

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 6.4 million individual and institutional investors across the Mainland China. We find groups of investors with varying levels of wealth and hence investor sophistication engage in different trading strategies. Consistent with most existing studies, our analysis shows that Chinese institutions, though forming only 0.5% of the investing population, are momentum investors. In contrast with earlier studies, we show that Chinese individual investors cannot be characterized in a general way. Less sophisticated and less wealthy individuals tend to act as contrarians, whereas more sophisticated ones tend to behave like institutions when they buy stocks on the one hand, and behave like less sophisticated individuals when they sell on the other. Regardless of the level of investor sophistication, individual investors in general exhibit a strong disposition effect in that they tend to hold on to losing investments too long. Further analyses suggest that buy trades by various investor groups can help to reduce future stock volatility while sell trades can lead to a higher future volatility. Examining the effects of trades on future stock returns clearly suggests that institutional buying and selling of stocks are in the direction of future returns, but not individual investors buying and selling of stocks.

I. Introduction

Financial economists are always intrigued by the trading behavior of institutional and individual investors in the financial markets. The recent availability of more proprietary data has afforded them the opportunity to empirically study 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 reaction to past price performance and 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. Lakonishok, Shleifer, and Vishny (1992) find little evidence of positive feedback trading by U.S. all-equity pension funds. However, Grinblatt, Titman, and Wermers (1995) and Wermers (1999) provide evidence of momentum trading by mutual fund managers, and Nofsinger and Sias (1999) find similar trading behavior by various types of financial institutions. After controlling for size, Gompers and Metrick (2001) subsequently show no evidence of momentum trading by institutional investors. But a recent study by Badrinath and Wahal (2002) show that institutions are momentum traders when they buy stocks and are contrarian traders when they sell or rebalance their holdings of stocks.

Other empirical 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. In contrast, however, they show that individual investors exhibit mainly negative-feedback trading or contrarian trading behavior. Using individual investment accounts from a large U.S. brokerage firm, Odean (1998, 1999) and Barber and Odean (2000) find that on average individual investors are “antimomentum” investors: they tend to buy stocks that have recently underperformed the market and sell stocks that have performed well in recent weeks. Based on the executed buy and sell orders of individuals, Kaniel, Saar, and Titman (2004) find that individuals trade as if they are contrarians, at least in the short-run.

Some researchers look at the trading behavior of investors in foreign markets. Choe, Kho, and

Stulz (1999) find daily positive-feedback trading by Korean and foreign institutional investors and short-run contrarian trading by individual investors in Korea. Grinblatt and Keloharju (2000, 2001) look at all the market participants in the Finnish market and report that Finnish domestic investors, generally, tend to be contrarian investors, while foreign investors tend to be momentum investors. Jackson (2003) has similar findings in a study of Australian individuals.

While the existing results offer important insights into the differential trading behaviors between institutional and individual investors, they are derived from studies that focus mainly on developed markets. There is lack of similar 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 trading behavior of individual and institutional investors in one of the most rapidly growing emerging markets in the world, the Mainland Chinese equity markets. Primarily, we examine whether the buy-sell decisions of various Chinese investor groups are influenced by past stock returns and also investigate whether their trading behavior have any impact on future stock volatility and stock returns.

There are two key reasons why studying Chinese equity markets is important and how this study will contribute to the existing literature. Firstly, China has the largest and one of the fast growing economies in the world. However, its equity markets are still in its nascent stage. 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 size of the two exchanges now ranks second in Asia after Japan. By the end of 2002, the number of domestic investor accounts opened at both exchanges reached 66.7 millions:¹ 66.4 millions (or 99.5%) are individual accounts and only about 345 thousands (0.5%) are institutional accounts (Chinese Securities Depository & Clearing Co. Ltd, 2002).

¹Out of 66.7 millions, 35.5 million investor accounts opened in SHSE. However, only about 10 millions of these accounts have been active in the market. The reason is that many accounts were opened for the purpose of initial public offering subscriptions or of receiving privatization shares in the case of employees from state-owned enterprises.

The Chinese markets are clearly dominated by individual investors, as compared to developed equity markets where a form of polarization between individual and institutional investors is evident.² Given the short history of the local markets, the Chinese investors' trading experience and hence level of sophistication is unlikely to be comparable to that of investors from developed markets. Therefore, does the vast heterogeneity of Chinese individual investors behave like other individual investors from developed markets? In other words, will this mass population of Chinese individuals act mainly as contrarians and the small percentage of Chinese institutions as momentum traders? How does the trading behavior of Chinese individuals differ from existing evidence from other markets?

Secondly, we employ a large sample of data that are compiled by SHSE. These data are similar to the NYSE's Consolidated Equity Audit Trail Data and also contain detailed information on all orders that execute on SHSE. The detailed trade records contain account identifiers that allow us to differentiate the trades initiated by institutions and those by individual investors. Our data set contains 77.12 million executed trades of A shares initiated by 7.24 million institutional and individual investment accounts across Mainland China for the period 17 April 2001 through 8 August 2002. While the turnover of our sample constitutes at least 32% of the total market turnover, the distribution of individual and institutional accounts in our sample is similar to the overall distribution of the investor population in Mainland China. Our sample therefore is a fairly adequate representation of the investor population. Nevertheless, it has by far the largest number of investment accounts ever studied, as compared to the fewer than 100,000 household accounts examined by existing U.S. studies, or a small number of about 8,000 Chinese individual investment accounts studied by Feng and Seasholes (2004). The huge sample enables us to examine for evidence of any similarities or differences in the trading strategies employed by local Chinese individual and institutional investors, and also to determine the robustness of previous findings.

It is important to emphasize that our sample of trade records from a vast heterogeneity of

²See Davis (2000).

investors in Chinese equity markets allows us to perform a comprehensive and thorough analysis of the trading patterns of individual investors. Our panel of data also increases our power to detect any systematic trading patterns of stocks by individual investors. 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 initiated by a large investing group of individual investors.

We begin by examining the relation between trading decisions of various investor classifications and past stock returns. We employ the average trade value of an investor as a criterion to classify the huge diversity of Chinese individual investors into four groups.³ With no margin trading and short-selling allowed in Chinese equity markets, an investor's average trade value ought to serve as a reasonably good proxy for her wealth level and hence degree of sophistication. Such classifications will, hopefully, enable us to capture the cross-sectional variation in the level of investor sophistication, which is shown to influence investor trading behavior (see Grinblatt and Keloharju (2000)).

Our results show that past positive and negative stock returns exhibit differential effects on the buy and sell decisions of individual and institutional investors. Institutions act as momentum traders when they buy and sell stocks. On the contrary, the three groups of less sophisticated individual investors, comprising about 93.3% of the total investing individual investors in the sample and whose aggregate trade value constituting only about 50.7% of the total trade value of the sample, behave as contrarian investors when they buy stocks, but they have the tendency to hold on to stocks with past poor performance. Interestingly, the Largest Group of individual investors, whose aggregate trade value constitutes about 43.1% of the total trade value of the sample, tend to behave more like institutions when they buy, but behave more like those of the three groups of less sophisticated individuals when they sell. In other words, the most

³Given the institutional setting of Chinese equity markets, the average trade value of an investor ought to serve as a reasonable proxy for her wealth level and hence level of sophistication.

sophisticated and wealthier individuals are likely to pursue momentum buy-investing, and at the same time they also exhibit a strong disposition effect.

Our study therefore proceeds to investigate how the above documented trading behavior contributes to future stock volatility and future stock returns. Independent of investor sophistication and of investment strategies, the results suggest that investors buying of stocks can help lower future stock volatility while their selling can lead to an increase in future volatility. However, the findings indicate that buying large stocks does not necessarily help to significantly reduce stock volatility, but buying small stocks does. Moreover, investors selling large stocks, while not necessarily small stocks, might contribute to an increase in volatility of the stocks. Increasing stock volatility of large stocks is mainly attributable to excess selling by individual investors with lower trade value and hence less sophistication. We show no evidence suggesting that institutional positive-feedback trading of stocks would destabilize stock prices.

