The effect of investor category trading imbalances on stock returns

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Abstract

Trading is the mechanism of the economist's 'invisible hand;' the means by which price discovery occurs. We use daily shareholdings data from the Australian equities clearinghouse to investigate the impact of the trading imbalances of investor categories on stock returns. Our evidence does not contradict the behavioural finance assumption that the trading of individual investors contributes to price discovery. Furthermore, we find that the trading of individual investors is distinct from that of the other investor categories. While the trading of all investor categories Granger-causes returns, returns Granger-cause trading only for the individual investor category. In the short term of up to one month, individual investors engage in feedback trading.

1 Introduction

Professionals may dismiss anecdotes of retail investors engaging in stock price manipulations as irrelevant, but these stories capture the attention of the public and thereby challenge universal acceptance of efficient pricing of financial assets and related theories of trading behaviour. Efficient pricing of financial assets, maximization of expected utility, risk aversion, Bayesian updating, and rational expectations theories are appealing, not the least because they enable us to quantify and model financial markets and decision-making. However, Thaler (1987) exhorts us to distinguish between these normative models, which help us to understand how markets work, and descriptive models, which attempt to describe what investors actually do. Most economists acknowledge that the behaviour of the individuals they observe does not fit with the mean optimizing, utility maximizing behaviour assumed in the models. The question becomes whether that behaviour affects asset prices as determined by the market. De Bondt and Thaler (1994) argue that it does, and champion the emergence of finance theories based on psychological principles. Fama (1998) disagrees. He asserts that the theories comprising behavioural finance, though explaining specific phenomena, do not provide a satisfactory general model that could supplant that of market efficiency. Bossaerts, Plott and Zame (2003) support Fama, concluding that in experimental financial markets, individual portfolios differ from the mean variance optimal portfolio of theory, but those differences average out across the market so that prices nonetheless conform to rational models. However, behavioural finance models continue to capture the attention of researchers and practitioners.

In this paper, we contribute to the discussion by considering whether the trading of the investor group most exposed to behavioural biases, individual investors, affects the market price of financial assets. In choosing individuals as our proxy for biased investors, we are not suggesting that institutional investors are other than human, but rather that the constraints most institutions impose, including stated investment objectives, dedicated research teams and sophisticated computer models, somewhat shield their managers' decisions from these cognitive errors. We also investigate the causal relationship between trading and returns for each investor category. Economic theory assumes that the demand of market participants, expressed through their trading, determines equilibrium prices. However, some behavioural models, generalized as feedback models, posit that stock returns can lead to investor demand.

To conduct our tests, we use data from the Australian Stock Exchange Clearinghouse Register. These data confer several advantages. The Australian Stock Exchange (ASX) is one of the largest by market capitalization in the world. It is well-diversified; the top 20 stocks represent 46 percent of the market capitalization, and concentration drops precipitously for larger samples. As stocks must be registered with the clearinghouse before they can be traded on the exchange, the data encompass virtually all of the trading on the Australian Stock Exchange. The data are aggregated daily by investor category for each stock in the All Ordinaries index, allowing for subsequent division of the data by stock characteristics. These features, and the other features detailed in the data description, enable us to investigate the effect of investor category excess demand on asset returns and the causal relationship between investor category trading and asset returns for a representative capital market.

Our findings are inconclusive on the behavioural finance assumption that the trading of individual investors contributes to price discovery. However, we do find that the trading of individual investors is distinct from that of the other investor categories and is influenced by the cognitive error of trading based on price changes rather than on fundamentals. While the trading of all investor categories Granger-cause returns, returns Granger-cause trading only for the individual investor category. That is, only individual investors engage in feedback trading.

The paper proceeds as follows. Section 2 develops our hypotheses, including how they are related to previously published papers. Data are described in the Section 3, followed by a section describing our empirical tests. In Section 5 we discuss our results, and in the final section we conclude.

2 Excess demand, cognitive error and returns

Traditional economic theory argues that irrationality in individual decision-making will not affect the final results of the collective human actions of the marketplace, but recent behavioural finance theories posit otherwise. Andreassen (1988) indicates that investors believe in short term mean reversion for stock prices. Barberis, Shleifer and Vishny (1998) attribute market under- and overreactions to representativeness bias and conservatism. Daniel, Hirshleifer and Subrahmanyam (1998), suggest that overconfidence and biased self-attribution of informed traders leads to mispricing of stocks. Implications of the Kahneman and Tversky (1979) prospect theory have been used to explain the disposition effect (Odean (1998), Brown, Chappel, da Silva Rosa and Walter (2006)). Barberis and Shleifer (2003) include an element of investor trend chasing in their model. These models explicitly link returns to flawed decision-making mechanisms of investors, implying that the trading of those investors influences prices.

To consider the merit of models based on cognitive error, we must first determine whether the traders exhibiting those characteristics influence market prices. Unfortunately, it is not possible to measure a specific investor's susceptibility to a specific cognitive error and then correlate that information with his or her respective impact on financial markets, though such tests have been conducted in a laboratory setting (Kluger and Wyatt (2004)). However, it is generally accepted that individual investors are more likely to violate the axioms of rationality than are institutional investors. For example, Barberis and Huang (2001) begin an argument with the assumption: “Moreover, if we think of 'narrow framers' as being individual investors and the arbitrageurs as being mainly institutions…” (p.1286) to establish the basis for their model. Individual investors have comparatively few resources; institutional investors make decisions with the benefit of institutional controls and guidelines. Therefore, we rely on individual investors as our proxy for investors most susceptible to cognitive errors and test whether their trading affects market prices.

Experimental financial markets, where equilibrium prices can be controlled, provide the foundation for our first hypothesis. Vernon Smith has experimented with models of financial markets for decades, introducing refinements to make the controlled environment mimic the real world. Caginalp, Porter and Smith (2000) conclude that excess demand is a persistent predictor of asset price bubbles even in the presence of elements designed to dampen deviations from equilibrium prices. Asparouhova, Bossaerts and Plott (2003) find evidence in experimental data that excess demand for securities drives stock prices. Based on their findings, we expect to find that excess demand, measured as investor category trading imbalance, propels returns in equity markets. Furthermore, we expect that trading of the individual investor category will affect returns. If individual investor trading, with its vulnerability to cognitive biases, influences returns, then behavioural finance models of asset pricing cannot be disregarded.

Our second hypothesis relates to a specific genre of asset pricing model generalized as feedback models. Feedback models argue that returns can cause trading. Positive feedback traders, or momentum traders, buy stocks that have increased in value over some recent time interval. Contrarian, or negative feedback, traders buy stocks that have fallen in value. Jegadeesh and Titman (1993) find that momentum trading can be profitable, a violation of the efficient market hypothesis. Grinblatt and Keloharju (2000) identify foreign investors as positive feedback traders in the Finnish securities market and find that they are the overall winners. Nofsinger and Sias (1999) investigate herding and feedback trading by different types of investors.

Other studies consider feedback trading as a possible explanation for the observed serial correlation in asset returns. Sentana and Wadhwani (1992) argue that feedback traders will have a greater influence on prices in times of rising volatility, and that therefore serial correlation will rise with volatility. Their model predicts that positive feedback trading will result in negative autocorrelation of returns, while negative feedback trading, as well as non-synchronous trading, will result in positive autocorrelation in returns. Safvenblad (2000), however, studies autocorrelation of individual stock returns. He finds that alternative theories, including non-synchronous trading, do not fit the evidence, and concludes that trading strategies, particularly feedback trading, are responsible for the observed return autocorrelation patterns.

Others approach the question of feedback trading from the perspective of a portfolio. The evidence reported by Mech (1993) is consistent with a microstructure explanation of portfolio autocorrelation, that it is related to transaction costs and the associated delay in price updates. Alternatively, Bange (2000) considers variations in the equity holdings of small investors over time. Her evidence, contrary to that of this study and others, shows small investors to be positive feedback traders. She finds that equity portfolios in her sample increase in size after market increases, and decrease after downturns, and argues that this result is evidence for positive feedback trading.

However, these studies do not explicitly test causality. Do investors buy more stocks because stock prices have increased, or do prices increase because investors are buying? Do momentum investors make positive profits because they buy stocks whose prices have increased, or does their demand for these stocks drive the prices up? Based on traditional economic theory, we expect to find that, for most investor categories, trading causes returns, rather than returns causing trading.

Our overall thesis, though, is that individual investors will trade differently from institutional investors. The Finnish individual investors of Grinblatt and Keloharju (2000) are negative feedback traders, and Dhar and Kumar (2001) find that the buying and selling of individual investors at a major discount brokerage house is influenced by short term price trends. Furthermore, the structure of the market may affect our results. The ASX is an order driven market. Of all of the investor categories, individual investors are the most likely to be part-time participants in the securities market. As such, they are the most likely to place limit orders and to revise them (relatively) infrequently. A buy limit order placed somewhat below the market price will only be executed if the price falls, possibly over several days; a sell order only if the price rises.[1] We expect to find that for individual investors, returns Granger-cause trading, consistent with the findings of Mech (1993) that stale orders are not an important determinant of portfolio autocorrelation. However, we will consider both daily and weekly data in an effort to confirm that our findings are the result of feedback trading and not of market structure effects.

