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The trading behavior of institutions and individuals in Chinese equity markets

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Abstract

This paper employs a unique data set to analyze the trading behavior of 4.74 million individual and institutional investors across Mainland China. Results show that groups of individual investors with varying trade values (as proxies for wealth levels) engage in different trading strategies. Chinese institutions are momentum investors, while less wealthy Chinese individual investors at large are contrarian investors. The results also indicate that a small group of wealthiest Chinese individuals tend to behave like institutions when they buy stocks, and behave like less wealthy individuals when they sell. Furthermore, only the trading activities of institutions and of wealthiest individuals can affect future stock volatility, but those of Chinese individual investors at large have no predictive power for future stock returns.

JEL classification: G11; G15

Keywords: Trading behavior; Momentum and contrarian strategies; Stock volatility

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1. Introduction

Financial economists are often intrigued by the trading behavior of institutional and individual investors in financial markets. The recent availability of more proprietary data has afforded researchers the opportunity to empirically examine the issue. Much of the evidence shows that past price performance significantly influences how institutions and individuals trade. Existing findings indicate that institutions and individuals differ systematically in their reactions to past price performance and in the degree to which they follow momentum and contrarian strategies.

A number of empirical studies examine the behavior of institutions, but produce somewhat mixed results. Grinblatt et al. (1995), while not Lakonishok et al. (1992) and Gompers and Metrick (2001), find evidence of positive feedback trading by US institutions. Other studies, on the other hand, investigate the behavior of individual investors and provide evidence that individual investment choices are also affected by past stock performance. Odean (1998, 1999) and Barber and Odean (2000) find that on average individual investors are "antimomentum" investors. Griffin et al. (2003) examine the trading behavior of of both US individuals and institutions, and show that institutional buying, while individual selling, reveals strong momentum investing.

Some researchers look at the trading behavior of investors in foreign markets. Choe et al. (1999) find daily positive-feedback trading by Korean institutional investors but short-run contrarian trading by Korean individual investors. Grinblatt and Keloharju (2001) document that Finnish domestic investors, generally, tend to be contrarian investors, while foreign investors tend to be momentum traders. Shapira and Venezia (2006) focus on the trading behavior of Israeli investors and find that individuals increase, while institutions transact fewer, sells and buys after the weekend.

While the existing results offer important insights into the differential trading behaviors of institutional and individual investors, they focus mainly on developed markets. Except for Korea and Israel, there is little research on emerging markets, possibly due to the difficulty of obtaining similar data on these markets. In this study, we employ a new unique data set that allows us to examine the equity trading behaviors of individual and institutional investors in Mainland China. There are two key reasons why studying Chinese equity markets is important and how this study contributes to the existing literature.

First, China has the largest and one of the fast growing economies in the world. Its two domestic stock exchanges, the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE), were only established in December 1990 and July 1991, respectively. With robust developments over the last decade, the combined market capitalization of the two exchanges has grown from Renminbi (RMB) 104 billion in 1992 to RMB 3.83 trillion in 2002,[2] with corresponding increase in annual market turnover from RMB 68.1 billion to RMB 2.8 trillion. Also, the number of domestic investor accounts has increased from 2.2 millions to 68.8 millions; 99.5% of the latter are individual accounts and 0.5% are institutional accounts (Chinese Securities Depository & Clearing Co. Ltd, 2002). The Chinese equity markets are clearly dominated by individual investors, compared to developed equity markets where a form of polarization between individual and institu-

[2] During our sample period, the Chinese currency Renminbi was pegged to the US dollar at 8.28. On 21 July of 2005, China relaxed its currency's peg to the dollar by revaluing it against a basket of currencies.

tional investors is evident. Given the short history of the local markets, the Chinese investors' trading experiences and hence levels of sophistication are unlikely to be comparable with those of investors from developed markets. This unique institutional setting motivates us to examine whether the large group of Chinese individual investors behave like other individual investors from developed markets.

Second, our analyses employ detailed information of the orders executed on the SHSE.[3] The trade records contain account identifiers that allow us to differentiate the trades executed by institutions and individual investors. Our data set contains 77.12 million trades of A shares executed by 7.24 million institutional and individual investment accounts across Mainland China for the period April 2001 through August 2002. The turnover of our sample constitutes at least 32% of the total market turnover, but more importantly, the distribution of individual and institutional accounts in our sample is similar to the overall distribution of the investor population in Mainland China. It is important to emphasize that our large sample of investor trade records not only allows us to perform a comprehensive and thorough analysis of the trading patterns of individual investors, but also increases our power to detect any similarities or differences in their trading patterns. We recognize that there might be many other important influences on any given trading activity, and some variation in trading activity might be driven by individual investors' behavioral biases as well as economic events and news. Given the high variability of trading activities, it is critical to maximize power by employing a large number of trades executed by a large investing group of individual investors.

To facilitate our analyses, we classify the large cross-section of individual investors into three groups based on their average trade values. With no margin trading and short-selling permitted in Chinese equity markets, an investor's average trade value ought to serve as a reasonably good proxy for her wealth level. Results show that past positive and negative stock returns exhibit differential effects on the buy and sell decisions of individual and institutional investors. While Chinese institutions act as momentum traders when they buy and sell stocks, individuals with varying trade values exhibit different trading behaviors. For example, less wealthy individuals behave as contrarian investors in general, whereas wealthiest individuals behave like institutions when they buy but like less wealthy individuals when they sell.

Our study further shows that only the net buying of stocks by wealthiest individuals and the net selling by institutions help decrease future stock volatility. There is some evidence that institutions act as net sellers of some stocks whose net buyers are the wealthiest individuals. In contrast, the majority of individual investors who are less wealthy and are small players in the market exert no significant influence on stock volatility. Moreover, there is no evidence that institutional and individual investor trades have return predictability. The lack of return predictability is probably due to the speculative nature of Chinese equity markets (see Mei et al., 2005) and the relatively inexperienced Chinese individual investors.

