Institutional Trading and Share Returns*

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ABSTRACT

Using a unique database of daily transactions from Australian equity managers, we investigate the relation between institutional trading and share returns. We find these institutional investors have statistically and economically significant predictive power in forecasting future stock returns over the ten days following their trades. Detailed analysis indicates that manager style is important in understanding the link between institutional trading and stock returns. We find style-neutral and growth-oriented managers are momentum traders, while value managers are contrarian. Further, the contemporaneous relation between institutional trading depends on relative trade size and investment style --- there is a negative contemporaneous relation between trades and returns for value / contrarian managers and a positive contemporaneous relation between trades and returns for style neutral and growth managers.

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Institutional Trading and Stock Returns

As significant holders of stocks on the world's exchanges, professional fund managers have the capacity to influence profoundly share returns and trading volume. Given the significant value of assets under their management, these professional investors may not only make up a noticeable percentage of daily trading volume, they also have access to a wide pool of resources to gather costly information and expertise. As such, key institutional investors have the capacity to move prices directly through their own trading, as well as indirectly, by influencing the trading decisions of other market participants who may observe their actions.

In this paper we investigate the daily trading of a sample of Australian equity fund managers. This gives an unprecedented view of the transactions of institutional investors and allows us to understand better the market's response to their trades. The Australian market is of particular interest for a number of reasons. First, it is a relatively small market by global standards, and so institutional investors may have a greater impact than in larger markets. Second, unlike other markets, fund managers have, as a group, consistently beaten passive benchmark indices over the past several years. This makes it more likely that their skills are related to a better understanding of share valuations or future share price movements.

To study the relation between fund trading and share returns we consider two broad effects. The first is that professional managers, as a group, at times possess particular expertise or insights that allow them to predict or anticipate future price changes. This would make them comparable to the informed traders in most microstructure models (see for example Kyle (1985) and Glosten and Milgrom (1985)). As we are using daily data, we need to consider the possibility that any information held by fund managers is long-lived, i.e., has return consequences for more than one day, or throughout the day. Further, there may be more than one fund manager with similar beliefs about future share values at any point in time. We refer to this broad set of issues as *informational* effects, recognizing that consequences for price movements are likely to be dynamic and influenced by competition among investment professionals.

The second possible effect on returns from professional trades is that a fund may submit orders based wholly on investor contributions / redemptions, rebalancing, *et cetera*. That is, there are times when fund managers need access to markets yet they have no particular insights or views on market fundamentals. We refer generally to these effects as *liquidity* related. As sophisticated investors, we expect institutional investors to exercise considerable care and discretion when implementing liquidity-motivated trades, and so we can describe this potential role of institutional traders as *discretionary liquidity traders*. Recent microstructure models examining the implication of actions by these traders can be found in Admati and Pfleiderer (1988) and Foster and Viswanathan (1990).

A key contribution of this paper is to link subsequent share returns to the trading of professionally managed funds, and relate these subsequent price adjustments to both informational and liquidity motives of fund managers. Finding a robust way of breaking out these two effects is not immediately obvious. While we have detailed information on their trading each day we do not have daily information on the motive for trading from any reporting investment fund. Absent clear evidence of a motive, we have to find a technique using observable features of the institution's order flow that to infer an impetus to trade. To achieve this we turn to insights from the microstructure literature, focusing on results that describe how information motivated trading may differ from discretionary liquidity trading.

To proxy for liquidity effects we compute the unanticipated trading volume from all institutional investors in a particular share each day. If institutional investors are aware of liquidity in the market, we would expect that they would choose to trade at times where the market is more accepting of unusually large flows and hence their orders would likely have a limited effect on share returns. This is consistent with the objective of discretionary liquidity traders used in Admati and Pfleiderer (1988) and Foster and Viswanathan (1990). Our analysis of the data is consistent with abnormally high buying and selling volume being unrelated to share returns, and is consistent with the view that such trades are drawn from (discretionary) liquidity trading.

The implication that unanticipated institutional trading volume has been skilfully allocated to times when the market is likely to more easily absorb the orders means that simply following patterns in trading volume is unlikely to allow us to pinpoint times when fund managers are likely trading with information-related motives. To allow for a better view of information-related trading we consider competition between funds and rely on microstructure literature that considers multiple informed traders with (potentially) long-lived information.

To proxy for information effects we consider the unanticipated *number* of fund managers buying or selling on each day. If a fund manager has discretion and is managing a pure liquidity shock, when share prices are especially sensitive to orders they would alter their planned trading program. Alternatively, if the institutional investor is trading because of a particular view about future returns, they may be unable to defer transactions – competition from other fund managers who trade and thereby eradicate any perceived mis-pricing, or announcement of information through the news media would both serve to limit discretion. From microstructure models we expect these forces to be especially striking when information is highly correlated and when the insight fully revealed through a public signal in the near future (see for example, Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993, 1996)).

If information or insights are costly to acquire and we see a number of mutual fund managers trading in the same manner on the same day (i.e. failing to exercise discretion), we argue that it is more likely that motive for trade is information-based, and that prices will be more sensitive to the order flow. Indeed, we find that the number of institutional investors buying (selling) on a given day is more important in understanding subsequent returns than the number of shares bought (sold) by institutional investors each day.

To explore the implications of informed versus discretionary liquidity motives for trading even further we also incorporate information about the "style" of the institutional investor. Our entire sample of mutual funds all claim to have the ability to provide superior risk-adjusted returns after fees. Obviously there are a large number of ways in which professional managers can "beat the market", and we note that the link between their trades and share returns depends on their stated expertise, which we proxy by their investment style. We use the institutional investors' stated style with the well-known categories of value, growth, and neutral. We find that style is particularly relevant in understanding the contemporaneous link between trading and share returns, with the contrarian actions of value managers being especially striking.

The remainder of the paper is organised as follows. Section I is a review of the background literature and outlines the theoretical foundations of our study. Section II provides a description of the data and reviews basic descriptive statistics. Section III outlines the research design while Section IV reports the empirical results. Finally, Section V concludes and provides suggestions for further research.

I. Background

To document the effects of fund management decisions on the share market we need to draw together two distinct parts of the finance literature. The first examines price formation, competition among informed traders, and the efficiency of markets. The second investigates how excess market returns might be achieved, the predictability of returns, and the relation between investment performance, return predictability, and investment style as stated by the fund manager.

In an efficient market, historical stock returns should not be a predictor of future returns, so historical returns should not be a critical component in a rational portfolio investment strategy. However, a number of empirical studies document significant abnormal returns to both contrarian and momentum trading. Studies focusing on contrarian strategies find buying past losers and selling past winners yield significant abnormal returns over the long-term (see for example DeBondt and Thaler (1985, 1987) and the short-term (see for example Jegadeesh (1990) and Lehmann (1990)). However, the majority of the empirical research documents positive autocorrelation, i.e. momentum strategies (see for example Lo and MacKinlay (1988), Conrad and Kaul (1988), Jegadeesh and Titman (1993), Chan, Jegadeesh and

Lakonishok (1996) and Jegadeesh and Titman (2001) who find positive autocorrelation over a one-year horizon, but negative autocorrelation over horizons longer than one year).

Given that past stock returns have been documented to predict future stock returns, it comes as no surprise that studies investigating the trading activity of institutional investors find that historical returns influence institutional trading. A number of studies find that institutional investors are contrarian (see for example Gompers and Metrick (2001) and Cohen, Gompers and Vuolteenaho (1998)) however most studies document a preference for momentum (see for example Grinblatt, Titman and Wermers (1995), Nosfinger and Sias (1999), Pinnuck (2003) and Cai and Zheng (2003)).

In this paper we use the extant research on the link between past returns and future performance to relate the choices of fund managers to the investment style employed. For example, "contrarians" are likely to focus on negative serial correlations in returns and "momentum" investors are likely to focus on positive autocorrelation in returns. Linking style to the existing literature allows us to incorporate information about *how* the fund manager seeks to out-perform the market with their trades. Knowing this, and being aware of possible differences between discretionary and other forms of trade, gives us much sharper tests when trying to proxy for the motive of transactions and relate the inferred motive to subsequent share market performance.

We contribute to the literature on momentum trading by documenting the relation between institutional trading and short-term past stock returns. We find that in aggregate, managers are contrarian traders, although growth and style neutral managers tend to be momentum traders. Overall, our sample of active Australian equity managers are short-term (over 10 days) contrarian traders, however when we partition by investment style, we find that style neutral and growth oriented investment managers (growth managers and Growth At a Reasonable Price (GARP) managers) are momentum traders, while value managers are contrarian. Our findings are indeed consistent with the self-reported investment styles of the institutional traders. The traditional proxy for "growth" stocks, book-to-market ratio, is directly influenced by stock price. If stock prices rise, then growth managers are more likely to purchase the stock since by definition the stock's book-to-market ratio will fall and hence growth managers should behave like momentum investors. Value managers, however, will be more likely to purchase stocks that have experienced a decline in price, since this will increase the stock's book-to-market ratio and hence value managers should behave like contrarian investors.