Our data enable us to investigate the impact of trading on security returns more fully than other studies. Chordia, Roll and Subrahmanyam (2002) establish a relation between daily market wide ‘order’ (inferred by signing transactions with the Lee and Ready (1991)

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[1] Linnanma (2003) discusses this fact with a persuasive example.

algorithm) imbalance and returns for New York Stock Exchange (NYSE) data, however, their study is aggregated at the market level for traders and stocks. In a subsequent paper, Chordia and Subrahmanyam (2004) investigate intraday order imbalance for individual NYSE stocks, but with a focus on market maker reaction to large trades. Studies incorporating individual investor trades using U.S. data rely on closed end fund data (Lee, Shleifer and Thaler (1991); Gemmill and Thomas (2002)) and small volume trades as a proxy for trades by individuals, or use an extensive data set from a major discount brokerage house (Odean (1998); Kumar and Lee (2006)). Although these studies provide important insights, none of their data sets encompass all of the trader categories in the U.S. capital markets. Grinblatt and Keloharju (2000) and Linnainmaa (2003) use the comprehensive Finnish market data set to draw conclusions about the behaviour and performance of different categories of investor. However, although the data are a complete record of the market, the market itself is not necessarily representative of most developed markets. Linnainmaa (2003) reports that a single stock, Nokia, is the source of 65 percent of the Finnish market capitalization. Kim, Lee and Morck (2004) use limit orders from the Korean exchange to estimate investor category supply and demand elasticities before and after the Asian financial crisis, finding that domestic individual investor supply and demand is less elastic than that of institutions and foreigners. Oh, Parwada and Walter (2004) use data from the same market to compare the trading behaviour and performance of online investors to other investor categories. They conclude that online investors do not affect market returns and "are likely to be just noise trading."(p. 48) Kamesaka, Nofsinger and Kawakita (2003) consider the trading, aggregated weekly at the market level, of various investor categories for the Tokyo Stock Exchange, finding no Granger-causal relation between trading and returns.

3 Data

3.1 CHESS data description

The data for this paper come from the Clearinghouse Electronic Sub-register System (CHESS) database of the Australian Stock Exchange (ASX). CHESS represents one of two ways investors can register shareholdings in Australia. Shareholders can also choose to register on an issuer sponsored sub-register. However, investors with shares in more than one company would require a separate registration for each holding; the CHESS register can consolidate all shareholdings in various listed companies. Holdings in 97 percent of the companies listed on the ASX are recorded in CHESS, covering about 70 percent of the total market capitalization of the Australian market. More importantly, to trade shares on the ASX, the shares must be registered with CHESS. An investor whose shares are issuer registered must first have them transferred to CHESS before he or she can trade them on the exchange. Therefore, the data used in our study effectively capture free float in the Australian secondary securities market. Figure 1 illustrates the growth in the CHESS register over the study period.

Insert Figure 1 about here

The initial sample data consist of the daily holdings, purchases and sales aggregated by investor category for each of the approximately 750 companies that were included in the Australian All Ordinaries Index at any point during the period from January, 1996 through March 1, 2002. Companies with no CHESS registered shares and companies with data for fewer than 50 trading days are eliminated from the sample. The resulting data include a daily average of more than 500 companies with an average aggregate market capitalization of over A$400 billion. The daily CHESS holdings, purchases and sales of each stock are aggregated into six investor categories, comprising retirement funds (domestic superannuation), domestic government, domestic industry (banks, insurances and trusts), domestic individuals, foreign industry and foreign individuals.

Figure 2 illustrates the quantity of shares held in the CHESS register by each investor category over the sample interval. The number of shares held in the CHESS register more than doubles over the interval, from just under 50 billion to over 110 billion in the six years. Much of the growth in holdings comes from foreign investors. Foreign investors account for around 45 billion shares in 2002, up from 20 billion at the end of 1995. Domestic holdings increase from just over 20 billion to just over 35 billion shares, due primarily to the increases in the holdings of retirement funds. Government holdings decrease, largely in line with an increase in holdings of domestic individuals.

Insert Figure 2 about here

In addition to CHESS data, we obtain total shares outstanding and volume weighted average prices (VWAPs)[2] for each share for each day in the sample from the Securities Industry Research Centre of Asia-Pacific (SIRCA). Since the CHESS register is updated daily, the VWAP approximates the price paid by the aggregated investor categories for each traded stock. Settlement occurs under two different regimes (five- and three-day) during our sample period; we lead the register data by the appropriate interval to match the trades with the price changes.

3.2 Calculation of variables

The raw data require manipulation to address the questions we pose. We multiply the number of shares outstanding by the VWAP to create a variable that serves as measure for market capitalization. Daily and weekly log returns for each company are calculated using the VWAP. To assess the impact on returns of investor category trading, we calculate an

[2] Calculated as follows, where *i* denotes the trade and *n* is the total number of trades in the day:

$$VWAP = \frac{\sum_{i=1}^{n} volume_i * price_i}{\sum_{i=1}^{n} volume_i}$$

indicator variable like that of Barber and Odean (2002). Our daily buy-sell imbalance (BSI) indicator is computed for each investor category for each stock with Equation (1):

$$BSI_{jit} = \frac{(p_{jit} - s_{jit})}{(p_{jit} + s_{jit})} \qquad (1)$$

in which p_{jit} (s_{jit}) is the number of shares of stock i purchased (sold) on day t by investor category j. This transformation results in a variable that varies between -1 and 1, indicating the direction of category trading while eliminating the confounding effects of different trading volumes. Since average VWAPs for stocks in the sample range from less than A$0.25 to greater than A$100, raw volume numbers do not convey useful information for a cross-sectional study. Moreover, since the aim of the study is to consider the correlation between daily (weekly) log returns and investor category trading, this indicator variable is a better fit in the vector autoregression (VAR) models we use. Stock characteristics, including percent of individual investor ownership, market capitalization, and liquidity are used in subsequent tests to form subsets of the original sample. We sort the sample into deciles based on each of the above three characteristics and consider the top decile separately from the balance of the sample.

4 Vector Autoregression Analysis and Granger-causality

4.1 Models

In this study we consider the relation between investor, particularly individual investor, trading imbalances and stock price changes. We begin with a Pearson correlation matrix that indicates the degree of correlation between the trading imbalances of the six investor categories and the stock returns lagged for up to one week.

To extend the analysis, we ask whether category trading causes returns, returns cause trading, or both. This question partially addresses propositions made in recent behavioural finance models that some investors trade stocks based on recent price movements. Momentum, or positive feedback, traders buy (sell) stocks whose prices have increased (decreased) recently. Contrarian, or negative feedback, traders sell (buy) stocks whose prices have increased (decreased) recently. If the trading of these style investors is influential enough, it will distort market prices and may provide opportunities for other investors to earn excess returns. With our model, we can determine whether returns Granger-cause the trading patterns of influential categories of investors and thereby comment on the implication of these models. We can also evaluate the importance of previous category trading on current trading, as well as confirm the well-documented autocorrelation present in returns.

We use a bivariate vector autoregression analysis (VAR), following Froot, O'Connell and Seasholes (2001), to investigate Granger-causality between the variables. Our regressions are cross-sectional, that is, the return and category trading variables for each company for each day are considered as separate observations. As in an event study, this construction minimizes the impact of systematic market effects and autocorrelation of returns, enabling our focus on the effects of company specific buying and selling pressure from different investor categories. The VAR is specified as in Equation (2):

$$\mathrm{Z}_{t,i} = \mathrm{A} + \sum_{n=1}^{p} \mathrm{B}_n \mathrm{Z}_{t-n,i} + \mathrm{E}_{t,i} \tag{2}$$

where

$$\mathrm{Z}_{t,i} = \begin{bmatrix} r_{t,i} \\ BSI_{jit} \end{bmatrix},\ \mathrm{A} = \begin{bmatrix} \alpha_r \\ \alpha_{BSI_j} \end{bmatrix},\ \mathrm{B} = \begin{bmatrix} \beta_{1,1,n} & \beta_{1,2,n} \\ \beta_{2,1,n} & \beta_{2,2,n} \end{bmatrix},\ \mathrm{E} = \begin{bmatrix} \varepsilon_{r,i} \\ \varepsilon_{BSI_{jit}} \end{bmatrix}$$

Granger-causality procedures test whether the lagged values of a variable are significant in explaining the variations in the dependent variable in the presence of lagged values of the dependent variable. As an example, in a regression in which return (r_t) is the dependent variable, we examine the coefficients of the lagged values of the trading imbalance variable ($\beta_{1,2,n}$) for significance. While *t*-tests for each of the $\beta_{1,2,n}$ and $\beta_{2,1,n}$ coefficients provide one measure of statistical significance, a partial *F*-test is more robust. For our partial *F*- test we consider the difference in mean squared error (MSE) between a restricted model, in which the independent variables are lagged values of the dependent, and the full model including the lagged values of the dependent as well as lagged values of a second (potentially causal) variable. The restricted model is specified as in Equation (3):

$$z_{t,i} = \alpha + \sum_{n=1}^{p} \beta_n z_{t-n,i} + \varepsilon_{t,i} \qquad (3)$$

where $z_{t,i} \in \{r_{t,i}, BSI_{jit}\}$

To illustrate: to test whether changes in the buy-sell imbalance of retirement funds Granger-causes changes in stock returns, we compare the MSE of a regression of return against lagged returns (restricted model) with that of return against lagged returns and lagged retirement fund transaction imbalance, or BSI (full model).