The remainder of the paper is organized as follows. Section 2 describes our sample data and variables that we employ in our analyses. Section 3 discusses the methodology and the results. Section 4 looks at the impact of investor trading behavior on future stock volatility and returns, and the final section summarizes.

[3] This information is similar to that contained in the NYSE's Consolidated Equity Audit Trail data.

2. Data and variable definitions

2.1. Sample description

This study employs a sample of daily trading data that are compiled by the SHSE for the purpose of audit trail between the Exchange and member brokerage firms. Given the large scale of trading records, it is impossible for SHSE and also, as we understand, it is not their policy to provide all trading information to their subscribers. Our sample therefore contains daily detailed records of 77.12 million trades of SHSE A shares transacted by 7.24 million institutional and individual brokerage accounts across Mainland China for the period April 2001 through August 2002.[4]

Each trade record contains in detail all key elements of a stock transaction, including the stock code, the number of shares purchased or sold, the execution price and date, and an account identifier. Based on the account identifiers, 99.5% of the accounts are individual investor accounts, and the remaining 0.5% are institutional accounts. The compositions of individual and institutional brokerage accounts are similar to the aggregate proportions of individual and institutional accounts reported by Chinese Securities Depository & Clearing Co. Ltd in 2002.

2.2. Trading activity, trade size, and investors

We focus on the trade records of only active investors that have at least one buy and one sell transactions during the entire sample period. As a result, our sample size is reduced to 4.72 million individual investor accounts and 11.6 thousand institutional accounts, and this selected sample shall be used throughout this study. Because of the exceptional size of individual investors trades, it is computational infeasible to perform the statistical analysis on the cross-section at the investor level. For this reason, we aggregate our data on investors at the trade value level, as this criterion provides a means to gauge their wealth level.

In China, margin trading is prohibited, and this restriction suggests that individuals can only trade with immediate cash available. However, this does not necessarily preclude them from borrowing externally to finance their stock purchases. Whether individuals use their cash savings or external borrowing, their available cash holdings and borrowing ability ought to reflect, to a certain extent, their wealth level. Hence we divide individual accounts into three groups based on their average trade values. Individual investors with average trade values of greater than or equal to RMB 50,000 are in the ‘Largest Group’, those with average trade values of greater than or equal to RMB 10,000 but less than RMB 50,000 are in the ‘Middle Group’, and finally, those with average trade values of less than RMB 10,000 are in the ‘Smallest Group’.

Panel A of Table 1 summarizes the aggregate trade-record statistics of various investor categories, and Panel B breaks down the statistics by type of trading activity. Only about 0.24% (11,586) of our sample investment accounts are institutions, about 7% (319,675) are individual investors with average trade values of at least RMB 50,000, and about 56%

[4] The turnover of our sample stocks accounts for approximately 32% of the total market turnover of A shares traded on SHSE.

Table 1
Trade records, institutions, and individual investor groups

	Institutions	Individual investors grouped by trade value		
		Largest	Middle group	Smallest
Panel A: aggregate statistics				
No. of accounts	11586 (0.24%)	319675 (6.75%)	1767112 (37.32%)	2636871 (55.69%)
No. of trades†	0.24 (0.33%)	5.12 (6.93%)	29.73 (40.21%)	38.84 (52.53%)
Value of trades‡	98.12 (6.16%)	687.08 (43.13%)	584.46 (36.68%)	223.54 (14.03%)

	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Panel B: statistics by type of trading activity								
No. of trades †	0.12	0.12	2.61	2.51	15.65	14.07	20.57	18.27
No. of shares traded ‡	14.03	12.8	43.18	42.77	32.47	31.47	12.95	12.22
Trade value ‡	51.99	46.13	348.37	338.72	298.44	286.02	115.52	108.03

Panel A shows the total number of accounts and the total number and value of trades across institutions and different groups of individual investors, with their value/number as a fraction (in %) of the overall sample reflected in parentheses. We divide the sample of 4.72 million individual investor accounts into 3 groups based on the average trade value. Individual investors with average trade value of greater than or equal to RMB 50,000 are in the 'Largest Group', those with average trade value of greater than or equal to RMB 10,000 but less than RMB 50,000 are in the 'Middle Group', and finally, those with average trade value of less than RMB 10,000 are in the 'Smallest Group'. Panel B shows the statistics by type of activity. The sample period is between April 2001 and August 2002. The † and ‡ symbols denote that the value (or number) is expressed in millions and billions, respectively.

(2,636,871) with average trade values of less than RMB 20,000. The remaining 37% of individual investors have mean trade values of between RMB 10,000 and RMB 50,000. This ordering of average trade values across investor categories almost corresponds to the ordering of the groups' number of trades. The trading volumes of the top two individual investor groups account for about 80% of the total trade value of the sample, and that of institutions accounts about 6%. Panel B shows evidence of more buying than selling of shares of stocks across all investor categories.

2.3. Returns and control variables

We employ two other databases to obtain stock returns and stock-specific news announcements: (i) daily stock returns from Datastream, and (ii) stock-specific news announcements from Fen Xi Jia database. We use 8 past market-adjusted positive and negative return variables over 4 non-overlapping trading-day intervals, which include $R(-1)$, $R(-2,-5)$, $R(-6,-27)$, and $R(-28,-119)$.[5] For example, $R(-1)$ denotes the one-day holding-period return prior to the trading day, and $R(-28,-119)$ represents the holding-period return that is calculated between 28 and 119 days prior to the trading day.

[5] Time 0 is excluded because the data contain no information to differentiate effects of intra-day returns on investor trade imbalances from effects of investor intra-day behavior on contemporary price patterns. Also, the return computations exclude non-trading days such as public holidays and stock-specific trading halts.