Our analyses further show no systematic patterns that suggest the return predictability of individual investor trades. Essentially, individual investors' monthly accumulated buys and sells have very little bearing on the subsequent month's stock returns. In contrast, however, institutional buys and sells appear to help predict future stock returns. This perhaps implies that institutions are better informed and more investment savvy than individual investors.

The remainder of the paper is organized as follows. The next section describes our sample data and the variables that we employ in our analysis. Section III discusses the methodology and the results. Section IV looks at the impact of investors trading behavior on volatility and the final section concludes.

II. Data and Variable Definitions

A. Sample Description

This study employs a sample of daily trading data that are compiled by the Shanghai Stock Exchange (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 and also, as we understand, is not the policy of SHSE to provide all trading information to their subscribers. Our sample therefore contains daily detailed records of 77.12 million trades of A shares initiated by 7.24 million institutional and individual brokerage accounts across the Mainland China for the period 17 April 2001 through 8 August 2002.

The sample data have two appealing features. One, 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. Note that each investor can only open one brokerage account, and individual investor accounts are opened using their National Identity Card. Based on the account identifiers, 99.5% of the accounts are individual investor accounts, while 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. Thus, our sample is fairly representative of the individual and institutional trading in the Chinese markets. Two, the turnover of stocks in our sample accounts for approximately 32% of the total domestic market turnover of A shares. It is worthwhile to point out that a Chinese company can issue A and B shares that aim at different types of investors. Domestic investors are allowed to trade A and B shares,⁴ while foreign investors are restricted to trading B shares, even though the two shares are identical with respect to shareholder rights. Firms that issue only A shares account for about 90% of total listed firms. The annual turnover of A Shares in 2002 is US\$399.1 billion relative to US\$12.5 billion of B shares.

To the best of our knowledge, our sample is by far the largest and most comprehensive as compared to those employed by existing studies that mainly use investment accounts data from one brokerage firm. For example, Odean (1999), Barber and Odean (2000) use fewer than 100,000 household accounts to examine the behavior of U.S. individual investor, and Feng and Seasholes (2004) examine the correlated trading of Chinese A-Shares listed on the SZSE that are initiated

⁴Prior to June 2001, the Chinese domestic investors were restricted to trading only in the A-share market.

merely by 7,973 individual investment accounts from a single brokerage firm in Mainland China. Our significantly larger sample data therefore allow us to conduct a comprehensive study on the trading behavior of both individuals and institutions in the Chinese market.

B. 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 trades of shares during the entire sample period. As a result, our sample size is reduced to 4.72 million active individual investor accounts and 11.6 thousand active institutional accounts, and this smaller sample shall be used throughout our analysis in this study. Given the large heterogeneity of individual investors, it is reasonable to expect the 4.72 millions of individual investors to exhibit vastly different trading behavior. It is therefore imperative that we classify the individuals into groups in a way that will help capture their similarities in trading behavior within groups and their differences between groups.

Empirically, investor trading behavior is shown to be driven by the level of investor sophistication. For example, using Finnish data, Grinblatt and Keloharju (2000, 2001) show that sophisticated investors, mainly foreign investors, tend to be momentum traders, and domestic investors, particularly the less sophisticated investor categories, tend to be contrarians. For this study, we use the average trade value as a proxy for sophistication level. We assume that an individual's average trade value provides a good proxy for her wealth level and hence her level of sophistication. Unlike that in the United States, margin trading is prohibited in China. This restriction suggests that individuals can only trade with immediate cash available. Even though individuals are not allowed to trade on margin, this does not necessarily preclude them from borrowing externally to finance their trades. 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. Intuitively, individuals would be more likely to place a lot of their money at stake if they are more familiar with stock investments. Hence, we argue that their average trade value should somewhat commensurate with the level of sophistication. Based on

this grouping criterion, we divide individual accounts into four categories. Individual investors with average trade value of greater than or equal to RMB50,000 are in the ‘Largest Group’, those with average trade value of greater than or equal to RMB10,000 but less than RMB50,000 are in ‘Group 2’, those with average trade value of greater than or equal to RMB3,000 but less than RMB10,000 are in ‘Group 3’, and finally, those with average trade value of less than RMB3,000 are in the ‘Smallest Group’.

Panel A of Table I summarizes the aggregate trade-record statistics of various investor categories, and Panel B breaks down the trade-record statistics by type of trading activity. As indicated above, there are 4.74 millions of active investment accounts in our sample. Out of which, only about 12 thousands (0.3%) are institutions and about 320 thousands (6.8%) are individual investors with largest average trade value of at least RMB50,000. About 392 thousand (8.3%) individual investors have average trade value of less than RMB3,000. This ordering of the size of average trade value across investor categories almost corresponds to the ordering of the groups’ volumes of trades. Even though with the smallest number of investors, the Largest Group has the largest total trade value. With about the same number of investors as in the Largest Group, the Smallest Group has the smallest trade value. The trades of the top two individual investor groups account for about 80% of the total trade value in the sample, and those of the Smallest group contribute only less than 1%. Institutional trading, on the other hand, accounts for about 6% of the sample’s total trade value.

Panel B provides a detailed analysis of the aggregate trade records reported in Panel A. The panel reveals two distinct observations. One, it is evident that there is more buying than selling in terms of the number of trades, trade value, and number of shares traded across all investor categories. But there is no dramatic difference in their order of magnitude between purchases and sales. Two, for institutions and the top two investor groups, their median trade value and median number of shares traded are substantially lower than their mean counterparts. Apparently, many of the investment accounts within these two groups trade in smaller value and in smaller number of shares per trade. On the other hand, the mean and median statistics in

the case of the two lower investor groups are about the same, indicating that the two variables are more normally distributed within these groups.

C. Returns and Control Variables

This study also employs 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. For ease of comparison with the results reported in Grinblatt and Keloharju (2001), we use 20 past market-adjusted positive and negative return variables over 10 non-overlapping trading-day intervals. Daily market-adjusted past returns on individual stocks are calculated in excess of the corresponding returns on the SHSE composite index for 10 non-overlapping holding periods,⁵ which include four within-week days $t - k$ ($k = 1, 2, 3$, and 4),⁶ and a series of multi-day horizons between day $t - m$ ($m = 19, 39, 59, 119, 179$, and 239) and day $t - n$ ($n = 5, 20, 40, 60, 120$, and 180), correspondingly, prior to investor trading day t .

Note that the return computations exclude non-trading days such as public holidays and stock-specific trading halts. Trading is typically halted due to trading imbalance, news pending, and news dissemination and can occur when (1) the price of a stock has consecutively hit price limits (up or down 10% of the previous day's closing price) during three trading days; (2) the price of a stock has consecutively fluctuated by 15% during three trading days; and (3) the daily trading volume of a stock has consecutively hit 10 times the previous month's daily average trading volume during five trading days.

The choice of the length of the seven holding periods is primarily based on certain unique aspects of the local markets. Our preliminary analyses indicate that the majority of the investor population possess a short-term investment incentive, and that long-horizon past stock returns have little significant influence on the investors' current investment decisions. Our preliminary results are consistent with the findings reported by Grinblatt and Keloharju (2001) that past

⁵The SHSE Composite index consists of all stocks listed on the SHSE.

⁶Time 0 is excluded because the data set provides no information to differentiate the effects of intra-day returns on investor buy-sell imbalances from the effects of investor intra-day behavior on contemporary price patterns.

returns of more than six months have very little effect on the buying decisions of their various Finnish investor groups.

The control variables are motivated by extant literature on investor trading behavior (see, for example, Grinblatt and Keloharju (2001)). 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 the highest and lowest prices during the past month. We control for all these 11 effects in our regression models throughout this study.

