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Are investors consistent in their trading strategies? An examination of individual investor-level data

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ABSTRACT

While it has been demonstrated that momentum or contrarian trading strategies can be profitable in a range of institutional settings, less evidence is available concerning the actual trading strategies investors adopt. Standard definitions of momentum or contrarian trading strategies imply that a given investor applies the same strategy to both their buy and sell trades, which need not be the case. Using investor-level, transaction-based data from China, where tax effects are neutral, we examine investors' buy-sell decisions separately to investigate how past returns impact differentially on the trading strategies investors adopt when buying and selling stock. After controlling for a wide range of stock characteristics, extreme price changes and portfolio value, a clear asymmetry in trading is observed; with investors displaying momentum behavior when buying stocks, but contrarian behavior when selling stocks. This asymmetry in behavior is not driven purely by reactions to stock characteristics or extreme stocks. We discuss behavioral and cultural explanations for our findings.

1. Introduction

Momentum or contrarian trading strategies have been shown to produce abnormal profits over varying time horizons in the US (e.g. DeBondt & Thaler, 1985, 1987; Jegadeesh & Titman, 1993), the UK (e.g. Galariotis, Holmes, & Ma, 2007) and other European stock markets (Rouwenhorst, 1998). In China, the institutional setting of the current paper, Kang, Liu, and Ni (2002) report abnormal profits for short-horizon contrarian and intermediate-horizon momentum strategies, while Naughton, Truong, and Veeraraghavan (2008) report evidence of profitable momentum strategies for the Shanghai Stock Exchange. In contrast Wang (2004) reports that the intermediate-horizon returns to relative strength strategies of buying winners and selling losers in the Chinese stock market are negative for horizons of 6 months to 2 years. More recently, Wu (2011) examines daily data for the Shanghai and Shenzhen exchanges from inception to December 2001 and documents positive excess returns for a pure contrarian strategy, but not for a pure momentum strategy.

The empirical evidence of price momentum or reversal, coupled with the profitability of trading strategies based on past returns, would suggest that investors may follow momentum or contrarian based strategies. While there is less direct empirical evidence of the trading strategies investors adopt, due in part to limitations surrounding data availability, there is evidence to suggest that different investor types follow different strategies. For example, mutual fund managers follow momentum strategies (Grinblatt, Titman, & Wermers, 1995), as do sophisticated individual investors, while less sophisticated investors follow contrarian strategies (Grinblatt & Keloharju, 2001). Ng and Wu (2007) find that Chinese institutions and wealthy individuals are momentum investors, while less wealthy individuals are contrarian investors. In a recent study, Wongchoti, Wu, and Young (2009) investigate buy and sell dynamics following high market returns in China and find that large trade-size investors adopt momentum strategies following high returns (increasing their buy volume), while small trade-size investors adopt contrarian strategies following high returns (increasing their sell volume).

The accepted definitions of momentum (buying positive return stocks and selling negative return stocks) or contrarian (selling positive return stocks and buying negative return stocks) trading strategies imply that a given investor applies the same strategy to both sides of their trades (i.e. to their buys and sells). These assumptions have yet to be conclusively tested, though there is some limited evidence to suggest this need not be the case. Using a portfolio-based method,

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Badrinath and Wahal (2002) decompose institutional trades into entries (new positions), exits (clearing positions), and adjustments to on-going holdings, finding that institutions are momentum traders for entries, but contrarian traders for exits or adjustments. While limited to institutions, their results suggest that investors may apply different strategies across their buy-sell decisions. There is some indirect evidence to support this view. Choe, Bong-Chan, and Stulz (1999) report a lack of symmetry between net-buy and net-sell order imbalances in the Korean market, while Ng and Wu (2007) examine excess buys and excess sells to find that wealthy individual investors in China are momentum traders when buying and contrarian traders when selling. Grinblatt and Keloharju (2001) note unreported evidence that investors' buys and sells are associated with positive past returns in the Finnish market, similarly Barber, Odean, and Zhu (2009) report US evidence to suggest that investors systematically buy stocks with positive past returns, but also sell stocks with positive past returns.

In summary, while there is a wealth of evidence on the profitability of momentum or contrarian trading strategies, less direct evidence is available concerning the actual trading strategies employed by investors in general and individual investors in particular. Furthermore, while relatively few studies examine investor trading behavior separately for buy versus sell decisions, even fewer recognize the potential for investors to adopt different trading strategies across their buy and sell decisions.

This paper helps fill this gap in knowledge by examining the trading strategies of individual investors,[1] addressing directly the issue of whether past returns impact differentially on their buy and sell decisions. We combine the approaches of Grinblatt and Keloharju (2001) and Badrinath and Wahal (2002), providing a transaction-based analysis of the impact of past returns on buy-sell decisions coupled with an investigation of how such returns impact on trading strategies when adding to or reducing existing stock holdings in portfolios. We contribute to the literature in several ways. First, we extend the analysis of Grinblatt and Keloharju (2001) by controlling for a wide range of individual stock characteristics, thus providing a clearer picture of the impact of past returns per se on buy-sell decisions. Prior studies demonstrate that investors display preferences for specific stock characteristics, including firm size, liquidity, beta, volatility, earnings per share, book-to-market (see e.g., Duxbury, Hudson, Keasey, Yang, & Yao, 2013; Kumar, 2009; Ng & Wu, 2006). Controlling for the impact of such variables on investors' buy and sell decisions allows us to isolate the effect of past returns on their adoption of trading strategies. Second, we control for reference price effects (Grinblatt & Keloharju, 2001) and attention effects (Barber & Odean, 2008; Seasholes & Wu, 2007) to further remove the possibility that evidence of investors adopting momentum or contrarian strategies is driven largely by their reactions to extreme, attention grabbing stocks. Third, following other studies we adopt a quintile based approach (see e.g., Kaniel, Saar, & Titman, 2008; Ng & Wu, 2006), which we use to examine separately investors' buy and sell decisions, thus providing evidence of the extent to which they adopt different trading strategies across such decisions. Fourth, we extend the portfolio-based analysis of Badrinath and Wahal (2002) to include individual investors and examine further how past returns influence investors' portfolio decisions. Fifth, using investor-level, transaction-based data from China, we examine investors' buy-sell decisions in an institutional setting where tax effects are neutral, thus removing the effect of tax motivated trading and further isolating the impact of past returns.

In general, we find investors adopt momentum strategies when adding stocks to their portfolios and contrarian strategies when selling stocks. By controlling for specific stock characteristics, reference price effects and attention effects, we demonstrate that the adoption of momentum or contrarian trading strategies is not merely an artifact of investors' reactions to characteristics of particular stocks nor is it driven purely by an attraction to extreme price changes. Our findings can be explained by behavioral and cultural considerations. The remainder of the paper proceeds as follows. Section 2 discusses related literature and motivates the hypothesis to be examined. Section 3 begins by describing the institutional setting and data sample, before turning to a discussion of the method of analysis employed. Section 4 reports the empirical results, while Section 5 draws conclusions and discusses behavioral and cultural explanations of our findings.

2. Related literature and hypothesis development

We briefly review empirical literature examining the trading decisions of individual investors, largely focusing on those studies examining trading strategies based on past returns and those that distinguish between investors' buy and sell decision.[2] Drawing on the findings in this literature, we develop a testable hypothesis of trading strategies.

2.1. Literature

Using brokerage account data from China, Chen, Kim, Nofsinger, and Rui (2007) investigate the trading performance of individual investors and the extent to which they succumb to various behavioral biases. The investors make poor trading decisions, such that the stocks they sell subsequently outperform those they buy and, consistent with the disposition effect, they sell stocks that have increased in price, while resisting the sale of stocks that have fallen in price. Also based on brokerage data from China, Feng and Seasholes (2005) examine whether investor sophistication and trading experience reduce the extent to which investors succumb to behavioral biases. They find that sophistication and experience, together, eliminate the reluctance of investors to realize losses, but are unable to eliminate their enthusiasm to realize gains. Feng and Seasholes (2008) also examine the trading behavior of individual investors in China, focusing on potential gender differences. While men tend to hold larger portfolios and make larger trades than women, both genders display similar degrees of home bias and generate comparable trading performances as measured by calendar–time portfolio returns (buys minus sells).