Daily market-adjusted past returns on individual stocks are calculated as the raw returns on a stock in excess of the corresponding returns on the SHSE composite index.[6] The choice of these varying return holding periods primarily stems from the preliminary analyses indicate that long-horizon past stock returns have little influence on the investors' current investment decisions.

Our analyses also include a number of control variables that are previously found to affect investor trading behavior. There is overwhelming evidence that stock-specific "good" and "bad" news can influence investor trading decisions. To control for such news, we include dummies that identify whether the contemporaneous and one-day lagged stock-specific news announcements are "good" or "bad". Similarly, we also include dummies to capture day-of-the-week effects (excluding Wednesday), a dummy for a stock's initial public offering effects, and finally two dummy variables for "reference point" effects, which equal one if the stock price is at the monthly highest or lowest level and zero otherwise.

2.4. Measures of investor trading activities

To gauge how investors buy and sell stock i at time t, we examine their excess buys ($\mathrm{XB}_{i,t}$) and excess sells of the stock ($\mathrm{XS}_{i,t}$), separately. For this purpose, we employ slight variations of the excess buying and selling measures introduced by Lakonishok et al. (1992), and the two measures for each investor group G are constructed as follows.

$$\mathrm{XB}_{i,t}^{G} = \mathrm{NB}_{i,t}^{G} - E(B_{i,t}^{G}), \tag{1}$$

$$\mathrm{XS}_{i,t}^{G} = \mathrm{NS}_{i,t}^{G} - E(S_{i,t}^{G}), \tag{2}$$

where

$$\mathrm{NB}_{i,t}^{G} = \frac{\sum_{g=1}^{N_G}\mathrm{Buy}_{i,t}^{g} - \sum_{g=1}^{N_G}\mathrm{Sell}_{i,t}^{g}}{\sum_{g=1}^{N_G}\mathrm{Buy}_{i,t}^{g} + \sum_{g=1}\mathrm{Sell}_{i,t}^{g}},$$

$$\mathrm{NS}_{i,t}^{G} = \frac{\sum_{g=1}^{N_G}\mathrm{Sell}_{i,t}^{g} - \sum_{g=1}^{N_G}\mathrm{Buy}_{i,t}^{g}}{\sum_{g=1}^{N_G}\mathrm{Buy}_{i,t}^{g} + \sum_{g=1}^{N_G}\mathrm{Sell}_{i,t}^{g}},$$

$\mathrm{Buy}_{i,t}^{g}$ and $\mathrm{Sell}_{i,t}^{g}$ are the respective dollar purchase and dollar sale of stock i by investor g ($g = 1,\ldots,N_G$) in Group G; the superscript N_G denotes the number of investors in group G. $E(B_{i,t}^{G})$ and $E(S_{i,t}^{G})$ are the average values of $NB_{i,t}^{G}$'s and $\mathrm{NS}_{i,t}^{G}$'s for all stocks that investor group G trades at time t, respectively. In (1) and (2), we have adjusted for the group's average excess buying and selling of all stocks at time t. As a result, an investor group G's excess buying and selling of stock i, $\mathrm{XB}_{i,t}^{G}$ and $\mathrm{XS}_{i,t}^{G}$, reflect their net buying and net selling of stock i in excess of their respective average net buying and net selling of all stocks at time t.

3. Investor trading behavior and past stock returns

3.1. Investor buy and sell decisions

We employ panel data (cross-sectional and time series) fixed effects ordinary least-square (OLS) regressions to examine how various Chinese investor groups trade relative

[6] The SHSE Composite index consists of all stocks listed on the SHSE.

to past stock performance.[7] The dependent variables are excess buys and excess sells of each investor group, as defined in Eqs. (1) and (2), respectively. The independent variables are past positive (negative) stock performance over varying time intervals and all stock-specific controls. Results are offered in Table 2, with t – statistics adjusted for panel-corrected standard errors (PCSE) reported in parentheses.

Table 2 shows systematic and consistent patterns of past-returns effects on the trading activities of different groups of investors. Both positive and negative past returns play a significant role in investor trading decisions, but their roles vary across investor categories and across trading horizons. The trading patterns suggest that Chinese institutions act as momentum traders when they buy and sell stocks – the larger the recent positive past market-adjusted returns of a stock, the larger is the institutional sale of the stock. The coefficient on $R(-1)$ associated with regressions for institutions is 0.69 with PCSE-adjusted t – statistic of 2.2, whereas their counterpart return coefficients of longer horizons are all statistically insignificant. In contrast, the larger negative returns of up to the past month have a negative impact on institutional sale. That is, institutions sell more poorly performing stocks; the associated coefficients on $R(-2,-5)$ and $R(-6,-27)$ are -0.49 and -0.17 and are at least statistically significant at the 10% level.

Like institutions, wealthiest individuals also pursue momentum investing, especially in the buys than sells. Unlike institutions, their momentum investing is more pronounced in the sense that past returns of up to the past week have a statistically significant influence on their buying decisions. The buy coefficients on both $R(-1)$ and $R(-2,-5)$ for this group of investors are positive and highly significant. However, the effects of past negative returns on their selling decisions are less distinct. It is apparent that they act more like contrarians when past stock performance is poor; their sell coefficients on $R(-2,-5)$ and $R(-6,-27)$ are positive and statistically significant at the 10% level.

One can argue that momentum investing by both wealthiest individual investors and institutions might be driven by stealth trading. It is likely that these investors strategically split their trades into smaller quantities across time in order to reduce execution costs (see Chan and Lakonishok, 1995; Keim and Madhavan, 1995). To rule out this possibility, we have re-estimated the models of Table 2 by incorporating the past-week trading activities of both groups of investors. After controlling for lagged trading effects, the unreported results still show significant momentum investing.

