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Stock returns, order imbalances, and commonality: Evidence on individual, institutional, and proprietary investors in China

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Abstract

Using a unique dataset from the Shanghai Stock Exchange, we study the relation between daily open-to-close stock returns and order imbalances, and the commonality in order imbalances across individual, institutional, and proprietary investors. We find that institutional (proprietary) order imbalances have a larger price impact, but account for a significantly smaller proportion of daily price fluctuations. Commonality is much stronger for individual, rather than institutional (proprietary), order imbalances. Institutional (proprietary) investors favor large capitalization stocks, and co-movement in institutional (proprietary) order imbalances is stronger for these stocks.

JEL classification: G10; G15

Keywords: Order imbalance; Commonality; Individual; Institutional; Proprietary investors

1. Introduction

This study exploits a novel data set to explore two related questions in market microstructure. First, we study individual, institutional, and proprietary account order imbalances and their associations with stock returns.[1] In general, order imbalances are highly persistent and positively related to contemporaneous stock returns on an individual stock basis. Second, we study the commonalities in order imbalances among different account types.[2] For a large cross-section of stocks on the NYSE, Chordia et al. (2000) report significant and positive loadings on a market-wide liquidity factor for about a third of their sample stocks while Hasbrouck and Seppi (2001) report stronger commonality in order imbalances.[3]

Institutions often break an order into smaller pieces (Chan and Lakonishok, 1995; Biais et al., 1995) and brokers trade based on their own in-house research or imitate the trades of informed clients (Sarkar, 1990), thereby inducing correlation in order imbalances. Given their size and potential information content, the impact of institutional trades should be larger than that of individual trades. The trading patterns of individual investors can also be persistent and strongly influence stock returns for a variety of reasons ranging from public information arrival to noisy trading. The contrast between the effects of institutional versus individual order imbalances is particularly interesting if we view institutions as informed professionals and individuals as information-poor and more subject to behavioral biases.

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[1] See Chordia et al. (2002, 2005a), Griffin et al. (2003), Chordia and Subrahmanyam (2004), Lee (1992), Hasbrouck and Seppi (2001), Corwin and Lipson (2000), among others.

[2] See Chordia et al. (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001).

[3] Other studies of commonality examine stocks handled by the same specialist firm (Coughenour and Saad, 2004), stocks traded in limit order markets (Friederich and Payne, 2002), stocks in different countries (Stahel, 2003), and stocks and bonds (Chordia et al., 2005b; Goyenko, 2005).

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A number of explanations for commonality have been proposed. Shleifer and Summers (1990) suggest that individual investors may herd if they follow the same signal, such as brokerage recommendations. Individual investors may also herd if they engage in positive-feedback trading (Lakonishok et al., 1994) or negative feedback trading (Shefrin and Statman, 1995). If institutions are better informed, institutional investors will be more likely to herd in under-valued stocks (Nofsinger and Sias, 1999) which, in turn, induces stronger commonality in the order imbalances of winner stocks. Herding studies are usually based on quarterly or annual holdings disaggregated into institutional versus individual holdings. However, the commonality literature typically does not distinguish between different types of investors.[4] Indeed, Chordia and Subrahmanyam (2004) call for additional research to "analyze imbalance caused by different agents (that is, institutions versus individual investors)" and to "identify informed traders and liquidity traders in a more precise manner".

Our study considers the relative importance of order imbalances from individual, institutional, and proprietary investors in determining daily individual stock returns and the degree of commonality in order imbalances among different account types. This substantial extension of the existing literature is made possible by the recent availability of a proprietary tick data set from the Shanghai Stock Exchange (SSE). The limit order trading system on the SSE records the identity and shareholdings of each investor who trades in China. With this data, we can classify each trade as initiated from an individual, an institution (ordinary firms, listed firms, insurance companies), or a proprietary account (brokerage firms, mutual funds, and Qualified Foreign Institutional Investors, QFIIs). Broadly speaking, institutional investors are more sophisticated than individual investors, and proprietary accounts are likely to be more sophisticated than those of other institutions. For example, mutual fund managers have more professional training, richer experience, and stronger incentives to perform than other investors do. Similarly, QFIIs are typically well-capitalized foreign financial institutions with a great deal of experience investing in international stock markets. Aside from offering the data needed to support a more detailed study of order imbalances, the Chinese stock market is particularly interesting because of its size, volatility, large presence of individual investors, and substantial scope for information asymmetries given poor disclosure and governance standards.

Our main findings can be summarized as follows. First, with an average autocorrelation of 0.378, proprietary order imbalances are most persistent, and have the largest impact on daily returns. However, the association between order imbalances and daily price movements is significantly lower for institutional (proprietary) investors than it is that for individual investors. By itself, individual order imbalances explain as much as 21.8% of the fluctuation in daily open-to-close returns, followed by proprietary order imbalances (5.8%) and institutional order imbalances (3.1%). Proprietary and institutional investors jointly explain 8.5% of daily price movements. Second, individual order imbalances exhibit a strong pattern of co-movement that is larger than the corresponding pattern for institutions (proprietary investors). For a majority (95.5%) of stocks in the sample, individual imbalances respond significantly to movement in market-wide individual imbalances. In contrast, institutional imbalances co-move significantly with market-wide institutional imbalances for only 24.7% of stocks. The proportion of stocks that exhibit commonality in proprietary imbalances is also low at 36.9%.[5]

The rest of the paper is organized as follows: Section 2 describes the data set and sample selection. Section 3 reports summary statistics. Section 4 documents the relation between daily stock returns and order imbalances of individual and institutional investors while Section 5 documents commonality in order imbalances of individual and institutional investors. Section 6 summarizes and concludes the study.

2. Data and sample selection

Our sample consists of 198 stocks, including the current components of the Shanghai 180 index, plus 18 stocks that were replaced after December 2003. The component stocks of this index comprise more than half of the total market capitalization of the SSE as of December 2003. Data on individual trades are supplied by the SSE for the period from October 2003 to March 2004, a total of 117 trading days. Each record includes the investor identity code for both sides of the trade, date, trade sequence, exchange seat code, trade size, stock holding after transaction for both sides of the trade, stock code, order time, trade time, trade price, trade amount, order sequence number, and other variables. The investor identity code allows us to classify both sides of each trade as originating from an individual account, institutional account (ordinary firms, listed firms, insurance companies), or a proprietary account (brokerage firms, mutual funds, and QFIIs). The order sequence number allows us to distinguish which party initiates the transaction.