The consensus across empirical studies examining individual investors' trading strategies seems to suggest, on the whole, that such investors tend to follow contrarian strategies. Choe et al. (1999), for example, examine the trading behavior of Korean individual investors and find evidence of short-horizon contrarian strategies. Goetzmann and Massa (2002) examine the trading behavior of index fund investors using individual accounts in an S&P 500 index mutual fund and, based on the distribution for inflows and outflows into individual accounts, report that contrarian investors are slightly more prevalent than momentum investors. Also examining US data, Kaniel et al. (2008) provide evidence of individual investors buying stocks following price declines and selling following price increases, suggesting they may follow contrarian-based trading strategies.

We turn next to look in more detail at the relatively few studies to distinguish between investors' buy and sell decisions. For a given investor category on a given day, Grinblatt and Keloharju (2000) investigate the difference between the buy ratio for past winning stocks (top quartile of returns) and that for past losing stocks (lowest quartile of returns), with a positive difference indicative of momentum-oriented trading and contrarian-oriented if negative. They conclude that Finnish investors, particularly households, follow contrarian trading strategies, with the degree of contrarianism inversely related to investor sophistication. In a related study, Grinblatt and Keloharju (2001) examine further the impact of past returns on individual investors' buy versus sell

[1] While our data includes a handful of institutional investors, these represent <2% of our sample. Hence our primary concern is with buy-sell decisions of individual investors and in analyses to follow we separate out individual and institutional investors.

[2] A more comprehensive review of the behavior of individual investors in general is provided by Barber and Odean (2011).

decisions, reporting that less sophisticated investors are more predisposed to sell than to buy stocks with large past returns, thus conforming to a contrarian strategy. In results perhaps at odds with the notion that low sophistication is associated with the adoption of contrarian strategies, Grinblatt, Keloharju, and Linnainmaa (2012) find that High-IQ investors, who may be thought of on some level as being more sophisticated, are more contrarian than Low-IQ investors, with their sell-versus-buy decisions responding dramatically to extreme price movements (whereby a stock hits its high price within the past month) in a contrarian way.

Wongchoti et al. (2009) investigate the extent to which investors with differing opinions about past return information may employ different trading strategies. Using measures buy-sell imbalance as proxies for difference of opinion, they find that large investors increase their buy volume following high prior day returns, while small investors increase their sell volume, thus indicating that different classes of investors may adopt different trading strategies. This view is supported by results in Ng and Wu (2007) who, examining excess buys and excess sells, report that Chinese institutions and wealthy individuals are momentum investors, while less wealthy individuals are contrarian investors.

While the accepted definitions of momentum (buying/selling positive/negative return stocks) or contrarian (selling/buying positive/negative return stocks) trading strategies imply that a given investor applies the same strategy to both sides of their trades (i.e. to their buys and sells), there is limited evidence to suggest that this need not be the case. Using institutional portfolio holding data, Badrinath and Wahal (2002) decompose trades into entry (buying new stock not held), exit (sale of complete stock holding), and adjustments to ongoing holdings. They report that institutions are momentum traders for entries, but contrarian traders for exits or adjustments. While restricted to institutions, their results suggest that investors in general could apply different strategies across their buy-sell decisions. There is some indirect evidence in support of this view. Choe et al. (1999) report a lack of symmetry between net-buy and net-sell order imbalances in the Korean market, while, in unreported work, Grinblatt and Keloharju (2001; see footnote 13, p.612) note “that both buys and sells tend to be associated with positive past returns” in the Finnish market. Analyzing excess-buys and excess-sells separately, Ng and Wu (2007, p.2697) report that Chinese institutions are momentum traders and less wealthy individuals are contrarian traders, while the “wealthiest individuals behave like institutions when they buy but like less wealthy individuals when they sell.” In an examination of how investors' stock preferences shift in response to past returns, Kumar (2009) reports that investors exhibit preferences for stocks with extreme momentum characteristics, which is taken as evidence indicating that individual investors adopt both momentum and contrarian trading strategies, though this may be across different stocks. Finally, and perhaps most directly, Barber et al. (2009) examine individual trading behavior separately for buy and sell decisions and “show that individual investors are systematic in their cross-sectional trading; that is, they are net buyers of some stocks and net sellers of other stocks to a degree far greater than one would expect from chance” (p. 550). For a given stock in a given month, Barber et al. (2009) report separate analyses of the number of buys and number of sells, scaled by the number of positions in the stock. They find that individual investors buy and sell stocks with strong past performance, but that they are net sellers of such stocks.

2.2. Hypothesis

The findings in Grinblatt and Keloharju (2001), Ng and Wu (2007), Kumar (2009) and Barber et al. (2009), in particular, suggest that individual investors may approach their buy and sell decisions differently. Thus while standard definitions of momentum or contrarian trading strategies imply that a given investor applies the same strategy to both their buys and sells, this need not be the case. We test the following null hypothesis (H_0) by examining investors' buy and sell trades.

H0. *Investors' trading strategies based on past returns are applied consistently to both sides of their trades; investors will be inclined to i) buy positive return stocks and sell negative return stocks or ii) sell positive return stocks and buy negative return stocks.*

We are the first to test this implication directly, after controlling for a number of factors shown to influence investors' trading decisions in the prior literature. Our empirical approach complements and extends those in Grinblatt and Keloharju (2001), Ng and Wu (2007) and Barber et al. (2009), controlling for a wide range of stock characteristics shown to impact on investor preferences (Duxbury et al., 2013; Kumar, 2009; Ng & Wu, 2006), attention (Barber & Odean, 2008; Seasholes & Wu, 2007) and reference price effects (Grinblatt & Keloharju, 2001), along with portfolio values (Badrinath & Wahal, 2002).

3. Background, data and method

3.1. Institutional background

Over the last two decades China has made significant progress developing its stock market, culminating in impressive growth rates and significant contributions to China's economy. By 2010 the Chinese stock market (comprised of the Shanghai (SHSE) and Shenzhen (SZSE) exchanges formally established on December 19, 1990 and July 3, 1991, respectively) had a total market capitalization of $3.5 trillion (compared to a market capitalization of approximately $15.3 trillion for the US stock markets),[3] equivalent to about 60% of GDP. The market is a pure order-driven market, with orders centralized and automatically matched in two electronic trading systems, Securities Trading Automated Quotations System (STAQS) and National Electronic Trading System (NETS). The trading system is a continuous auction, other than a short call auction to generate an equilibrium price at the opening of the market. There are two types of shares, A and B, traded on both exchanges.

In China, unlike other developed economies such as the US and UK, there is no capital gains tax. During our sample period, the tax on trading is a fixed percentage (0.2%) of the transaction value and is applied to both the buy and sell sides of a trade. The tax system in China is, therefore, neutral in the sense that it does not distort investor behavior and as such China represents an ideal setting to examine investors' trading strategies free from the potentially confounding effect of tax motivated trades.

While there are other institutional differences between the Chinese stock market and other major developed stock markets in the world, one in particular requires commenting on in light of our interest in how past returns influence trading strategies. Unlike other stock markets such as the US and UK, the Chinese market has a price limit mechanism that halts trade when a stock's price moves outside $\pm 10\%$ of the previous closing price, thus we control for this in the analysis to follow. The price limit reform was introduced to the Chinese stock market in 1996 with the intention of restricting the possibility that stock prices were driven by institutional investors. Wang, Liu, and Gu (2009) study the effect of the reform on the Shenzhen stock exchange, concluding that the exchange has become more efficient since the price limits were introduced.

3.2. Data

Our primary dataset is investor-level account data from a brokerage in China,[4] which records all the trading data, static position data, and

[3] Source: World Federation of Exchanges, October 2010.