D. Measures of Investor Trading Activities

To gauge how investors buy and sell stock i at time t , we examine their excess buying ($XB_{i,t}$) and excess selling of the stock ($XS_{i,t}$), separately. For this purpose, we employ slight variations of the excess buying and selling measures introduced by Lakonishok, Shleifer, and Vishny (1997), and the two measures for each investor group G are constructed as follows.

$$XB_{i,t}^G = B_{i,t}^G - E(B_{i,t}^G), \quad (1)$$

and

$$XS_{i,t}^G = S_{i,t}^G - E(S_{i,t}^G), \quad (2)$$

where

$$B_{i,t}^G = \frac{\sum_{g=1}^G \text{Buy}_{i,t}^g - \sum_{g=1}^G \text{Sell}_{i,t}^g}{\sum_{g=1}^G \text{Buy}_{i,t}^g + \sum_{g=1}^G \text{Sell}_{i,t}^g},$$

$$S_{i,t}^G = \frac{\sum_{g=1}^G \text{Sell}_{i,t}^g - \sum_{g=1}^G \text{Buy}_{i,t}^g}{\sum_{g=1}^G \text{Buy}_{i,t}^g + \sum_{g=1}^G \text{Sell}_{i,t}^g}.$$

$\text{Buy}_{i,t}^g$ and $\text{Sell}_{i,t}^g$ are the respective dollar purchase and dollar sale of stock i by investor g who belongs to investor group G ; $E(B_{i,t}^G)$ and $E(S_{i,t}^G)$ are the average values of $B_{i,t}^G$ ’s and $S_{i,t}^G$ ’s for all

stocks that investor group G are net buyers and net sellers at time t , respectively. In (1) and (2), we have adjusted for the group's average excess buying and selling of all stocks at a given time t . As a result, an investor group G 's excess buying and selling of stock i , $XB_{i,t}^G$ and $XS_{i,t}^G$, reflect their net buying and net selling of stock i in excess of their average net buying and net selling of all stocks in their portfolios.

III. Investor Trading Behavior and Past Stock Returns

A. Methodology

To examine how various Chinese investor groups trade relative to past stock performance, we employ a panel data (cross-sectional and time series) fixed effects (FE) ordinary least-square (OLS) regression and FE logit regression approaches. The two basic regression models for investor excess buying $XB_{i,t}^G$ are as follows.

FE OLS regression:

$$XB_{i,t}^G = \alpha_i^G + \sum \beta_{i,\phi} \text{Max}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \varepsilon_{i,t}^G; \quad (3)$$

FE Logit regression:

$$P(XB_{i,t}^G > 0) = \frac{e^{\sum \beta_{i,\phi} \text{Max}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \alpha_i^G}}{1 + e^{\sum \beta_{i,\phi} \text{Max}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \alpha_i^G}}; \quad (4)$$

where $Ret_{i,\phi}^G$ denotes a vector of past returns variables with varying time-intervals and $\pi_{i,t}^G$ is a set of control variables. Correspondingly, the basic models for investor excess selling $XS_{i,t}^G$ are:

FE regression:

$$XS_{i,t}^G = \alpha_i^G + \sum \beta_{i,\phi} \text{Min}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \varepsilon_{i,t}^G \quad (5)$$

FE Logit regression:

$$P(XS_{i,t}^G > 0) = \frac{e^{\sum \beta_{i,\phi} \text{Min}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \alpha_i^G}}{1 + e^{\sum \beta_{i,\phi} \text{Min}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \alpha_i^G}} \quad (6)$$

In all regression models, we incorporate one intercept α_i^G for each stock in the sample so as to capture any stock-specific characteristics that also explain investor trading behavior.⁷ This therefore allows us to focus on determinants of investor trading activities associated with past stock performance. Finally, all regressions are estimated with panel corrected standard errors (PCSE). The PCSE specification allows the error terms to be contemporaneously correlated and heteroskedastic across investor trades and autocorrelated within each investor group’s time series.

The regressions are performed for each investor group. We find that the FE OLS and FE logit approaches yield similar distinct trading patterns across institutions and four different individual investor groups. For brevity, throughout this study, we shall report only those estimates using the FE logit method, but for the purpose of illustration, we shall show results of both approaches in Table II.⁸

B. Investor Buy and Sell Decisions

Panels A and B of Table II show the extent to which the buy and sell decisions of both institutional and individual investors are affected by past returns. They also offer evidence of the relative effects of positive (negative) past market-adjusted returns on the buy (sell) decisions and of the relative influence of varying historical returns on such decisions. Both panels show, separately, effects of positive past market-adjusted returns on ‘Buy’ decisions and of negative past market-adjusted returns on ‘Sell’ decisions. Both past market-adjusted returns are over 10 nonoverlapping trading-day horizons: the four days prior (days -1 , -2 , -3 , and -4) and six trading-interval returns (-19 to -5 ; -39 to -20 , -59 to -40 ; -119 to -60 ; -179 to -120 ; and -239 to -180). FE-OLS regression estimates of the 10 nonoverlapping return variables for Buy (i.e. Model 3) and Sell (i.e. Model 5) are presented in Panel A, and their FE-logit counterparts

⁷We also estimated the models by taking into account any time-varying effects associated with investors’ trading preferences. However, we did not report them, because the qualitative results were substantially the same as those reported in the paper.

⁸FE OLS estimates not reported in other tables shown in the paper are available from the authors upon request.

for Buy (i.e. Model 4) and Sell (i.e. Model 6), with PCSE-adjusted t -statistics in parentheses, are in Panel B.⁹

Table II shows systematic patterns of past-returns effects on the trading activities of investors, and are consistent across Panels A and B. Both positive and negative past returns play a significant role in investor trading decisions, but their role varies across different investor categories and across different trading-horizons. The past-returns effects on the buy and sell decisions suggest that institutions and certain groups of individual investors exhibit distinctly different investment behavior. Institutions tend to be momentum investors, while individual investors with lower trade-size value tend to be contrarian investors.

The Buy columns of Panels A and B indicate that the larger the positive recent past market-adjusted returns of a stock, the more likely an institution and an investor from Group 1, while the less likely an individual investor from Groups 2-4, will buy the stock. For example, in Panel A, the day -1 's Buy coefficients for institutions and Group 1 individual investors are 0.68 (t -statistic = 2.2) and 0.91 (t -statistic = 8.3), as compared to -0.42 (t -statistic = 6.7) to -2.70 (t -statistic = -38.3) for Groups 2-4 individual investors. In almost all cases, the previous day's return has the largest and most significant effect on the buy decision. The buy effect of positive past returns persists up to a week for institutions and Group 1 individuals, but on average is strong up to two months for Groups 2-4 investors. Even though the logit regression estimates indicate investors' nonlinear propensities to buy as a function of past return values, the results of Panel B produce similar patterns as those of Panel A. Interestingly, the past return-effect patterns for all investor categories weakly reverse, as the positive past return horizons become more distant from the day when the buy decision is made.

The Sell columns in Table II reveal another interesting difference in the trading behavior between institutions and individual investors. The larger the negative past returns of a stock, the less likely individual investors in general will sell the stock. The sell effect of negative past

⁹Given that our focus is on the impact of past returns on the buy and sell decisions of each investor group, estimates of the control variables are not reported in the table.

returns is most pronounced in Groups 2-4, with recent past returns having the greatest influence on their sell decisions. For instance, in Panel B the statistically significant logit estimates for Group 2's sell-effects of past returns are between 0.41 (-119 to -60) and 9.09 (-1), and for the Smallest Group's are from 0.48 (-39 to -40) and 12.13 (-1). Similar patterns are depicted in Panel A. In contrast, however, the larger negative past returns will likely to induce institutions to sell the stock. While the negative past returns have a negative sell effect on institutions up to about three months, but only the coefficients associated with the returns over the three days prior to the sell decisions and the trading intervals of (-39 to -20) and (-59 to -40) are statistically significant. We observe that like institutions, Group 1 investors tend to buy the stock when its prior day's return is highly negative, but unlike institutions, they tend to sell when distant past returns are negative.