The SSE is open from Monday to Friday, with 9:15 am to 9:25 am reserved for an opening batch auction while 9:30 am to 11:30 am and 1:00 pm to 3:00 pm are reserved

[4] An exception is Griffin et al. (2003). For a sample of NASDAQ 100 stocks, they examine daily and intraday associations between stock returns and the trading of individual and institutional investors.

[5] Our study is related to the work of Lee et al. (2004) on buy and sell orders submitted to the Taiwan Stock Exchange for the 30 largest stocks over the period from September 1996 through April 1999. Their dataset allows them to identify each order as having been submitted by a domestic individual, a domestic institution, or a foreign institution. In contrast to our analysis of 198 individual stocks, they focus on value-weighted average imbalances and average stock returns from 30 largest stocks on the Taiwan Stock Exchange.

Table 1
Summary statistics

	Mean	Median	Mean	Median
Market capitalization	2414	1600		
Daily open-to-close percentage return	0.111	0.111		
Autocorrelation of daily open-to-close return (% significant at 10% level)	−0.094	−0.095		
	(0.0)			
Cross-correlation of returns (raw)	0.324	0.328		
Cross-correlation of returns (market-adjusted)	−0.003	−0.011		
Percentage of days with institutional trades	80.9	85.6		
Percentage of days with proprietary trades	65.5	67.4		
	Number of trades		Share volume	
Average daily measure of trading activity				
Total	3354	2190	5,371,000	2,717,000
Percentage from individual accounts	91.76	94.96	87.31	92.45
Percentage from institutional accounts	3.52	2.17	5.31	3.43
Percentage from proprietary accounts	6.46	4.40	9.86	6.60
Average percentage daily order imbalance				
Individual accounts	−6.28	−7.17	−4.98	−6.79
Institutional accounts	−0.21	−0.14	0.05	−0.17
Proprietary accounts	−0.26	−0.49	−0.20	−0.61
Autocorrelation of order imbalances				
Individual accounts (% significant at 10% level)	0.180	0.162	0.183	0.167
	(55.6)		(54.6)	
Institutional accounts (% significant at 10% level)	0.171	0.167	0.161	0.145
	(50.0)		(44.9)	
Proprietary accounts (% significant at 10% level)	0.378	0.381	0.362	0.367
	(76.6)		(77.2)	
Median cross-correlation of returns and order imbalances (number of trades)				
Daily return	1.000			
Individual accounts	0.489	1.000		
Institutional accounts	0.107	0.101	1.000	
Proprietary accounts	0.047	−0.091	0.049	1.000
Median cross-correlation of returns and order imbalances (share volume)				
Daily return	1.000			
Individual accounts	0.451	1.000		
Institutional accounts	0.082	0.045	1.000	
Proprietary accounts	0.032	−0.176	−0.031	1.000

The sample covers 198 stocks listed on the Shanghai Stock Exchange (SSE), including Shanghai 180 index constituent stocks plus 18 stocks that were replaced after December 2003. The sample period is from October 2003 to March 2004. Proprietary traders are brokerages, mutual funds, and foreigners. Institutional traders are other corporations. For individual, institutional, and proprietary investors in each stock, we calculate the daily number of trades, share volume, and order imbalance as a percentage of total daily trading activity measures (number of trades or share volume). These daily measures are then averaged over 117 trading days for each stock. Order imbalances for institutional and proprietary traders are calculated over days when there is positive trading activity for the group. The figures in parentheses below the autocorrelation figures represent the percentage of 198 stocks that have a significant autocorrelation at lag-one. Market capitalizations (end-of-month averages in million yuan) are from the China Stock Market Research dataset (CSMAR). All other statistics are calculated using trade and order files from the SSE.

for regular consecutive bidding. We examine daily open-to-close returns and order imbalances during the regular morning and afternoon sessions.[6] We use the first quote mid-point after 9:30 am and the last quote mid-point before 3:00 pm to calculate open-to-close returns. We measure trading activity by the number of trades, the volume of shares traded, and turnover measured in local currency, although results for turnover are not reported since they are virtually identical to those for volume. Additional key variables are the order imbalance in terms of numbers of trades (the number of buyer-initiated trades minus the number of seller-initiated trades divided by the total number of trades) and the order imbalance in terms of volume (buyer-initiated volume minus seller-initiated volume divided by total volume). Each of these two measures is computed daily for each stock in the sample and for each of the three investor types: individual, institutional, and proprietary.

3. Summary statistics

Table 1 presents summary statistics for our sample of 198 stocks and 6 months. Across all sample stocks, the mean daily market capitalization is 2414 million yuan (about 300 million US dollars) and the mean daily open-to-close return is 0.111%. The mean lag-one autocorrelation of daily

[6] We also exclude block trading (trades exceeding 50 million shares or 3 million yuan) which takes place between 3:00 pm and 3:30 pm.

stock returns is −0.094, though none of the 198 individual autocorrelation estimates is significant at the 10% level. The mean cross-correlation of raw returns ($198 \times 197/2 =$ 19,503 pairs of individual stocks) is 0.324 and the mean cross-correlation between excess returns is −0.003.

To measure how frequently institutional investors trade each of the 198 stocks over our 117 trading day period, for each stock we calculate the number of days on which there is institutional or proprietary trading, then divide this by 117. The cross-sectional mean is 80.9% for institutional trading and 65.5% for proprietary trading. Additional summary statistics for these types of investors exclude days with no institutional or proprietary trading. For a typical stock on a typical trading day, the average number of trades is 3354, of which 91.76% is initiated by individual investors, 3.52% by institutional investors, and 6.46% by proprietary investors. The average daily trading volume is 5,371,000 shares. When trading activity is measured with share volume, institutional and proprietary investors account for 5.31% and 9.86% of volume respectively while individuals account for 87.31%, given the relatively smaller size of their trades. Over the sample period, individuals are net sellers, with average order imbalances of −6.28% and −4.98% of the number of trades and share volume, respectively.