[4] The brokerage dataset has been employed by Duxbury et al. (2013) to examine differences in the characteristics of stocks investors *hold* in their portfolios following positive and negative prior *realized* outcomes and by Duxbury, Hudson, Keasey, Yang, and Yao (2015) to examine jointly the tendency of investors to succumb to the disposition effect and the house money effect, distinguishing prior outcomes across two dimensions; *unrealized*/*realized* and *stock*/*portfolio* level.

personal information of each investor registered with the brokerage. For each transaction of an investor, we have the transaction date, quote time, transaction time, trading volume, transaction price, stock code and trading label (purchase or sale). The position data gives the stock codes and share volumes in the investors' portfolios at the end of each trading day. The brokerage provides the transaction data and portfolio data for 3139 individual and 49 institutional investors. Our sample period is from February 27, 2001 to December 16, 2004 and comprises 314,932 transactions (174,093 buys; 140,839 sells).[5] In China investors register with a single brokerage, thus the dataset provides full information of investors' trades and portfolio holdings. Our second dataset includes daily stock price and return data, comprising the daily open price, close price, the highest price, the lowest price, and adjusted return of each stock in the market, collected from the China Financial Research Centre, Tsinghua University and cross checked for accuracy with data from Yahoo Finance.[6]

We restrict our analysis to A-share stocks because they dominate the Chinese stock market in terms of the number of companies listed, daily trading values and market capitalization[7] and because of the very low volume of domestic trade in B-share stocks with only a small proportion of domestic investors registered to trade them. During our sample period, there were a total of 506 A-share stocks on the Shenzhen stock exchange, and 834 A-share stocks listed on the Shanghai stock exchange, respectively. Chinese A-shares can be classified as state-owned shares, legal-person shares, and public shares, with only the latter category of shares tradable on the exchanges.

We report descriptive statistics in Table 1 by stocks traded on the Shanghai and Shenzhen exchanges (including the number of trades on each stock, the number of days on which the stock was traded, the number of investors who have ever traded the stock, the total number of traded shares of a stock) by investors registered with the brokerage providing the account data. On average, each stock is traded 231.55 (237.13) times and on 107.09 (97.89) days on average on the Shanghai (Shenzhen) exchange, while each stock is traded on average by 33.60 (35.12) investors during the sample period. As can be seen in Table 1, the statistics do not differ substantively across the two exchanges. Yan, Powell, Shi, and Xu (2007) identify bull and bear market regime turning points for the two Chinese stock exchanges from 1991 to 2006. During our sample period the SHSE and the SZSE move in perfect tandem (see Fig. 1 in Duxbury et al., 2013) through three bull and three bear market cycles. For these reasons, we combine the data from the SHSE and the SZSE, to provide a joint examination of the two exchanges in the analyses to follow. Furthermore, following the evidence in Galariotis, Holmes, Kallinterakis, and Ma (2014), that market states (i.e. rising or falling) have little effect on momentum profits, we conduct analyses on the whole sample.

Table 2 reports descriptive statistics (including number of trades, total trading value, trade size, buy size and sell size, etc.) by investor category separately for individuals and institutions. For all variables, the statistics are calculated for each investor first, and then averaged across investors. The trade size means the average trading value (in RMB) of each transaction. The stock position is the mean of the market values of investor's portfolios at the beginning of each trade day. The average individual and institutional investor make 72.9 and 1595.7 trades, respectively, during the sample period and turn over their portfolio 1.01 and 2.12 times, respectively, per month. For individual investors, the average buy size and sell size do not differ by much, while for institutions the average buy size is over twice as large as the sell size (though median values do not differ greatly). On average, the individual and institutional investor holds 2.91 and 3.84 stocks, worth on average RMB 179,163 and RMB 4,989,804, respectively. Comparisons with the sample of individual investors investigated by Feng and Seasholes (2008, Table 3) reveal very similar statistics. Median stocks held per individual investor (2) are the same across the two studies, while our average and median stock positions of 179,163 and 28,098, respectively, are close to their values of 136,777 and 34,442, respectively. We have confidence in concluding, therefore, that our data is representative of the Chinese stock market generally.

While our data includes transactions involving all stocks traded on the two exchanges, we filter IPOs during our sample period for a number of reasons: firstly, because data pertaining to some of the control variables included in our analysis (see Section 3.2, below) is not initially available; secondly, because the extremely high initial (first day) returns experienced by Chinese IPOs (see e.g., Guo & Brooks, 2008; Su & Brookfield, 2013; who report mean initial returns ranging from 70.17–136.49%, and 71.72–138.37%, respectively, for the four full calendar years covering our sample period) might conceivably bias our analysis of investors' sell decisions towards contrarian strategies if they sold IPO stock soon after their initial listing to realize such exceptional returns (see e.g., Su, Bangassa, & Brookfield, 2011, who report a turnover ratio of 69.35% for IPOs from 1996 to 2005 on the first trading day after listing); thirdly, to exclude potentially distorting effects of the IPO allocation reform in April 2001, whereby the government controlled quota system was replaced by a more market-orientated approval system (see e.g., Su, 2015, who reports a change in the influence of investor bank reputation on long-term stock price performance pre and post the reform). In light of the empirical methods we employ (see Section 3.3, below), we also filter inactive accounts (i.e., those with no buys or sells) and those with zero holdings (i.e. zero portfolio value), to leave 2528 individual and 49 institutional investors in our sample.

3.3. Empirical methods

We employ three empirical approaches to investigate the impact of past returns on investors' buy-sell decisions and trading strategies. First, we begin by undertaking an investor-level investigation of trading decisions to determine the effect of prior returns on investors' tendencies to buy or sell stocks. Following Grinblatt and Keloharju (2001) we compare purchases with sales, examining investors' decisions to buy or sell using binary logit models.[8] On each day the investor trades, the dependent variable equals 1 for a sale (whole or partial holding) and 0 for a buy. The models incorporate independent variables capturing cumulative returns of the traded stock over the past week, month, and six months, thus capturing the time series momentum of a given stock.[9] These represent the main variables of interest and provide direct

[5] The investor-level account data is highly sensitive and was made available on the understanding that the brokerage and its clients would remain anonymous. Such data is not easily obtainable and we are unable, unfortunately, to extend the data beyond the current sample period. Our situation is similar to other studies using investor-level data. For example, Kumar (2009) employs investor-level data from 1991 to 1996. While it would be interesting, in part for robustness purposes, to extend our analyses to subsequent time periods, perhaps that pertaining to the 2007–2008 financial crisis, such data is not available to us. However, while the impact of the 2007–2008 financial crisis was felt globally, there is evidence to suggest that the Chinese stock market was not impacted to the same extent as other countries (Wang, 2014; Hasan and Mohammad, 2015). Such findings lead us to believe the financial crisis is unlikely to have changed stock market investment in China fundamentally. Furthermore, while the Chinese stock market has witnessed dramatic shifts during distinct bubble-crash cycles in 2005–2007 and 2008–2009 (Jiang et al., 2010), outside of these episodes the swings in the market are not so dissimilar over time. Shi et al. (2015) find long-term contrarian profits are possible for the period 1997–2012, including sub-period analysis split pre- and post-2007. Hence, while our investor-level account data is from 2001 to 2004, we have no reason to believe that the phenomena at play in the trading behavior we examine are time variant, thus supporting the general applicability of our findings

[6] Daily returns are computed based on log current price divided by log previous closing price, after adjusting for dividends and stock splits.

[7] In 2001, the start of our sample, the number of companies listed with A shares were ten times the number listed with B share and the total market capitalization of A shares was over thirty three times that of B shares.

[8] Grinblatt and Keloharju (2001) also report results from logit models of the sell-hold decision in their examination of the disposition effect, as do O'Connell and Teo (2009) and Grinblatt et al. (2012), for example. Our research question, whether past returns (i.e. stock price movements) impact differentially on the trading strategies investors adopt when buying and selling stock, does not require such an approach.

[9] See Moskowitz, Ooi, and Pedersen (2012) for a discussion of the distinction between time series and cross-sectional momentum.