Of course, institutional trading may influence prices regardless of information content through a liquidity mechanism. Trades initiated by institutions may move the holdings of other market participants away from their optimal inventory or portfolio levels (see for example Stoll (1978) and Grossman and Miller (1988)). However the empirical research overwhelmingly rejects the liquidity hypothesis (see for example see Scholes (1972), Holthausen *et al.* (1990), Kraus and Stoll (1972), Ball and Finn (1989), and Lakonishok *et al.* (1992)).

Understanding the relative importance of information and liquidity trading is the second foundation to our empirical tests. If institutions do possess superior private information (as evidenced by Grinblatt and Titman (1989), Daniel, Grinblatt, Titman and Wermers (1997), Wermers (2000), Cesari and Panetta (2002), and Pinnuck (2003)), then we expect institutional trading to have a contemporaneous effect on stock returns due to the information revealed through trading. So it is important for us to be able to disentangle the likely motive for trade using the historical record.

A fund manager has a strong inventive to match their trading to available market liquidity. That is, a skilled investor would trade aggressively when the price is unlikely to rise (fall) from their purchases (sales).[1] With significant flexibility it is possible that a professional investor could turn over a portfolio with little adverse price impact. This being the case we would expect there to be relatively small share price impact from professional trades, irrespective of their underlying motive. However, an investor trading on a special insight or

[1] There of course is a basic question about whether we see any discretionary trading at all among fund managers. Some evidence consistent with discretionary liquidity trading is that the trading volume from our sample of fund managers is significantly lower on Monday than any other trading day of the week. This is consistent with a basic prediction of Foster and Viswanathan (1990).

analysis may not have wide flexibility in timing trades. In particular, the information may be firm or industry specific, therefore they are not able to buy any stock, but are restricted to a single stock (or a select list of stocks). Further, the insight that they have may be relatively short-lived as there insight can be announced by the firm, or by a research provider to the general market, or by a reporter. Finally, there may be other fund managers who the same (or similar) views, and they have an incentive to trade quickly so as to front-run other investors with an information motive.

The effects of these economic forces on price formation have been extensively studied in the theoretical microstructure literature. Authors have considered the effects of competition among informed investors where the information is identical (perfectly positively correlated) or merely related. When there is a large number of trading periods (the information is long-lived in calendar time, or when there is continuous trading) we expect to se dramatic changes to the intensity of trade by informed investors, price responses and expected profits to informed traders.

Examples of this can be found in papers by Holden and Subrahmanyam (1992), Foster and Viswanathan (1993, 1996), and Back, Cao and Willard (2000). For example, with identical information and "near" continuous trading we expect to see very aggressive trade by the informed investors, low total expected profits from the information and low market liquidity in response to their actions. This is markedly different from the case of a single informed investor, and the duopoly case is not unlike those with many informed traders. Examples of this can be found in Figures 4, 5, and 6 of Holden and Subrahmanyam (1992). For cases that do not assume identical information Foster and Viswanathan (1996) show what happens for correlated information. In these settings we also see initial strong competition among informed traders when the conditional correlation between their information is positive (see their Figures 5 and 6). This decomposition is also roughly consistent with evidence found in empirical studies such as Sias, Starks and Titman (2001), who suggest that the impact of informed trading is related to the number of traders rather than their trading volume.

Hence, when we have a number of potentially informed traders all buying (selling) the same stock on the same day it is more likely that (i) they have an positive (negative) information about the company's future share price, and (ii) that their information is more likely to be positively correlated, or last for a limited amount of time. Further, if we find that investors with similar styles are making similar trades our belief that the motive for trade is based on correlated information is strengthened. Also, even having two such traders can change dramatically the price dynamics, relative to a single potentially informed investor.

In our empirical work we use unexpected trading volume as a proxy for trades with ambiguous motive, or those for which we cannot reject being liquidity motivated – the fund manager is comfortable increasing trade intensity with the expectation that the market will accommodate the transaction. To be more certain that there is an information motive for a transaction we also require that such trades occur when more than one of the firms in our sample is making similar (e.g. buying) trades in the same stock on the same day. With this corroborating evidence we declare such trades to be have an information motive and treat them accordingly in our tests.

To explore further the motive for trade and the consequences for subsequent share returns we also consider the style of the fund manager. Value and GARP managers are referred to as momentum traders and value managers are considered to be contrarian traders.

II. Data

A. Data Collection

Data on institutional investor trading data is sensitive, confidential and proprietary information. Accordingly, independent studies with actual trading data of professional investors are scarce. Our sample comprises 34 active Australian equity managers, sourced from the *Portfolio Analytics Database*. This database was constructed with the support of Mercer Investment Consulting, whereby periodic monthly holdings and daily trade information was provided by individual investment managers under strict conditions, including confidentiality. While the database includes all transactions in stocks, futures contracts, and options securities, this study provides an evaluation of trading performance related to equity securities. Our sample contains information from 2 January 1995 to 31 December 2001, however since not all managers were able to provide data as far back as 1995, we examine the two-year period from 2 January 2000 to 31 December 2001.

The *Portfolio Analytics Database* was constructed using an 'invitation' approach where a group of managers were requested to provide data. Managers were selected to be invited after consulting with Mercers Investment Consulting who provided a list of the largest Australian equity managers in Australia coupled with several smaller managers. In total, 45 individual data requests were sent to the investment managers. Of the 45 invitations, 34 fund management firms provided data in a usable format.

The investment managers were asked to provide information about their largest pooled active Australian equity funds (where appropriate) that were open to institutional investors. The definition of an 'active' fund was explicitly deemed as funds exhibiting a target ex-ante tracking error greater than 100 basis points per annum. The term 'largest' was defined as the marked-to-market valuation of assets under management as at 31 December 2001, and was used as an indicative means of identifying portfolios that were truly representative of the investment manager.

The study also relies on stock price information that is sourced from the Australian Stock Exchange Automated Trading System (SEATS) provided by SIRCA. The SEATS data includes all trade information for stocks listed on the Australian Stock Exchange (ASX). Accounting information for the book-to-market ratio was obtained from the ASPECT database.

B. Survivorship and Selection Bias

Due to the nature of the collection procedure, several data issues are likely to arise – in particular, survivorship and selection bias. Survivorship bias occurs when a sample only contains data from funds that have continued to exist through until the collection date of this sample period. As a consequence, if data from failed funds are not included in the sample, conclusions drawn from the pool of "successful" funds having survived the sample period will overstate overall performance. The second form of bias in managed fund studies is selection bias. This occurs when the fund sample contains data that has been selected for inclusion based on specific criteria. In this case, it is possible that managers managing multiple funds may present information for their most successful funds, skewing the sample as a result.

We can gain some insight into the extent of the survivorship and selection bias by comparing the performance of our data sample with that of the population of investment managers which includes non-surviving funds. These data are sourced from the Mercer Investment Consulting Manager Performance Analytics (MPA) database. Over our entire sample window (1995 to 2001), the average outperformance of the average manager over the ASX/S&P 200 index is 1.78 percent per annum with a standard deviation of 1.39 percent. For our sample the mean manager outperformed the average MPA manager, weighted by manager years, by 0.34 percent per annum. While this indicates that our sample outperforms the industry, we find that the magnitude of the outperformance is low compared to the dispersion of performance. So it appears that selection bias is unlikely to be a significant problem. Over the 2001 calendar year, the mean performance of the industry-wide population was 12.42 percent with a standard deviation of 3.8 percent, while the mean performance of our sample was 12.68 percent with a standard deviation of 5.5 percent.

C. Descriptive Statistics

Descriptive statistics regarding the number of trades recorded by the managers in the database, the manager style and the distributional characteristics of the trades are presented in Table I. Panel A shows our sample comprises predominantly style neutral and value managers. As a consequence, much of the empirical analysis regarding manager style requires aggregating growth and GARP managers into the classification "growth oriented" funds to maintain an adequate number of observations in that style class. The objective of growth managers is to select stocks that are perceive to have long term capital growth prospects, possibly not reflected in accounting numbers like book value. The objective of GARP managers is similar to growth managers; however, these institutions add the qualification that the selection of such stocks should be done so at a reasonable price relative to fundamentals. Since both investment philosophies aim to invest in stocks with long term growth potential, we group them as “growth oriented”.

[INSERT TABLE I ABOUT HERE]

Panels B and C of Table I provide the distribution of the trades for the entire database both inside and outside the top 50 stocks (purchases and sales, respectively) in terms of three measures of trade size; dollar value of trade, trade size relative to mean daily volume and trade size relative to the number of shares outstanding. Trade size relative to volume is the number of shares traded expressed as a percentage of the mean daily share trading volume calculated over the 20 days prior to the trade. Trade size relative to shares outstanding is the number of shares traded expressed as a percentage of the number of shares outstanding as at the time of the trade. The median trade size for purchases and sales represents 1.63 and 1.53 percent, respectively, of mean daily trading volume. These figures suggest that if several managers were to trade in the same direction at the same time, their aggregate trading volume may represent a significant proportion of the day’s trading.