The order imbalances are typically highly auto-correlated. For individuals, the average autocorrelation at lag-one is 0.180, and 55.6% of the 198 order imbalance autocorrelations are significant at the 10% level. For institutions, the average lag-one autocorrelation is 0.171, and 50.0% are highly significant. Proprietary investors display an even stronger pattern of order persistence, with an average lag-one autocorrelation of 0.378, and 76.6% of the individual autocorrelation coefficients are highly significant. The evidence is consistent with Lee et al. (2004) who report similar patterns in autocorrelations for individuals, domestic institutions, and foreign institutions on Taiwan's stock exchange.

Finally, Table 1 reports cross-sectional mean correlations between daily open-to-close returns and order imbalances. All three mean correlations between daily open-to-close returns and order imbalances are positive, with the largest, 0.489, for individual order imbalances. Furthermore, individual order imbalances are positively correlated with institutional order imbalances but negatively correlated with proprietary order imbalances. The correlation between institutional and proprietary order imbalances is very low.

4. Daily stock returns and order imbalances

4.1. Contemporaneous order imbalances

Since herding, order-splitting, and other aspects of order submission can extend over more than one day, our first test examines how both contemporaneous and lagged order imbalances affect daily stock returns. We begin by measuring the impact of contemporaneous order imbalances with regressions of individual stock daily returns on contemporaneous order imbalances of individuals (INDV), institutions (INST), and proprietary investors (PROP)

$$r_{it} - r_{mt} = \delta_0 + \delta_{i,\mathrm{INDV}}\mathrm{imbal}_{it,\mathrm{INDV}} + \delta_{i,\mathrm{INST}}\mathrm{imbal}_{it,\mathrm{INST}} + \delta_{i,\mathrm{PROP}}\mathrm{imbal}_{it,\mathrm{PROP}} + \varepsilon_{it}, \quad (1)$$

where r_{it} is the daily open-to-close return for stock i on day t and r_{mt} is an equal-weighted portfolio return on day t. We use excess returns instead of raw returns because the latter display a high degree of cross-correlation, as is evident in Table 1. The independent variables, $\mathrm{imbal}_{it,\ j}$, are order imbalances (computed using the number of trades or trading volume in different specifications) for individual, institutional, and proprietary investors respectively for day t and stock i.

Table 2 reports that, for individual investors, the average impact of contemporaneous order imbalances on daily open-to-close returns, measured by the slope coefficient, $\delta_{i,\mathrm{INDV}}$, is 0.046 with a highly significant t-statistic of 33.68. The averages of $\delta_{i,\mathrm{INST}}$ and $\delta_{i,\mathrm{PROP}}$ are 0.080 and 0.088, respectively, for institutional and proprietary investors. The corresponding t-statistics are 12.62 and 3.65, respectively.

We follow the procedure outlined in Appendix B of Chordia and Subrahmanyam (2004) to calculate the standard errors of the average coefficients from individual firm time-series regressions. Specifically, we first calculate the covariance between the regression coefficients across two stocks i and j, $\mathrm{cov}(\beta_i, \beta_j) = \sigma_{ij}(X_i'X_i)^{-1}X_i'X_j(X_j'X_j)^{-1}$, where X_i and X_j are the matrices of time-series observations for the independent variables in regressions i and j. Second, we construct the variance–covariance matrix of the estimated parameters $(\beta_1, \ldots, \beta_N)$, $N = 198$. Finally, we calculate the variance of the mean coefficient $(\beta_1 + \cdots + \beta_N)/N$ by applying the vector $\{1/N, \ldots, 1/N\}$ to the variance–covariance matrix.

The average coefficients suggest that proprietary order imbalances have the greatest impact on daily returns. Ninety-six percent of the slope coefficients for individual order imbalances are positive and significant. Forty-nine percent of coefficients for institutional investors are positive and significant; for proprietary investors, 74% of coefficients are positive and significant. Inferences based on medians are similar except that the median $\delta_{i,\mathrm{PROP}}$ also becomes highly significant under the Wilcoxon sign-rank test. Additional non-parametric Wilcoxon sign-rank tests for pairwise groups of individual, institutional, and proprietary coefficients confirm that institutional and proprietary order imbalances have a significantly larger impact on daily open-to-close return than individual order imbalances do.[7]

[7] The regression results using order imbalances measured using share volume, rather than number of trades, are similar except that adjusted R^2 are lower with share volume. This confirms the findings of Jones et al. (1994) that the number of transactions plays a more important role in determining stock returns than share volume does.

Table 2
Daily stock returns, and individual, institutional, and proprietary order imbalances

	Average coefficient	Median coefficient	Percentage positive	Percentage positive and significant	Percentage negative and significant
$\delta_{i,\mathrm{INDV}}$	0.046^{**}	0.044^{++}	99.0	96.4	0.0
	(33.68)	(12.15)			
$\delta_{i,\mathrm{INST}}$	0.080^{**}	0.060^{++}	88.8	49.2	1.5
	(12.62)	(10.73)			
$\delta_{i,\mathrm{PROP}}$	0.088^{**}	0.066^{++}	93.9	74.1	0.0
	(3.65)	(10.83)			
Adjusted R^2	0.309	0.312			
	P-value (median $\delta_{i,\ \mathrm{INDV}} = \delta_{i,\mathrm{INST}}$): 0.000				
	P-value (median $\delta_{i,\mathrm{INDV}} = \delta_{i,\ \mathrm{PROP}}$): 0.000				
	P-value (median $\delta_{i,\mathrm{INST}} = \delta_{i,\mathrm{PROP}}$): 0.213				

This table summarizes regressions of individual stock excess returns on contemporaneous order imbalances of individuals (INDV), institutions (INST), and proprietary traders (PROP):

$$r_{it} - r_{mt} = \delta_0 + \delta_{i,\mathrm{INDV}}\mathrm{imbal}_{it,\mathrm{INDV}} + \delta_{i,\mathrm{INST}}\mathrm{imbal}_{it,\mathrm{INST}} + \delta_{i,\mathrm{PROP}}\mathrm{imbal}_{it,\mathrm{PROP}} + \varepsilon_{it}, \tag{1}$$

where r_{it} is the daily open-to-close return for stock i on day t, and r_{mt} is an equally-weighted portfolio return on day t, $t = 1, 2, \ldots, 117$, $i = 1, 2, \ldots, 198$. Independent variables $\mathrm{imbal}_{it,j}$, j = INDV, INST, and PROP, are daily percentage order imbalances in number of trades. The table reports cross-sectional average and median coefficients, percentage of positive coefficients, percentage of positive and significant coefficients ($t > 1.65$), percentage of negative and significant coefficients ($t < -1.65$), and average and median adjusted R^2. t-Statistics and Wilcoxon sign-rank z-statistics are reported in parentheses. ** indicates significance of t-statistics at the 5% level; $^{++}$ indicates significance of z-statistics at the 5% level.