Table 1
Descriptive statistics by stocks traded by investors in the brokerage data on the Shenzhen and Shanghai exchanges.
This table reports descriptive statistics by stocks traded by investors in the brokerage data. *Number of trades* is the number of trades on each stock by the investors registered with brokerage. *Number of days traded* is the number of days on which each stock was traded by the investors registered with brokerage. *Number of investors* is the number of investors registered with brokerage who traded each stock during the sample period. *Traded shares* is the total number of traded shares of each stock during the period by investors registered with brokerage.

	Shenzhen Stock Exchange				Shanghai Stock Exchange			
	Mean	Median	Lower quartile	Upper quartile	Mean	Median	Lower quartile	Upper quartile
Number of trades	231.55	117.08	60.51	224.11	237.13	107.03	55.92	198.34
Number of days traded	107.09	84.00	48.25	139.00	97.89	76.50	41.00	126.75
Number of investors	33.60	25.00	16.00	41.00	35.12	25.00	16.00	41.00
Traded shares	997,297	277,406	126,428	675,020	882,347	252,044	107,655	578,632

evidence of how past returns impact on investors' buy and sell decisions. Stivers and Sun (2013) examine the effect of market cycles on the profitability of relative strength trading strategies, concluding that profitability tends to be higher within a market state (i.e. bull or bear markets), but lower as markets move between states. They note that short to medium term strategies are less likely to span across market transitions than longer duration strategies. Hence, in light of the evidence in Yan et al. (2007) that the SHSE and the SZSE move through three bull and three bear market cycles during our sample period, we focus our attention on the impact of short to medium term past returns on investors' buy-sell decisions.

Table 2
Descriptive statistics by investor type: Individual and institutional investors.
This table presents descriptive statistics for the two groups of investors; institutions and individuals. The descriptive statistics for all variables are calculated for each investor first, and then averaged across investors. *Number of trades* is the total number of transactions by each investor in the sample period. *Total trading value* is the sum of the trading values for each investor, where trading value equals actual transaction price multiplied by trade volume. *Trade size* is the average trading value per transaction, which is decomposed further between *buy size* (the average trading value per buy transaction) and *sell size* (the average trading value per sell transaction). *Stock position* measures the average beginning-trade-day market values of investors' portfolios. *Number of stocks* in portfolio indicates the number of stocks an investor holds, on average, in their portfolio during the sample period. *Monthly turnover* is calculated as monthly trading value divided by monthly stock position value.

		Investor Type	
		Institution	Individual
Number of trades	Mean	1595.7	72.9
	Median	142.0	22.0
	5th percentile	7.0	1.0
	95th percentile	5040.0	291.0
Total trading value	Mean	81,924,732	1,568,861
	Median	9,325,236	227,123
	5th percentile	91,177	5545
	95th percentile	341,144,263	7,049,793
Trade size	Mean	138,092.1	23,343.1
	Median	57,093.0	9177.5
	5th percentile	11,900.0	1990.9
	95th percentile	368,174.0	83,357.4
Buying size	Mean	210,514.50	22,089.90
	Median	53,334.30	8381.00
	5th percentile	20,974.00	1959.00
	95th percentile	413,354.00	77,246.80
Selling size	Mean	98,494.30	21,506.60
	Median	56,941.90	7966.90
	5th percentile	11,900.00	1928.00
	95th percentile	311,745.00	78,999.50
Stock position	Mean	4,989,803.6	179,163.2
	Median	1,036,187.9	28,098.1
	5th percentile	1085.9	836.9
	95th percentile	18,567,799.9	716,946.1
Number of stocks	Mean	3.84	2.91
	Median	2.90	2.00
	5th percentile	1.00	1.00
	95th percentile	11.10	7.70
Monthly turnover	Mean	2.12	1.01
	Median	0.54	0.33
	5th percentile	0.06	0.04
	95th percentile	9.48	4.33

Prior studies demonstrate that investors display preferences for specific stock characteristics, including firm size, beta, volatility, earnings per share, book-to-market (see e.g., Duxbury et al., 2013; Kumar, 2009; Ng & Wu, 2006). Extending the approach in Grinblatt and Keloharju (2001), we also include in the logit models a range of control variables capturing a variety of stock characteristics[10] to allow a clearer picture of how past returns can influence investors' buy and sell decisions.

We control for a large number of stock characteristics and these can be grouped conveniently into three categories; measures of stock risk[11] (size, stock variance, beta, idiosyncratic risk, P/E ratio, and B/M ratio), measures of stock liquidity (turnover and the percentage of tradable shares) and measures of other stock characteristics (the percentage of state shares, how long the stock has been listed and stock price), which, while not generally considered to be standard risk factors, could reasonably be interpreted as such. We briefly define each of the stock characteristics control variables. *Size* is the log of the market capitalization computed as the total number of shares multiplied by the stock price, while *Turnover* is the average monthly turnover. *B/M* is the book-to-market ratio computed as book value (total assets less total liabilities) divided by the market value of equity (market capitalization) and *P/E ratio* is the price-to-earnings ratio computed as market price divided by earnings per share.[12] B/M and P/E ratio are included to control for growth and value characteristics of the stocks. *Beta* is estimated from the three-factor market model of Fama and French (1993), with monthly stock returns regressed on the market index returns, a firm-size factor and a value-growth factor over the preceding three years (or the period available, if less than this), while *Idiosyncratic risk* is the residual variance from the three-factor model. As noted previously, during our sample, which pre-dates split-share structural reform of 2005, Chinese A-shares can be classified as state-owned shares, legal-person shares, and public shares, with only the latter category of shares tradable on the exchanges, hence we employ two variables to capture these features of ownership structure in China: *%tradable* is the amount of tradable stock as a percentage of total stock and *%state* is the number of state-owned shares as a percentage of total shares. *Listing* is the length of time that the stock has been listed on the exchange. *Price* is the previous day closing stock price, while *Volatility* is the variance of daily returns over the previous six months. Inclusion of these control variables, allows us to isolate the impact of past returns on investors' choice of trading strategies, free from the effect of specific stock characteristics. Such an approach is essential in light of the debate between Conrad and Kaul (1998) and Jegadeesh and Titman (2002) over the role of cross-sectional differences in expected returns and time series dependence in expected returns in relation to momentum profits.

[10] We adopt the same set of stock characteristics as those examined in Ng and Wu (2006) and Duxbury et al. (2013).
[11] Prior studies (see initially Conrad & Kaul, 1998, and more recently Agarwal & Taffler, 2008) suggest that momentum profits may represent compensation for risk, hence it would seem necessary to control for stock risk in order to isolate the impact of past returns on investors' buy-sell decisions.
[12] Book value and earnings per share data are obtained from half-yearly company reports.

In addition, we include dummy variables to control for the reference price effect (Grinblatt & Keloharju, 2001) and the attention effect (Barber & Odean, 2008; Seasholes & Wu, 2007) to remove the possibility that evidence seemingly in support of momentum or contrarian strategies is being driven by investors' reactions to stocks with extreme price changes or merely reflects their reactions to attention grabbing stocks. *Price* > max and *Price* < min are two dummy variables set equal to 1 when the closing price hits the maximal or minimal price over the past month, respectively, and 0 otherwise. *Upper-limit* and *Lower-limit* are two dummy variables set equal to 1 when the current price reaches the upper or lower price limit (±10%), respectively, and 0 otherwise.

Second, we adopt a quintile based analysis (see e.g., Kaniel et al., 2008; Ng & Wu, 2006) for buy and sell decisions separately to examine the percentage of buys and of sells for stocks in quintiles sorted by past returns over one week, one month, and 6 months. In addition to the past returns of the traded stock in question, we also compute the cumulative returns for other stocks in the market. If investors adopt random strategies there should be no differences in the percentage of buys and percentage of sells across the quintiles of past returns. However, a high proportion (>20%) of buys in the top quintile can be regarded as evidence of momentum trades, while high proportion (>20%) of buys in the bottom quintile can be regarded as evidence of contrarian trades. For sells the relationship is reversed.