For the purpose of this study, we restrict the sample of stocks under investigation to the top (i.e. largest) 50 stocks as ranked by manager trading activity over the sample period. This restriction is in place in order to maintain a reasonable number of manager trades per day per stock. Manager trading activity is defined as the number of purchases plus the number of sales made in a stock by the managers in the database over the sample period. We rank and select stocks according to trading activity rather than capitalization since our study focuses on manager trading activity, nevertheless, many of the top 50 stocks according to capitalization are included in the selected stocks. Statistics regarding the manager trading activity in the selected stocks are presented in Table II. The mean number of purchasing and selling managers in the top 15 stocks is 1.11 and 0.85 respectively. As a percentage of mean daily trading volume, the mean number of shares purchased per day in the 15 most actively traded stocks by the managers in the database is 2.1 and 1.5 percent respectively. For the purpose of further analysis, we standardize manager trading activity according to the mean and standard deviation of manager trading in each stock.

[INSERT TABLE II ABOUT HERE]

III. Research Design

To understand the relation between institutional trading and stock returns, we examine the two variables across three temporal zones; (a) the influence of past stock returns on current fund trading, (b) the contemporaneous impact of fund trading on stock returns, and (c) the ability of professional investors to forecast future stock returns. We develop regression tools for each of these three settings in the remainder of this section.

A. The influence of stock returns on institutional trading

If the stock market is at least weak-form efficient, then observing historical stock returns should offer no predictive power in forecasting future stock returns. As a consequence, a rational stock trading strategy should not include historical stock returns. Accordingly, our null hypothesis is that past stock returns have no influence on institutional trading.

However, a large body of empirical research (see for example Lo and MacKinlay (1988), Conrad and Kaul (1988), Jegadeesh and Titman (1993), and Chan, Jegadeesh and Lakonishok (1996)) shows that past stock returns do offer some predicative power. Thus, it comes as little surprise that studies investigating the role of historical stock returns on institutional trading overwhelming reject our null hypothesis (see for example Grinblatt, Titman and Wermers (1995), Nosfinger and Sias (1999), Pinnuck (2003) and Cai and Zheng (2003)). Furthermore, self reported investment styles suggest a relation between institutional trading and past stock returns. For example, the “value” investment philosophy seeks to identify stocks that are “cheap” in comparison to their fundamental level. Therefore, if deviations in price are not accompanied with deviations in the fundamental valuation of the stock, then value managers are likely to trade in an attempt to profit from the perceived mispricing. Conversely, as stocks rise in price relative to their book-to-market ratio, the stock will become more attractive to growth managers who specialize in growth stocks (characterized by low book-to-market ratios). In later tests, we include the influence of investment style, however for the purposes of describing the main research design, we leave the discussion of investment style for later sections.

To test our null hypothesis, we regress standardized institutional trading (purchasing and selling separately) against lagged stock returns, lagged institutional trading, and the lagged values of aggregate shares traded by the institutions in the sample. We also include a number of control variables for; the market return, book-to-market ratio, size and momentum. If past stock returns do not influence the trading decisions of institutional traders, then the slope coefficients of lagged stock returns should not be statistically different from zero.

We include lagged institutional trading to investigate the extent to which institutional trading is serially correlated. Serially correlated trading could occur for a number of reasons; temporally correlated information, herding, or because fund managers may trade over several days in order to reduce market impact (see Chan and Lakonishok (1995)). To isolate the effect of past returns on institutional trading from any effects of the buying or selling pressure caused by past manager trading, lagged values of aggregate shares traded by the institutions in the sample are included. We include common risk factors (market, book-to-market, size and momentum) since such factors have been shown to explain the cross section of stock returns and therefore should have an influence on the trading decisions of institutional investors.

We test our hypotheses with a panel data model, where we allow the coefficients on the control variables to vary according to each stock in the sample. The regression equation is as follows:

$$y_{s,t} = \sum_{j=1}^{j=10} b_j R_{s,t-j} + \sum_{k=1}^{k=10} b_k MgrBuy_{t-k} + \sum_{l=1}^{l=10} b_l MgrSell_{t-l} + \sum_{m=1}^{m=10} b_l SharesBuy_{t-m} + \sum_{n=1}^{n=10} b_l SharesSell_{t-n}$$

$$+ \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.Size_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t} \tag{1}$$

The dependent variable $y_{s,t}$ is one of four variables, $MgrBuy_t$, $MgrSell_t$, $SharesBuy_t$, and $SharesSell_t$. *MgrBuy* is the standardized number of managers purchasing stock '*s*' on day '*t*', although we leave out the stock subscript. *MgrSell* is the standardized number of managers selling stock 's' on day '*t*'. We standardize by subtracting the mean and dividing by the standard deviation of the institutional trading variable particular to each stock over the sample period. $R_{s,t}$ is the return on stock 's' on day '*t*'. *SharesBuy* is the total number of shares bought by managers in stock '*s*' on day '*t*' divided by the mean daily volume calculated over the prior 20 days (approximately a trading month). *SharesSell* is the total number of shares sold by managers in stock '*s*' on day '*t*' divided by the mean daily volume calculated over the prior 20 days.

Explanatory variables include lags of the dependent variables as well as risk control variables.[2] *Market* is the return on the value weighted portfolio of all stocks listed on the ASX300 (the largest 300 stocks on the exchange, not to be confused with the ASX/S&P 300 which is an index constructed by Standard and Poor's) on day '*t*'. *Size*, is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by market capitalisation) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *BMRatio* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by book to market ratio) in the ASX300 less the value weighted return on a portfolio of stocks

[2] We use a lag length of 10 for included dependent variables in our tests. In unreported results, we consider lags of up to 20 (essentially a full trading month) and the results do not change significantly. We find the influence of variables with lags greater than 10 are never statistically different from zero.

comprised of the smallest quintile of stocks in the ASX300. *Momentum* is the value-weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by stock return calculated over the last 130 days) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. d is an indicator variable for each stock.

In measuring stock returns, we use the midpoint of the closing bid and ask, rather than the last trade as at the close. Frino, Mollica and Walter (2003) show that the bid ask bounce at the close of the trading day may influence measurements of market impact (and therefore returns). In unreported results we reproduce our results using the closing price and do not find any significant difference.

B. The contemporaneous price impact of institutional trading

From our prior discussion we know that the contemporaneous relation between institutional trading and share returns can be divided into liquidity and information effects. If institutional trades are small, or do not require the provision of additional liquidity, then we expect no contemporaneous effect on stock prices. This would be the case, for example, if institutional trades have only a temporary liquidity impact that is dissipated by the end of the trading day. Hence our first null hypothesis is that there would be no contemporaneous association between trades and excess share price returns.

It is possible however, that the "liquidity" impact may stretch beyond the day on which the trade was made. In this instance the trade impact has become something potentially more permanent. In particular, if there is an information motive to the trade, we would expect that the market price would shift with the liquidity impact and that the shift would be permanent and extend beyond the current day. To adjust for a possible impact through a trading motive we examine the effects when we proxy for information content by the number of institutions purchasing or selling. This gives us our second null hypothesis; contemporaneous stock returns are not related to the number of institutions purchasing or selling. Hence we are able to decompose any price impact into liquidity and information components with the model given in expression (2).

$$r_{s,t} = \sum_{j=0}^{j=10} b_j MgrBuy_{t-j} + \sum_{k=0}^{k=10} b_k MgrSell_{t-k} + \sum_{l=0}^{l=10} b_l SharesBuy_{t-l} + \sum_{m=0}^{m=10} b_m SharesBuy_{t-m}$$
$$+ \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.SIZE_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t} \quad (2)$$

Where the dependent variable is the stock return on day '*t*' in stock 's' and other variables are as defined above. Note that expression (2) explicitly considers the possibility that institutional trading may itself be positively autocorrelated.

Past studies of the role of liquidity *versus* information in share returns overwhelming rejects a pure liquidity explanation (see for example see Scholes (1972), Holthausen *et al.* (1990), Kraus and Stoll (1972), Ball and Finn (1989), and Lakonishok *et al.* (1992)). If information effects dominate, then we expect contemporaneous stock returns to be positively (negatively) correlated to the contemporaneous number of institutions purchasing (selling) rather than their contemporaneous aggregate volume of shares purchased (sold).

C. The ability of institutional traders to forecast future stock returns

Expression (2) also contains information on the link between current returns and past institutional trades. Hence we can document the influence from institutional trades as many as 10 trading days previous on current returns. If past institutional trades continue to have impact we expect that they are more likely to be information motivated, and that this is evidence that fund managers are able to anticipate future returns.

Specifically, we would expect that measured liquidity influences would not persist through time, whereas information influences would be relatively permanent. Hence, we expect stock returns to be positively (negatively) correlated with lagged numbers of institutions purchasing (selling). Further we expect stock returns to be unrelated to lagged institutional trading volume.