4.2. Contemporaneous and lagged order imbalances

Since order imbalances from both individual and institutional investors are auto-correlated at lag 1, we extend specification (1) above to include lagged order imbalance terms. Though not reported, regressions are estimated with both the number of trades and trading volume measures of order imbalances. The overall contribution of the lagged order imbalance is marginal. When the number of trades is used to measure order imbalance, the mean adjusted R^2 rises from 0.309 in Table 2 to 0.321, and the only lagged variable with both significant t- and z-statistics is the individual order imbalance with average slope coefficient (t-test) of -0.005 (1.75) and median slope (z-test) of 0.005 (7.81).[8,9,10]

[8] Chordia and Subrahmanyam (2004) explain negative signs on lagged order imbalances as resulting from "over counting" of the impact of persistence in order imbalances: the impact of persistent order imbalances appears in the slope coefficients on both the contemporaneous and lagged order imbalances. The negative slope on the lagged order imbalance "corrects" for this overweighting.

[9] We estimate regressions that exclude contemporaneous order imbalance terms. Only 4% of coefficients for lagged individual order imbalances, $\lambda_{i,\mathrm{INDV}}$, are positive and significant. About 6% of coefficients for institutions and 11% of coefficients for proprietary trades are positive and significant. The lack of significance of lagged order imbalances may be due to the smaller sample size than that studied in Chordia and Subrahmanyam (2004). For a sample of NASDAQ 100 stocks, Griffin et al. (2003) also report no evidence that past institutional trading imbalances can forecast daily returns, unlike Chordia and Subrahmanyam (2004).

[10] Lee et al. (2004) tried to predict daily value-weighted average returns for the 30 largest stocks on the TWSE using lagged positive and negative daily order imbalances and lagged positive and negative value-weighted average returns. They report weak forecasting ability by lagged imbalances.

4.3. Marginal explanatory power of individual and institutional order imbalances

In this section, we measure the relative importance of the three different types of traders in explaining daily fluctuations in stock returns using multiple and partial correlation coefficients from OLS regressions. The multiple correlation (that is, the adjusted R^2) measures the proportion of the variance in daily returns that independent variables jointly explain. For example, $R^2_{\mathrm{INDV\_INST\_PROP}}$ measures how much variance the order imbalances of individual, institutional, and proprietary traders explains. A partial correlation coefficient, such as $r^2_{\mathrm{INDV,Others}}$, measures how much variance the individual order imbalance can explain after institutional and proprietary order imbalances are included.

Table 3 presents the mean, median, 25th, and 75th percentiles of the multiple and partial correlation coefficients from estimates of Eq. (1). By themselves, individual order imbalances have the highest explanatory power, with an average multiple correlation coefficient of 0.218. Proprietary order imbalances have an average multiple correlation of 0.058 and institutional order imbalances have an average multiple correlation of only 0.031. When order imbalances of both institutional and proprietary trades are used in the regressions, the adjusted R^2 rises to 0.085. This remains smaller than that the explanatory power from individual investor order imbalances. The adjusted R^2 at the 75 percentile of the 198 stocks is 0.330 and 0.138 for individual traders and the sum of institutional and proprietary investors, respectively. The partial correlation coefficients confirm these findings. Order imbalances from individual investors have an average marginal explanatory power of 0.248 after order imbalances from both institutional and proprietary investors are included. The average marginal

Table 3
Multiple and partial correlations for order imbalances from individual, institutional, and proprietary investors

	Mean	25%	Median (50%)	75%
R^2_{INDV}	0.218	0.105	0.214	0.330
R^2_{INST}	0.031	−0.001	0.015	0.046
R^2_{PROP}	0.058	−0.001	0.035	0.095
$R^2_{\mathrm{INST\_PROP}}$	0.085	0.018	0.056	0.138
$R^2_{\mathrm{INDV\_INST\_PROP}}$	0.309	0.228	0.312	0.393
$r^2_{\mathrm{INDV,Others}}$	0.248	0.157	0.241	0.341
$r^2_{\mathrm{INST,Others}}$	0.036	0.002	0.017	0.050
$r^2_{\mathrm{PROP,Others}}$	0.092	0.018	0.072	0.138
	P-value (median $R^2_{\mathrm{INDV}} = R^2_{\mathrm{INST\_PROP}}$): 0.000			
	P-value (median $r^2_{\mathrm{INDV,Others}} = r^2_{\mathrm{INST,Others}}$): 0.000			
	P-value (median $r^2_{\mathrm{INDV,Others}} = r^2_{\mathrm{PROP,Others}}$): 0.000			
	P-value (median $r^2_{\mathrm{INST,Others}} = r^2_{\mathrm{PROP,Others}}$): 0.000			

This table reports the mean, median, 25 percentile, and 75 percentile multiple and partial correlations from regressing daily open-to-close stock returns on order imbalances measured in number of trades. The regressions take the form of Eq. (1) in Table 2. Capital letter R^2 denotes the multiple correlation coefficients. For example, $R^2_{\mathrm{INDV\_INST\_PROP}}$ measures the joint explanatory power of all three types of investors. To examine the marginal contribution of each order imbalance measure, partial correlation coefficients (r^2) are also reported. For example, $r^2_{\mathrm{INDV,Others}}$ denotes the explanatory power of order imbalances from individual investors after order imbalances from both institutional and proprietary investors are included in the regressions.

explanatory power for institutions and proprietary traders is 0.036 and 0.092, respectively.