Third, employing a portfolio-based method similar to Badrinath and Wahal (2002)[13] we compute two strategy measures for each investor based on quintiles of past stock returns. For each investor, the *increase* investment strategy measure is defined as the percentage of the increase in value of stocks within the top quintile over the total increase in portfolio value less the percentage of the increase in value of stocks within the bottom quintile over the total increase in portfolio value, see (1) below. The *decrease* investment strategy measure is defined in a similar way, see (2) below.

$$\text{Strategy measure}_{i,t}^{\text{Increase},T} = \frac{\sum_{S_{i,k,t+1}>S_{i,k,t}}^{R_{k,t}^{T}\in Q5}|S_{i,k,t+1}-S_{i,k,t}|P_{k,t}}{\sum_{S_{i,k,t+1}>S_{i,k,t}}|S_{i,k,t+1}-S_{i,k,t}|P_{k,t}} - \frac{\sum_{S_{i,k,t+1}>S_{i,k,t}}^{R_{k,t}^{T}\in Q1}|S_{i,k,t+1}-S_{i,k,t}|P_{k,t}}{\sum_{S_{i,k,t+1}>S_{i,k,t}}|S_{i,k,t+1}-S_{i,k,t}|P_{k,t}} \quad (1)$$

$$\text{Strategy measure}_{i,t}^{\text{Decrease},T} = \frac{\sum_{S_{i,k,t+1}<S_{i,k,t}}^{R_{k,t}^{T}\in Q5}|S_{i,k,t+1}-S_{i,k,t}|P_{k,t}}{\sum_{S_{i,k,t+1}<S_{i,k,t}}|S_{i,k,t+1}-S_{i,k,t}|P_{k,t}} - \frac{\sum_{S_{i,k,t+1}<S_{i,k,t}}^{R_{k,t}^{T}\in Q1}|S_{i,k,t+1}-S_{i,k,t}|P_{k,t}}{\sum_{S_{i,k,t+1}<S_{i,k,t}}|S_{i,k,t+1}-S_{i,k,t}|P_{k,t}} \quad (2)$$

where $Strategy\,measure_{j,t}^{Increase,T}$ and $Strategy\,measure_{j,t}^{Decrease,T}$ denote increase and decrease strategy measures, respectively, for investor i in month t; $S_{i,k,t}$ is the number of shares of stock k held at the beginning of month t; $P_{k,t}$ is the close price of stock k at the beginning of month t; $R_{k,t}^{T}$ is cumulative return of stock k over the past T days (week, month, or six months) before month t.

By way of illustration, assume in month t that an investor increases their positions on two stocks, A and B, whose prices are $1 and $2 at the beginning of the month, by 100 shares and 200 shares, respectively. Thus, the total increase in share value is $500. Further suppose that the past cumulative return of A is in quintile 1 while that of B is in quintile 5. Then the investment strategy measure for increase of shares is calculated as ($400/$500) − ($100/$500) = 60%. Note that a positive value of the increase strategy measure indicates an investor is more likely to buy stocks with higher past performance (i.e. a momentum strategy) and that a negative value indicates an investor is more likely to invest in stocks with poorer past performance (i.e. a contrarian strategy), while the reverse interpretation holds for the decrease strategy measure in relation to an investor's sell decisions.

Short sale restrictions limit investors' sells to those stocks held in their portfolios, however, investors' buys can theoretically be selected from all stocks traded on the exchanges. While this distinction might potentially bias a comparison across buys and sells, we do not expect this to be problematic due to investors' limited cognitive abilities and their inability to process the mass of information available to them concerning the past performance of all the stocks traded on the exchanges. The finding that investors tend to hold under-diversified portfolios would support this view (e.g. Goetzmann & Kumar, 2008; Polkovnichenko, 2005). Furthermore, it is conceivable that investors' limited cognitive abilities might bias their selection of stocks to buy towards those that grab their attention, while this is less likely to be the case for stocks to sell given the smaller opportunity set available to them (Barber & Odean, 2008). It is for this reason that we include variables in the logit models to control for reference price effects (Grinblatt & Keloharju, 2001) and attention effects (Barber & Odean, 2008; Seasholes & Wu, 2007). We conclude, therefore, that it is appropriate to analyze investors' buy and sell decisions despite theoretical differences across opportunity sets.

4. Empirical results

Following the approach in Ng and Wu (2007), we draw a distinction between institutional[14] and individual investors, categorizing the latter into different classes using the average value of their monthly portfolio as a proxy of wealth level. We define individual investors with average portfolio values of greater than RMB 1,000,000 as the "High wealth" group; those with average position values of greater than RMB 100,000 but less than or equal to RMB 1,000,000 as the "Middle wealth" group, and those with average position values of less than or equal to RMB 100,000 as the "Low Wealth" group. In the empirical analyses to follow we report results for the sample as a whole and for the above classes of investor.

We begin by undertaking an investor-level investigation of trading decisions to determine the effect of prior returns on investors' tendencies to buy or sell stocks. Extending the approach in Grinblatt and Keloharju (2001) to control for a range of stock characteristics, reference price effects and attention effects, we report the results of binary logit models demonstrating that past stock returns have a strong impact on buy-sell decisions (see Table 3). Positive/negative coefficients for past returns indicate a higher/lower likelihood of a sell than a buy decision the higher the value of the coefficient. After controlling for individual stock characteristics and extreme price changes, past stock returns have a strong impact on investors' buy and sell decisions. For investors on the whole, the coefficients for past returns over one week and one month are significantly positive (indicating a higher likelihood of sale), while those for past returns over six months are significantly negative (indicating a higher likelihood of purchase). While there is some difference in the statistical significance of these results across the different classes of investor, the signs of the coefficients are consistent (with the exception of the coefficient on the 6 month return variable for low wealth individuals, which while positive is not significantly different from zero). This initial evidence, therefore, suggests that Chinese investors are contrarian traders in the short term but are momentum traders in the intermediate term and as such complements the results in Kang et al. (2002) of profitable short-horizon contrarian and intermediate-horizon momentum strategies. The inclusion of controls for specific stock characteristics demonstrate that momentum and contrarian trading strategies are not merely manifestations of investors reacting to characteristics of particular stocks (such as variance, turnover, beta, etc.), while controls for extreme price movements demonstrate that

[13] We decompose trades into two categories. An "increase" in the stock position occurs when shares are purchased, irrespective of whether this creates a new position or is an addition to an existing position, while a "decrease" occurs when shares are sold, irrespective of whether the sale reduces an existing position or eliminates it.

[14] Institutional investors here refer to investors that are corporate bodies rather than singularly identifiable individuals.

Table 3
Investor-level analysis of the impact of past returns on investors' trading decisions: Determinants of buy-sell decisions.
This table reports binary logit models of the buy-sell decision. On each day the investor trades the dependent variable equals 1 for a sale and 0 otherwise. Following Ng and Wu (2007) individual investors are split by low, medium and high wealth. Cumulative market-adjusted and market returns are calculated for intervals of one week, one month, and six months. A range of variables are included to control for the impact of disparate stock characteristics on buy and sell decisions. *Size* is the log of the market capitalization, while *Turnover* is the average monthly turnover. *B/M* is the book-to-market ratio and *P/E ratio* is the price-to-earnings ratio. *Beta* is estimated from the three-factor market model of Fama and French (1993), while *Idiosyncratic risk* is the residual variance from the three-factor model. *%tradable* is the amount of tradable stock as a percentage of total stock and *%state* is the number of state-owned shares as a percentage of total shares. *Listing* is the length of time that the stock has been listed on the exchange. *Price* is the previous day closing stock price, while *Volatility* is the variance of daily returns over the previous six months. Four dummy control variables capture reference price effects and attention affects: *Price* > max and *Price* < min equal 1 when the closing price hits the maximal or minimal price over the past month, respectively, while *Upper-limit* and *Lower-limit* equal 1 when the current price reaches the upper or lower price limit (±10%), respectively.