Unlike other studies (Cha and Lee (2001)), we do not try to separate the effects on prices of changes in stock fundamentals from the effects of investor category trading. Though changes in fundamentals should affect stock prices, the new information is impounded in prices through the trading process, and therefore captured by our model. Moreover, our model is cross-sectional across individual stocks, rather than time-series for the entire market.

The cross sectional nature of the model attributes equal weight to all observations. To test the possibility that characteristics of certain stocks unduly influence the results, we form subsets of the data by stock characteristic and re-estimate the regressions. The characteristics we isolate are market capitalization, liquidity and individual ownership. Market capitalization is measured as the VWAP multiplied by the number of issued shares. We proxy liquidity with a turnover ratio calculated as the total shares of the company purchased by all of the investor categories over an interval divided by the number of issued shares. Individual ownership is the individual investor shareholdings expressed as a percentage of the CHESS registered shares for the company. For each of the characteristics, we sort the data set into deciles and consider the top decile of stocks separately from the balance of the sample.

4.2 Time interval

The data are recorded daily. Using daily data in the models enables us to evaluate the immediate impact of category trading and to make inferences about the microstructure influences of trading in the absence of confounding market risk factors. However, the daily data are noisy and preclude conclusions about longer term effects. Accordingly, we repeat the analysis with data aggregated to weekly intervals. The VAR models for daily data include five lags, to capture one week of trading and returns; the models at weekly intervals extend the analysis to one month (four lags).

5 Results

Summary statistics in Table 1 reveal the frequency and average direction of category trading. With the exception of the domestic government, all of the categories are net buyers over the sample period[3], corroborating the evidence in Figure 2. Individuals, both domestic and foreign, are the largest net buyers, with an average daily buy-sell imbalance (BSI) ratio of 20 percent. The daily buy-sell imbalance (BSI) ratio for retirement funds is just above neutral, at 4 percent. Retirement funds trade the most often of all of the categories, recording a participation rate, measured as the ratio of trading activity per category to the opportunity to trade (in which, for the specified interval, each stock represents one opportunity) of 93 percent[4], followed closely by foreign industry at 87 percent. Domestic individuals are a salient force in the Australian market, recording trades on 44 percent of the opportunities.

Insert Table 1 about here

The statistics for the weekly interval show the same patterns. All categories except the domestic government are net buyers; the buy-sell imbalance (BSI) ratio is 18 percent for individuals and just above neutral at 0.9 percent for retirement funds. Participation rates increase for all categories, with retirement funds recording trades in 97 percent of the weekly opportunities and the domestic individual participation rate increasing to 72 percent.

The first of our hypotheses concerns the influence of individual investor trading on stock returns. The correlation matrices in Table 2 shows a strong (*p*-value < 0.0001) negative correlation between the BSI for individual investors and contemporaneous returns, signifying that individual investor trading is linked to changes in equity prices. The relation persists for each of the five daily lags in Table 2, as well as for the entire month represented by the

[3] All significant at the 1% level.

[4] Note that this statistic does not represent the participation of the investor categories in the market as a whole. For example, though retirement funds trade every day the market is open, since the study is cross-sectional, to get a 100% participation rate, they would have to trade every stock every day.

weekly lags.[5] The BSI of foreign individuals is also strongly correlated with contemporaneous and lagged returns for the week and month. The BSIs of government and foreign industry are significantly (p-value < 0.0001) correlated with contemporaneous daily returns, and all of the categories' BSIs are correlated with weekly contemporaneous return. However, none of the other categories show the persistence of the relation that is present for individuals and foreign individuals. Interestingly, the only significantly positive correlation between returns and BSI occurs for retirement funds. The strong (p-values ranging from 0.0009 to < 0.0001) correlation between retirement funds and all of the other categories suggests that, net of intra- category trading, the five other categories trade against the retirement funds.

The correlation matrix confirms a relation between returns and trading, but does not show causality. In order to draw inferences about which of the investor categories influence short term stock returns, and specifically about whether the trading of individual investors matters in the price discovery process, we conduct Granger-causality tests with a bivariate VAR.

Insert Table 2 about here

Panel A of Table 3 shows the results of the VAR regressions for which daily log returns are the dependent variable and lagged log returns and lagged category BSI comprise the independent variables. The results show the expected autocorrelation in daily returns. However, the significance of the coefficients of the lagged category BSIs indicates that trading does influence returns. More formally, as all of the partial F-test statistics are significant at the one percent level, we can state that the trading of each of the investor categories Granger-causes returns. These results are particularly strong for the trading of

[5] The correlation matrix for weekly data, omitted for brevity, is consistent with that of the daily data. It is available from the authors on request.

retirement funds, foreign industry and domestic individuals, all of which have partial *F*-statistics that are greater than 100. Our findings contradict those of Kamesaka, Nofsinger and Kawakita (2003), who find that neither investment flow nor past market returns Granger-cause current returns for the Japanese market. However, their data are aggregated to the market level, and the focus of their study is not trade – return causality. Since our data are aggregated by stock, we have a much richer data set from which to investigate this effect. The significantly positive coefficients for retirement funds indicate that increases in the holdings of retirement funds over the past week cause increases in returns. Australian individuals, foreign industry and foreign individuals on average sell into rising markets, providing liquidity to the domestic retirement funds.

Insert Table 3 about here

Panel B of Table 3 reports the results of the part of the daily VAR in which the investor categories are the independent variables. At the daily frequency, we find that for individual investors, stock returns Granger-cause trading. The negative coefficients are consistent with Jackson (2003), Grinblatt and Keloharju (2000), Odean (1998) and others' findings that individual investors are contrarian investors, though we do not find Grinblatt and Keloharju's (2000) two day momentum anomaly. Our evidence does not support the Sentana and Wadhwani (1992) theory that negative feedback investing will result in positive autocorrelation of returns.

Individual investors trade differently from the other categories; there is little or no evidence[6] that changes in returns Granger-cause category trading imbalances for the other investor categories. However, we argued earlier that the negative feedback trading pattern

[6] The partial *F* statistic for domestic retirement funds is significant at the 1% level, but at 3.07 it barely exceeds the critical $F_{0.01,5,\infty}$ value. We refer to comments by Grinblatt and Keloharju (2001) that for such large sample sizes, "isolated *t*-statistics of less than three for coefficients that are not part of a pattern are unimpressive, even though such *t*-statistics represent statistical significance at the one percent level."(page 598)

could be attributed to a market structure effect. To further investigate the viability of these conflicting theories, we will revisit trading and returns at a weekly frequency in Table 4.

The results in Panel B of Table 3 generate another interesting inference. With very few exceptions, the coefficients of the lagged category trading imbalances are positive and highly significant. That is, categories that buy (sell) on a given day are likely to have bought (sold) for the past five days. This evidence corroborates the Kumar and Lee (2006) and Nofsinger and Sias (1999) findings that individual investors and institutional traders, respectively, follow the trading patterns of others in their category (i.e., herd).

The results of the regressions at the weekly interval[7], presented in Table 4, support the conclusions of Table 3. Panel A of Table 4 indicates that trading imbalances measured on a weekly interval Granger-cause weekly log returns. Panel B shows that weekly returns Granger-cause trading imbalances for individuals for at least two weeks. The persistence of the negative coefficients and the large values of the partial F-statistics (28.5 for domestic individual investors, 20.48 for foreign individual investors) indicate that the result is not an artefact of market structure. Individual investors exhibit the behavioural bias of negative feedback trading; other investor categories show neither negative nor positive feedback trading tendencies. The coefficients of the category lags in Panel B of Table 4 are positive and significant, as were the daily lags in Panel B of Table 3. Previous intra-category trading is a better predictor of current trading than are previous returns.