4.4. Institutional and proprietary trading sorted on firm size

Next, we examine associations between daily stocks returns and order imbalances for stocks sorted by firm size. Institutional investors tend to hold large capitalization stocks. For example, mutual fund managers may prefer large stocks because they are more liquid (Falkenstein, 1996) and enjoy more extensive and precise information that is less costly to obtain (Wermers, 1999). Institutional investors may also be better informed as they can devote more resources to collecting and analyzing information. Thus, institutional investors may be better able to identify under-valued stocks to which they herd (Wermers, 1999).[11] Therefore, we expect a greater impact of order imbalances from institutional and proprietary traders on stocks with larger capitalization.

Table 4 summarizes the median values of firm size (market capitalization), institutional and proprietary trading, and individual, institutional, and proprietary order imbalances for stocks in quintile groups 1, 3, and 5 from sorting independently based on the following three criteria: (1) firm size; (2) percentage trading by institutions; and (3) percentage trading by proprietary traders. Table 4 shows that both institutional and proprietary investors trade large stocks more heavily than small stocks, consistent with Falkenstein (1996). Average institutional trading is 3.37% for the largest size group versus 1.06% for the smallest size group. Average proprietary trading is 6.97% for the largest size group and 1.40% for the smallest size group. While individuals sell more small stocks than large stocks, there is no evidence of bias in institutional and proprietary order imbalances towards either small or large stocks.

4.4.1. Open-to-close returns and order imbalances for firms sorted on market capitalization

Next, we examine associations between daily open-to-close returns and order imbalances when firms are sorted by market capitalization. Table 5 presents results for firm size quintiles 1, 3, and 5. For brevity, we only report results for order imbalance measured using the number of trades as results are very similar for order imbalances measured using share volume. Overall, the contemporaneous positive association between daily stock returns and order imbalances from individual, institutional, and proprietary groups are significant and robust across all size groups. Additional interesting empirical facts are also evident.

First, slope coefficients on order imbalances of each of the three investor groups typically decrease as firm size increases. Thus, the impact of order imbalance on daily stock returns tends to decline with firm size, as do the regression R^2 coefficients. Second, the percentage of positive and significant coefficients for individual order imbalances declines as firm size increases, while the opposite is true for institutional and proprietary trading. Mirroring these results, the median partial correlation for individual investors, $r^2_{\mathrm{INDV,Others}}$, drops significantly from 0.327 for the smallest firms to 0.165 for the largest firms. In contrast, the corresponding average partial correlations rise with size for institutional and, particularly, proprietary traders. However, comparing these correlations across investor groups shows that individual order imbalances remain the most important explanatory factor for all stocks.

4.5. Is the price movement temporary or permanent?

This section explores another important question: are the documented price moves which are due to individual or institutional (INST and PROP) order imbalances temporary or permanent? We address two related issues: the horizon (daily or monthly) over which order imbalances are measured, and the horizon over which subsequent stock performance is evaluated. Institutional investors are more likely to hold stocks and assess their portfolio performance over a longer horizon, suggesting that monthly measures are more appropriate for institutional investors. Unfortunately, our sample only covers a 6-month period so the time-series of observations is too small for us to examine longer-run performance.

Nonetheless, we provide a glimpse of the issue by regressing 2-, 3-, 5-, and 10-day ahead cumulative excess returns on

[11] We have examined whether INST or PROP investors buy stocks (1 or 3 months prior to the end of the fiscal year, 31st December 2003) that subsequently experience a positive earnings surprise or superior market-adjusted excess returns. The results are inconclusive, perhaps because our 6-month sample period spans only one earnings surprise per stock.

Table 4
Institutional and proprietary trading sorted on firm size

	Median firm size (mil. yuan)	Median INST trading (%)	Median PROP trading (%)	Median INDV order imbalance (%)	Median INST order imbalance (%)	Median PROP order imbalance (%)
Panel A: Quintile groups sorted on firm size						
1	723	1.06	1.40	−8.92	−0.19	−0.43
3	1603	1.87	2.66	−7.80	−0.23	−0.25
5	4342^{++}	3.37^{++}	6.97^{++}	-5.10^{++}	−0.41	−0.54

This table sorts the sample of 198 stocks into quintile groups on the SSE based on firm size measured by the average month-end market capitalization over the 6-month sample period. For quintile groups 1, 3, and 5, the table reports the cross-sectional median of firm size, average INST trading, average PROP trading, and average order imbalances from INDV, INST, and PROP, respectively. Wilcoxon rank sum tests are performed to test the null hypotheses that median values are the same between quintile groups 1 and 5 sorted on each of the four variables, respectively. $^{++}$ and $^{+}$ indicate significance of z-statistics at the 5 and 10% levels, respectively.

Table 5
Daily stock returns and order imbalances sorted on firm size

	Median coefficient	Percentage positive and significant		Median coefficient
Size quintile 1, smallest				
$\delta_{i,\text{INDV}}$	0.057^{++}	100.0	$r^2_{\text{INDV,Others}}$	0.327
$\delta_{i,\text{INST}}$	0.099^{++}	40.0	$r^2_{\text{INST,Others}}$	0.012
$\delta_{i,\text{PROP}}$	0.083^{++}	62.5	$r^2_{\text{PROP,Others}}$	0.053
Adjust R^2	0.345			
Size quintile 3				
$\delta_{i,\text{INDV}}$	0.042^{++}	100.0	$r^2_{\text{INDV,Others}}$	0.255
$\delta_{i,\text{INST}}$	0.051^{++}	42.5	$r^2_{\text{INST,Others}}$	0.014
$\delta_{i,\text{PROP}}$	0.060^{++}	77.5	$r^2_{\text{PROP,Others}}$	0.073
Adjust R^2	0.297			
Size quintile 5, largest				
$\delta_{i,\text{INDV}}$	0.033^{++}	86.8	$r^2_{\text{INDV,Others}}$	0.165
$\delta_{i,\text{INST}}$	0.057^{++}	63.2	$r^2_{\text{INST,Others}}$	0.029
$\delta_{i,\text{PROP}}$	0.060^{++}	86.8	$r^2_{\text{PROP,Others}}$	0.093
Adjust R^2	0.300			