					Individuals					
	All investors		Institutions		High wealth > RMB1,000,000		Middle wealth RMB(100,000, 1,000,000]		Low wealth ≤ RMB100,000	
Variables	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.
Past returns:										
Cumulative market-adjusted returns [week]	0.275	*4.80******	0.925	*1.94*****	1.032	*2.99******	0.559	*5.47******	0.108	*1.51*
Cumulative market-adjusted returns [month]	0.143	*4.05******	0.479	*1.76****	0.455	*2.21*****	0.009	*0.14*	0.204	*4.58******
Cumulative market-adjusted returns [6 months]	−0.037	*−2.34*****	−0.434	*−3.77******	−0.029	*−0.32*	−0.083	*−2.97******	0.003	*0.13*
Cumulative market returns [week]	−0.208	*−2.25*****	2.795	*4.75******	0.570	*1.13*	−0.194	*−1.26*	−0.403	*−3.39******
Cumulative market returns [month]	−0.268	*−4.47******	1.055	*2.79******	−0.050	*−0.15*	−0.315	*−3.15******	−0.322	*−4.09******
Cumulative market returns [6 months]	−0.126	*−5.23******	0.101	*0.67*	0.148	*1.15*	−0.056	*−1.35*	−0.203	*−6.50******
Stock characteristics control variables:										
Size	−0.012	*−3.03******	−0.046	*−1.70****	−0.046	*−2.14*****	−0.006	*−0.94*	−0.011	*−1.13*
Turnover	−0.338	*−5.80******	−0.366	*−0.77*	−1.167	*−3.20******	−0.384	*−3.72******	−0.275	*−3.72******
Beta	−0.018	*−3.46******	−0.045	*−1.75****	−0.038	*−1.31*	−0.011	*−2.15*****	−0.020	*−2.97******
Idiosyncratic risk	−0.714	*−1.40*	−0.471	*−0.25*	0.200	*0.05*	−1.375	*−1.61*	−0.411	*−0.59*
B/M	0.031	*3.64******	0.034	*1.60****	0.068	*1.98*****	0.042	*2.95******	0.018	*1.65****
P/E ratio	3.3E−06	*0.79*	1.1E−04	*2.00*****	7.3E−05	*2.67******	−9.5E−06	*−1.34*	1.2E−06	*0.20*
%tradable	−0.076	*−4.01******	−0.318	*−2.19*****	−0.006	*−0.05*	−0.073	*−2.25*****	−0.066	*−2.72******
%state	−0.002	*−0.42*	0.009	*0.25*	−0.021	*−0.77*	−0.008	*−1.00*	0.004	*0.63*
Listing	1.2E−04	*1.61*	5.7E−04	*1.66****	−4.1E−04	*−1.22*	5.5E−05	*0.53*	1.6E−04	*1.91****
Price	−0.001	*−1.43*	0.008	*1.32*	−0.001	*−0.35*	−0.002	*−1.79****	−0.001	*−1.18*
Volatility	0.569	*0.56*	0.372	*0.04*	−25.817	*−1.25*	4.808	*1.21*	−0.377	*−0.33*
Extreme stocks control variables:										
Price > max	0.291	*34.89******	0.144	*2.48*****	0.250	*5.75******	0.418	*30.04******	0.220	*19.90******
Price < min	−0.389	*−35.98******	−0.311	*−5.01******	−0.201	*−3.68******	−0.469	*−25.57******	−0.354	*−24.60******
Upper-limit	0.200	*8.45******	0.175	*0.93*	0.265	*2.47*****	0.306	*7.64******	0.135	*4.45******
Lower-limit	−0.200	*−4.74******	−0.048	*−0.15*	−0.066	*−0.32*	−0.106	*−1.46*	−0.281	*5.16******
Pseudo–R squared	0.1123		0.0998		0.1035		0.1165		0.1227	

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

nor are they driven solely by reactions to stocks that attract the attention of investors due to extreme price changes.

The above results are found after controlling for specific stock characteristics, along with reference price effects and attention effects. It is informative to consider briefly, so as not to detract from our primary intention of examining the extent to which trading strategies based on past returns might differ across investors' buy and sell decisions, the impact of such stock characteristics on investors' trading decisions in their own right. In respect of stock risk we find that standard measures such as variance and idiosyncratic risk have no differential impact on investors' buy and sell decisions, while the significant, negative coefficients on beta indicate investors have a greater tendency to buy high beta stocks, though this seems to be more the case for low and middle-wealth individuals than institutional or high-wealth individual investors. The B/M ratio has significant, positive coefficients for all category of investor, while and the same is true of the P/E ratio for high wealth and institutional ones, suggesting for these two stock characteristics that higher values are associated with an increased tendency to sell stocks, though to varying degrees. In contrast, the size variable has significant, negative coefficients for high wealth individuals and institutions suggesting an increased tendency for these investor classes to buy stocks of larger firms. Turning to liquidity, both turnover and the percentage of tradable shares have significant, negative coefficients (though there is some difference across investors categories), suggesting an increased tendency to buy stocks with high values for such these characteristics. While the remaining stock characteristics, including the percentage of state shares, listing length and stock price, seem to play little or no role in determining the tendency for investors to buy or sell stock. Our individual investor-level analysis, therefore, provides direct support for Zhou's (2010) suggestion, based on aggregate analyses, that individual investors in China prefer high-volume (turnover) to low-volume stocks (see the negative and significant coefficient on turnover in Table 3, indicating that stocks with higher turnover are associated with a higher likelihood of a buy decision), but does not support the conclusion that they prefer small-size to large-size stocks (see the negative coefficient on size in Table 3).

Consistent with the reference price effect of Grinblatt and Keloharju (2001), it can be seen that whether the price is at a monthly high or a monthly low influences investors' trading decisions, with prices at a monthly high (Price > max) increasing the propensity to sell significantly and prices at a monthly low (Price < min) increasing the propensity to buy significantly for investors in our sample. The attention effect is present in our data for investors in aggregate and is particularly strong for individuals with low wealth levels, but has no impact on institutional investors' trading decisions. Consistent with Seasholes and Wu (2007) we find that when the price of a stock goes up extremely quickly individual investors have a higher propensity to sell the stock. Moreover, extending Seasholes and Wu (2007) to consider extreme downward price movements, we also find that a price hitting the lower price limit increases the propensity to buy a given stock, though this effect is present only for individuals with low wealth levels.

An alternative explanation for the finding that investors are contrarian traders in the short term but are momentum traders in the intermediate term, however, is the possibility that the direction of effect of past

Table 4
Decomposing investors' trading strategies across buy-sell decisions sorted by past returns: A quintile based analysis.
This table presents the percentage of buys and of sells for stocks in quintiles sorted by past returns over one week, one month, and 6 months. Percentages summing to other than 100% are due to rounding errors. For each buy or sell, the stock is sorted in ascending order with all stocks on the market by past returns one week, one month, and 6 months before the trading day. The proportion for each quintile is calculated as the number of buys or sells located in the quintile divided by the total number of buys or sells made by this type of investors. Stocks in higher quintiles have higher past returns than those in lower quintiles. For each quintile *t*-tests evaluate the hypothesis that the percentage is equal to 20%. For the Q5-Q1 difference z-tests evaluate the hypothesis that the difference is zero.