Expressions (1) and (2) form a recursive system of equations that can be estimated with OLS.

IV. Results

A. The influence of stock returns on institutional trading

The estimated regression coefficients from equation 1 are reported in Table III. To conserve space we do not report the coefficients of risk control factors since there is an intercept, a market, a size, a book-to-market and a momentum slope estimate for each of the 50 stocks in our sample). We report lagged coefficients as sums; sums of coefficients up to lag 5 and sums of coefficients up to lag 10. The results show that in aggregate (although in later sections we investigate the role of investment style on the relationship between historical stock returns and institutional trading), institutions are contrarian traders. That is, drops in share prices induced fund managers to buy, as opposed to continue to sell as would be the case for a momentum investor.

From the table we see that the sum of the coefficients of lagged stock returns from '*t*' to '*t-5*' is -4.8277 and 4.8346 for purchases and sales respectively, indicating that a fall (rise) in price over the last 5 days induces institutions to purchase (sell). We may also gain some insight by directly analyzing the change in price required to induce a certain number of managers to purchase or sell. For example, the stock code BHP is a well known large capitalization stock on the Australian Stock Exchange (ASX). The mean number of managers purchasing on any given day in our sample is 1.67, with a standard deviation of 1.47. Therefore, for a 15 percent fall in the price of BHP over 5 days, the model predicts that on average, one manager will be induced to buy (-4.8277 * -0.15 * 1.47 = 1.06).

[INSERT TABLE III ABOUT HERE]

Our finding that institutions are on average contrarian traders is consistent with Gompers and Metrick (2001) and Cohen, Gompers and Vuolteenaho (1998), however it is inconsistent with Grinblatt, Titman and Wermers (1995), Nosfinger and Sias (1999), Pinnuck (2003) and Cai and Zheng (2003). However the frequency of their data varies from monthly to annual, while our data is daily. It is quite possible that institutions have a positive feedback trading strategy over longer-term horizons while trading in a contrarian fashion over the short-term. Perhaps the closest studies to our own, in terms of data similarity, include Chan and Lakonishok (1995), Keim and Madhavan (1997) and Chiyachanthana et al. (2004). Interestingly, Chan and Lakonishok (1995) find that for institutional purchases using daily trading data on a value-weighted basis, institutions are momentum traders. However on a simple-weighted basis, institutions are contrarian. For sales, institutions are found to be contrarian on both a value and simple-weighted basis. The results in Chan and Lakonishok (1995) are consistent with our findings in that our regression framework does not weight each observation by value, and hence we compare our results with the simple weighted results following Chan and Lakonishok (1995).

Table III also shows that institutional trading is indeed serially correlated. The sum of the lagged institutional purchasing (selling) is highly positively correlated with current institutional purchasing (selling), indicating that institutional trading induces further trading in the same direction in the future. This may be caused by a variety of factors; institutions may be herding (for serially correlated information, or behavioral reasons), or institutions may be purchasing or selling trade packages over several days in order to reduce market impact (see Chan and Lakonishok (1995)). We deal with the issue of packages in later sections, however in unreported results, we find similar results when we repeat the analysis using trade packages as defined by Chan and Lakonishok (1995).

In practical terms, the highly significant coefficients on lagged institutional trading shows that an increase in the number of institutions purchasing yields an increase in institutions purchasing in the future. For example, in BHP, if we observe three managers more than average purchasing in one day over the last 10 days (three more managers represents roughly two standard deviations above the mean since the standard deviation is 1.47) then we expect an increase of one manager purchasing (2*0.52 = 1.04). These results are consistent with the findings of studies that show institutions engage in "herding" behavior (see for example Grinblatt, Titman and Wermers (1995), Nosfinger and Sias (1999), Wermers (1999) and Sias, Starks and Titman (2001)). Our results are also consistent with Sias (2004) who finds institutional trading is more related to lagged institutional trading than past stock returns.

B. The contemporaneous price impact of institutional trading

If institutions have a contemporaneous price impact on stock returns through the information content of their trades, then we expect that stock returns on day '*t*' should be positively (negatively) correlated with the number of institutions purchasing (selling) on day '*t*'. If however, institutions have a contemporaneous price impact due to the liquidity pressures placed on liquidity providers, then we expect that stock returns on day '*t*' should be positively (negatively) correlated with the number of shares purchased (sold) on day '*t*' by the managers in the database.

We test these hypotheses using equation 2, and the results are reported in Table IV. To ensure that we measure the liquidity impact of institutional trading correctly, we proxy the liquidity effect with two alternative measures; the number of shares purchased (sold) by the managers in our database relative to; (a) the number of shares outstanding (Model 1), and (b) the mean daily share trading volume measured over the prior 20 days (Model 2).

[INSERT TABLE IV ABOUT HERE]

The results indicate that there is no significant contemporaneous effect. The coefficient of manager buying for Model 2 is 0.000055, while that of selling is -0.00001, neither statistically significant at traditional levels. This result is surprising since we expect institutional trades to have some informational impact, especially in light of our findings in the next section indicating that managers are indeed able to forecast stock returns. There are a number of reasons why we do not find a contemporaneous effect, and we explore these possibilities in section D.

Turning to the liquidity hypothesis, we find no evidence of a contemporaneous effect for buys, though for sales we find a positive effect. These results may be obscured by the possibility that managers are transacting trading packages over several days, as suggested by Chan and Lakonishok (1995). We repeat the results using trading packages, where the number of managers purchasing (selling) is defined as the number of managers currently in the market following the approach of Chan and Lakonishok (1995). The results using trade packages are reported in Table V. The results remain inconsistent with both the information and liquidity hypotheses. Furthermore, the adjusted R-squared statistic is lower for packages, and thus from this point forward we discard the trade packages adjustment. Additionally, since Model 2 of Table IV has the highest adjusted R-square we use aggregate shares purchased or sold relative to mean daily volume from this point forward.

It is possible that our zero liquidity results may be caused by the construction of the volume measure. Say managers purchase heavily over a period of several days, then this has the effect of increasing the mean daily trading volume. Therefore, subsequent purchasing may be measured to be below mean daily trading volume. Subsequent purchasing should also coincide with positive stock returns, since it follows a period of heavy purchasing and hence our finding of a zero or negative contemporaneous effect. Another possibility is that since the large managers that dominate the volume measures of trading are outperformed by small managers (see Chan, Faff, Gallagher and Looi (2004)), the volume measures give a zero or negative contemporaneous effect. Finally, it is possible that managers are simply adept at hiding the information content of their trades reducing the contemporaneous effect to statistically insignificant levels. One should note however, that whilst our findings of a zero contemporaneous effect when measured over the close to close period, our findings do not say anything about the market impact costs incurred by each manager individually. For example Chan and Lakonishok (1993) show that managers experience market impact costs when measured against open or closing price benchmarks.

[INSERT TABLE V ABOUT HERE]

C. The ability of institutional traders to forecast future stock returns

Consistent with studies showing institutional traders possess private information (see for example Daniel, Grinblatt, Titman and Wermers (1997), Wermers (1999, 2000), Nosfinger and Sias (1999), Sias, Starks and Titman (2001) and Pinnuck (2003)), the results presented in Tables IV and V show that lagged values of the number of institutions purchasing (selling) are correlated with stock returns. Further, the correlation between lagged aggregate institutional trading volume and stock returns is not as statistically significant as the number of institutions purchasing (selling). So our *information* measure of fund activity is able to predict future returns, while the *liquidity* measure of fund activity is not. This suggests that, as a group, the trades of institutions have predictive power to forecast future stock returns over and above any permanent liquidity pressures fund managers may cause through their transactions. These results are robust over the specification of the liquidity effect (aggregate institutional trading relative to mean daily trading volume or the number of shares outstanding) and persist independently of trade package specification (indicating forecasting ability past the end of the package).

In terms of economic relevance, the predictive power of institutional trading can be significant. For example, according to Table IV, Model 2, in BHP, an increase in the number of managers purchasing of three over the average (which is two standard deviations) has a total effect on returns of 0.29 percent over the following 10 days (0.00146 * 2 = 0.0029). The effect for sales is not quite as strong, with the sum of the lag coefficient of manager selling being -0.000854 (although still statistically different from zero at the 1 percent level) as compared to 0.00146 for purchases in Table IV, Model 2.

D. Further tests on the contemporaneous effect and forecasting power of institutional trading activity

In Section D, our findings suggest that managers have no contemporaneous effect on stock prices, whether through the information content of their trades, or through a liquidity mechanism. The observed insignificance of a contemporaneous effect may be the result of; (1) institutions observing price changes prior to their trade and using that information to trade thereby obscuring our results, (2) the relative size of the institutional trades is unaccounted for, thus by including trade size, we may increase the power of our tests, or (3) investment manager style may have a powerful influence on trading strategy which in turn may influence their contemporaneous price impact (see Chan and Lakonishok (1995)).