Groups 1 versus 5: P-value (adjusted R^2 same): 0.086
Groups 1 versus 5: P-value ($\delta_{i,\text{INDV}}$ same): 0.000, P-value ($r^2_{\text{INDV,Others}}$ same): 0.000
Groups 1 versus 5: P-value ($\delta_{i,\text{INST}}$ same): 0.003, P-value ($r^2_{\text{INST,Others}}$ same): 0.358
Groups 1 versus 5: P-value ($\delta_{i,\text{PROP}}$ same): 0.008, P-value ($r^2_{\text{PROP,Others}}$ same): 0.001

This table first sorts the firms into quintile groups based on the average month-end market capitalization during the sample period. Then for quintile groups 1, 3, and 5, the table reports the cross-sectional median coefficients from regressions of individual stock excess returns on contemporaneous order imbalances from individual, institutional, and proprietary investors. The regressions take the form of Eq. (1). Partial correlation such as $r^2_{\text{INDV,Others}}$ denotes the explanatory power of order imbalance from individual investors after order imbalances from institutional and proprietary investors are included in the regressions. Wilcoxon sign-rank z-statistics are calculated. $^{++}$ and $^{+}$ indicate significance of z-statistics at the 5% and 10% levels, respectively.

the daily order imbalances of INDV, INST, and PROP investors. The intuition is that, if the effects of order imbalances are temporary, we will not observe predictability when returns are cumulated over a longer horizon. Alternatively, if the effects of order imbalances are permanent, predictability will remain when returns are measured over longer horizons. The regressions take the following form:

$$\sum_{j=0}^{n} r_{it,j} - \sum_{j=0}^{n} r_{mt,j} = \delta_0 + \delta_{i,\text{INDV}}\text{imbal}_{it,\text{INDV}} + \delta_{i,\text{INST}}\text{imbal}_{it,\text{INST}} + \delta_{i,\text{PROP}}\text{imbal}_{it,\text{PROP}} + \varepsilon_{it}, \tag{2}$$

where $n = 1, 2, 4, 9$ days and indicates the number of days over which excess returns are cumulated. r_{it} is the daily close-to-close return for stock i on day t, and r_{mt} is an equally-weighted portfolio of individual stock close-to-close returns.

The results are summarized in Table 6. Overall, the predictive ability of INDV and INST investors remains the same when returns are cumulated over 2-, 3-, 5-, and 10-day windows. However, the predicative power of PROP order imbalances disappears when 3-, 5-, and 10-day ahead cumulative returns are employed in the regression. This is somewhat counter-intuitive as we might expect the more professional PROP orders to have more predictive power. One possible explanation, as mentioned earlier, is that the daily return horizon may not be the appropriate horizon in which to evaluate the predictive power PROP order imbalances.

To further investigate this issue, we measure the current month and 3-month ahead (including the current month) cumulative excess returns for each stock and regress the

Table 6
Return predictability and order imbalances

Cumulative excess return	$\delta_{i,\text{INDV}}$	$\delta_{i,\text{INST}}$	$\delta_{i,\text{PROP}}$
Panel A: Daily return predictability			
2-day ahead	0.051	0.073	0.094
	(31.03)**	(9.95)**	(3.09)**
3-day ahead	0.052	0.058	0.060
	(18.28)**	(3.83**	(0.91)
5-day ahead	0.056	0.061	0.052
	(14.19)**	(2.99)**	(0.55)
10-day ahead	0.062	0.071	−0.089
	(9.34)**	(2.23)**	(−0.55)
Cumulative excess return	$\lambda_{i,\text{INDV}}$	$\lambda_{i,\text{INST}}$	$\lambda_{i,\text{PROP}}$
Panel B: Monthly return predictability			
Fixed effects panel regressions			
1-month	0.535	0.839	0.990
	(10.72)**	(5.95)**	(13.51)**
3-month	0.328	0.071	0.709
	(4.03)**	(0.28)	(5.13)**
Random effects panel regressions			
1-month	0.314	0.646	0.902
	(7.34)**	(5.27)**	(13.61)**
3-month	0.186	0.192	0.881
	(2.11)**	(0.78)	(6.36)**

Panel A reports regressions of 2-, 3-, 5-, and 10-day ahead cumulative excess returns on the daily order imbalances of INDV, INST, and PROP investors. The regressions take the form of Eq. (2):

$$\sum_{j=0}^{n} r_{it,j} - \sum_{j=0}^{n} r_{mt,j} = \delta_0 + \delta_{i,\text{INDV}}\text{imbal}_{it,\text{INDV}} + \delta_{i,\text{INST}}\text{imbal}_{it,\text{INST}} + \delta_{i,\text{PROP}}\text{imbal}_{it,\text{PROP}} + \varepsilon_{it},$$

where $n = 1, 2, 4, 9$ days, measures the number of days over which excess returns are cumulated. r_{it} is the daily close-to-close return for stock i on day t, and r_{mt} is an equally-weighted portfolio of individual stock close-to-close return on day t, $t = 1,2,\ldots,117$, $i = 1,2,\ldots,198$. Independent variables $\text{imbal}_{\text{it, j}}$, j = INDV, INST, and PROP, are daily percentage order imbalances. Panel B shows the current month and 3-month ahead cumulative excess returns for each stock and their regression on the average daily order imbalances over the current month. The panel regressions are carried out using Eq. (3):

$$\sum_{j=0}^{n} R_{it,j} - \sum_{j=0}^{n} R_{mt,j} = \lambda_0 + \lambda_{i,\text{INDV}}\text{imbal}_{it,\text{INDV}} + \lambda_{i,\text{INST}}\text{imbal}_{it,\text{INST}} + \lambda_{i,\text{PROP}}\text{imbal}_{it,\text{PROP}} + \varepsilon_{it},$$

where $n = 0, 2$ months measures the number of months over which excess returns are cumulated; R_{it} is the monthly return for stock i in month t, t = October 2003, ..., March 2004; and R_{mt} is an equally-weighted portfolio of individual stock monthly returns. Independent variables $\text{imbal}_{it,j}$, j = INDV, INST and PROP, are the average daily percentage order imbalances over the current month t. ** indicates significance of t-statistics at the 5% level.