	Buy %						Sell %					
Quintile	Q1 (low)	Q2	Q3	Q4	Q5(high)	Q5-Q1 difference	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5-Q1 difference
Panel A: Week												
All investors	21.1***	15.4***	15.3***	17.4***	30.6***	9.5***	19.7*	15.4***	15.5***	18.4***	30.9***	11.2***
Institutions	20.6	15.6***	16.5***	20.6	26.2***	5.6***	19.7	17.0***	16.4***	20.3	26.6***	6.9***
High wealth individuals	21.1	16.5***	15.5***	17.3***	29.5***	8.4***	18.2**	16.2***	14.8***	19.7	31.1***	12.9***
Middle wealth individuals.	21.2***	16.0***	15.7***	17.5***	29.3***	8.1***	19.2***	15.4***	15.8***	18.4***	31.1***	11.9***
Low wealth individuals	21.0***	15.0***	15.0***	17.1***	31.7***	10.7***	20.2	15.3***	15.4***	18.2***	31.0***	10.8***
Panel B: Month												
All investors	21.1***	14.4***	15.0***	17.8***	31.5***	10.4***	19.1***	14.8***	15.4***	18.1***	32.7***	13.6***
Institutions	20.8	14.7***	16.5***	19.4	28.2***	7.4***	19.6	12.7***	16.3***	19.6	31.9***	12.3***
High wealth individuals	21.5**	15.4***	14.7***	17.5***	30.8***	9.3***	16.9***	15.9***	14.6***	20.2	32.4***	15.6***
Middle wealth individuals.	20.5**	14.8***	15.5***	18.3***	30.7***	10.2***	18.7***	15.0***	15.6***	18.7***	32.0***	13.3***
Low wealth individuals	21.5***	14.0***	14.7***	17.5***	32.2***	10.8***	19.5***	14.7***	15.3***	17.5***	33.2***	13.7***
Panel C: 6 months												
All investors	19.8	14.6***	15.9***	21.0***	28.5***	8.7***	19.3***	14.7***	16.2***	21.0***	28.9***	9.6***
Institutions	18.3**	13.5***	12.9***	21.4*	33.5***	15.1***	18.4*	13.4***	13.7***	20.6	33.9***	15.4***
High wealth individuals	17.1***	14.0***	14.4***	23.5***	30.9***	13.8***	17.0***	14.2***	15.5***	20.8	32.5***	15.5***
Middle wealth individuals.	19.8	15.6***	16.2***	20.5***	27.7***	7.9***	19.5*	15.2***	16.6***	20.5**	28.1***	8.6***
Low wealth individuals	20.1	14.1***	15.9***	21.1***	28.7***	8.5***	19.3***	14.4***	16.0***	21.3***	28.9***	9.5***

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

returns differs across buying and selling decisions. To investigate this we decompose investors' portfolios separately into purchases and sales and examine the distributions of transactions across different quintiles of past stock returns. If investors select stocks randomly (i.e. not based on past stock returns), the proportion of purchases or sales in each quintile should be equal (i.e. 20%), whereas trading based on momentum or contrarian strategies would lead to trades being dispersed unequally across the quintiles (i.e. a greater preponderance of buys/sells in the top return quintile would be expected based on momentum/contrarian trading). The results in Table 4 reject the random distribution of both buys and sells, individually, across return quintiles. While some differences across investor classes and time horizons exist, in general investors are momentum traders when buying stocks. The proportion of buys with high past returns is significantly larger than 20% predicted when distributed randomly (26.2%–33.5%). This holds for all categories of investors in our sample and over all time frames, with the proportion of buys following high returns significantly higher than the proportion of buys following low returns (Q5 and Q1, respectively, in Table 4). While there is some mixed evidence at short-horizons of individual investors being inclined to buy stocks in the bottom quintile too, this is only slightly more so than 20% predicted at random even when statistically significant. In contrast, over intermediate-horizons investors in our sample show evidence of buying on momentum, with institutions and high wealth individuals inclined to buy proportions significantly below 20% in the lowest return quintile. The trading pattern for sells does not mirror that for buys; instead investors are pure contrarian traders and are more likely to sell stocks in the top return quintile. Overall, therefore, the evidence suggests that investors choose to sell those stocks in their portfolios that have performed well (contrarian selling) and to replace these by buying other stocks that have also performed well in the past (momentum buying). While our results are broadly in line with those in Ng and Wu (2007), we find evidence of contrarian trading by institutions when selling and momentum trading by low wealth individuals when buying, which they do not.[15]

The above analysis takes no account of changes in portfolio value, which may explain differences across investor classes. To address this we turn to an analysis of the trading strategy measures as defined in (1)–(2) above, which include total increase in portfolio value in the denominator. The results in Table 5 are clear-cut; all investors in our sample are momentum traders when buying stocks and contrarian traders when selling stocks,[16] thus we extend the findings of Badrinath and Wahal (2002) to include individual investors. After taking account of portfolio value, our findings paint a clearer picture than those in Ng and Wu (2007). When buying stocks there are minor differences across return horizons and investor classes in the extent to which momentum strategies are followed, however, when selling stocks all individual investors follow contrarian strategies irrespective of the past return horizon, while institutions also follow contrarian strategies for return horizons of a month and six months.[17]

Collectively, our empirical results provide strong evidence in favor of rejecting the null hypothesis (H_0) that the trading strategies investors adopt based on past returns are applied consistently to both their buy and sell trades. Investors adopting a momentum-based strategy on their buy side trades do not appear to apply the same strategy to their sell side trades, adopting a contrarian-based strategy instead. Our results, based on a different market setting to that studied in Barber et al. (2009) support and extend their finding that investors buy stocks with strong past performances and also sell stocks with strong recent

[15] Ng and Wu's (2007) sample represents a sub-period of our sample, which may account for differences in findings.

[16] While initially this may appear at odds with notions of equilibrium, in the sense that not all investors can simultaneously be momentum buyers and contrarian sellers, this is not the case. For the transaction of a given stock to take place requires only that the momentum buyer (who buys stocks that rise in value) and contrarian seller (who sells stocks that rise in value) hold heterogeneous expectations at the point of trade about the future performance of the stock in question (though this does not negate that they may hold homogenous expectations about other stocks).

[17] These results are robust to computing the increase strategy measures based only on purchases of stocks new to the portfolio (i.e., stocks whose positions are zero at the beginning of the month) and the decrease strategy measures based only on sales of stocks that clear the position (i.e., stocks whose positions are zero at the end of the month). In fact, the results are even more clear-cut, with intuitions adopting contrarian strategies for sales across all three return horizons.

Table 5
Portfolio-based approach to trading strategy measures: Increases and decreases in stock holdings.
This table presents average monthly investment strategy measures for increases and decreases in stocks holdings based on the past week, month, and six months for different types of investors. Increase in a stock is defined as an increase in the number of shares in the stock in the portfolio, including adding more shares to an existing holding stock and building a new position in the stock, while decrease in a stock is defined as a decrease in the number of shares in the stock in the portfolio, including selling part of an existing holding of the stock and selling the whole holding. For each investor, the *increase* investment strategy measure is computed as the percentage of the increase in value of stocks within the top quintile over the total increase in portfolio value less the percentage of the increase in value of stocks within the bottom quintile over the total increase in portfolio value and the *decrease* investment strategy measure is computed in a similar way, see Eqs. (1) and (2), respectively, in the discussion of empirical methods.

	Increase strategy measure			Decrease strategy measure		
	Week	Month	6 months	Week	Month	6 months
All investors						
Mean	0.82%	3.63%	7.22%	4.68%	6.45%	9.48%
T-statistic	1.11	4.53***	8.45***	6.80***	8.63***	11.78***
Institutions						
Mean	3.35%	8.95%	14.97%	6.76%	10.89%	23.29%
T-statistic	0.67	1.19	1.87*	1.41	1.81*	3.24***
High wealth individuals						
Mean	1.96%	12.66%	12.44%	8.25%	8.91%	17.32%
T-statistic	0.46	2.71***	2.28**	2.88***	1.82*	3.28***
Middle wealth individuals						
Mean	1.76%	7.17%	11.15%	6.06%	6.97%	13.20%
T-statistic	1.26	4.95***	7.15***	4.84***	5.05***	8.45***
Low wealth individuals						
Mean	0.43%	2.28%	5.85%	4.14%	6.09%	8.07%
T-statistic	0.48	2.38**	5.75***	5.05***	6.89***	8.57***

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

returns, after controlling for stock characteristic preferences, along with attention and reference price effects, thus adding credence to the robustness of the effect.