Our empirical analyses in this subsection present three main findings. One, institutions act as momentum traders when they buy and sell stocks. While our result is consistent with those of Grinblatt, Titman and Wermers (1995), Wermers (1999), Nofsinger and Sias (1999), and Choe, Kho, and Stulz (1999), it is somewhat inconsistent with the recent findings of Badrinath and Wahal (2002). The two authors decompose institutional trading activity into institutions initiating new positions, exiting existing positions, and other adjustments to existing positions. Based on quarterly portfolio holdings of 1,200 U.S. financial institutions from the third quarter of 1987 to the third quarter of 1995, they find that institutions act as momentum investors when they initiate new positions and as contrarian investors when they exit or adjust their existing positions.

Two, the three lower trade-value groups of individual investors behave as contrarian investors when they buy stocks, but they have the tendency to hold on to stocks with past poor performance. The contrarian tendency characterized by these less-sophisticated individuals are consistent with earlier findings in studies of individual investors in Australia, Finland, and Korea. In addition, they also display a disposition effect of Shefrin and Statman (1985). Odean (1998) examines trading records for 10,000 individual investor accounts held at a U.S. discount

brokerage house from 1987 through 1993. He shows that individual investors have a strong preference to realize winning investments rather than losers and that they tend to hold losing investments too long.

Finally and interestingly, the Largest Group of individual investors tend to behave more like institutions when they buy on the one hand, and behave more like those of Groups 2-4 when they sell on the other. This group of investors that account for about 43% of the total trading value of the sample pursue momentum buy-investing, but like most individual investors they also tend to hold losing investments too long.

C. Investor Trading of Large and Small Stocks

Thus far, our analysis does not distinguish investor trading of small versus large stocks. Existing evidence shows that individual investors tend to tilt their investments toward small stocks (Barber and Odean (2000)). It is therefore imperative that we examine whether the buy and sell decisions of various investor groups found earlier are driven by the type of stocks. To perform this analysis, we divide all the 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 III we report FE logit regression estimates of past-return effects on the buy and sell decisions of small stocks (Panel A) and of large stocks (Panel B). 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 market-capitalization stocks. Similar to Table II, we also do not present the estimates of all the 11 control variables used in the regressions, and nor do we report FE OLS regression estimates of the same, since both approaches yield qualitatively the same results. All PCSE-adjusted t -statistics associated

with the regression estimates are shown in parentheses.

A few systematic patterns emerge from Table III, and in general, they are similar to those presented in Table II. The results show corroborating evidence that institutions tend to be 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 sell those with weak past return performance. In contrast, however, we find no past-return effect on institutional buying of large stocks, but strong effects on their selling of large stocks. Institutions have a greater propensity to get rid of large stocks that have performed poorly in the past. The institutional Buy coefficients of past returns on small stocks and Sell coefficients of past returns on large stocks are statistically significant for trading intervals of up to about three months. Beyond this interval, none of the coefficients are statistically significant, thereby indicating that institutions are short-term momentum investors. Our evidence that institutional positive-feedback trades are largely in small-sized stocks is consistent with the findings of Nofsinger and Sias (1999).

Furthermore, past returns have a stronger effect on the investment choices of Groups 2-4 for large than small stocks. Both the Buy and Sell coefficients on past returns are larger in the former than the latter. One interesting result is that these individual investors tend to hold on to losing small stocks for a longer period than they do to losing large stocks. Assuming that large stocks are associated with large cash investments and small stocks are associated with small cash investments. The result might indicate that individuals are more willing to cut losses on large equity positions than small equity positions. Alternatively, it might also imply that it is too costly for individuals to hold on to losing large-stock than small-stock positions. Nevertheless, it is evident that the stronger disposition effect is manifested more in small than large stocks. Additionally, individual investors in the three lower trade-value groups are more likely to buy winning stocks; past positive returns show statistically significant influence on the buy decisions of individual investors mainly in Groups 3-4.

We notice that individuals with the largest trade value do not adopt the same strategies when trading large versus small stocks. The findings show that unlike those of Groups 2-4, they are less inclined to buy small stocks, while more inclined to buy large stocks, with past strong performance. Moreover, they tend to sell large and small stocks when the prior day's past return is negative. However, more distant negative returns in the past have very little effect on the sell for small stocks, but like those of Groups 2-4, they display a strong disposition effect on large stocks. The coefficients of past returns beyond the recent one-day past return are positive and some are statistically significant at the 5% level.

IV. Investor Trading, Future Volatility, and Future Returns

We have established that trading decisions of Chinese institutions and individual investors are influenced by past stock return performance: institutions mainly follow momentum strategies, whereas individuals, depending on their level of sophistication, follow contrarian, momentum, or even both, strategies to decide when to buy and when to sell. A natural question that arises is how their trading strategies would affect future stock volatility and stock prices. This section addresses this particular issue.

A. Impact of Trading on Future Volatility

Friedman (1953) argues that irrational investors destabilize prices by buying when prices are high and selling when low and that rational speculators stabilize asset prices by buying when prices are low and selling when high. Therefore, the implication is that irrational or noisy investors move prices away from fundamentals, whereas rational investors move prices toward fundamentals. Cutler, Poterba, and Summers (1990) and De Long, Shleifer, Summers, and Waldmann (1990) show that positive feedback trading strategies can result in excess volatility, hence destabilizing stock prices. Froot, Scharfstein, and Stein (1992), Bikhchandani, Hirshleifer, and Welch (1992), and Hirshleifer, Subrahmanyam, and Titman (1994), 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.

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

$$\sigma_{i,t} = \phi_{i,0} + \phi_1 XB_{i,t-1}^G + \phi_2 XS_{i,t-1}^G + \phi_3 \sigma_{i,t-1} + \phi_4 \sigma_{M,t} + \phi_5 r_{i,t-1} + \epsilon_{i,t}, \quad (7)$$

where $\sigma_{i,t}$ is the monthly return volatility of stock i in month t , $XB_{i,t-1}^G$ and $XS_{i,t-1}^G$ 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 $t-1$, $\sigma_{M,t}$ is the return volatility of market in month t , and $r_{i,t-1}$ is the return on stock i in month $t-1$. In (7), we separate effects of excess buying and selling on future stock volatility, while controlling for marketwide volatility and lagged stock volatility. Table IV offers FE OLS estimates of (7) for each investor category, with PCSE-adjusted t -statistics in parentheses.

The table reveals a strikingly interesting finding: excess buying of various investor groups leads to a lower future stock volatility, whereas their excess selling causes a higher future stock volatility. Except for a marginally significant coefficient on $XB_{i,t-1}^G$ for Group 3, all the coefficients of $XB_{i,t-1}^G$ for institutions as well as for Groups 1, 2, and 4 are statistically significant at the 5% level. Except for an insignificant coefficient on $XS_{i,t-1}^G$ for institutions, those for Groups 1-4 are all statistically significant at conventional levels. Taken the results of Tables II and IV together, they suggest that, regardless of trading strategies employed, both institutional and individual investors buying of stocks contribute to reducing future stock volatility. Conversely, the results from the two tables also imply that individual investors, but not institutions, selling of stocks can significantly increase future stock volatility.

We also re-estimate (7) by type of stocks, and the results are contained in Table V. As in the format of Table III, we only present the regression estimates associated with large and small stocks that are traded by various investor types. A closer analysis by type of stocks shows that mainly buying of small stocks helps reduce future stock volatility, but the effect is only found to

be statistically significant for institutions and the Largest and Smallest Groups of individuals. In contrast, however, none of the buy trades of large stocks is statistically significant at the 5% level. Furthermore, selling large stocks by Groups 2-4 individual investors would lead to an increase in stock volatility, while selling the same by institutions would generate a lower volatility. Notice that the coefficients on $XS_{i,t-1}^G$ for the former are statistically significant at conventional levels, while that for the latter is only marginally significant.

Overall, we show that, independent of investor sophistication and of investment strategies, investors buying of stocks helps lower future volatility while their selling increases future volatility. A closer examination, however, indicates that buying large stocks does not necessarily help to significantly reduce stock volatility, but buying small stocks might significantly lead to a decrease in volatility. Furthermore, investors selling large stocks, while not necessarily small stocks, might contribute to an increase in future stock volatility. Increasing stock volatility of large stocks is mainly attributable to excess selling by individual investors with lower trade value and hence less sophistication. There is no evidence that institutional buying or selling of stocks destabilizes stock prices.