Finally, the majority of individual investors, who consist of about 93% of the investing population, are largely contrarians. They tend to decrease their purchases of winner stocks and also decrease their sales of loser stocks. For these two groups of investors, their buy coefficients are all negative and sell coefficients are all positive, and both buy and sell coefficients are statistically significant at conventional levels. Decreasing sales of loser stocks by individual investors, but not institutions, might suggest that the former are prone to the disposition effect of Shefrin and Statman (1985). Individual investors might tend to hold on to losing investments too long, and this inference is in line with the findings of Shapira and Venezia (2001) who show stronger disposition effects in the trades of amateurs than professionals.

[7] We also estimated random effects models and fixed effects logit regressions. The dependent variable of fixed effects logit models is a binary variable that equals one if an investor group's excess buy (sell) of a stock, $XB_{i,t}^{G}$ ($XS_{i,t}^{G}$), is positive and zero otherwise. Their unreported results were qualitatively the same as those reported in the paper.

Table 2
Investor trading decisions and past stock returns

	Institutions		Individual investors grouped by trade value					
			Largest		Middle		Smallest	
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
$R(-1)$	0.690*	−0.384	0.941*	−0.481*	−0.430*	1.477*	−2.725*	2.882*
	(2.22)	(−0.98)	(8.54)	(−4.08)	(−6.88)	(22.3)	(−39.2)	(38.8)
$R(-2,-5)$	0.188	−0.494*	0.137*	0.088	−0.503*	0.710*	−0.967*	0.821*
	(1.26)	(−2.72)	(2.67)	(1.71)	(−17.2)	(24.6)	(−29.8)	(25.4)
$R(-6,-27)$	0.080	−0.170	−0.034	0.098*	−0.189*	0.251*	−0.322*	0.263*
	(1.01)	(−1.91)	(−1.31)	(3.86)	(−12.7)	(17.5)	(−19.4)	(16.4)
$R(-28,-119)$	−0.068	0.067	−0.043*	0.024	−0.089*	0.107*	−0.094*	0.121*
	(−1.17)	(1.14)	(−2.67)	(1.41)	(−9.71)	(11.2)	(−9.22)	(11.3)
R^2	0.07%	0.08%	0.31%	0.28%	0.63%	1.14%	3.30%	3.14%
NObs	50004	50004	175527	175527	182115	182115	181755	181755

The table reports estimates of fixed effects OLS regressions of excess buying ('Buy') and excess selling ('Sell') of stocks by type of investor group. The dependent variables are excess buys and excess sells of each investor group, as defined in Eqs. (1) and (2) of the text, respectively. The independent variables are market-adjusted past returns calculated for 4 non-overlapping trading horizons, and 11 control variables. The control variables include two dummy variables for contemporaneous stock-specific "good" or "bad" news announcement and two for lagged news announcements; four dummy variables for day-of-the-week effects (excluding Wednesday); one dummy variable for a stock's IPO effect, which equals one at the date of public-listing and zero otherwise; and two dummy variables for 'reference point' effects, which equal one if the stock price is at the monthly highest or lowest level and zero otherwise. The approach used in classifying individual investors into 3 trade-value groups is given in Table 1. The sample period is between April 2001 and August 2002. t-statistics are based on panel corrected standard errors, NObs is the number of observations, and * symbol indicates 5% level of significance.

3.2. Investor trading of large and small stocks

Thus far, our analysis does not distinguish investor trading of small versus large stocks. Existing evidence has shown that institutions prefer large to small stocks (see Gompers and Metrick, 2001; Chan et al., 2005), and that individual investors tend to tilt their investments toward small stocks (see Barber and Odean, 2000). We therefore examine whether the buying and selling decisions of various investor groups found earlier are driven by firm size. To perform this analysis, we divide all stocks into three groups by market capitalization: the small-stock group contains the bottom 30% of stocks with the smallest market capitalization, the large-stock group contains the top 30% of stocks with the largest market capitalization, and the middle group contains the remaining stocks. Information on the market capitalization of all stocks is obtained from the information center of Shenzhen Securities Information Co., Ltd, a subsidiary of SZSE.

In Table 3, we report fixed effects OLS regression estimates of past-return effects on the buy and sell decisions of small stocks (Panel A) and of large stocks (Panel B); the format is similar to that of Table 2. Given that we intend to delineate the similarities or differences in the investment choices of various investor groups for small vs. large stocks, we do not report the results for the middle 40% of the ranked market-capitalization stocks.

A few systematic patterns emerge from Table 3, and in general, they are similar to those presented in Table 2. The results show corroborating evidence that institutions tend to be