Insert Table 4 about here

Our conclusion from the Granger-causality tests, supported by the evidence in the correlation matrices, is that excess demand, i.e., more buying than selling of a particular

[7] Notice that for the two least noteworthy categories, domestic government and domestic industry, the sample size is larger for the weekly VAR than for the daily. This apparent anomaly is caused by the relative infrequency of the categories' trades. There are only 697 five-day periods during which the domestic industry category trades a specific stock every day, but there are 1459 four-week periods during which the category trades a specific stock at least once per week.

stock, by individual investors Granger-causes negative returns or a reduction in the stock's price. Our tests indicate that the trading of the investor group most prone to cognitive biases does affect market prices, but in the opposite manner from that which economic theory predicts. This result merits future research as it has important implications for asset pricing models based on behavioural finance theories. For example, though it is generally assumed that (irrational) individual investor trading exacerbates asset price bubbles, these results suggest otherwise.

It is possible that the finding that individual investor trading significantly impacts returns is caused by a high concentration of individual investor ownership of a few stocks. To test the robustness of our results, we form subsets of the data. Table 5 reports results of estimating Equation (2) for a subset of the original daily data that excludes the stocks in the top decile of individual ownership. The results do not change; the coefficients of the regressions for which individual investor trading imbalances are the independent variables are still statistically significant. Individual investor trades Granger-cause stock returns even for the companies for which individual investor ownership is not the highest.

Insert Tables 5 and 6 about here

As a further robustness check, we consider additional sub-samples of the data. Table 6 reports the partial F statistics for the regressions estimated for the top decile and the balance of the data set for each of three stock characteristics: market capitalization, liquidity and individual investor ownership. For comparison, we include in the table the partial F statistics for the entire data sample. Our initial conclusions are supported. Category trading Granger-causes returns; for the individual investor category alone, returns Granger-cause trading.

6 Conclusion

We investigate the Granger-causality between returns and trading of different investor categories in the large, active and diverse Australian capital market. The data comprise purchases and sales by six different investor categories of some 750 stocks over a period from January 1, 1996 to March 30, 2002, capturing virtually all of the free float in the market. We use a cross-sectional design, minimizing the effects of size, systematic risk and time series distortions on the analysis.

We find that trading by all of the investor categories Granger-causes returns at both daily and weekly intervals. Of particular interest is the result that the trading decisions of individual investors influence market prices, though in a manner contrary to theory. Individual investors differ from the other categories in their reaction to previous returns. For individual investors, returns Granger-cause trading, consistent with the behavioural bias of negative feedback trading. The other investor categories do not share this bias. Finally, we highlight the autocorrelation in investor category trade imbalances, indicating that investors' trading decisions are more influenced by the previous trading within their category than they are by previous stock returns.

7 References

Andreassen, P. B., 1988, Explaining the Price—Volume Relationship: The Difference between Price Changes and Changing Prices, *Organizational Behavior and Human Decision Processes* 41, 371-389.

Asparouhova, Elena, Peter Bossaerts, and Charles Plott, 2003, Excess Demand and Equilibration in Multi-Security Financial Markets: The Empirical Evidence, *Journal of Financial Markets* 6, 1-21.

Bange, Mary M., 2000, Do the Portfolios of Small Investors Reflect Positive Feedback Trading?, *Journal of Financial and Quantitative Analysis* 35, 239-255.

Barber, Brad M., and Terrance Odean, 2002, All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, (University of California, Davis).

Barberis, N., and M. Huang, 2001, Mental Accounting, Loss Aversion, and Individual Stock Returns, *The Journal of Finance* 56, 1247-1292.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style Investing, *Journal of Financial Economics* 68, 161-91.

Barberis, Nicholas, Andrei Shleifer, and Robert W. Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-345.

Bossaerts, Peter, Charles Plott, and William R. Zame, 2003, Prices and Portfolio Choices in Financial Markets: Theory and Experiment, (California Institute of Technology).

Brown, Philip, Nick Chappel, Ray da Silva Rosa, and Terry S. Walter, 2006, The Reach of the Disposition Effect: Large Sample Evidence Across Investor Classes, *The International Review of Finance, forthcoming*.

Caginalp, Gunduz, David Porter, and Vernon L. Smith, 2000, Overreactions, Momentum, Liquidity, and Price Bubbles in Laboratory and Field Asset Markets, *The Journal of Psychology and Financial Markets* 1, 24-48.

Cha, H., and B. Lee, 2001, The Market Demand Curve for Common Stocks: Evidence from Equity Mutual Fund Flows, *Journal of Financial and Quantitative Analysis* 36, 195-220.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2002, Order Imbalance, Liquidity, and Market Returns, *Journal of Financial Economics* 65, 111-130.

Chordia, Tarun, and Avanidhar Subrahmanyam, 2004, Order Imbalance and Individual Stock Returns: Theory and evidence, *Journal of Financial Economics* 72, 485-518.

Daniel, K., David A. Hirshleifer, and A. Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *Journal of Finance* 53, 1839-1885.

De Bondt, Werner. F. M. , and Richard H. Thaler, 1994, Financial Decision-making in Markets and Firms: A Behavioral Perspective, in R. Jarrow, V. Maksimovic, and W.T. Ziemba, eds.: *Finance* (Elsevier, North Holland).

Dhar, Ravi, and Alok Kumar, 2001, A Non-Random Walk Down the Main Street: Impact of Price Trends on Trading Decisions of Individual Investors, (Yale International Center for Finance).

Fama, Eugene F, 1998, Market Efficiency, Long-Term Returns, and Behavioral Finance *Journal of Financial Economics* 49, 283-306.

Froot, K.A., P.G.J. O'Connell, and M.S. Seasholes, 2001, The portfolio flows of international investors, *Journal of Financial Economics* 59, 151-193.

Gemmill, G. , and D. Thomas, 2002, Noise Trading, Costly Arbitrage, and Asset Prices: Evidence from Closed-End Funds, *Journal of Finance* 57, 2571-94.
Grinblatt, Mark, and M. Keloharju, 2000, The Investment Behavior and Performance of Various Investor Types: A Study of Finland's Unique Data Set, *Journal of Financial Economics* 55, 43-67.
Jackson, Andrew, 2003, The Aggregate Behaviour of Individual Investors, Available at SSRN: http://ssrn.com/abstract=536942.
Jegadeesh, Narasimhan, and S. Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65-91.
Kahneman, D., and Amos Tversky, 1979, Prospect Theory: an Analysis of Decision Under Risk, *Econometrica* 47, 63-91.
Kamesaka, A., John R. Nofsinger, and H. Kawakita, 2003, Investment patterns and performance of investor groups in Japan, *Pacific-Basin Finance Journal* 11, 1-22.
Kim, J., J. Lee, and R. Morck, 2004, Heterogeneous Investors and their Changing Demand and Supply Schedules for Individual Common Stocks, (National Bureau of Economic Research).
Kluger, B.D., and S. B. Wyatt, 2004, Are Judgment Errors Reflected in Market Prices and Allocations? Experimental Evidence Based on the Monty Hall Problem, *Journal of Finance* 59, 969-997.
Kumar, Alok, and Charles M.C. Lee, 2006, Retail Investor Sentiment and Return Comovements, *Journal of Finance, forthcoming* Available at SSRN: http://ssrn.com/abstract=502843.
Lee, C., and M. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-747.
Lee, Charles M.C., Andrei Shleifer, and Richard H. Thaler, 1991, Investor Sentiment and the Closed End Fund Puzzle, *Journal of Finance* 46, 75-109.
Linnainmaa, J., 2003, Who Makes the Limit Order Book? Implications for Contrarian Strategies, Attention-Grabbing Hypothesis, and the Disposition Effect, (University of California, Los Angeles).
Mech, Timothy S., 1993, Portfolio Return Autocorrelation, *Journal of Financial Economics* 34, 3307-344.
Nofsinger, John R., and Richard W. Sias, 1999, Herding and Feedback trading by Institutional and Individual Investors, *Journal of Finance* 54, 2263-2295.
Odean, Terrance, 1998, Are Investors Reluctant to Realize Their Losses, *The Journal of Finance* 53.
Oh, Natalie Y., Jerry T. Parwada, and Terry S. Walter, 2004, Online investors' trading behavior and performance: Evidence from the Korean equity market, (University of New South Wales, Australia).
Safvenblad, Patrik, 2000, Trading volume and autocorrelation: Empirical evidence from the Stockholm Stock Exchange, *Journal of Banking and Finance* 24, 1275-1287.
Sentana, Enrique, and Sushil Wadhwani, 1992, Feedback Traders and Stock Return Autocorrelations: Evidence from a century of daily data, *The Economic Journal* 102, 415-425.
Thaler, Richard H., 1987, The psychology of choice and the assumptions of economics, in A. Roth, ed.: *Laboratory Experiments in Economics: Six Points of View* (Cambridge University Press, Cambridge).

