t-2,t-7}$ x $ID_{t-2,t-7}$	−0.054	−0.049
	(−0.56)	(−0.47)
$R_{t-2,t-7}$ x $LnVRevgw_{t-1}$	0.003	0.003
	(0.38)	(0.49)
$R_{t-2,t-7}$ x $LnCost\_Rev_{t-1}$	0.023	0.026
	(0.90)	(0.99)
$R_{t-2,t-7}$ x $LnFH_{t-1}$	−0.075	−0.114
	(−1.14)	(−1.62)
$R_{t-2,t-7}$ x $LnBM_{t-1}$	−0.004	0.005
	(−0.28)	(0.31)
$R_{t-2,t-7}$ x $LnIlliq_{t-1}$	0.005	0.010
	(0.38)	(0.72)
$R_{t-2,t-7}$ x $LnPrem_{t-1}$	0.036	0.065
	(0.98)	(1.73)
$LIof_{t-1}$	0.229	0.247
	(2.47)	(2.22)
$LnSZ_{t-1}$	0.312	0.442
	(0.77)	(0.94)
$ID_{t-2,t-7}$	0.523	−0.370
	(0.18)	(−0.12)
$LnVRevgw_{t-1}$	−0.111	−0.091
	(−0.59)	(−0.53)
$LnCost\_Rev_{t-1}$	−0.199	−0.190
	(−0.31)	(−0.32)
$LnFH_{t-1}$	5.567	5.961
	(2.72)	(2.61)
$LnBM_{t-1}$	−0.260	0.078
	(−0.67)	(0.19)
$LnIlliq_{t-1}$	0.108	0.269
	(0.30)	(0.64)
$LnPrem_{t-1}$	2.615	2.896
	(1.91)	(2.15)