5. Conclusions and discussion

While momentum or contrarian trading strategies have been shown to be profitable in a number of market settings, there is less direct evidence concerning the actual trading strategies adopted by investors. Those studies that do examine investors' trading strategies tend to focus on institutional investors more so than individual investors and relatively few studies draw a distinction between the trading strategies investors adopt for buy versus sell decisions. Using investor-level, transaction-based data from China, where the tax system is neutral in its effect on investor behavior, this paper examines whether past returns impact differentially on investors' buy and sell decisions. We combine the approaches of Grinblatt and Keloharju (2001) and Badrinath and Wahal (2002), providing a transaction-based analysis of investors' buy-sell decisions with an investigation of how past returns impact investors' decisions to add to or reduce existing stock holdings in their portfolios, based on trading strategy measures that control for changes in portfolio value.

We extend prior findings in a number of ways. First, controlling for individual stock characteristics and the effect of stocks with extreme price changes, we demonstrate that past returns have a strong impact on investors' tendencies to buy and sell given stocks. For past returns over one week and one month there is a higher likelihood of sale following positive price movements, while for past returns over six months there is a higher likelihood of purchase, thus supporting the view that Chinese investors are contrarian traders in the short term but are momentum traders in the intermediate term, which complements the findings in Kang et al. (2002) of profitable short-horizon contrarian and intermediate-horizon momentum strategies. Second, by including controls for stock characteristics, reference price effects and attention effects, we demonstrate that the adoption of momentum or contrarian trading strategies is not merely an artifact of investors' reactions to characteristics of particular stocks nor is it driven purely by an attraction to attention grabbing stocks with extreme price changes. Third, while some differences across investor classes and time horizons exist, investors are momentum traders when buying stocks. However, when selling stocks investors are pure contrarian traders, being more likely to sell stocks in the top return quintile, for all investor classes and time horizons. Fourth, extending the analysis of Badrinath and Wahal (2002) from institutions to include individual investors, the primary contribution of this paper is the finding of a clear asymmetry in the adoption of investment strategies, with all investors in our sample simultaneously following momentum strategies when buying stocks to add to their portfolios and contrarian strategies when selling stocks. Controlling for portfolio value provides a clearer picture of the impact of past returns on the adoption of disparate trading strategies across buy and sell decisions. Fifth, we use investor-level, transaction-based data from China, where tax effects are neutral, thus isolating the impact of past returns from the effect of tax motivated trading behavior. We provide conclusive evidence, therefore, to refute the null hypothesis that the trading strategies investors adopt based on past returns are applied consistently to both their buy and sell trades. Barber and Odean (2011) review the trading behavior and performance of individual investors, concluding in aggregate that their performance, even pre-transaction costs, tends to be poor, thus suggesting that individual investors make subpar trading decisions. The evidence reported here that individual investors do not consistently apply either momentum or contrarian based trading strategies, which have been shown to be profitable in a variety of institutional settings and over a range of time horizons, to both their buy and sell decisions likely plays a contributory role in this poor trading performance.

The asymmetry of trading strategies across investors' buy and sell decisions might be explained by behavioral and cultural factors, we consider these next. The extent to which investors succumb to behavioral biases such as the “hot hand fallacy” and “gambler's fallacy”[18] might have a role to play in understanding our findings. At the heart of such behavior are beliefs about sequence trend and whether this will continue or reverse. Prior studies examining implicit beliefs about how things develop and change over time suggest such beliefs are influenced by cultural difference. Ji, Nisbett, and Su (2001), for example, report that North Americans believe that objects or events tend to remain in their current state (i.e. objects currently in motion will remain so at the same rate and in the same direction), hence they tend to believe in trend continuation. In contrast, Chinese tend to believe that objects are constantly changing, both in rate of change and direction of travel, hence they tend to believe in trend reversal. Ji, Zhang, and Guo (2008) provide an experimental investigation of cross-cultural differences examining hypothetical intention to buy and intention to sell decisions based on increasing, decreasing and stable price trends. While such a study does not draw comparisons across buy and sell decisions, and so does not speak directly to our research question, it does suggest cultural differences in beliefs about price trends might be important determinants of investment decisions. While, for simple price trends, Ji et al. (2008) find that Chinese participants (students) were more likely to indicate intention to buy/sell stocks with decreasing/increasing price

[18] The “hot hand fallacy” is a mistaken belief that a trend will continue (i.e. positive correlation between previous and subsequent outcomes or events), while the “gambler's fallacy” is a mistaken belief that a trend will reverse (i.e. negative correlation between previous and subsequent outcomes or events). Such biases have informed the development of behavioral models of under and overreaction of stock prices (e.g. Barberis, Shleifer, & Vishny, 1998).

trends than North American participants, for more complex (or more realistic) price trends with distinct reversals, they find that Chinese participants were less/more likely to indicate intention to sell stocks with increasing/decreasing price trends than North American participants following an early reversal. When replicating intention to sell decisions with actual investors, Ji et al. (2008) Chinese investors were less likely to indicate intention to sell then North American investors for falling stock, but more likely to indicate intention to sell for rising stocks, though this latter difference was not statistically significant. Our finding of contrarian selling behavior for the Chinese investors we examine fits well with the experimental results in Ji et al. (2008), especially in those situations where comparisons are most valid, i.e. those based on more complex (or realistic) price trends and those reported for actual investors. While our finding of momentum buying behavior might seem not to fit with the experimental evidence on intention to buy, it must be noted that the results in Ji et al. (2008) are based on cross-cultural comparisons (i.e. differences in buy decisions across Chinese and North Americans) and as such do not support the view that Chinese are contrarian buyers, hence there is no contradiction between the two sets of results.

In an attempt to explain prior evidence that anomalies such as the momentum effect and the disposition effect, among others, are observed across the world's financial markets to varying degrees, Arkes, Hirshleifer, Jiang, and Lim (2010) extend their earlier work on reference point adaptation[19] (Arkes, Hirshleifer, Jiang, & Lim, 2008), to examine cross-cultural differences between Asians and Americans. In support of their earlier results, Arkes et al. (2010) report evidence of an asymmetric adaptation of reference points, with participants in all countries exhibiting greater adaption after a gain than after an equal-sized loss, but also note cross-cultural differences. Motivated by the contrarian tendency of Chinese investors demonstrated by Ji et al. (2008), Arkes et al. (2010) predict, and find, that Asian participants' reference prices adapt less to gains (increasing stock prices) and losses (decreasing stock prices) than those of Americans after a forced sale intervention designed to close the mental account for a prior outcome. While explanations of the asymmetry of trading strategies based on cross-cultural differences, either in beliefs about trends or adaptation of reference points, might suggest our findings are specific to the Chinese investors we study, Arkes et al.'s (2010) evidence of cross-cultural similarities, as well as differences, suggests such behavior is likely to be observed in other cultures and in stock markets more generally, though perhaps to varying extents. We leave it to future research to explore this further.

Our finding of asymmetric trading strategies, in particular momentum buy decisions, is in line with evidence suggesting individuals perceive variability or volatility differently in rising and falling sequences. Examining sequences (e.g. stock prices) with identical variance, but where one is the mirror image of the other thus changing sequence directionality, Dolansky and Vandenbosch (2012) find that sequences of increasing utility (e.g. rising prices and positive returns) are judged to be less variable than sequences of decreasing utility (e.g. falling prices and negative returns). Thus the adoption of momentum trading strategies when buying might be driven by a desire to reduce perceived risk or volatility (see Duxbury & Summers, 2017, for further discussion on how price sequences inform perceptions of risk and volatility, along with evidence that the two are not necessarily synonymous), with momentum buying perceived as lower risk than contrarian buying. Such an explanation, based on experimental findings in studies not confined to Chinese participants, would suggest the asymmetry of trading strategies across buy and sell decisions we report here need not be restricted to Chinese investors, but might hold more generally. Indeed, partial or indirect support of this view is provided by Grinblatt and Keloharju (2001) and Barber et al. (2009) in the context of Finnish and US investors, respectively.

[19] Reference points play a prominent role in prospect theory, a key psychological building block permeating many behavioral finance models (Duxbury, 2015).

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