Since we know active managers are on average short-term contrarian, then changes in price from the last closing price to the opening price may be influencing trading decisions and therefore obscuring our results. For example, if the stock opens higher than the previous day's close, then this increase in price may induce managers to sell. If this were the case, then (if changes in price overnight are not reversed throughout the day) positive returns should be negatively (positively) correlated with institutional purchasing (selling). Thus the manager's short term contrarian behavior may be working in opposition to any information-based price impact. In other words, if we measure the contemporaneous effect of institutional trading with stock returns from the previous close to the close on the current day, then we include the overnight return in the analysis which may be subject to a reaction by the fund manager trading rather than wholly their price impact. We can mitigate the effect of this possibility by measuring the contemporaneous stock return from the opening price to the closing price and then from closing price to subsequent opening price. The open-to-close return is often cited as the permanent effect of market impact; therefore we may test whether the permanent effect of institutional trading is correlated to information (the number of managers purchasing or selling) or to liquidity (the aggregate number of shares purchased or sold), by regressing the open-to-close return on the number of institutions purchasing or selling, and the number of shares purchased or sold.

The results of the open-to-close and last close-to-open returns are presented in Table VI. If the change in price, from the previous days close to the current days open, is influencing the trading decisions of institutional traders then we should find a negative relationship between last close to open returns and the number of institutions purchasing and vice versa for sales. For purchases, the sign of the coefficient is correct, however we cannot say the estimate is statistically different from zero at any traditional level of significance. For sales, the overnight change in price is significantly correlated with the number of institutions selling. The importance of overnight returns in selling rather than purchasing may be due to liquidity reasons for selling. If institutions have some discretion over the timing of their liquidity sells, but predominantly purchase for information reasons, then the importance of overnight changes in price are more likely to affect sales rather than purchases.

[INSERT TABLE VI ABOUT HERE]

Turning to the open-to-close return measure, we find that purchases and sales have statistically indistinguishable permanent effects of 0.000216 and -0.000258 for buys and sells respectively. The estimates are however an improvement over the close-to-close return results reported in the first column of Table VI. This indicates that although isolating the permanent effect from the open to the close increases our power to detect the contemporaneous effect of institutional trading, there may be other important omitted factors.

One such possible omitted factor that may be relevant in measuring the contemporaneous effect of institutional trading is trade size. Small trades are more likely to be liquidity motivated, perhaps motivated by redemptions or applications. Indeed, Edelen (1999) shows that mutual funds engage in a material volume of uninformed or liquidity-motivated trading. Large trades are more likely to be information motivated since a trader with more valuable information can profit more from the information by making a larger trade. Theoretical work by Easley and O'Hara (1987) suggests that larger trades have the capacity to impact upon the market more than small trades, and hence we expect the contemporaneous effect of large trades to exceed that of medium sized trades.

To account for trade size, we divide our sample of institutional trades into three groups; (1) the bottom quartile of trades ranked by standardized relative trade size, (2) the 25th to 75th percentile of trades ranked by standardized relative trade size, and (3) the top quartile of trades ranked by standardized relative trade size. We define trade size relative to both the market capitalization of the stock and the funds under management:

$$Tradesize = \frac{price \times quantity}{bmkweight \times FUM} \quad (3)$$

Where, *bmkweight* is the market capitalization of the stock as at the time of trade divided by the total value of the largest 300 stocks on the exchange. *FUM* is the total dollar value of holdings under management in the fund.

We use this measure of relative trade size rather than a measure relative to mean daily trading volume since this measure scales according to manager size as well as stock size. The relative trade size is then standardized across all the trades made by our sample of institutions in each particular stock. After obtaining the standardized relative trade size of each transaction in our database, we then divide the sample according to the three groups outlined above.

We remove the first "bucket" of bottom quartile trades since fund managers are most likely to be liquidity related and concentrate on the second and third groups of trades. We form two variables (and their lags) of institutional trading corresponding to the number of group 2 (mid sized) purchases and sales made on day '*t*' in each stock '*s*' and the number of group 3 (large sized) purchases and sales made on day '*t*' in each stock '*s*'. These variables are standardized according to the mean and standard deviation relevant for each stock in the sample. We then regress the close-to-close return, the open-to-close return, and the last close to open return on the standardized number of institutions purchasing and selling in the medium trade size category and the large trade size category as well as the risk control variables for market, stock size, book-to-market and momentum.

The results of the trade size regressions are presented in Table VII. Our findings indicate that the contemporaneous close to close returns are correlated with the number of large trades significant at the 10 percent level for purchases and at the 1 percent level for sales. The impact of mid sized trades on close-to-close returns is however not statistically different from zero for purchases or sales.

[INSERT TABLE VII ABOUT HERE]

Turning to the open-to-close returns, we find that open-to-close returns are contemporaneously positively (negatively) correlated to the number of large purchases (sales), statistically significant at the 1 percent level. This shows that the permanent effect of relatively large trades is indeed significant, lending support to the information hypothesis of price impact. The permanent effect is however non-existent for mid sized trades. Interestingly, we also find that the tendency for institutions to purchase (sell) after an overnight fall (rise) in price only occurs in mid-sized trades and not in large trades. This is consistent with such behavior being restricted to less information motivated trades.

Our results are consistent with Chan and Lakonishok (1993, 1995) who find market impact costs are positively correlated with trade size relative to mean daily trading volume. Care must be taken in comparing our results, however, since our definition of trade size is relative to funds under management, and stock size. Our measure is therefore more related to information, whilst that of Chan and Lakonishok (1993, 1995) is more related to liquidity (since their definition of trade size is relative to mead daily trading volume).

Comparing the contemporaneous effect of institutional trading against the forecasting ability of institutional trades, we find that the contemporaneous effect of large trades forms a considerable proportion of the total effect measured over the 10 days after the trade is made. The coefficient of large institutional purchasing is 0.000329, while the sum of the coefficients of lagged institutional purchasing over 10 days (the close to close return effect, not including the contemporaneous effect) is 0.001335. Thus, almost a quarter of the total price effect over the 10 days following a large purchase is contemporaneous.

Another possible factor influencing the measured contemporaneous impact of institutional trading is investment manager style. For example, value managers aim to purchase stocks at a cheap price relative to fundamentals. Therefore, if prices fall without a corresponding fall in fundamental value, then value managers are likely to purchase, making value managers short term contrarian traders. Growth managers however, should behave in the opposite fashion, purchasing stocks after a rise in price, since such a price rise lowers the book-to-market ratio, making the stock more attractive to growth managers. If managers exhibit this style related behavior then value managers may be participating in contrarian trading on an overnight basis more so than other managers. Hence, the results in Table VI may be strengthened by including the effect of investment manager style.

To investigate the influence of investment style on the contemporaneous effect of institutional trading, we first examine the influence of past stock returns on institutional trading, partitioned by investment style. We do so by regressing the standardized number of purchases and sales made on day '*t*' in stock '*s*' by managers of the same style, on past stock returns, and lagged institutional trading according to investment style. We present separate results for purchases and sales in Table VIII.

[INSERT TABLE VIII ABOUT HERE]

The results in Table VIII show that investment style has a profound impact on the relationship between past stock returns and institutional trading. Style neutral purchasing is positively related to past stock returns, although no such relationship exists for selling. Growth managers are momentum traders, with past stock returns positively correlated (although not statistically significant) with purchasing and negatively correlated with selling (significant at the 1 percent level). Value managers are strongly contrarian, with past stock returns negatively correlated with value manager purchasing and positively correlated with value manager selling, both statistically significant at the 1 percent level.

All investment styles are highly positively serially correlated with trading activity of their own style, although not necessarily with the trading activity of other styles. For example, value manager purchasing is negatively correlated with lagged growth manager purchasing and vice versa for sales. Most of the institutional trading is not correlated with lagged values of aggregate shares purchased or sold by managers in the database.

Finally, the importance of the price change between the last close and the open is shown most clearly for value managers where the estimated coefficient of ylag (last close to open) for purchasing is -1.98 compared to 0.47 for the combined results reported in Table III. This result confirms the importance of investment manager style on the relationship between past stock returns and institutional trading. In turn, the influence of investment style is likely to have important implications when measuring the impact of institutional trading (in terms of the contemporaneous permanent information effect).

We investigate the influence of investment style on the contemporaneous effect of institutional trading by regressing close-to-close, open-to-close, and last close-to-open, stock returns on the standardized number of neutral, growth, and value managers purchasing and selling on day '*t*' in stock '*s*' and their lagged values. We also include the risk control variables as discussed above. The results of the style regressions are reported in Table IX.

[INSERT TABLE IX ABOUT HERE]

The open-to-close regression results show that the contemporaneous effect of institutional trading depends on investment style. Style neutral purchasing has a significantly positive impact on contemporaneous close to close stock returns as well as the open-to-close return. However while the coefficient of style neutral selling is negative for both close-to-close and open-to-close stock returns, neither are statistically different from zero. Growth manager selling is significantly negatively correlated with open-to-close stock returns, however purchasing results are not statistically different from zero although they are of the correct sign.