Table 3
Investor trading of small vs. large stocks and past stock returns

	Institutions		Individual investors grouped by trade value					
			Largest		Middle		Smallest	
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Panel A: buying and selling of small stocks								
$R(-1)$	0.803	−2.434*	0.604*	−0.722*	−0.457*	1.364*	−2.560*	2.892*
	(1.21)	(−2.99)	(2.94)	(−3.35)	(−3.91)	(11.2)	(−20.0)	(21.6)
$R(-2,-5)$	1.145*	−0.816*	−0.026	−0.024	−0.573*	0.771*	−0.858*	0.828*
	(3.68)	(−2.12)	(−0.26)	(−0.25)	(−10.5)	(14.7)	(−14.2)	(14.4)
$R(-6,-27)$	−0.249	−0.482*	−0.170*	0.052	−0.240*	0.270*	−0.297*	0.255*
	(−1.43)	(−2.43)	(−3.36)	(1.13)	(−8.41)	(10.4)	(−9.47)	(8.95)
$R(-28,-119)$	0.085	0.036	−0.089*	−0.037	−0.127*	0.098*	−0.129*	0.131*
	(0.66)	(0.30)	(−2.94)	(−1.23)	(−7.47)	(5.67)	(−6.91)	(6.92)
R^2	0.33%	0.34%	0.25%	0.22%	0.58%	1.05%	2.44%	2.62%
NObs	10903	10903	50826	50826	53975	53975	53806	53806
Panel B: buying and selling of large stocks								
$R(-1)$	−0.753	−0.870	1.404*	−0.345	−0.544*	1.845*	−3.236*	3.394*
	(−1.54)	(−1.36)	(7.41)	(−1.60)	(−4.98)	(15.0)	(−26.1)	(24.1)
$R(-2,-5)$	−0.083	−0.734*	0.262*	0.144	−0.445*	0.775*	−1.076*	0.964*
	(−0.35)	(−2.41)	(2.98)	(1.51)	(−8.80)	(14.2)	(−18.8)	(15.5)
$R(-6,-27)$	0.145	−0.541*	0.040	0.198*	−0.096*	0.277*	−0.273*	0.354*
	(1.20)	(−3.44)	(0.91)	(4.04)	(−3.78)	(9.90)	(−9.49)	(11.1)
$R(-28,-119)$	−0.076	−0.059	−0.080*	0.170*	−0.053*	0.155*	−0.048*	0.114*
	(−0.86)	(−0.62)	(−2.77)	(5.65)	(−3.21)	(9.01)	(−2.57)	(5.84)
R^2	0.16%	0.22%	0.47%	0.42%	0.86%	1.62%	4.62%	4.24%
NObs	20685	20685	54976	54976	55939	55939	55886	55886

The table shows estimates of fixed effects OLS regressions of excess buying ('Buy') and excess selling ('Sell') of stocks by type of investor group on small- and large-sized stocks; those of medium-sized stocks are unreported. Stocks are categorized into 'large', 'medium' and 'small' stock groups based on the stock's market value as of 2000. Panels A and B present estimates for small and large stocks, respectively. The dependent variables are excess buys and excess sells of each investor group, as defined in Eqs. (1) and (2) of the text, respectively. The independent variables are market-adjusted past returns calculated for 4 non-overlapping trading horizons, and 11 control variables, which include two dummy variables for contemporaneous stock-specific ''good'' or ''bad'' news announcement and two for lagged news announcements; four dummy variables for day-of-the-week effects (excluding Wednesday); one dummy variable for a stock's IPO effect, which equals one at the date of public-listing and zero otherwise; and two dummy variables for 'reference point' effects, which equal one if the stock price is at the monthly highest or lowest level and zero otherwise. The approach used in grouping individual investors into 3 trade-value groups is given in Table 1. t-statistics are based on panel corrected standard errors, NObs is the number of observations, and * symbol indicates 5% level of significance. The sample period is between April 2001 and August 2002.

momentum investors, and their momentum investing is stronger in small than large stocks. Institutions are more likely to buy small stocks with strong past return performance and to sell those with weak past return performance. In contrast, the findings indicate strong past-return effects on institutional selling but not buying of large stocks, suggesting that institutions have a propensity to get rid of large stocks that have performed poorly in the past.

The table shows that past returns have a stronger effect on the investment choices of less wealthy individual investors for large than small stocks. Interestingly, less wealthy individual investors tend to reduce more sales of large than small loser stocks. For example, their 'Sell' coefficients, particularly those of $R(-1)$ and $R(-2,-5)$, associated with large stocks are slightly larger than those associated with small stocks. Given that large stocks generally involve large cash losses and small stocks with small cash losses, the result probably suggests that individuals are more willing to cut losses on small than large equity positions. Additionally, these less wealthy individual investors are more inclined to reduce purchases of large than small stocks when the stocks have shown positive performance of up to the past 2–3 months. The overall result suggests that these individual investors are generally contrarian investors.

4. Investor trading, future volatility, and future returns

We have established that the trading decisions of Chinese institutions and individual investors are influenced by past stock return performance: institutions mainly follow momentum strategies, while individual investors at large follow contrarian strategies. A natural question that arises is how their trading strategies would affect future stock volatility and stock prices. This section therefore addresses this particular issue.

4.1. Impact of trading on future volatility

Friedman (1953) argues that irrational investors destabilize stock prices by buying when prices are high and selling when prices are low, and that rational speculators stabilize asset prices by buying low and selling high. Therefore, the implication is that irrational or noisy investors move prices away from fundamentals, whereas rational investors move prices toward fundamentals. On the other hand, Cutler et al. (1990) and De Long et al. (1990) show that positive feedback trading strategies can result in excess volatility, hence destabilizing stock prices. Froot et al. (1992), and Bikhchandani et al. (1992) however, argue that if investors are better informed, then their herding or positive-feedback behavior can move prices toward than away from fundamental values. In this subsection, we test whether the effects of positive- and negative-feedback trading on future stock volatility.[8]

To test the impact of investor trading activity on future volatility, we employ the following empirical model.

[8] Note that the reason why we focus on the impact of future stock volatility, as opposed to market volatility, is that not all SHSE stocks are traded by both groups of institutions and individual investors. For example, the daily average number of stocks traded by the group of sample institutions is 285, which is approximately 41% of the total number of publicly listed stocks. We therefore need to conduct their trade imbalances against the return volatility at the stock level rather than at the market level.

$$\sigma_{i,t} = \phi_{i,0} + \phi_1 \mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0] + \phi_2 \mathrm{Max}[\mathrm{NS}^G_{i,t-1}, 0] + \phi_3 \sigma_{i,t-1} + \phi_4 \sigma_{\mathrm{M},t} + \phi_5 r_{i,t-1} + \epsilon_{i,t}, \tag{3}$$

where $\sigma_{i,t}$ is the monthly return volatility of stock i in month t, $\mathrm{NB}^G_{i,t-1}$ and $\mathrm{NS}^G_{i,t-1}$ are net buying and net selling of group G in stock i in month $t-1$, $\sigma_{i,t-1}$ is the lagged return volatility of stock i in month $t-1$, $\sigma_{\mathrm{M},t}$ is the return volatility of the market in month t, and $r_{i,t-1}$ is the return on stock i in month $t-1$. In (3), we separate effects of net buying and net selling on future stock volatility, while controlling for the market wide volatility and the stock's own lagged volatility.