average daily order imbalances over the current month. Since the time-series number of observations is small, we use a panel regression approach

$$\sum_{j=0}^{n} R_{it,j} - \sum_{j=0}^{n} R_{mt,j} = \lambda_0 + \lambda_{i,\text{INDV}}\text{imbal}_{it,\text{INDV}} + \lambda_{i,\text{INST}}\text{imbal}_{it,\text{INST}} + \lambda_{i,\text{PROP}}\text{imbal}_{it,\text{PROP}} + \varepsilon_{it}, \tag{3}$$

where $n = 0$ and 2 months and measures the number of months over which excess returns are cumulated; R_{it} is the monthly return for stock i in month t, where t = October 2003, ..., March 2004; and R_{mt} is an equally-weighted portfolio of individual stock monthly returns. Independent variables $\text{imbal}_{it,j}$, where j = INDV, INST and PROP, are the average daily percentage order imbalances over the current month t.

The panel regressions are run for both fixed and random effect specifications. The evidence suggests that, indeed, over monthly horizons, proprietary (PROP) order imbalances exhibit reliable predictability for the current month and 3-month ahead cumulative excess returns. The estimated coefficients for PROP order imbalances, $\lambda_{i,\text{PROP}}$, are not only highly significant for both the 1- and 3-month horizons, but also the largest among the three types of order imbalances. Individual order imbalances measured over monthly horizons also have significant predicative power. Whether or not this predictability is related to the trading patterns of individual investors documented in Odean (1999) remains to be explored in the future.

5. Commonalty in order imbalances

Having examined daily stock returns and order imbalances, we turn to our second issue: commonalities in order imbalances across different categories of investors. Using principal components, Hasbrouck and Seppi (2001) report significant commonality in signed volume measures (order flow) aggregated for different trade size groups over 15-min intervals for 30 Dow Jones stocks in 1994. They do not identify the source of the order flow commonality, but suggest that commonality may derive in part from mutual fund flows. Wermers (1999) tests for the relation between inflows of money and herding in stocks, and finds little evidence of correlation between money inflows and herding. Thus, herding may originate with fund managers' decisions rather than the investing or redemption decisions of individual investors. This does not exclude the possibility of correlated trading among individual investors in their personal portfolios. Because our dataset allows us to distinguish order flows of different categories of investors, we can directly measure the degree of correlated trading by individual and institutional investors.

Following Chordia et al. (2000) and Hasbrouck and Seppi (2001), we apply a "market model" to the daily time-series of order imbalances:

$$\text{imbal}_{it,j} = \beta_{i0} + \beta_{i,j}\text{imbal}_{mt,j} + \varepsilon_{it}, \tag{4}$$

where the order imbalance, $\text{imbal}_{it,j}$, is measured by either number of trades or volume, the subscript j denotes individual, institutional, or proprietary investors, and $\text{imbal}_{mt,j}$ is an equally-weighted portfolio of order imbalances on day t for investor type j. The market-wide order imbalance used in the regression for the ith stock excludes the order imbalance of the ith stock to minimize the cross-sectional dependence in the estimated slope coefficients.

Table 7 reveals strong evidence of commonality among order imbalances of individual investors. The mean coefficient of $\beta_{i,\mathrm{INDV}}$ is 0.984, with a t-statistic of 83.61. The percentage of positive and significant coefficients is as high as 96%, and the median adjusted R^2 is an impressive 0.279. The commonality in institutional order imbalances is weaker. The average coefficient of $\beta_{i,\mathrm{INST}}$ is 0.614, with a t-statistic of 10.34. About 25% of the slope coefficients are both positive and significant, and the median adjusted R^2 is 0.002. The average $\beta_{i,\mathrm{PROP}}$ is 0.731 with a t-statistic of 14.59, 37% are both positive and significant, and the median adjusted R^2 is 0.007. Clearly, other factors, or noise, largely determine the daily order imbalances of institutional and proprietary investors.

The dominance of herding behavior by individual investors in the Shanghai market echoes evidence from the US Previous authors have examined the herding behavior of US mutual funds (Wermers, 1999) and pension funds (Lakonishok et al., 1992). They report low levels of herding for these institutional investors, based on quarterly mutual fund holdings.

5.1. Commonality of order imbalances for large and small firms

Following earlier sections, stocks are sorted by market capitalization, and commonality regressions are estimated for each stock in quintile groups 1, 3, and 5. The following patterns can be observed from Table 8. First, median coefficients for individual investors, $\beta_{i,\mathrm{INDV}}$, decline significantly as firm size increases. The opposite is observed for $\beta_{i,\mathrm{INST}}$ and $\beta_{i,\mathrm{PROP}}$. Second, the percentage of positive and significant coefficients for individual investors in general declines with firm size, and, again, the opposite is observed for institutional and proprietary investors. Third,

Table 8
Commonality in order imbalance sorted by firm size

	Median coefficient	Percentage positive and significant	Median adjusted R^2
Size quintile 1, smallest			
$\beta_{i,\mathrm{INDV}}$	1.137^{++}	97.5	0.317
$\beta_{i,\mathrm{INST}}$	0.117^{++}	10.0	−0.004
$\beta_{i,\mathrm{PROP}}$	0.029	17.5	0.001
Size quintile 3			
$\beta_{i,\mathrm{INDV}}$	1.082^{++}	97.5	0.271
$\beta_{i,\mathrm{INST}}$	0.428^{++}	27.5	0.001
$\beta_{i,\mathrm{PROP}}$	0.213^{++}	22.5	0.001
Size quintile 5, largest			
$\beta_{i,\mathrm{INDV}}$	0.929^{++}	92.1	0.288
$\beta_{i,\mathrm{INST}}$	1.265^{++}	55.3	0.017
$\beta_{i,\mathrm{PROP}}$	1.506^{++}	60.5	0.033