B. Impact of Trading on Future Returns

A recent study by Kaniel, Saar, and Titman (2004) examines the investment choices of individual investors to test whether individual investors are noise traders, or are liquidity providers to institutions. Their results suggest that individual investors are in fact liquidity providers – excess returns after individual buying/selling are in the direction of the activity. If individuals are noise traders, their excess returns should be zero. Also, they show that individual investor trades do not buy riskier stocks than those they sell, thereby providing reinforcing evidence that individuals are not noise traders. Their results motivate us to explore the effects of individual buying/selling versus institutional buying/selling on future stock returns.

In this section, we perform a simple test,

$$r_{i,t} = \delta_{i,0} + \delta_1 XB_{i,t-1}^G + \delta_2 XS_{i,t-1}^G + \delta_3 r_{M,t} + \delta_4 r_{i,t-1} + \eta_{i,t}. \quad (8)$$

If individuals are noise traders, we expect no systematic relation between their trading activity and future stock returns, after controlling for market-wide movements and the lagged return on the stock. Similar to (7), we look at the effects of cumulative monthly trades of each investor group. Here we determine how the cumulative monthly buy and sell trades of each investor group affect future stock returns. Table VI contains fixed effects OLS regression estimates of (8) using all stocks in the sample, and Table VII shows those by type of stocks.

Table VI shows no evidence of any systematic effects of investor trades on future stock returns. In fact, only the coefficients on $XB_{i,t-1}^3$ and $XS_{i,t-1}^4$ are negative and statistically significant at the 5% level. The results seem to suggest that the greater the buy trades by individuals from Group 3, the lower is the future returns on the stocks. Additionally, the larger the sell trades by individuals from Group 4 (the Smallest Group), the smaller are the future stock returns. The overall evidence seems to suggest that Chinese individuals tend to be noise traders than liquidity providers as the directions of future returns contradict their investment choices. The results in Table VII produce similar findings as well; that is, there is no consistent pattern that allows us to draw any definite conclusion.

In contrast, however, institutional buys and sells of large stocks can help predict the directions of future stock returns. The coefficients on $XB_{i,t-1}^G$ and $XS_{i,t-1}^G$ are 1.06 (t -statistic = 2.09) and -1.38 (t -statistic = -2.78), respectively. This finding seems to suggest that institutions are better informed investors than individuals, and that Chinese individuals primarily are noise traders than liquidity providers.

V. Conclusions

This paper employs a new unique data set to examine the trading behavior of individual and institutional investors in an emerging market with the most robust growth in the world – the

Mainland Chinese equity markets. In particular, we determine whether the investment choices of various Chinese investor groups can be explained by past stock returns and also investigate whether their trading behavior have any impact on future stock volatility and stock returns.

We first analyze the relation between trading decisions of investors and past stock returns over 11 trading horizons. To facilitate our analysis, we classify the vast heterogeneity of Chinese individual investors into four groups based on their average trade value. Given that margin trading and short sales are not permitted in Chinese equity markets, an individual investor's trade value ought to provide a reasonably good proxy for her wealth level and hence level of sophistication. Results show that past positive and negative stock returns exhibit differential effects on the buy and sell decisions of individual and institutional investors. Institutions act as momentum traders when they buy and sell stocks. On the contrary, the lower three groups of less sophisticated individual investors, comprising about 93.3% of the investing individual investors in the sample and whose aggregate trade value constituting only about 50.7% of the total trade value of the sample, behave as contrarians when they buy stocks, but they also have the tendency to hold on to stocks with past poor performance. Furthermore, the group of most investment-savvy individuals, whose aggregate trade value constitutes about 43.1% of the total trade value of the sample, tend to behave more like institutions when they buy their stocks, but behave more like less-sophisticated individuals when they sell. In general, the most sophisticated and wealthier Chinese individuals are likely to pursue momentum buy-investing, and at the same time they exhibit a strong disposition effect.

We next investigate how the above differential trading behavior contributes to future stock volatility and future stock returns. When examining the impact of investor trades on future volatility, we find that in general investors buying of stocks leads to lower future volatility, while their selling causes an increase in future volatility. Our result is independent of investor sophistication and the type of investment strategies they employ. A closer examination, however, indicates that buying large stocks does not necessarily help to significantly reduce stock volatility, but buying small stocks does. We also find that less-sophisticated individual investors selling

large stocks, while not necessarily small stocks, might contribute to an increase in volatility of the stocks. Nonetheless, there exists no evidence suggesting that institutional positive-feedback trading of stocks would destabilize stock prices.

Furthermore, our analyses indicate that individual investors' monthly accumulated buys and sells have no significant effects on the subsequent month's stock returns. In contrast, however, institutional buys and sells are in the directions of future stock returns. The results imply that institutions are better informed and more investment savvy than individual investors in an individuals-dominated Chinese markets.

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Table I

Trade Records, Institutions, and Various Individual Investor Groups

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 four groups based on the average trade value. Individual investors with average trade value of greater than or equal to RMB50,000 are in the ‘Largest Group’, those with average trade value of greater than or equal to RMB10,000 but less than RMB50,000 are in ‘Group 2’, those with average trade value of greater than or equal to RMB3,000 but less than RMB10,000 are in ‘Group 3’, and finally, those with average trade value of less than RMB3,000 are in the ‘Smallest Group’. Panel B shows the total, median, and mean numbers of trades, values of trade size, and numbers of shares traded. The total number of trades and number of shares traded are in millions, whereas the total value of trade size is in millions of RMB. The sample period is between April 2001 and September 2002. The [†] and [‡] symbols denote that the value or number is expressed in millions and billions, respectively.

		Individual Investors Grouped by Trade Value									
		Institutions		Largest		Group 2		Group 3		Smallest	
Panel A: Aggregate Statistics											
No. of accounts	11586 (0.25%)		319675 (6.76%)		1767112 (37.3%)		2244460 (47.4%)		392411 (8.29%)		
No. of trades [†]	0.24 (0.32%)		5.12 (6.93%)		29.73 (40.2%)		34.49 (46.7%)		4.35 (5.88%)		
Trade value [‡]	98.12 (6.16%)		687.08 (43.1%)		584.46 (36.7%)		213.81 (13.4%)		9.73 (0.61%)		
Panel B: Statistics by Type of Trading Activity											
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	
No. of trades											
Total [†]	0.12	0.12	2.61	2.51	15.65	14.07	18.28	16.21	2.29	2.06	
Median	4	4	4	4	4	4	4	3	3	2	
Mean	10	10	8	7	8	7	8	7	5	5	
Trade value											
Total [‡]	51.99	46.13	348.37	338.72	298.44	286.02	110.40	103.42	5.12	4.61	
Median	112,100	48,776	90,726	87,453	15,765	16,499	5,790	6,032	2,176	2,141	
Mean	411,823	294,868	186,141	158,970	19,292	19,916	6,098	6,324	2,147	2,105	
No. of shares traded											
Total [†]	14.03	12.80	43.18	42.77	32.47	31.47	12.33	11.65	0.62	0.57	
Median	10,045	5,286	7,743	7,561	1,307	1,383	500	525	200	200	
Mean	80,846	63,254	21,775	18,794	2,049	2,117	671	701	268	272	

Table II
Investor Trading Decisions and Past Stock Returns

The table reports parameter estimates of excess buying ('Buy') and excess selling ('Sell') of stocks by each investor group. Panel A shows estimates of fixed effects OLS regressions of Models (3) and (5), while Panel B shows maximum likelihood estimates of fixed effects Logit regressions of Models (4) and (6) for each investor group. Models (3)-(6) are defined below. The independent variables are market-adjusted past returns calculated for 10 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 takes one at the date of public-listing and zero otherwise; and two dummy variables for 'reference point' effect, which take one if the stock price is at the monthly highest or lowest level and zero otherwise. The approach used in categorizing individual investors into four different trade-value groups is given in Table I. The sample period is between April 2001 and September 2002. t -statistics are based on panel corrected standard errors, and * symbol indicates 5% level of significance.