In terms of the ability of managers to forecast future stock returns, results reported in Tables VI, VII, and IX confirm that lagged values of the number of institutions purchasing are positively correlated with stock returns, and vice versa for sales. This indicates that over and above any liquidity pressures (since we control for the aggregate volume of shares traded by managers in our sample), institutional trading forecasts stock returns. Our finding is robust whether we measure the information content from close-to-close, or open-to-close. It is also robust over relative trade size, and to varying degrees, investment manager style. Consistent with prior studies we find that value managers have a superior forecasting ability in comparison to growth managers.

The contemporaneous effect of value managers is however, much stronger than style neutral or growth manager results and is of the opposite sign. Value managers displayed a statistically significant tendency to purchase after a rise in price overnight, as evidenced by the negatively significant relationship between last close to open stock returns and value manager purchasing, and vice versa for selling. Interestingly, even after we control for the value manager's tendency to purchase (sell) after overnight falls (rises) in price, by measuring the open-to-close impact, we find the number of value managers purchasing (selling) is negatively (positively) correlated with open-to-close stock returns. This result seems counter-intuitive since according to either the liquidity or information hypothesis, we should expect that the more managers that purchase, the higher the stock returns on that day. However, if value managers are behaving in a price stabilizing fashion, that is, selling when they perceive stock prices have risen above fundamental levels, as may be the case during a liquidity demand shock (and vice versa for purchases), then their contemporaneous effect on stock prices will be negative.

If value managers are stabilizing prices, then the extent of this activity should be correlated with a measure of stock price instability. In order to test this, we proxy instability with intra-day volatility and investigate the interaction effect between volatility and value manager trading activity. If value managers are stabilizing prices, then the negative contemporaneous effect should be made less strong during periods of low volatility. We regress stock returns on non-value manager trading activity, value manager trading activity, value manager trading activity multiplied by intra-day volatility, intra-day volatility, aggregate manager trading volume, and control variables for risk factors.

$$
\begin{aligned}
y_{s,t} = {} & \sum_{k=0}^{k=10} b_k NonValMgrBuy_{t-k} + \sum_{l=0}^{l=10} b_l NonValMgrSell_{t-l} + \sum_{m=0}^{m=10} b_l SharesBuy_{t-m} + \sum_{n=0}^{n=10} b_l SharesSell_{t-n} + \\
& \sum_{k=1}^{k=10} b_k ValBuy_{t-k} + \sum_{l=1}^{l=10} b_l ValSell_{t-l} \\
& + \sum_{k=0}^{k=10} b_m.Volatility_{t-k} * ValBuy_{t-k} + \sum_{l=0}^{l=10} b_n.Volatility_{t-k} ValSell_{t-l} + \sum_{l=0}^{l=10} b_o.Volatility_{t-k}
\end{aligned}
$$

$$+\sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.Size_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t} \tag{4}$$

Intra-day volatility is calculated as follows:

$$Volatility = \sqrt{\frac{(\sum n)(\sum nXX) - (\sum nX)^2}{(\sum n)(\sum n - 1)}} \tag{5}$$

where X is intra-day return, calculated as follows:

$$RETURN = \sum \ln \frac{First\ trade\ price}{Second\ trade\ price} + \ln \frac{Second\ trade\ price}{Third\ trade\ price} + \ldots.. + \ln \frac{Last\ trade\ price}{Second\ last\ trade\ price} \tag{6}$$

The results, reported in Table X, confirm our findings from Table IX, that the contemporaneous effect of value manager purchasing (selling) is negative (positive), while that of non-value manager purchasing (selling) is positive (negative). However, the negative value manager contemporaneous effect is made weaker during periods of low intra-day volatility, as evidenced by the statistically significant negative coefficient of *Valmgr*VolatilityBUY*. These results are consistent with the hypothesis that value managers are stabilising prices by purchasing after prices fall below fundamental levels, and vice versa for sales. For the case of sales, the evidence is also supportive although not quite as strong as for the purchases. This may reflect the fact that managers are unable to short sell, and hence value managers will be less able to behave in a price stabilizing fashion on the sell side. We also find that while volatility has an impact on the contemporaneous effect of value manager trading, it does not have any effect on the ability of value managers to forecast stock returns. This is reassuring since we do not expect price stabilising trading to forecast stock returns.

By investigating the interaction between value manager trading and intra-day stock return volatility, we see that institutional traders can be divided by investment philosophy. This division represents not only when institutions prefer to trade (buying after price falls for value managers, and vice versa for non-value managers), but also the effect of their trading on contemporaneous stock returns. Value managers behave in a price stabilising fashion, and hence, their trading is negatively correlated to stock returns. While non-value managers perform no such price stabilising, and thus their contemporaneous impact on stock returns is positive.

V. Conclusions

Using a unique database of active Australian equity manager transactions on a daily basis, we investigate the relation between institutional trading and stock returns. On an aggregate level, we find that institutions are, on average, contrarian traders for short-term horizons of about 10 days. When we partition according to investment style we find that style neutral and growth-oriented managers are momentum traders while value managers are contrarian. This is in accord with a manager's self-reported investment styles, where value managers attempt to purchase stocks 'cheaply' in comparison to fundamentals, and hence these fund managers 'buy low and sell high'. We also find that institutional trading is highly positively auto-correlated, and that such correlation extends only to trading of managers within the same investment style.

For example, value manager purchasing is positively correlated with lagged value manager purchasing, but is negatively correlated with growth-oriented manager purchasing. For all investment styles, the auto-correlation with lagged value of aggregate purchase or sell volume is of less importance than the lagged number of institutions within their own investment style purchasing or selling. From the pattern of auto-correlation within investment styles, we conclude that institutional traders may either engage in herding behavior, or may receive serially correlated signals. In either case, the evidence suggests that such behavior is rational, since we find no evidence of price reversals over the 10 days following their trades.

In terms of the contemporaneous effect of institutional trading, much of the literature finds a strong correlation between changes in institutional holdings (or inferred trades) and stock returns in the same period. Almost all of these studies, however, utilize monthly, quarterly or even annual data. With our daily transactions database, we have the opportunity to investigate the impact of institutional trading at a much finer granularity. Curiously, we find that institutional purchasing and selling is not correlated with contemporaneous stock returns. At first, this may appear counter-intuitive, however upon further investigation, we discover that there are several factors that cause this result.

Due to the overall contrarian behavior of the managers in our database, measuring the contemporaneous effect using close-to-close returns may potentially confuse our tests. This is because managers may be observing overnight changes in price from the previous close to the open, in order to use this information in trading decisions. As our sample is in aggregate contrarian, then a positive overnight change in price will be correlated with institutional selling, and *vice versa*. Thus, by measuring the contemporaneous effect using close-to-close returns, we allow the contrarian behavior of institutional traders to affect our results. We mitigate this effect by measuring the open-to-close returns and find that by doing so increases the power of our tests.

In terms of the ability of institutions to forecast future returns, we find that lagged values of the number of institutions purchasing or selling are correlated with stock returns. This suggests that institutions possess some predictive power. Our results are robust over trade size and investment style indicating that the information content of institutional trading exists over many dimensions.

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Table I
Descriptive Statistics

This table reports descriptive statistics for the *Portfolio Analytics Database* partitioned according to trade direction. Dollar trade value is the weighted average price of the trade multiplied by trade quantity. Trade size relative to volume is the number of shares traded as a percentage of the mean number of shares traded per day over the 20 days prior. Trade size relative to shares outstanding is the number of shares traded as a percentage of the number of shares outstanding. These statistics are for the sample period 2 January 2000 to 31 December 2001. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period.

Panel A - Manager Style and Number of Trades

Number of Growth Managers	3
Number of Value Managers	9
Number of GARP Managers	8
Number of Neutral Managers	14
Number of Trades	44793
Number of Purchases	24135
Number of Sales	20658

Panel B - Distribution of Trade Size (Purchases)

	Mean	Stdev	25th	50th	75th
Dollar Trade Value ('000's)	457	859	75	187	493
Trade Size relative to Volume	4.54	7.99	0.52	1.63	4.91
Trade Size relative to SharesOutstanding	0.0083	0.0153	0.0009	0.0028	0.0089

Panel C - Distribution of Trade Size (Sales)

Dollar Trade Value	469	878	64	175	479
Trade Size relative to Volume	4.73	8.44	0.47	1.53	4.98
Trade Size relative to SharesOutstanding	0.0089	0.0163	0.0009	0.0029	0.0095

Table II
Institutional Trading Activity

This table reports descriptive statistics for the number of institutions purchasing and selling per day for the top 50 stocks selected in our study. We select stocks on the basis of manager trading activity. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period. Trade size relative to volume is the number of shares traded as a percentage of the mean number of shares traded per day over the 20 days prior. Trade size relative to shares outstanding is the number of shares traded as a percentage of the number of shares outstanding.