Figure 1: CHESS register as percent of ASX Market

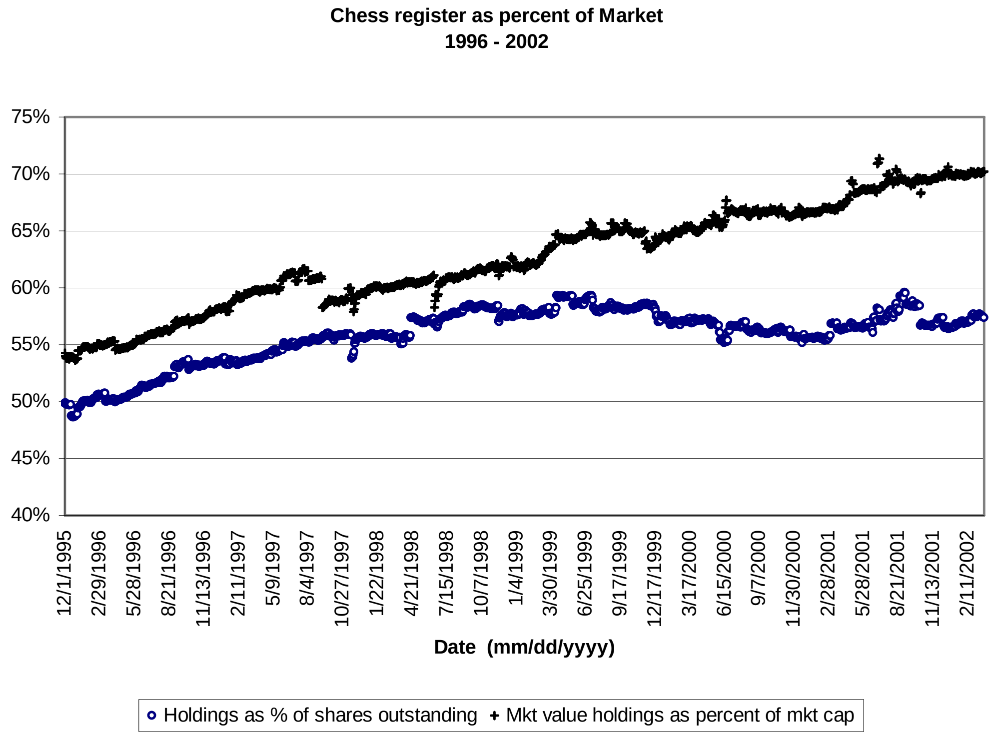

Figure 2: CHESS holdings (volume) by investor category, from 1996-2002. The holdings of foreign individuals and of domestic industry (distinct from domestic retirement funds) are so small, relatively, as to be barely discernible on this chart.

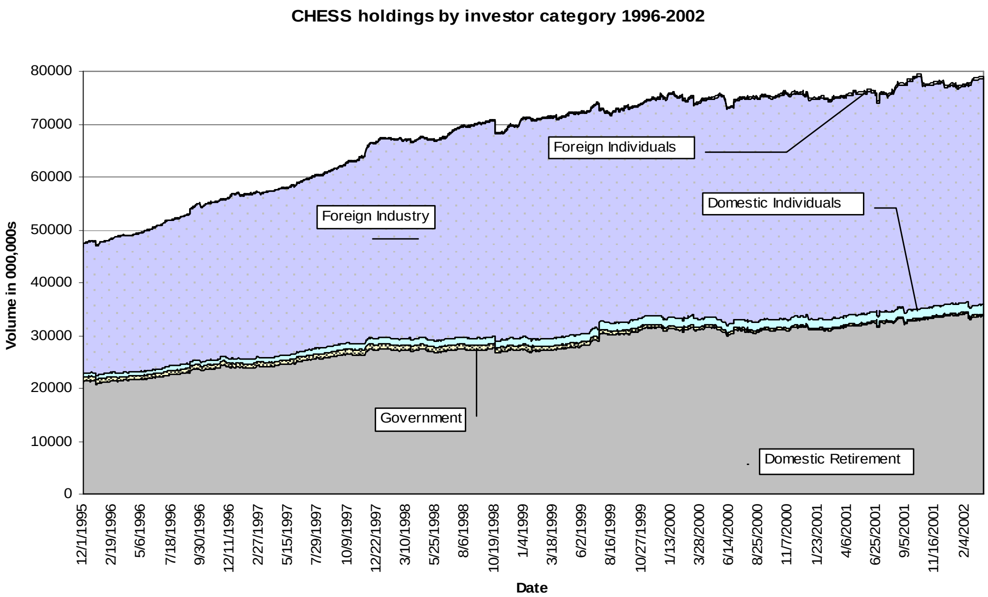

Table 1: Summary statistics

This table reports summary statistics for the variables used in the models. The sample comprises daily data for all stocks included in the Australian All Ordinaries Index at any point during the period December 1, 1995 through March 1, 2002. BSI refers to buy-sell imbalance, calculated as in Equation (1): $BSI_{jit} = \frac{(p_{jit} - s_{jit})}{(p_{jit} + s_{jit})}$.

Participation is the ratio of trading activity per category to the opportunity to trade, in which, for the specified interval, each stock represents one opportunity. The *t* statistics pertain to the null hypothesis that the corresponding mean BSI is equal to zero.

Variable	Obs.	Mean	Std Dev	*t*-stat	Participation
Panel A: Daily summary statistics					
BSI - Retirement funds	749040	0.0241	0.2886	(72.21)	92.8 percent
BSI - Government	70949	-0.0444	0.9552	(-12.38)	8.8 percent
BSI - Industry	16359	0.0965	0.9624	(12.82)	2.0 percent
BSI - Individuals	357198	0.2077	0.8177	(151.83)	44.2 percent
BSI - Foreign Industry	701245	0.0811	0.5929	(114.56)	86.8 percent
BSI - Foreign Individuals	144947	0.2023	0.8991	(85.64)	17.9 percent
Panel B: Weekly summary statistics					
BSI - Retirement funds	157989	0.0098	0.1864	(20.86)	97.3 percent
BSI - Government	35432	-0.0398	0.9001	(-8.31)	21.8 percent
BSI - Industry	11460	0.1138	0.9279	(13.13)	7.1 percent
BSI - Individuals	116448	0.1897	0.7116	(90.95)	71.7 percent
BSI - Foreign Industry	156273	0.0880	0.4305	(80.84)	96.2 percent
BSI - Foreign Individuals	66018	0.1973	0.8187	(61.94)	40.7 percent

Table 2: Correlation matrix daily BSI for investor categories and stock returns

This table presents pooled correlation estimates for daily cross-sectional buy-sell imbalance (BSI) by investor category. The sample comprises daily data for all stocks included in the Australian All Ordinaries Index at any point during the period December 1, 1995 through March 1, 2002. BSI is calculated as in Equation (1): $BSI_{jit} = \frac{(p_{jit} - s_{jit})}{(p_{jit} + s_{jit})}$. Returns are logarithmic volume weighted average price (VWAP) returns. Numbers in parentheses are *p*-values from a *t* -test for the difference from zero.

	Retirement funds	Government	Industry	Individuals	Foreign Industry	Foreign Individuals	Return	Return t-1	Return t-2	Return t-3	Return t-4	Return t-5
Retirement	1	-0.1054	-0.0456	-0.1583	-0.5286	-0.1043	-0.0014	-0.0004	0.0043	0.0020	0.0026	0.0004
Funds		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.2436)	(0.7077)	(0.0002)	(0.0801)	(0.0247)	(0.7273)
Government		1	0.0446	0.1120	0.0436	0.0411	-0.0153	-0.0110	-0.0058	-0.0101	-0.0056	-0.0110
			(0.0024)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0036)	(0.1211)	(0.0071)	(0.1359)	(0.0034)
Industry			1	0.1053	0.0648	0.1338	-0.0104	-0.0042	0.0053	-0.0014	-0.0120	-0.0078
				(<.0001)	(<.0001)	(<.0001)	(0.1855)	(0.5883)	(0.5027)	(0.8553)	(0.1249)	(0.3194)
Individuals				1	0.0914	0.1576	-0.0126	-0.0109	-0.0116	-0.0112	-0.0124	-0.0108
					(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Foreign					1	0.0909	-0.0083	-0.0059	-0.0036	-0.0033	-0.0045	-0.0009
Industry						(<.0001)	(<.0001)	(<.0001)	(0.0025)	(0.0062)	(0.0002)	(0.4578)
Foreign						1	-0.0290	-0.0209	-0.0168	-0.0185	-0.0159	-0.0147
Individuals							(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Return							1	0.0245	-0.0163	-0.0229	-0.0051	0.0017
								(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.1358)
Return t-1								1	0.0245	-0.0163	-0.0229	-0.0051
									(<.0001)	(<.0001)	(<.0001)	(<.0001)
Return t-2									1	0.0245	-0.0163	-0.0229
										(<.0001)	(<.0001)	(<.0001)
Return t-3										1	0.0245	-0.0163
											(<.0001)	(<.0001)
Return t-4											1	0.0245
												(<.0001)
Return t-5												1