It is important to stress that in estimating (3), we only employ sample of stocks that we can determine both net sellers and net buyers within the sample. In other words, for every stock, we identify a group(s) of investors who are net buyers of the stock and a group(s) of investors who are the net sellers that act on the opposite side of the transactions. This approach allows us to gauge the relative impact of one group's net selling to another's net buying of a stock. Table 4 offers fixed effects OLS estimates of (3) for each investor category, with PCSE-adjusted t – statistics in parentheses.

The table reveals one striking result. Only the net buying of stocks by wealthiest individuals (the largest trade-value sorted group) and net selling by institutions help decrease future stock volatility. Their respective coefficients of −1.22% ($t = -4.1$) and −0.26% ($t = -4.3$) are statistically significant at conventional levels. This observation perhaps

Table 4
The impact of investor trading on future stock volatility

	Institutions	Individual investors grouped by trade value		
		Largest	Middle	Smallest
$\mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0]^\dagger$	0.051	−1.218*	0.480	−0.283
	(0.87)	(−4.11)	(1.32)	(−1.43)
$\mathrm{Max}[\mathrm{NS}^G_{i,t-1}, 0]^\dagger$	−0.255*	0.249	−0.006	−0.242
	(−4.26)	(0.93)	(−0.02)	(−1.39)
$\sigma_{i,t-1}$	0.168*	0.118*	0.099*	0.132*
	(11.4)	(5.86)	(5.22)	(8.24)
$\sigma_{\mathrm{M},t}$	0.956*	0.905*	0.864*	0.975*
	(54.3)	(37.9)	(36.9)	(51.0)
$r_{i,t-1}{}^\dagger$	−0.735*	−0.495*	−0.285	−0.861*
	(−4.68)	(−2.29)	(−1.41)	(−4.59)
R^2	46.12%	34.86%	30.11%	41.37%
NObs	4136	2925	3370	4118

The table reports fixed effects OLS estimates of

$$\sigma_{i,t} = \phi_{i,0} + \phi_1 \mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0] + \phi_2 \mathrm{Max}[\mathrm{NS}^G_{i,t-1}, 0] + \phi_3 \sigma_{i,t-1} + \phi_4 \sigma_{\mathrm{M},t} + \phi_5 r_{i,t-1} + \epsilon_{i,t},$$

where $\sigma_{i,t}$ is the monthly return volatility of stock i in month t, $\mathrm{NB}^G_{i,t-1}$ and $\mathrm{NS}^G_{i,t-1}$ are net buying and selling of group G in stock i in month $t-1$, $\sigma_{i,t-1}$ is the lagged return volatility of stock i in month $t-1$, $\sigma_{\mathrm{M},t}$ is the market return volatility in month t, and $r_{i,t-1}$ is the return on stock i in month $t-1$. The approach used in categorizing individual investors into 3 trade-value groups is given in Table 1. t-statistics, in parentheses, are based on panel corrected standard errors, NObs is the number of observations, † coefficients are multiplied by 100, and * symbol indicates 5% level of significance. The sample period is between April 2001 and August 2002.

suggests that institutions are net sellers of some stocks where the group of wealthiest individual investors are net buyers, and that trading by wealthier individual investors and institutions does not destabilize stock prices in Chinese equity markets. In comparison, the coefficients on net buys and net sells of the remaining two groups of less wealthy individual investors are statistically insignificant at conventional levels. These findings suggest that less wealthy individual investors who are generally small players in the markets exert no influence on the volatility of the stocks.

To gain more insights into our above findings, we re-estimate (3) by type of stocks formed based on market capitalization. The results are contained in Table 5 with a format similar to that of Table 3. We find that institutional net buying of small stocks increases future volatility, whereas institutional net selling of large stocks decreases future volatility. Their coefficient estimates are 0.23% ($t = 2.1$) and −0.21% ($t = -1.9$), respectively. Interestingly, wealthiest individuals net buying of small and large stocks help to significantly reduce future stock volatility; the coefficient estimates are −1.43% ($t = -2.2$) and −0.97% ($t = -2.1$). These results have two implications. One, the evidence implies that, on average, institutions act as net sellers of some stocks whose net buyers are the group of wealthiest individuals. Two, the size of the coefficient estimates suggests that these

Table 5
The impact of investor trading on future stock volatility by type of stocks

	Institutions		Individual investors grouped by trade value					
			Largest		Middle		Smallest	
	Small	Large	Small	Large	Small	Large	Small	Large
$\text{Max}[\text{NB}^G_{i,t-1},0]^\dagger$	0.230*	−0.054	−1.433*	−0.965*	0.598	0.447	−0.192	−0.369
	(2.09)	(−0.50)	(−2.24)	(−2.13)	(0.79)	(0.77)	(−0.43)	(−1.16)
$\text{Max}[\text{NS}^G_{i,t-1},0]^\dagger$	−0.179	−0.211	0.118	0.364	0.194	0.228	−0.703*	−0.413
	(−1.58)	(−1.86)	(0.20)	(0.96)	(0.36)	(0.57)	(−2.04)	(−1.43)
$\sigma_{i,t-1}$	0.159*	0.254*	0.075	0.174*	0.113*	0.069*	0.086*	0.159*
	(5.68)	(9.92)	(1.87)	(5.34)	(3.03)	(2.14)	(2.71)	(5.94)
$\sigma_{\text{M},t}$	0.949*	0.860*	0.967*	0.867*	0.841*	0.851*	0.913*	0.988*
	(28.3)	(29.2)	(20.8)	(22.7)	(19.1)	(21.9)	(23.4)	(33.1)
$r_{i,t-1}{}^\dagger$	0.713*	−1.165*	−0.814	−0.393	−0.612	−0.155	−0.947*	−0.480
	(−2.37)	(−4.22)	(−1.81)	(−1.18)	(−1.61)	(−0.42)	(−2.77)	(−1.38)
R^2	46.94%	46.50%	39.35%	35.88%	30.68%	31.09%	37.01%	47.19%
NObs	1165	1317	763	1027	938	1116	1139	1346