	Rank 35 to 50		Rank 16 to 34		Rank 1 to 15	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
Number of Purchasing Managers	0.53	0.76	0.58	0.80	1.11	1.12
Number of Selling Managers	0.45	0.75	0.58	0.84	0.85	1.04
Trade Size relative to Volume (purchases)	4.2801	10.6370	3.2880	7.3919	2.1149	3.7621
Trade Size relative to Volume (sales)	4.4874	14.8630	3.3537	8.0540	1.4910	3.1288
Trade Size relative to SharesOutstanding (purchases)	0.0079	0.0185	0.0055	0.0128	0.0038	0.0067
Trade Size relative to SharesOutstanding (sales)	0.0077	0.0207	0.0057	0.0136	0.0027	0.0055

Table III
Institutional Trading and Past Stock Returns

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{j=1}^{j=10} b_j R_{s,t-j} + \sum_{k=1}^{k=10} b_k MgrBuy_{t-k} + \sum_{l=1}^{l=10} b_l MgrSell_{t-l} + \sum_{m=1}^{m=10} b_l SharesBuy_{t-m} + \sum_{n=1}^{n=10} b_l SharesSell_{t-n} +$$
$$+ \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.Size_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t}$$

The dependent variable y is one of four variables, MgrBuy, MgrSell, SharesBuy, and SharesSell. *MgrBuy* is the standardized number of managers purchasing stock 's' on day 't', although we leave out the subscripts. *MgrSell* is the standardized number of managers selling stock 's' on day 't'. We standardize by subtracting the mean and dividing by the standard deviation of the institutional trading variable particular to each stock over the sample period. R(t) is the return on stock 's' on day 't', *SharesBuy* is the total number of shares bought by managers in stock 's' on day 't' divided by the mean daily volume calculated over the prior 20 days. *SharesSell* is the total number of shares sold by managers in stock 's' on day 't' divided by the mean daily volume calculated over the prior 20 days. *Market* is the return on the value weighted portfolio of all stocks listed on the ASX300 (the largest 300 stocks on the exchange) on day 't'. *Size*, is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by market capitalisation) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *BMRatio* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by book to market ratio) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *Momentum* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by stock return calculated over the last 130 days) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. d is an indicator variable for each stock. These results are for the sample period 2 January 2000 to 31 December 2001. Only trades in the top 50 stocks as ranked by manager trading activity are included. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period. We report the sum of the lagged coefficients as follows, (t-1:t-10) is the sum of the lags from t-1 to t-10.

Panel A - Adjusted R-Squared

Adjusted R-Squared	0.11893	0.12488	0.096393	0.12516

Panel B - Regression Estimates

	MgrBuy		MgrSell		SharesBuy		SharesSell	
	Coefficent	*t-stat*	Coefficent	*t-stat*	Coefficent	*t-stat*	Coefficent	*t-stat*
Ret(t-1:t-5)	**-4.8277**	-5.32	**4.8346**	5.28	**-0.2354**	-3.38	0.0668	0.78
Ret(t-1:t-10)	**-3.4168**	-2.57	**6.5240**	4.83	**-0.2732**	-2.70	0.1995	1.54
MgrBuy(t-1:t-5)	**0.4207**	23.25	0.0242	1.57	**0.0054**	4.06	-0.0002	-0.19
MgrBuy(t-1:t-10)	**0.5162**	24.33	**0.0566**	2.99	**0.0071**	4.53	-0.0002	-0.11
MgrSell(t-1:t-5)	-0.0224	-1.54	**0.4117**	24.81	**-0.0043**	-3.92	**0.0049**	2.29
MgrSell(t-1:t-10)	-0.0257	-1.55	**0.5627**	29.95	**-0.0056**	-4.55	**0.0057**	2.07
SharesBuy(t-1:t-5)	**1.0536**	4.23	-0.3379	-1.63	**0.3345**	10.63	-0.0245	-0.87
SharesBuy(t-1:t-10)	**0.7685**	2.49	**-0.9665**	-3.38	**0.3395**	9.46	-0.0161	-0.28
SharesSell(t-1:t-5)	0.0372	0.24	**0.5735**	2.96	0.0124	0.69	**0.3228**	5.88
SharesSell(t-1:t-10)	0.0265	0.14	0.3691	1.58	0.0069	0.32	**0.4010**	5.29

Standard errors are calculated using White's heteroskedasticity consistent estimators
Bolded coefficients are statistically significant at the 5 percent level or better

Table IV
Institutional Trading, Contemporaneous Effect and Forecasting

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{j=0}^{j=10} b_j MgrBuy_{t-j} + \sum_{k=0}^{k=10} b_k MgrSell_{t-k} + \sum_{l=0}^{l=10} b_l SharesBuy_{t-l} + \sum_{m=0}^{m=10} b_m SharesBuy_{t-m} +$$

$$+ \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.SIZE_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t}$$

The dependent variable y is close to close return stock 's' on day 't', although we leave out the subscripts. *MgrBuy* is the standardized number of managers purchasing stock 's' on day 't'. *MgrSell* is the standardized number of managers selling stock 's' on day 't'. We standardize by subtracting the mean and dividing by the standard deviation of the institutional trading variable particular to each stock over the sample period. R(t) is the return on stock 's' on day 't'. For Model 1, *SharesBuy* is the total number of shares bought by managers in stock 's' on day 't' divided by the total number of shares outstanding. *SharesSell* is the total number of shares sold by managers in stock 's' on day 't' divided by the total number of shares outstanding. For Model 2, *SharesBuy* is the total number of shares bought by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *SharesSell* is the total number of shares sold by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *Market* is the return on the value weighted portfolio of all stocks listed on the ASX300 (the largest 300 stocks on the exchange) on day 't'. *Size*, is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by market capitalisation) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *BMRatio* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by book to market ratio) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *Momentum* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by stock return calculated over the last 130 days) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. d is an indicator variable for each stock. These results are for the sample period 2 January 2000 to 31 December 2001. Only trades in the top 50 stocks as ranked by manager trading activity are included. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period. We report the sum of the lagged coefficients as follows, (t-1:t-10) is the sum of the lags from t -1 to t -10.

Panel A - Adjusted R-Squared

Adjusted R-Squared	0.11195	0.11382

Panel B - Estimated Coefficients

	Model 1		Model 2	
	Coefficient	*t-stat*	Coefficient	*t-stat*
MgrBuy(t)	0.000009	0.05	0.000055	0.34
MgrBuy(t-1:t-5)	**0.000638**	2.07	**0.001106**	3.93
MgrBuy(t-1:t-10)	**0.001017**	2.70	**0.001460**	4.30
MgrSell(t)	-0.000060	-0.34	-0.000010	-0.06
MgrSell(t-1:t-5)	**-0.000804**	-2.64	**-0.001139**	-4.18
MgrSell(t-1:t-10)	**-0.001039**	-2.89	**-0.000854**	-2.66
SharesBuy(t)	-0.362445	-0.26	-0.001564	-0.76
SharesBuy(t-1:t-5)	-1.233829	-0.50	-0.006575	-1.71
SharesBuy(t-1:t-10)	-3.078855	-0.97	**-0.011155**	-2.29
SharesSell(t)	0.748456	0.55	**0.003129**	2.14
SharesSell(t-1:t-5)	-1.753284	-0.78	0.003368	1.24
SharesSell(t-1:t-10)	1.846640	0.69	0.006088	1.63

Standard errors are calculated using White's heteroskedasticity consistent estimators
Bolded coefficients are statistically significant at the 5 percent level or better

Table V
Institutional Trading, Contemporaneous Effect and Forecasting, using Packages

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{j=0}^{j=10} b_j MgrBuy_{t-j} + \sum_{k=0}^{k=10} b_k MgrSell_{t-k} + \sum_{l=0}^{l=10} b_l SharesBuy_{t-l} + \sum_{m=0}^{m=10} b_m SharesBuy_{t-m} +$$
$$+ \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.SIZE_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t}$$

The dependent variable y is close to close return stock 's' on day 't', although we leave out the subscripts. *MgrBuy* is the standardized number of managers in the market purchasing stock 's' on day 't'. *MgrSell* is the standardized number of managers in the market selling stock 's' on day 't'. A manager is defined as in the market by the Chan and Lakonishok (1995) trading package 5 day rule. This rule states that a trading package is made up of trades made in the same stock in the same direction with a gap of no more than 5 trading days between each successive trade. We standardize by subtracting the mean and dividing by the standard deviation of the institutional trading variable particular to each stock over the sample period. R(t) is the return on stock 's' on day 't'. For Model 1, *SharesBuy* is the total number of shares bought by managers in stock 's' on day 't' divided by the total number of shares outstanding. *SharesSell* is the total number of shares sold by managers in stock 's' on day 't' divided by the total number of shares outstanding. For Model 2, *SharesBuy* is the total number of shares bought by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *SharesSell* is the total number of shares sold by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *Market* is the return on the value weighted portfolio of all stocks listed on the ASX300 (the largest 300 stocks on the exchange) on day 't'. *Size*, is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by market capitalisation) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *BMRatio* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by book to market ratio) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *Momentum* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by stock return calculated over the last 130 days) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. d is an indicator variable for each stock. These results are for the sample period 2 January 2000 to 31 December 2001. Only trades in the top 50 stocks as ranked by manager trading activity are included. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period. We report the sum of the lagged coefficients as follows, (t-1:t-10) is the sum of the lags from t-1 to t-10.