Table 3: VAR daily returns and BSI

This table presents results for the cross-sectional bivariate vector autoregressive model specified in Equation (2) as:

$$Z_{t,i} = A + \sum_{n=1}^{p} B_n Z_{t-n,i} + E_{t,i} \quad \text{where} \quad Z_{t,i} = \begin{bmatrix} r_{t,i} \\ BSI_{jit} \end{bmatrix},\ A = \begin{bmatrix} \alpha_r \\ \alpha_{BSI_j} \end{bmatrix},\ B = \begin{bmatrix} \beta_{1,1,n} & \beta_{1,2,n} \\ \beta_{2,1,n} & \beta_{2,2,n} \end{bmatrix},\ E = \begin{bmatrix} \varepsilon_{r,i} \\ \varepsilon_{BSI_{jit}} \end{bmatrix}$$

The sample comprises daily data for all stocks included in the Australian All Ordinaries Index at any point during the period December 1, 1995 through March 1, 2002. The independent variables are lagged daily logarithmic volume weighted average price (VWAP) returns and lagged daily category buy-sell imbalances (BSIs), where category BSI refers to the daily BSI of the investor category at the column head. In Panel A the dependent variable is logarithmic volume weighted average price (VWAP) returns. In Panel B the dependent variable is the category BSI at the column head. The numbers in parentheses are *p* values for *t* tests of the coefficients. The partial *F* test tests the null hypothesis that the coefficients of all of the second group of independent variables (lagged category BSI in Panel A, lagged returns in Panel B) are equal to zero. Three stars, ***, indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, * indicates significance at the 10 percent level.

		Retirement funds	Government	Industry	Individuals	Foreign Industry	Foreign Individuals
Panel A: Dependent variable return							
N obs.		687850	7404	697	161840	590221	29822
F for regression		328.1 ***	40.34 ***	14.87 ***	374.08 ***	416.46 ***	141.13 ***
Adj. R^2		0.0047	0.0504	0.1659	0.0225	0.0070	0.0449
Constant		-0.0003 ***	-0.0002	0.0003	0.0011 ***	0.0003 ***	0.0018 ***
		(<0.0001)	(0.3723)	(0.7123)	(<0.0001)	(<0.0001)	(<0.0001)
Return	t-1	0.0491 ***	0.2255 ***	0.1402 ***	0.1214 ***	0.0643 ***	0.1703 ***
		(<0.0001)	(<0.0001)	(0.001)	(<0.0001)	(<0.0001)	(<0.0001)
	t-2	-0.0149 ***	-0.0261 **	-0.0317	-0.0296 ***	-0.0122 ***	-0.0657 ***
		(<0.0001)	(0.0365)	(0.4491)	(<0.0001)	(<0.0001)	(<0.0001)
	t-3	-0.0163 ***	0.0327 ***	-0.0006	-0.0003	-0.0154 ***	0.0048
		(<0.0001)	(0.008)	(0.9871)	(0.8753)	(<0.0001)	(0.3193)
	t-4	-0.0045 ***	-0.0378 ***	0.1065 ***	0.0052 **	-0.0043 ***	0.0035
		(0.0002)	(<0.0001)	(0.0067)	(0.0178)	(0.0008)	(0.4693)
	t-5	0.0023	-0.0146	0.1051 ***	-0.0038 ***	0.0036 ***	-0.0083
		(0.0545)	(0.0951)	(<.0001)	(0.0841)	(0.0042)	(0.0899)
Category BSI	t-1	0.0010 ***	-0.0002	0.0012	-0.0005 ***	-0.0003 ***	-0.0016 ***
		(<0.0001)	(0.3889)	(0.2542)	(<0.0001)	(<0.0001)	(<0.0001)
	t-2	0.0023 ***	-0.0009 ***	-0.0008	-0.0013 ***	-0.0015 ***	-0.0021 ***
		(<0.0001)	(0.0024)	(0.4723)	(<0.0001)	(<0.0001)	(<0.0001)
	t-3	0.0033 ***	0.0000	-0.0028 **	-0.0014 ***	-0.0018 ***	-0.0028 ***
		(<0.0001)	(0.8865)	(0.0134)	(<0.0001)	(<0.0001)	(<0.0001)
	t-4	0.0037 ***	-0.0004	-0.0014	-0.0012 ***	-0.0016 ***	-0.0016 ***
		(<0.0001)	(0.1979)	(0.2149)	(<0.0001)	(<0.0001)	(<0.0001)
	t-5	0.0013 ***	0.0000	-0.0003	0.0005 ***	0.0000	0.0006 **
		(<0.0001)	(0.9348)	(0.7699)	(0.0002)	(0.929)	(0.0368)
Partial *F*-statistic		227.73 ***	4.94 ***	5.33 ***	105.54 ***	256.13 ***	60.14 ***

Table 3 cont.: VAR daily returns and BSI

		Retirement funds	Government	Industry	Individuals	Foreign Industry	Foreign Individuals
Panel B: Dependent variable BSI categories							
N obs.		679043	5140	545	148512	576800	24950
F for regression		83.75 ***	126.3 ***	9.78 ***	1318.26 ***	1310.78 ***	188.39 ***
Adj. R^2		0.0012	0.1960	0.1387	0.0815	0.0222	0.0699
Constant		0.0149 ***	0.0137	-0.0999 ***	0.1105 ***	0.0521 ***	0.0927 ***
		(<0.0001)	(0.2238)	(0.0009)	(<0.0001)	(<0.0001)	(<0.0001)
Category BSI	t-1	0.0265 ***	0.2354 ***	-0.1238 ***	0.1723 ***	0.0970 ***	0.1379 ***
		(<0.0001)	(<0.0001)	(0.005)	(<0.0001)	(<0.0001)	(<0.0001)
	t-2	-0.0051 ***	0.1321 ***	0.1713 ***	0.0944 ***	0.0463 ***	0.1008 ***
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
	t-3	0.0012	0.0932 ***	0.1892 ***	0.0733 ***	0.0450 ***	0.0774 ***
		(0.3428)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
	t-4	0.0133 ***	0.0998 ***	0.2670 ***	0.0617 ***	0.0435 ***	0.0552 ***
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
	t-5	0.0163 ***	0.0738 ***	0.0481	0.0566 ***	0.0449 ***	0.0639 ***
		(<0.0001)	(<0.0001)	(0.2465)	(<0.0001)	(<0.0001)	(<0.0001)
Return	t-1	-0.0066	-0.0845	2.5863	-0.0967 **	-0.0162	-0.2945 ***
		(0.424)	(0.8897)	(0.1812)	(0.034)	(0.3883)	(0.0095)
	t-2	0.0315 ***	-1.0990	0.7398	-0.1695 ***	0.0263	-0.1505
		(0.0001)	(0.0878)	(0.7017)	(0.0002)	(0.162)	(0.1803)
	t-3	0.0127	0.5352	-2.9717	-0.1393 ***	-0.0151	-0.1992
		(0.1276)	(0.3949)	(0.0605)	(0.002)	(0.4209)	(0.0622)
	t-4	0.0137	0.0509	2.1079	-0.1968 ***	-0.0307	-0.2531 **
		(0.0978)	(0.938)	(0.2905)	(<0.0001)	(0.0985)	(0.0154)
	t-5	0.0077	0.0132	0.0465	-0.1339 ***	0.0214	0.0196
		(0.3494)	(0.9833)	(0.9192)	(0.0037)	(0.2435)	(0.8537)
Partial *F*-statistic		3.08 ***	0.70	1.78	13.52 ***	1.41	4.70 ***

Table 4: VAR weekly returns and BSI

This table presents results for the cross-sectional bivariate vector autoregressive model specified in Equation (2) as:

$$Z_{t,i} = A + \sum_{n=1}^{p} B_n Z_{t-n,i} + E_{t,i} \quad \text{where} \quad Z_{t,i} = \begin{bmatrix} r_{t,i} \\ BSI_{jit} \end{bmatrix},\ A = \begin{bmatrix} \alpha_r \\ \alpha_{BSI_j} \end{bmatrix},\ B = \begin{bmatrix} \beta_{1,1,n} & \beta_{1,2,n} \\ \beta_{2,1,n} & \beta_{2,2,n} \end{bmatrix},\ E = \begin{bmatrix} \varepsilon_{r,i} \\ \varepsilon_{BSI_{jit}} \end{bmatrix}$$

The sample comprises weekly data for all stocks included in the Australian All Ordinaries Index at any point during the period December 1, 1995 through March 1, 2002. The independent variables are lagged weekly logarithmic volume weighted average price (VWAP) returns and lagged weekly category buy-sell imbalances (BSIs), where category BSI refers to the weekly BSI of the investor category at the column head. In Panel A the dependent variable is logarithmic volume weighted average price (VWAP) returns. In Panel B the dependent variable is the category BSI at the column head. The numbers in parentheses are p values for t tests of the coefficients. The partial F- test tests the null hypothesis that the coefficients of all of the second group of independent variables (lagged category BSI in Panel A, lagged returns in Panel B) are equal to zero. Three stars, ***, indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, * indicates significance at the 10 percent level.