The table reports fixed effects OLS estimates of

$$\sigma_{i,t} = \phi_{i,0} + \phi_1 \text{Max}[NB^G_{i,t-1},0] + \phi_2 \text{Max}[NS^G_{i,t-1},0] + \phi_3\sigma_{i,t-1} + \phi_4\sigma_{\text{M},t} + \phi_5 r_{i,t-1} + \epsilon_{i,t},$$

where $\sigma_{i,t}$ is the monthly return volatility of stock i in month t, $\text{NB}^G_{i,t-1}$ and $\text{NS}^G_{i,t-1}$ are excess buying and selling of group G in stock i in month $t-1$, $\sigma_{i,t-1}$ is the lagged return volatility of stock i in month $t-1$, $\sigma_{\text{M},t}$ is the market return volatility in month t, and $r_{i,t-1}$ is the return on stock i in month $t-1$. The approach used in categorizing individual investors into 3 trade-value groups is given in Table 1. Stocks are categorized into 'large', 'medium' and 'small' stock groups based on stocks' market value as of 2000. The table reports only results of large and small stocks. t-statistics, in parentheses, are based on panel corrected standard errors, NObs is the number of observations, † coefficients are multiplied by 100, and * symbol indicates 5% level of significance. The sample period is between April 2001 and August 2002.

wealthiest individual investors' net buys have a stronger impact on future stock volatility than institutional net sells. This finding perhaps can be explained by the descriptive statistics shown in Table 1 that the wealthiest group of individual investors trade in larger volumes and in larger RMB value. As such, they are the bigger players in the market than institutions and hence might have a larger influence on stock volatility. In contrast, however, there is little evidence that net selling by individual investors at large and net buying by less wealthy individuals have any impact on future volatility.

4.2. Impact of trading on future returns

In this subsection, we examine whether the trading activities of institutions and of individual investors have the ability to forecast future stock returns. To do so, we perform a simple test,

$$r_{i,t} = \delta_{i,0} + \delta_1 \mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0] + \delta_2 \mathrm{Max}[\mathrm{NS}^G_{i,t-1}, 0] + \delta_3 r_{\mathrm{M},t} + \delta_4 r_{i,t-1} + \eta_{i,t}. \tag{4}$$

Similar to (3), (4) allows us to look at the effects of cumulative monthly trades of each investor group in order to determine how such trades affect future stock returns, while controlling for market-wide movements and the lagged return on the stock. If individuals are noise traders, there should be no systematic relation between their trading activity and future stock returns. In other words, the estimated δ_1 and δ_2 coefficients in (4) should be insignificantly different from zero or should bear signs suggesting that future returns are in counter direction to the trading activity. Table 6 contains fixed effects OLS regression estimates of (4) using all stocks in the sample, and Table 7 shows those by type of stocks.

Table 6
The impact of investor trading on future stock returns

	Institutions	Individual investors grouped by trade value		
		Largest	Middle	Smallest
$\mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0]^\dagger$	0.014	4.775*	0.595	0.009
	(0.03)	(2.65)	(0.27)	(0.01)
$\mathrm{Max}[\mathrm{NS}^G_{i,t-1}, 0]^\dagger$	0.753	2.332	−0.638	−1.474
	(1.89)	(1.45)	(−0.40)	(−1.23)
$r_{i,t-1}$	−0.080*	−0.041*	−0.069*	−0.043*
	(−7.50)	(−3.07)	(−5.59)	(−3.39)
$r_{\mathrm{M},t}$	0.829*	0.806*	0.796*	0.853*
	(54.2)	(44.8)	(46.7)	(53.8)
R^2	43.74%	42.57%	41.37%	43.31%
NObs	4136	2925	3370	4118

The table reports parameter estimates of fixed effects OLS regressions of

$$r_{i,t} = \delta_{i,0} + \delta_1 \mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0] + \delta_2 \mathrm{Max}[\mathrm{NS}^G_{i,t-1}, 0] + \delta_3 r_{\mathrm{M},t} + \delta_4 r_{i,t-1} + \eta_{i,t},$$

where $r_{i,t}$ is the return of stock i in month t, $\mathrm{NB}^G_{i,t-1}$ and $\mathrm{NS}^G_{i,t-1}$ are net buying and selling of group G in stock i in month $t-1$, $r_{\mathrm{M},t}$ is the return of the market in month t, and $r_{i,t-1}$ is the return on stock i in month $t-1$. The approach used in categorizing individual investors into 3 trade-size groups is given in Table 1. t-statistics, in parentheses, are based on panel corrected standard errors, NObs is the number of observations, † coefficients are multiplied by 100, and * symbol indicates 5% level of significance. The sample period is between April 2001 and August 2002.

Results of Tables 6 and 7 suggest that the trading activities of both Chinese institutions and the majority of Chinese individual investors have no predictive power for future stock returns. The evidence that trading by institutions provides no prediction of future stock returns is somewhat surprising. The coefficient on $\mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0]$ is positive and statistically insignificant for all stocks where institutions are net buyers, and the coefficient estimates are negative and statistically insignificant for their net purchases of small and large stocks. This finding contradicts existing evidence that institutions are typically more sophisticated and more informed than individual investors. It is likely that the trading activities of our sample of institutions do not necessarily reflect the trading behavior of a typically well informed institution. Alternatively, it might suggest that it is harder to form any reliable prediction of future stock returns, given the existence of non-fundamental components of Chinese stock prices. A recent study by Mei et al. (2005) finds evidence that speculative trading is an important determinant of Chinese stock prices.