Panel A: Fixed Effects OLS Regression Estimates										
	Individual Investors Grouped by Trade Value									
	Institutions		Largest		Group 2		Group 3		Smallest	
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
$R(-1)$	0.684* (2.19)	-0.325 (-0.83)	0.912* (8.26)	-0.491* (-4.14)	-0.421* (-6.72)	1.414* (21.2)	-2.700* (-38.3)	2.801* (37.1)	-1.838* (-17.4)	2.662* (23.4)
$R(-2)$	0.357 (1.08)	-0.257 (-0.64)	0.457* (4.13)	0.059 (0.49)	-0.463* (-7.38)	0.964* (14.3)	-1.253* (-17.8)	1.092* (14.3)	-1.318* (-12.5)	0.945* (8.17)
$R(-3)$	0.679* (2.10)	-0.822* (-2.04)	0.359* (3.27)	0.064 (0.54)	-0.283* (-4.55)	0.619* (9.28)	-0.986* (-14.1)	0.734* (9.71)	-1.092* (-10.4)	0.693* (6.08)
$R(-4)$	0.207 (0.62)	0.460 (1.11)	0.110 (0.99)	0.186 (1.57)	-0.216* (-3.47)	0.508* (7.61)	-0.562* (-8.00)	0.546* (7.22)	-0.600* (-5.67)	0.244* (2.13)
$R(-5 - 19)$	0.186* (1.98)	-0.258* (-2.44)	0.007 (0.23)	0.111* (3.65)	-0.257* (-14.2)	0.289* (16.9)	-0.441* (-21.6)	0.341* (17.6)	-0.567* (-18.4)	0.364* (12.5)
$R(-20 - 39)$	0.013 (0.15)	-0.023 (-0.24)	-0.139* (-4.97)	0.089* (3.18)	-0.095* (-6.01)	0.179* (11.5)	-0.059* (-3.34)	0.153* (8.63)	-0.154* (-5.71)	0.132* (4.87)
$R(-40 - 59)$	-0.019 (-0.21)	-0.269* (-2.58)	-0.065* (-2.34)	0.066* (2.37)	-0.051* (-3.27)	0.121* (7.65)	-0.032 (-1.78)	0.115* (6.45)	-0.088* (-3.26)	0.052 (1.94)
$R(-60 - 119)$	-0.100 (-1.50)	0.067 (1.03)	-0.029 (-1.52)	-0.015 (-0.76)	-0.059* (-5.51)	0.081* (7.36)	-0.034* (-2.85)	0.089* (7.09)	-0.013 (-0.71)	0.019 (1.02)
$R(-120 - 179)$	0.042 (0.68)	-0.100 (-1.46)	-0.071* (-3.87)	-0.024 (-1.21)	0.048* (4.68)	0.010 (0.85)	0.141* (12.2)	0.016 (1.26)	0.112* (6.27)	0.023 (1.19)
$R(-180 - 239)$	0.113* (2.05)	-0.159* (-2.19)	-0.050* (-3.03)	-0.011 (-0.54)	0.071* (7.55)	-0.084* (-6.99)	0.124* (11.7)	-0.071* (-5.21)	0.127* (7.81)	-0.043* (-2.09)
Nobs	50,004	50,004	175,527	175,527	182,115	182,115	181,596	181,596	162,996	162,996

Table II - Continued

Investor Trading Decisions and Past Stock Returns

Model (3): $XB_{i,t}^G = \alpha_i^G + \sum \beta_{i,\phi} \text{Max}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \varepsilon_{i,t}^G;$

Model (5): $XS_{i,t}^G = \alpha_i^G + \sum \beta_{i,\phi} \text{Min}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \varepsilon_{i,t}^G;$

Model (4): $P(XB_{i,t}^G > 0) = \frac{e^{\sum \beta_{i,\phi} \text{Max}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \alpha_i^G}}{1 + e^{\sum \beta_{i,\phi} \text{Max}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \alpha_i^G}};$

Model (6): $P(XS_{i,t}^G > 0) = \frac{e^{\sum \beta_{i,\phi} \text{Min}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \alpha_i^G}}{1 + e^{\sum \beta_{i,\phi} \text{Min}[Ret_{i,\phi}^G] + \sum \lambda_{i,t} \pi_{i,t}^G + \alpha_i^G}};$

where $XB_{i,t}^G$ and $XS_{i,t}^G$, reflect investor group G 's net buying and net selling of stock i in excess of their average net buying and net selling of all stocks in their portfolios, $Ret_{i,\phi}^G$ denotes a vector of past returns variables with varying time-intervals, and $\pi_{i,t}^G$ is a set of control variables.

Panel B: Fixed Effects Logit Regression Estimates										
	Individual Investors Grouped by Trade Value									
	Institutions		Largest		Group 2		Group 3		Smallest	
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
$R(-1)$	1.714*	-0.231	4.382*	-2.480*	-0.424	9.086*	-17.22*	17.95*	-7.546*	12.13*
	(2.20)	(-0.24)	(9.12)	(-4.84)	(-0.88)	(17.0)	(-33.6)	(31.2)	(-14.9)	(21.6)
$R(-2)$	0.712	-0.937	2.519*	0.758	-1.579*	5.449*	-7.913*	6.421*	-5.666*	3.682*
	(0.86)	(-0.94)	(5.25)	(1.46)	(-3.29)	(10.2)	(-15.9)	(11.6)	(-11.2)	(6.63)
$R(-3)$	0.968	-2.157*	2.214*	0.600	-1.352*	3.714*	-5.757*	3.755*	-5.048*	3.758*
	(1.20)	(-2.15)	(4.65)	(1.17)	(-2.84)	(7.09)	(-11.7)	(6.99)	(-10.1)	(6.89)
$R(-4)$	0.557	0.187	0.841	0.473	-0.442	3.472*	-2.784*	2.300*	-2.609*	1.521*
	(0.67)	(0.18)	(1.76)	(0.92)	(-0.93)	(6.64)	(-5.68)	(4.31)	(-5.21)	(2.79)
$R(-5, -19)$	0.269	-0.892*	-0.033	0.543*	-0.933*	1.657*	-1.985*	1.622*	-2.323*	1.535*
	(1.15)	(-3.29)	(-0.24)	(4.13)	(-6.70)	(12.3)	(-13.9)	(11.8)	(-15.8)	(10.9)
$R(-20, -39)$	-0.021	-0.590*	-0.555*	0.340*	-0.309*	1.015*	0.065	0.660*	-0.522*	0.483*
	(-0.10)	(-2.36)	(-4.59)	(2.83)	(-2.55)	(8.37)	(0.52)	(5.36)	(-4.09)	(3.80)
$R(-40, -59)$	-0.003	-0.947*	-0.199	0.096	0.136	0.418*	0.000	0.577*	-0.143	0.081
	(-0.02)	(-3.60)	(-1.65)	(0.80)	(1.12)	(3.45)	(0.00)	(4.67)	(-1.11)	(0.64)
$R(-60, -119)$	-0.393*	0.314	-0.234*	-0.100	-0.211*	0.407*	-0.104	0.406*	0.083	0.026
	(-2.37)	(1.94)	(-2.86)	(-1.18)	(-2.58)	(4.77)	(-1.24)	(4.67)	(0.94)	(0.29)
$R(-120, -179)$	0.075	-0.216	-0.197*	-0.125	0.340*	-0.011	0.724*	0.194*	0.499*	0.123
	(0.49)	(-1.26)	(-2.50)	(-1.44)	(4.30)	(-0.13)	(8.90)	(2.19)	(5.89)	(1.36)
$R(-180, -239)$	0.220	-0.354*	-0.165*	-0.056	0.486*	-0.650*	0.700*	-0.365*	0.540*	-0.162
	(1.59)	(-1.96)	(-2.29)	(-0.61)	(6.73)	(-6.98)	(9.40)	(-3.87)	(7.02)	(-1.68)
Nobs.	50004	50004	175527	175527	182115	182115	181596	181596	162996	162996

Table III

Investor Trading of Small vs. Large Stocks and Past Stock Returns

The table shows maximum likelihood estimates of fixed effects logit regressions of excess buying ('Buy') and excess selling ('Sell') of stocks by each investor group on small- and large-sized stocks; those of middle-sized group are unreported. Stocks are categorized into 'large', 'medium' and 'small' stock groups based on stocks' tradable market value as of 2000. Panels A and B present estimates for small and large stocks respectively. The dependent variable is a binary response variable that takes the value of one when an investor group's excess buying or selling is positive and zero if otherwise. The independent variables are market-adjusted past returns calculated for 10 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 takes one at the date of public-listing and zero otherwise; and two dummy variables for 'reference point' effects, which take one if the stock price is at the monthly highest or lowest level and zero otherwise. The approach used in categorizing individual investors into four different trade-value groups is given in Table I. t -statistics are based on panel corrected standard errors, and * symbol indicates 5% level of significance. The sample period is between April 2001 and September 2002.