		Retirement funds	Government	Industry	Individuals	Foreign Industry	Foreign Individuals
Panel A: Dependent variable return							
N obs.		148332	13610	1459	82954	144643	31361
F for regression		78.06 ***	18.35 ***	1.76 *	31.57 ***	80.76 ***	11.48 ***
Adj. R^2		0.0041	0.0101	0.0041	0.0029	0.0044	0.0027
Constant		-0.0009 ***	0.0004	-0.0037	-0.0006	-0.0004	-0.0008
		(<0.0001)	(0.3364)	(0.0577)	(0.0651)	(0.1105)	(0.1059)
Return	t-1	-0.0509 ***	-0.0989 ***	-0.0206	-0.0264 ***	-0.0467 ***	-0.0117 **
		(<0.0001)	(<0.0001)	(0.3496)	(<0.0001)	(<0.0001)	(0.0365)
	t-2	0.0089 ***	-0.0086	-0.0078	0.0228 ***	0.0102 ***	0.0258 ***
		(0.0006)	(0.314)	(0.6985)	(<0.0001)	(<0.0001)	(<0.0001)
	t-3	0.0041	-0.0064	-0.0031	0.0134 ***	0.0037	0.0073
		(0.1134)	(0.4682)	(0.8782)	(<0.0001)	(0.156)	(0.1579)
	t-4	0.0063 **	0.0121	-0.0218	0.0107 ***	0.0077 ***	0.0114 **
		(0.0137)	(0.1659)	(0.2352)	(0.0013)	(0.0029)	(0.0271)
Category BSI	t-1	0.0177 ***	0.0000	-0.0072 ***	-0.0046 ***	-0.0092 ***	-0.0049 ***
		(<0.0001)	(0.9807)	(0.002)	(<0.0001)	(<0.0001)	(<0.0001)
	t-2	0.0025 **	-0.0002	0.0035	0.0017 ***	0.0014 ***	0.0009
		(0.0387)	(0.7488)	(0.1444)	(0.0001)	(0.0075)	(0.1692)
	t-3	-0.0002	0.0012	-0.0018	-0.0002	0.0012 **	0.0002
		(0.845)	(0.0518)	(0.4511)	(0.6157)	(0.0297)	(0.7944)
	t-4	-0.0003	-0.0010	-0.0002	0.0012	0.0015 ***	-0.0003
		(0.8209)	(0.0789)	(0.948)	(0.0065)	(0.0065)	(0.623)
Partial *F*-statistic		53.90 ***	1.43	2.96 **	30.76 ***	76.22 ***	13.60 ***

Table 4 cont.: VAR weekly returns and BSI

		Retirement funds	Government	Industry	Individuals	Foreign Industry	Foreign Individuals
Panel B: Dependent variable BSI categories							
N obs.		147971	11421	1000	78831	143945	28219
F for regression		83.87 ***	138.98 ***	8.36 ***	561.15 ***	778.37 ***	163.93 ***
Adj. R^2		0.0045	0.0881	0.0556	0.0538	0.0414	0.0442
Constant		0.0070 ***	-0.0150 **	-0.0167	0.1134 ***	0.0528 ***	0.1092 ***
		(<0.0001)	(0.0418)	(0.5207)	(<0.0001)	(<0.0001)	(<0.0001)
Category BSI	t-1	-0.0025	0.2138 ***	0.1376 ***	0.1619 ***	0.1143 ***	0.1390 ***
		(0.3357)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
	t-2	0.0388 ***	0.1149 ***	0.1435 ***	0.0789 ***	0.0846 ***	0.0678 ***
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
	t-3	0.0444 ***	0.0630 ***	0.0667 **	0.0551 ***	0.0768 ***	0.0564 ***
		(<0.0001)	(<0.0001)	(0.0437)	(<0.0001)	(<0.0001)	(<0.0001)
	t-4	0.0308 ***	0.0258 ***	0.0349	0.0553 ***	0.0652 ***	0.0525 ***
		(<0.0001)	(0.0059)	(0.2799)	(<0.0001)	(<0.0001)	(<0.0001)
Return	t-1	0.0068	-0.2103	0.1360	-0.2293 ***	-0.0225	-0.3527 ***
		(0.2121)	(0.121)	(0.6242)	(<0.0001)	(0.079)	(<0.0001)
	t-2	0.0147 ***	0.0196	-0.1253	-0.1845 ***	0.0147	-0.2082 ***
		(0.0073)	(0.8903)	(0.6632)	(<0.0001)	(0.2512)	(<0.0001)
	t-3	0.0064	-0.0395	-0.2498	-0.0447	0.0316 **	-0.0875
		(0.2382)	(0.7775)	(0.3494)	(0.1012)	(0.0135)	(0.0595)
	t-4	0.0124 **	0.1195	-0.1233	-0.0229	0.0100	-0.0951 **
		(0.023)	(0.3937)	(0.5414)	(0.4018)	(0.4322)	(0.037)
Partial F-statistic		3.66 ***	0.82	0.40	28.50 ***	3.16 **	20.48 ***

Table 5: VAR daily returns and BSI excluding stocks in the top decile of individual investor ownership

This table presents results for the cross-sectional bivariate vector autoregressive model specified in Equation (2) as:

$$Z_{t,i} = A + \sum_{n=1}^{p} B_n Z_{t-n,i} + E_{t,i} \quad \text{where} \quad Z_{t,i} = \begin{bmatrix} r_{t,i} \\ BSI_{jit} \end{bmatrix},\ A = \begin{bmatrix} \alpha_r \\ \alpha_{BSI_j} \end{bmatrix},\ B = \begin{bmatrix} \beta_{1,1,n} & \beta_{1,2,n} \\ \beta_{2,1,n} & \beta_{2,2,n} \end{bmatrix},\ E = \begin{bmatrix} \varepsilon_{r,i} \\ \varepsilon_{BSI_{jit}} \end{bmatrix}$$

The sample comprises daily data for all stocks included in the Australian All Ordinaries Index at any point during the period December 1, 1995 through March 1, 2002 EXCLUDING the stocks in the highest decile of individual ownership, measured for each stock as individual investor shareholding as a percentage of CHESS registered shares. The independent variables are lagged daily logarithmic volume weighted average price (VWAP) returns and lagged daily category buy-sell imbalances (BSIs), where category BSI refers to the daily BSI of the investor category at the column head. In Panel A the dependent variable is logarithmic volume weighted average price (VWAP) returns. In Panel B the

		Retirement funds	Government	Industry	Individuals	Foreign Industry	Foreign Individuals
Panel A: Dependent variable return							
N obs.		531306	7240	673	129833	454460	26602
F for regression		193.95 ***	36.35 ***	5.65 ***	264.81 ***	255.09 ***	125.48 ***
Adj. R^2		0.0036	0.0466	0.0646	0.0199	0.0056	0.0447
Constant		-0.0003 ***	-0.0002	0.0008	0.0011 ***	0.0002 ***	0.0018 ***
		(<.0001)	(0.275)	(0.3215)	(<.0001)	(<.0001)	(<.0001)
Return	t-1	0.0437 ***	0.2167 ***	0.0907 **	0.1098 ***	0.0588 ***	0.1693 ***
		(<.0001)	(<.0001)	(0.0426)	(<.0001)	(<.0001)	(<.0001)
	t-2	-0.0070 ***	-0.0267 **	-0.0501	-0.0236 ***	-0.0026 *	-0.0689 ***
		(<.0001)	(0.0333)	(0.2398)	(<.0001)	(0.0743)	(<.0001)
	t-3	-0.0160 ***	0.0285 **	0.0921 **	-0.0018	-0.0143 ***	0.0006
		(<.0001)	(0.022)	(0.0127)	(0.4511)	(<.0001)	(0.9098)
	t-4	-0.0031 **	-0.0382 ***	0.1911 ***	0.0072 ***	-0.0030 **	0.0016
		(0.0212)	(<.0001)	(<.0001)	(0.0027)	(0.0381)	(0.7646)
	t-5	0.0029 **	-0.0153 *	-0.1488 ***	-0.0063 ***	0.0039 ***	-0.0041
		(0.0338)	(0.0822)	(0.0013)	(0.0075)	(0.0063)	(0.4428)
Category BSI	t-1	0.0010 ***	-0.0002	0.0018 *	-0.0007 ***	-0.0003 ***	-0.0017 ***
		(<.0001)	(0.3996)	(0.0863)	(<.0001)	(0.0009)	(<.0001)
	t-2	0.0023 ***	-0.0009 ***	-0.0004	-0.0013 ***	-0.0015 ***	-0.0023 ***
		(<.0001)	(0.0036)	(0.6845)	(<.0001)	(<.0001)	(<.0001)
	t-3	0.0028 ***	0.0000	-0.0028 ***	-0.0013 ***	-0.0015 ***	-0.0025 ***
		(<.0001)	(0.9656)	(0.0086)	(<.0001)	(<.0001)	(<.0001)
	t-4	0.0032 ***	-0.0003	-0.0020 *	-0.0009 ***	-0.0013 ***	-0.0014 ***
		(<.0001)	(0.2416)	(0.0578)	(<.0001)	(<.0001)	(<.0001)
	t-5	0.0010 ***	0.0000	-0.0013	0.0007 ***	0.0001	0.0009 ***
		(<.0001)	(0.9742)	(0.2146)	(<.0001)	(0.2337)	(0.0017)
Partial *F*-statistic		134.24 ***	4.11 ***	3.16 ***	82.95 ***	148.26 ***	58.07 ***