Similarly, almost all coefficient estimates on $\mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0]$ and $\mathrm{Max}[\mathrm{NS}^G_{i,t-1}, 0]$ are statistically insignificant for individual investors. The exception is the coefficient estimate on $\mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0]$ associated with wealthiest investors' trading of all stocks; the estimate is 4.78% with t-statistic = 2.7. Overall, there appears little evidence that trading by individual investors helps predict future stock returns. As we discussed earlier, given the short history of Chinese equity markets, these individual investors are probably relatively inexperienced, compared to those from developed markets. Thus, it is less surprising to find their

Table 7
The impact of investor trading on future stock returns by type of stocks

	Institutions		Individual investors grouped by trade value					
			Largest		Middle		Smallest	
	Small	Large	Small	Large	Small	Large	Small	Large
$\mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0]^\dagger$	−0.068	−0.101	6.498	4.789	4.037	−4.748	4.222	−2.401
	(−0.09)	(−0.14)	(1.82)	(1.57)	(0.87)	(−1.37)	(1.45)	(−1.16)
$\mathrm{Max}[\mathrm{NS}^G_{i,t-1}, 0]^\dagger$	0.790	0.063	3.482	1.198	−2.425	−2.737	1.895	−1.689
	(1.05)	(0.08)	(1.08)	(0.47)	(−0.73)	(−1.15)	(0.81)	(−0.87)
$r_{i,t-1}$	−0.086*	−0.107*	−0.000	−0.065*	−0.039	−0.107*	−0.027	−0.076*
	(−4.22)	(−5.83)	(−0.01)	(−2.93)	(−1.66)	(−4.90)	(−1.16)	(−3.24)
$r_{\mathrm{M},t}$	0.825*	0.827*	0.742*	0.827*	0.814*	0.733*	0.904*	0.788*
	(26.9)	(32.3)	(20.0)	(28.3)	(23.3)	(27.0)	(28.2)	(30.4)
R^2	40.92%	46.73%	35.36%	45.99%	39.00%	42.15%	42.92%	43.31%
NObs	1165	1317	763	1027	938	1116	1139	1346

The table reports parameter estimates of fixed effects OLS regressions of

$$r_{i,t} = \delta_{i,0} + \delta_1 \mathrm{Max}[\mathrm{NB}^G_{i,t-1}, 0] + \delta_2 \mathrm{Max}[\mathrm{NS}^G_{i,t-1}, 0] + \delta_3 r_{\mathrm{M},t} + \delta_4 r_{i,t-1} + \eta_{i,t},$$

where $r_{i,t}$ is the return of stock i in month t, $\mathrm{NB}^G_{i,t-1}$ and $\mathrm{NS}^G_{i,t-1}$ are net buying and selling of group G in stock i in month $t-1$, $r_{\mathrm{M},t}$ is the return of the market in month t, and $r_{i,t-1}$ is the return on stock i in month $t-1$. The approach used in categorizing individual investors into 3 trade-size groups is given in Table 1. Stocks are categorized into 'large', 'medium' and 'small' stock groups based on stocks' market value as of 2000. To highlight the differences in the results, this table reports only those of large and small stocks, leaving out those of medium-sized stocks. t – statistics, in parentheses, are based on on panel corrected standard errors, NObs is the number of observations, † coefficients are multiplied by 100, and * symbol indicates 5% level of significance. The sample period is between April 2001 and August 2002.

trading activities to lack forecasting ability. To sum, there seems no evidence that the majority of Chinese individual investors are making sound investment decisions.

5. Summary

This paper employs a new unique data set to examine the trading behaviors of individual and institutional investors in Mainland Chinese equity markets. In particular, we determine whether the investment choices of various Chinese individual investor groups with varying wealth levels, as proxied by their trade values, can be explained by past stock returns. We also investigate whether their trading behaviors have any significant impact on future stock volatility and future stock returns.

We find significant effects of past stock returns on the trading decisions of investors over four varying non-overlapping trading horizons. Results show that past stock returns exhibit differential effects on the buying and selling decisions of individual and institutional investors. Institutions pursue momentum investing when they buy and sell stocks. In contrast, less wealthy groups of individual investors, who comprise about 93.1% of the sample individual investors and whose aggregate trade value constitutes about 50.7% of the total trade value of the sample, mainly adopt contrarian strategies. They reduce purchases of winner stocks and also decrease sales of loser stocks. On the other hand, the group of wealthiest individuals, whose aggregate trade value constitutes about 43.1% of the sample total trade value, tend to behave like institutions when they buy stocks, and behave like less wealthy individuals when they sell. In general, wealthier Chinese individuals are likely to increase purchases of winner stocks and to decrease sales of loser stocks.

We next investigate how the above differential trading behavior contributes to future stock volatility and future stock returns. We find that institutional sales, particularly of large stocks, can help lower future stock volatility, but institutional purchases of small stocks can lead to an increase in future stock volatility. On the contrary, trading activities of less wealthy individual investors, in general, have no significant impact on future stock volatility. However, purchases of stocks by wealthiest individuals, who form about 7% of the sample individual investors, have a statistically significant impact on future volatility of both large and small stocks. While trading activities of both institutional and individual investors have varying impacts on future stock volatility, they have little impact on future stock returns.

Our overall results offer some implications about asset prices of this robust growing emerging market. The general lack of return predictability in institutional and individual investor trading might simply reflect the dominance of inexperienced individual investors in Mainland Chinese markets. The evidence is also consistent with the recent finding that there is a large speculative component associated with Chinese asset prices. For instance, Mei et al. (2005) show that speculation rather than liquidity drives trading in A-share markets in Mainland China.

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