Groups 1 versus 5, P-value ($\beta_{i,\mathrm{INDV}}$ same): 0.002, P-value (INDV adj. R^2 same): 0.653
Groups 1 versus 5, P-value ($\beta_{i,\mathrm{INST}}$ same): 0.000, P-value (INST adj. R^2 same): 0.000
Groups 1 versus 5, P-value ($\beta_{i,\mathrm{PROP}}$ same): 0.000, P-value (PROP adj. R^2 same): 0.001

This table first sorts all firms into quintile groups based on the average month-end market capitalization during the sample period. Then for quintile groups 1, 3, and 5, the table summarizes the cross-sectional median coefficients from regression of individual order imbalances on market-wide individual order imbalances and institutional (proprietary) order imbalances on market-wide institutional (proprietary) order imbalances. The regressions take the form of Eq. (4) in Table 7. The daily sample covers a total of 117 trading days from October 2003 to March 2004, with $t = 1,\ldots,117$. The cross-sectional sample covers 198 stocks with $i = 1,\ldots,198$. Wilcoxon sign-rank z-statistics are calculated. $^{++}$ and $^{+}$ indicate significance of z-statistics at the 5% and 10% levels, respectively.

Table 7
Commonality in individual, institutional, and proprietary order imbalances

	Mean coefficient (t-statistic)	Median coefficient (z-statistic)	Percentage positive	Percentage positive and significant	Percentage negative and significant	Median adjusted R^2
$\beta_{i,\mathrm{INDV}}$	0.984^{**} (83.61)	1.030^{++} (12.17)	97.4	95.5	0.0	0.279
$\beta_{i,\mathrm{INST}}$	0.614^{**} (10.34)	0.379^{++} (8.32)	77.3	24.7	1.5	0.002
$\beta_{i,\mathrm{PROP}}$	0.731^{**} (14.59)	0.245^{++} (7.01)	74.2	36.9	4.0	0.007

P-value (median $\beta_{i,\mathrm{INDV}} = \beta_{i,\mathrm{INST}}$): 0.000 P-value (median adj. R^2 same for INDV and INST): 0.000
P-value (median $\beta_{i,\mathrm{INDV}} = \beta_{i,\mathrm{PROP}}$): 0.000 P-value (median adj. R^2 same for INDV and PROP): 0.000
P-value (median $\beta_{i,\mathrm{INST}} = \beta_{i,\mathrm{PROP}}$): 0.929 P-value (median adj. R^2 same for INST and PROP): 0.001

This table summarizes regression results of individual order imbalances on market-wide individual order imbalances and institutional (proprietary) order imbalances on market-wide institutional (proprietary) order imbalances. The regressions take the following forms:

$$\mathrm{imbal}_{it,j} = \beta_i 0 + \beta_{i,j}\mathrm{imbal}_{mt,j} + \varepsilon_{it}, \tag{2}$$

where $\mathrm{imbal}_{it,j}$ denotes order imbalance of stock i on day t for investors type j, measured using number of trades. Subscript j = INDV, INST, and PROP stand for individual, institutional, and proprietary investors, respectively. The independent variable $\mathrm{imbal}_{mt,j}$ represents an equal-weighted portfolio of order imbalance on day t for investor type j. Calculation of market-wide order imbalances excludes order imbalances from the ith stock in the ith regression. The daily sample covers a total of 117 trading days from October 2003 to March 2004, with $t = 1,\ldots,117$. The cross-sectional sample covers 198 stocks with $i = 1,\ldots,198$. t-Statistics and Wilcoxon sign-rank z-statistics are reported in parentheses. ** indicates significance of t-statistics at the 5% level; $^{++}$ indicates significance of z-statistics at the 5% level.

adjusted R^2 coefficients follow a similar pattern. In summary, the co-movement in individual (institutional and proprietary) order imbalances is much stronger in small (large) firms, mirroring our earlier evidence that institutional and proprietary (individual) investors trade large (small) capitalization stocks more heavily.

6. Summary and conclusions

This study addresses two issues. The first is the relation between daily open-to-close stock returns and order imbalances of individual investors and two types of institutional investors. The second is whether there exists any commonality in order imbalances among different types of investors. Our proprietary dataset from the SSE allows us to categorize trades by three types of investors: individual, institutional, and proprietary. Our major findings are as follows.

Order imbalances explain about 31.2% of daily fluctuations in open-to-close excess returns. The marginal explanatory power of individual investor order imbalances is higher than the marginal explanatory power of institutional and proprietary investor order imbalances. Although the impact of institutional and proprietary order imbalances is larger as measured by slope coefficients, they explain a significantly lower proportion of daily price movements. We also document a strong pattern of commonality among individual order imbalances, with 96% slope coefficients positive and the statistically significant and median explanatory power an impressive 27.9%. The commonality in institutional and proprietary order imbalances is in general much weaker.

Our findings complement recent work on behavioral finance based on Chinese evidence. Feng and Seasholes (2004) study daily transaction records of individual investors from two regions in China: Shanghai and Guangdong. They find high contemporaneous correlation in individual transactions, particularly when conditioning on the location of the trades. Put another way, groups of geographically close investors tend to trade in the same way. Our sample includes all individual investors from within the country in 198 stocks listed on the SSE. Chen et al. (2004) find evidence of classical behavioral patterns, such as overconfidence, in a different sample of individual Chinese investors' brokerage records. The strength of these behavioral patterns, combined with the overwhelming presence of individual investors in the Shanghai market, are likely explanations for the associations we document, particularly the divergence between the impact of individual order imbalances and the impact of order imbalances of professional investors.

Our ability to distinguish order imbalances as falling into three types has generated important evidence on the questions we focus on. An agenda for additional research is as follows. To further understand the interaction between order imbalances and daily returns, feedback from order imbalances to lagged market or individual stock returns can be measured. Furthermore, feedback across order imbalances from different categories of investors can be measured. The impact of order imbalances on spreads is also interesting. Whether and how this impact is related to the co-movement in quoted and effective spreads remains an interesting issue worth exploring in the future. Finally, the strength of our results from one market, China, where individual investors predominate, raises the question of whether the patterns we document are unique to China or can also be found in other emerging and developed markets.

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