Table 5 cont.: VAR daily returns and BSI excluding stocks in the top decile of individual investor ownership

dependent variable is the category BSI at the column head. The numbers in parentheses are *p* values for *t* tests of the coefficients. The partial *F* test tests the null hypothesis that the coefficients of all of the second group of independent variables (lagged category BSI in Panel A, lagged returns in Panel B) are equal to zero. Three stars, ***, indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, * indicates significance at the 10 percent level.

		Retirement funds	Government	Industry	Individuals	Foreign Industry	Foreign Individuals
Panel B: Dependent variable BSI categories							
N obs.		524443	5049	535	120046	443950	22472
F for regression		80.81 ***	113.03 ***	9.82 ***	1177.69 ***	1089.15 ***	190.56 ***
Adj. R^2		0.0015	0.1816	0.1416	0.0893	0.0239	0.0778
Constant		0.0145 ***	0.0183	-0.0951 ***	0.1052 ***	0.0461 ***	0.0903 ***
		(<.0001)	(0.1095)	(0.0015)	(<.0001)	(<.0001)	(<.0001)
Category BSI	t-1	0.0289 ***	0.2312 ***	-0.1354 ***	0.1765 ***	0.0977 ***	0.1431 ***
		(<.0001)	(<.0001)	(0.0024)	(<.0001)	(<.0001)	(<.0001)
	t-2	0.0029 **	0.1290 ***	0.1654 ***	0.1005 ***	0.0523 ***	0.1074 ***
		(0.0393)	(<.0001)	(0.0002)	(<.0001)	(<.0001)	(<.0001)
	t-3	0.0066 ***	0.0900 ***	0.1805 ***	0.0767 ***	0.0472 ***	0.0820 ***
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
	t-4	0.0159 ***	0.0966 ***	0.2539 ***	0.0621 ***	0.0434 ***	0.0584 ***
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
	t-5	0.0167 ***	0.0700 ***	0.0416	0.0593 ***	0.0463 ***	0.0627 ***
		(<.0001)	(<.0001)	(0.3284)	(<.0001)	(<.0001)	(<.0001)
Return	t-1	-0.0026	-0.0693	2.0964	-0.1310 **	-0.0299	-0.3523 ***
		(0.7822)	(0.911)	(0.2916)	(0.0121)	(0.1615)	(0.0083)
	t-2	0.0377 ***	-1.1197 *	0.3125	-0.2089 ***	0.0028	-0.1101
		(<.0001)	(0.0875)	(0.8744)	(<.0001)	(0.8956)	(0.3999)
	t-3	0.0192 **	0.5742	-5.3442 ***	-0.1086 **	-0.0306	-0.2356 *
		(0.0426)	(0.3703)	(0.0022)	(0.0344)	(0.1516)	(0.0689)
	t-4	0.0166 *	0.0457	3.0708	-0.1997 ***	-0.0325	-0.2308 *
		(0.0767)	(0.9453)	(0.1719)	(0.0001)	(0.1232)	(0.0643)
	t-5	0.0137	0.0062	4.6395 **	-0.1645 ***	0.0150	-0.1704
		(0.1417)	(0.9924)	(0.029)	(0.0017)	(0.4751)	(0.1833)
Partial *F*-statistic		6.14 ***	0.71	3.52 ***	12.05 ***	1.41	4.07 ***

Table 6: Partial *F* statistics for sub-samples of the data.

This table presents partial *F* statistics for tests for Granger-causality with sub-samples of the original data set. Each stock in the data set is ranked and sorted into deciles for each of three characteristics: percent of individual ownership, market capitalization and liquidity. The bivariate VAR model and the restricted model (equations (2) and (3)) are estimated for the stocks in the highest decile of each characteristic and for the balance of the stocks, i.e., excluding the highest decile. Panels A & B report results for daily data; Panels C & D results are for weekly data. The partial *F*- test tests the null hypothesis that the coefficients of all of the second group of independent variables (lagged category BSI in Panels A & C, lagged returns in Panels B & D) are equal to zero. In Panels A & C, significance indicates that category trading Granger-causes returns. In Panels B & D, significance indicates that returns Granger-cause category trading. Three stars, ***, indicates significance at the 1 percent level, ** indicates significance at the 5 percent level.

	Retirement funds		**Government**		**Industry**		**Individuals**		**Foreign industry**		**Foreign individuals**	
Panel A: Daily data, dependent variable is return												
Entire sample	227.73	***	4.94	***	5.33	***	105.54	***	256.13	***	60.14	***
Without top decile of individual ownership	134.24	***	4.11	***	3.16	***	82.95	***	148.26	***	58.07	***
Top decile of individual ownership	45.95	***	0.58		2.56	**	16.07	***	60.63	***	2.73	**
Without top decile of market cap	276.38	***	1.17		2.20		75.37	***	308.25	***	19.08	***
Top decile of market cap	5.00	***	4.80	***	2.63	**	52.17	***	7.07	***	70.63	***
Without top decile of turnover	91.16	***	1.79		1.65		38.63	***	105.48	***	15.93	***
Top decile of turnover	218.66	***	3.43	***	2.01		70.05	***	196.95	***	42.21	***

Table 6 cont.: Partial *F* statistics for sub-samples of the data.

	Retirement funds		Government	Industry		Individuals		Foreign industry		Foreign individuals	
Panel B: Daily data, dependent variable is BSI											
Entire sample	3.08	***	0.70	1.78		13.52	***	1.41		4.70	***
Without top decile of individual ownership	6.14	***	0.71	3.52	***	12.05	***	1.41		4.07	***
Top decile of individual ownership	0.17		0.08	N/A		1.28		1.41		1.89	
Without top decile of market cap	5.60	***	1.26	3.36	***	6.59	***	1.30		2.26	**
Top decile of market cap	1.75		0.53	1.83		9.17	***	3.41	***	8.24	***
Without top decile of turnover	5.48	***	0.87	1.13		7.53	***	0.66		3.90	***
Top decile of turnover	2.45	**	0.33	2.81	**	6.04	***	0.90		2.15	
Panel C: Weekly data, dependent variable is return											
Entire sample	53.90	***	1.43	2.96	**	30.76	***	76.22	***	13.60	***
Without top decile of individual ownership	44.68	***	1.55	3.19	**	25.08	***	61.25	***	12.73	***
Top decile of individual ownership	28.74	***	0.16	0.38		16.86	***	43.25	***	5.05	***

Table 6 cont.: Partial *F* statistics for sub-samples of the data.

	Retirement funds		Government	Industry		Individuals		Foreign industry		Foreign individuals	
Panel C: Weekly data, dependent variable is return											
Without top decile of market cap	55.46	***	0.55	2.53	**	26.30	***	82.04	***	5.10	***
Top decile of market cap	1.81		1.45	1.67		4.57	***	1.52		16.87	***
Without top decile of turnover	35.29	***	1.80	2.22		19.47	***	50.71	***	9.81	***
Top decile of turnover	36.01	***	1.03	2.14		15.16	***	37.48	***	5.91	***
Panel D: Weekly data, dependent variable is BSI											
Entire sample	3.66	***	0.82	0.40		28.50	***	3.16	**	20.48	***
Without top decile of individual ownership	3.76	***	0.93	0.46		29.72	***	1.56		21.09	***
Top decile of individual ownership	2.65	**	1.01	0.23		2.93	**	2.44	**	3.88	***
Without top decile of market cap	3.58	***	0.92	0.51		15.00	***	4.43	***	7.18	***
Top decile of market cap	0.17		2.16	1.19		18.88	***	2.53	**	24.62	***
Without top decile of turnover	3.61	***	0.55	0.59		28.64	***	3.07	**	18.95	***
Top decile of turnover	2.97	**	0.86	1.16		3.16	**	1.45		3.33	**