	Individual Investors Grouped by Trade Value									
	Institutions		Largest		Group 2		Group 3		Smallest	
Panel A: Buying and Selling of Small Stocks										
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
$R(-1)$	2.277 (1.42)	-5.877* (-2.92)	1.618 (1.92)	-2.754* (-3.10)	-0.421 (-0.50)	7.900* (8.64)	-15.60* (-17.4)	16.80* (17.1)	-4.598* (-5.20)	10.45* (10.7)
$R(-2)$	2.498 (1.52)	-4.447* (-2.28)	1.449 (1.73)	0.391 (0.43)	-3.223* (-3.87)	5.557* (6.06)	-6.333* (-7.37)	7.654* (8.08)	-3.694* (-4.18)	4.307* (4.42)
$R(-3)$	3.593* (2.24)	-1.628 (-0.81)	1.141 (1.36)	0.189 (0.21)	-1.097 (-1.32)	4.456* (4.93)	-5.253* (-6.15)	3.244* (3.54)	-2.891* (-3.28)	4.653* (4.86)
$R(-4)$	3.985* (2.42)	-0.264 (-0.12)	0.109 (0.13)	-0.401 (-0.45)	-1.511 (-1.83)	3.837* (4.28)	-2.347* (-2.77)	3.601* (3.96)	-2.211* (-2.52)	0.067 (0.07)
$R(-5, -19)$	0.097 (0.19)	-1.929* (-3.16)	-0.741* (-2.96)	0.358 (1.58)	-1.316* (-5.28)	1.590* (7.01)	-1.510* (-5.92)	1.290* (5.61)	-1.572* (-5.88)	1.212* (5.05)
$R(-20, -39)$	-0.384 (-0.83)	-1.779* (-3.36)	-0.835* (-3.84)	-0.037 (-0.17)	-0.601* (-2.79)	1.236* (6.00)	-0.090 (-0.40)	1.270* (6.06)	-0.295 (-1.27)	0.598* (2.72)
$R(-40, -59)$	0.143 (0.29)	-1.337* (-2.28)	-0.170 (-0.78)	-0.186 (-0.88)	-0.073 (-0.34)	0.706* (3.41)	-0.312 (-1.41)	0.522* (2.48)	-0.153 (-0.65)	-0.072 (-0.32)
$R(-60, -119)$	-0.330 (-0.91)	0.426 (1.38)	-0.103 (-0.70)	-0.160 (-1.11)	-0.233 (-1.62)	0.429* (2.99)	-0.300* (-2.04)	0.598* (4.10)	-0.286 (-1.80)	0.242 (1.60)
$R(-120, -179)$	0.169 (0.55)	-0.500 (-1.47)	-0.238 (-1.74)	-0.144 (-0.96)	0.319* (2.32)	0.398* (2.70)	0.598* (4.36)	0.828* (5.51)	0.264 (1.81)	0.230 (1.48)
$R(-180, -239)$	0.014 (0.04)	-0.027 (-0.07)	0.163 (1.33)	-0.262 (-1.62)	0.584* (4.85)	-0.334* (-2.09)	0.593* (4.82)	-0.153 (-0.95)	0.353* (2.73)	-0.125 (-0.74)
Nobs.	10,903	10,903	50,826	50,826	53,975	53,975	53,738	53,738	45,509	45,509

Table III - Continued

Investor Trading of Small vs. Large Stocks and Past Stock Returns

	Individual Investors Grouped by Trade Value									
	Institutions		Largest		Group 2		Group 3		Smallest	
	Panel B: Buying and Selling of Large Stocks									
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
$R(-1)$	-1.685 (-1.34)	-3.400* (-2.07)	7.383* (8.26)	-2.533* (-2.51)	-1.444 (-1.61)	11.46* (10.9)	-21.56* (-22.1)	22.51* (19.3)	-13.28* (-13.9)	17.31* (15.2)
$R(-2)$	0.179 (0.13)	-0.104 (-0.06)	3.275* (3.70)	2.106* (2.07)	-0.828 (-0.92)	7.423* (7.00)	-9.804* (-10.5)	6.587* (5.96)	-8.585* (-9.16)	6.186* (5.60)
$R(-3)$	0.189 (0.14)	-2.077 (-1.24)	3.334* (3.79)	0.793 (0.78)	-0.289 (-0.32)	4.004* (3.86)	-7.099* (-7.76)	5.956* (5.50)	-6.902* (-7.47)	4.588* (4.23)
$R(-4)$	0.431 (0.31)	-0.711 (-0.41)	1.996* (2.26)	0.767 (0.76)	0.925 (1.03)	3.645* (3.53)	-3.198* (-3.49)	2.977* (2.79)	-4.796* (-5.17)	4.532* (4.19)
$R(-5, -19)$	0.063 (0.16)	-1.823* (-3.80)	0.477 (1.91)	0.939* (3.47)	-0.248 (-0.98)	1.627* (5.88)	-2.238* (-8.65)	2.299* (8.01)	-3.130* (-11.9)	2.470* (8.48)
$R(-20, -39)$	-0.132 (-0.37)	-0.374 (-0.87)	-0.214 (-0.97)	1.366* (5.58)	0.083 (0.37)	0.679* (2.73)	-0.089 (-0.38)	0.244 (0.96)	-0.766* (-3.29)	0.692* (2.67)
$R(-40, -59)$	-0.352 (-0.94)	-1.273* (-2.97)	-0.308 (-1.39)	0.906* (3.69)	0.264 (1.18)	0.300 (1.207)	0.539* (2.32)	0.307 (1.20)	-0.014 (-0.06)	0.344 (1.34)
$R(-60, -119)$	-0.288 (-1.13)	-0.093 (-0.33)	-0.435* (-2.89)	0.192 (1.16)	-0.571* (-3.76)	0.535* (3.17)	-0.179 (-1.14)	-0.020 (-0.11)	0.016 (0.10)	-0.296 (-1.70)
$R(-120, -179)$	0.445 (1.83)	-0.246 (-0.85)	-0.232 (-1.55)	-0.180 (-1.05)	0.034 (0.22)	-0.338* (-1.96)	0.241 (1.55)	-0.267 (-1.50)	0.218 (1.36)	0.172 (0.96)
$R(-180, -239)$	0.287 (1.33)	-0.301 (-1.04)	-0.161 (-1.18)	0.072 (0.43)	0.298* (2.14)	-0.888* (-5.23)	0.548* (3.82)	-0.881* (-5.08)	0.455* (3.10)	-0.504* (-2.88)
Nobs.	20,685	20,685	54,976	54,976	55,939	55,939	55,848	55,848	52,740	52,740

Table IV

The Impact of Investor Trading on Future Stock Volatility

The table reports fixed effects OLS estimates of

$$\sigma_{i,t} = \phi_{i,0} + \phi_1 XB_{i,t-1}^G + \phi_2 XS_{i,t-1}^G + \phi_3 \sigma_{i,t-1} + \phi_4 \sigma_{M,t} + \phi_5 r_{i,t-1} + \epsilon_{i,t},$$

where $\sigma_{i,t}$ is the monthly return volatility of stock i in month t , $XB_{i,t-1}^G$ and $XS_{i,t-1}^G$ 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 $t-1$, $\sigma_{M,t}$ 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 four different trade-value groups is given in Table I. t -statistics, in parentheses, are based on panel corrected standard errors, and * symbol indicates 5% level of significance. The sample period is between April 2001 and September 2002.

	Individual Investors Grouped by Trade Value				
	Institutions	Largest	Group 2	Group 3	Smallest
XB_{t-1}^G	-0.073* (-3.06)	-0.420* (-6.71)	-0.211* (-2.28)	-0.112 (-1.66)	-0.210* (-3.63)
XS_{t-1}^G	0.0096 (0.38)	0.132* (2.53)	0.503* (6.50)	0.305* (4.88)	0.149* (2.57)
$\sigma_{i,t-1}$	0.094* (14.2)	0.087* (13.8)	0.089* (14.2)	0.090* (13.9)	0.088* (14.0)
$\sigma_{M,t}$	1.168* (133.4)	1.168* (138.2)	1.170* (138.4)	1.168* (138.3)	1.167* (138.3)
$r_{i,t-1}$	0.103 (1.46)	0.208* (2.92)	0.233* (3.26)	0.248* (3.14)	0.127 (1.64)
Nobs.	9,971	11,079	11,084	11,082	11,061

Table V

The Impact of Investor Trading on Future Stock Volatility by Type of Stocks

The table reports fixed effects OLS estimates of

$$\sigma_{i,t} = \alpha_i + \beta_1 XB_{i,t-1}^G + \beta_2 XS_{i,t-1}^G + \gamma_1 \sigma_{i,t-1} + \gamma_2 \sigma_{M,t} + \lambda_1 r_{i,t-1} + \varepsilon_{i,t},$$

where $\sigma_{i,t}$ is the monthly return volatility of stock i in month t , $XB_{i,t-1}^G$ and $XS_{i,t-1}^G$ 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 $t-1$, $\sigma_{M,t}$ 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 four different trade-value groups is given in Table I. Stocks are categorized into ‘large’, ‘medium’ and ‘small’ stock groups based on stocks’ tradable market value as of 2000. t -statistics, in parentheses, are based on panel corrected standard errors, and * symbol indicates 5% level of significance. The sample period is between April 2001 and September 2002.

	Individual Investors Grouped by Trade Value									
	Institutions		Largest		Group 2		Group 3		Smallest	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
XB_{t-1}^G	-0.092* (-2.29)	0.010 (0.20)	-0.497* (-4.57)	-0.216 (-1.82)	-0.198 (-1.30)	-0.241 (-1.27)	-0.157 (-1.52)	0.001 (0.01)	-0.288* (-3.15)	0.012 (0.10)
XS_{t-1}^G	0.040 (0.93)	-0.094 (-1.91)	0.128 (1.48)	-0.033 (-0.30)	0.433* (3.37)	0.805* (5.19)	0.175 (1.67)	0.678* (5.44)	0.137 (1.35)	0.288* (2.53)
$\sigma_{i,t-1}$	0.120* (10.9)	0.071* (5.14)	0.124* (11.3)	0.064* (5.04)	0.125* (11.6)	0.062* (4.98)	0.123* (11.1)	0.065* (5.08)	0.120* (10.9)	0.067* (5.24)
$\sigma_{m,t}$	1.114* (79.2)	1.211* (63.5)	1.110* (81.3)	1.193* (65.9)	1.112* (81.2)	1.198* (66.7)	1.109* (80.7)	1.197* (66.8)	1.107* (80.7)	1.193* (66.4)
$r_{i,t-1}$	-0.287* (-2.39)	0.426* (2.96)	-0.223* (-1.86)	0.577* (3.99)	-0.202 (-1.66)	0.608* (4.22)	-0.262 (-1.91)	0.753* (4.86)	-0.389* (-2.85)	0.621* (4.13)
Nobs.	3,124	2,669	3,266	3,213	3,266	3,216	3,266	3,215	3,265	3,198

Table VI

Impact of Investor Trading on Future Stock Returns

The table reports parameter estimates of fixed effects OLS regressions of

$$r_{i,t} = \delta_{i,0} + \delta_1 XB_{i,t-1}^G + \delta_2 XS_{i,t-1}^G + \delta_3 r_{M,t} + \delta_4 r_{i,t-1} + \eta_{i,t},$$

where $r_{i,t}$ is the return of stock i in month t , $XB_{i,t-1}^G$ and $XS_{i,t-1}^G$ are excess buying and selling of group G in stock i in month $t-1$, $r_{M,t}$ 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 four different trade-size groups is given in Table I. t -statistics, in parentheses, are based on panel corrected standard errors, and * symbol indicates 5% level of significance. The sample period is between April 2001 and September 2002.

	Institutions	Individual Investors Grouped by Trade Value			
		Largest	Group 2	Group 3	Smallest
XB_{t-1}^G	0.292 (1.18)	0.587 (0.93)	0.284 (0.30)	-2.291* (-3.52)	-0.662 (-1.16)
XS_{t-1}^G	-0.471 (-1.88)	0.884 (1.72)	-0.608 (-0.78)	-0.984 (-1.56)	-2.792* (-4.77)
$r_{i,t-1}$	-0.052* (-7.60)	-0.043* (-6.42)	-0.040* (-5.96)	-0.055* (-7.45)	-0.054* (-7.41)
$r_{M,t}$	0.946* (96.5)	0.958* (102.3)	0.958* (102.0)	0.955* (101.7)	0.957* (102.2)
Nobs.	9,971	11,079	11,084	11,082	11,061

Table VII

Impact of Investor Trading on Future Stock Returns by Type of stocks

The table reports parameter estimates of fixed effects OLS regressions of

$$r_{i,t} = \delta_{i,0} + \delta_1 X B_{i,t-1}^G + \delta_2 X S_{i,t-1}^G + \delta_3 r_{M,t} + \delta_4 r_{i,t-1} + \eta_{i,t},$$

where $r_{i,t}$ is the return of stock i in month t , $X B_{i,t-1}^G$ and $X S_{i,t-1}^G$ are excess buying and selling of group G in stock i in month $t-1$, $r_{M,t}$ 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 four different trade-size groups is given in Table I. Stocks are categorized into ‘large’, ‘medium’ and ‘small’ stock groups based on stocks’ tradable market value as of 2000. t -statistics, in parentheses, are based on on panel corrected standard errors, and * symbol indicates 5% level of significance. The sample period is between April 2001 and September 2002.

	Individual Investors Grouped by Trade Value									
	Institutions		Largest		Group 2		Group 3		Smallest	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
$X B_{t-1}^G$	0.242 (0.56)	1.055* (2.09)	-1.344 (-1.15)	-0.463 (-0.41)	-0.079 (-0.04)	0.313 (0.17)	-2.446* (-2.29)	-3.173* (-2.30)	-0.471 (-0.48)	-1.053 (-0.90)
$X S_{t-1}^G$	-0.297 (-0.65)	-1.377* (-2.78)	2.803* (3.09)	1.049 (1.04)	-1.074 (-0.77)	-0.300 (-0.20)	-1.061 (-0.94)	-0.687 (-0.57)	-1.646 (-1.51)	-4.798* (-4.39)
$r_{i,t-1}$	-0.073* (-5.97)	-0.047* (-3.50)	-0.078* (-6.33)	-0.034* (-2.75)	-0.072* (-5.78)	-0.032* (-2.59)	-0.091* (-6.45)	-0.047* (-3.49)	-0.082* (-5.80)	-0.051* (-3.88)
$r_{M,t}$	0.940* (56.1)	0.975* (47.9)	0.941* (57.1)	0.993* (53.2)	0.941* (56.8)	0.992* (53.1)	0.937* (56.6)	0.989* (52.9)	0.941* (56.9)	0.992* (53.2)
Nobs.	3,124	2,669	3,266	3,213	3,266	3,216	3,266	3,215	3,265	3,198