Panel A - Adjusted R-Squared

Adjusted R-Squared	0.11151	0.1132

Panel B - Estimated Coefficients

	Model 1		Model 2	
	Coefficient	*t*-stat	Coefficient	*t*-stat
MgrBuy(t)	-0.000333	-1.69	-0.000272	-1.46
MgrBuy(t-1:t-5)	0.000309	1.13	**0.000697**	2.72
MgrBuy(t-1:t-10)	**0.000845**	2.67	**0.001170**	3.97
MgrSell(t)	-0.000144	-0.79	-0.000038	-0.23
MgrSell(t-1:t-5)	**-0.000572**	-2.08	**-0.000781**	-3.07
MgrSell(t-1:t-10)	-0.000607	-1.95	-0.000492	-1.74
SharesBuy(t)	0.577655	0.44	0.000018	0.01
SharesBuy(t-1:t-5)	0.702420	0.30	-0.002332	-0.64
SharesBuy(t-1:t-10)	-1.516959	-0.51	-0.007055	-1.53
SharesSell(t)	0.914567	0.70	**0.003319**	2.34
SharesSell(t-1:t-5)	-2.662576	-1.23	0.001512	0.56
SharesSell(t-1:t-10)	0.422853	0.16	0.004495	1.21

Standard errors are calculated using White's heteroskedasticity consistent estimators
Bolded coefficients are statistically significant at the 5 percent level or better

Table VI
Institutional Trading, Contempo raneous Effect, Forecasting, and Overnight Returns

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{j=0}^{j=10} b_j MgrBuy_{t-j} + \sum_{k=0}^{k=10} b_k MgrSell_{t-k} + \sum_{l=0}^{l=10} b_l SharesBuy_{t-l} + \sum_{m=0}^{m=10} b_m SharesBuy_{t-m} +$$
$$+ \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.SIZE_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t}$$

The dependent variable y is close-to-close, open-to-close or last close-to-open return stock 's' on day 't', although we leave out the subscripts. *MgrBuy* is the standardized number of managers purchasing stock 's' on day 't'. *MgrSell* is the standardized number of managers selling stock 's' on day 't'. We standardize by subtracting the mean and dividing by the standard deviation of the institutional trading variable particular to each stock over the sample period. R(t) is the return on stock 's' on day 't'. *SharesBuy* is the total number of shares bought by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *SharesSell* is the total number of shares sold by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *Market* is the return on the value weighted portfolio of all stocks listed on the ASX300 (the largest 300 stocks on the exchange) on day 't'. *Size*, is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by market capitalisation) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *BMRatio* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by book to market ratio) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *Momentum* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by stock return calculated over the last 130 days) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. d is an indicator variable for each stock. These results are for the sample period 2 January 2000 to 31 December 2001. Only trades in the top 50 stocks as ranked by manager trading activity are included. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period. We report the sum of the lagged coefficients as follows, (t-1:t-10) is the sum of the lags from t -1 to t -10.

Panel A - Adjusted R-Squared

Adjusted R-Squared	0.11382	0.067142	0.097342

Panel B - Estimated Coefficients

	Return		Open to Close		Last Close to Open	
	Coefficient	*t-stat*	Coefficient	*t-stat*	Coefficient	*t-stat*
MgrBuy(t)	0.000055	0.34	0.000216	1.33	-0.000090	-1.19
MgrBuy(t-1:t-5)	**0.001106**	3.93	**0.000752**	2.64	**0.000309**	2.13
MgrBuy(t-1:t-10)	**0.001460**	4.30	**0.001242**	3.63	0.000162	0.96
MgrSell(t)	-0.000010	-0.06	-0.000258	-1.67	**0.000322**	4.43
MgrSell(t-1:t-5)	**-0.001139**	-4.18	**-0.001045**	-3.84	-0.000079	-0.59
MgrSell(t-1:t-10)	**-0.000854**	-2.66	**-0.001230**	-3.83	0.000333	2.13
SharesBuy(t)	-0.001564	-0.76	-0.002055	-1.01	0.000493	0.51
SharesBuy(t-1:t-5)	-0.006575	-1.71	-0.004437	-1.17	-0.001382	-0.72
SharesBuy(t-1:t-10)	**-0.011155**	-2.29	-0.005994	-1.25	-0.004286	-1.86
SharesSell(t)	**0.003129**	2.14	**0.003226**	2.19	0.000061	0.09
SharesSell(t-1:t-5)	0.003368	1.24	0.002310	0.81	-0.000187	-0.15
SharesSell(t-1:t-10)	0.006088	1.63	**0.008828**	2.29	**-0.003182**	-2.08

Standard errors are calculated using White's heteroskedasticity consistent estimators
Bolded coefficients are statistically significant at the 5 percent level or better

Table VII
Institutional Trading, Contemporaneous Effect, Forecasting, and Relative Trade Size

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{k=1}^{k=10} b_k MgrBuy_{t-k} + \sum_{l=1}^{l=10} b_l MgrSell_{t-l} + \sum_{m=1}^{m=10} b_l SharesBuy_{t-m} + \sum_{n=1}^{n=10} b_l SharesSell_{t-n} + \sum_{k=1}^{k=10} b_k LRGMgrBuy_{t-k} + \sum_{l=1}^{l=10} b_l LRGMgrSell_{t-l}$$
$$+ \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.Size_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t}$$

The dependent variable y is close-to-close, open-to-close or last close-to-open return stock 's' on day 't', although we leave out the subscripts. *MgrBuy* is the standardized number of managers purchasing stock 's' on day 't' of the mid sized trade size. *MgrSell* is the standardized number of managers selling stock 's' on day 't' of the mid sized trade size. LRG*MgrBuy* is the standardized number of managers purchasing stock 's' on day 't' of the large sized trade size. LRG*MgrSell* is the standardized number of managers selling stock 's' on day 't' of the large sized trade size. Trade size is defined by the dollar value of the trade divided by the weight of the stock in the ASX300, further divided by funds under management. Mid sized trades are those falling within the 25^{th} to 75^{th} percentile of trade ranked by relative trade size. Large sized trades are those larger than the 75^{th} percentile of trade ranked by relative trade size. We standardize by subtracting the mean and dividing by the standard deviation of the institutional trading variable particular to each stock over the sample period. R(t) is the return on stock 's' on day 't'. *SharesBuy* is the total number of shares bought by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *SharesSell* is the total number of shares sold by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *Market* is the return on the value weighted portfolio of all stocks listed on the ASX300 (the largest 300 stocks on the exchange) on day 't'. *Size*, is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by market capitalisation) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *BMRatio* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by book to market ratio) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *Momentum* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by stock return calculated over the last 130 days) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. d is an indicator variable for each stock. These results are for the sample period 2 January 2000 to 31 December 2001. Only trades in the top 50 stocks as ranked by manager trading activity are included. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period. We report the sum of the lagged coefficients as follows, (t-1:t-10) is the sum of the lags from t -1 to t -10.

Panel A - Adjusted R-Squared

Adjusted R-Squared	0.11421	0.066934	0.097751

Panel B - Estimated Coefficients

	Return		Open to Close		Last Close to Open	
	Coefficient	*t-stat*	Coefficient	*t-stat*	Coefficient	*t-stat*
MgrBuy(t)	-0.000078	-0.52	0.000095	0.64	-0.000108	-1.57
MgrBuy(t-1:t-5)	**0.000826**	3.13	**0.000593**	2.23	0.000190	1.42
MgrBuy(t-1:t-10)	**0.000943**	2.95	**0.000894**	2.78	-0.000004	-0.02
MgrSell(t)	0.000111	0.76	-0.000135	-0.92	**0.000310**	4.60
MgrSell(t-1:t-5)	**-0.001091**	-4.27	**-0.001026**	-3.98	-0.000055	-0.44
MgrSell(t-1:t-10)	**-0.000810**	-2.64	**-0.001133**	-3.67	0.000273	1.83
LRG MgrBuy(t)	0.000289	1.78	**0.000329**	2.03	-0.000010	-0.13
LRG MgrBuy(t-1:t-5)	**0.000751**	2.73	0.000436	1.59	**0.000303**	2.23
LRG MgrBuy(t-1:t-10)	**0.001335**	4.17	**0.000805**	2.48	**0.000507**	3.24
LRG MgrSell(t)	**-0.000342**	-2.22	**-0.000376**	-2.47	0.000064	0.84
LRG MgrSell(t-1:t-5)	-0.000284	-1.07	-0.000237	-0.89	-0.000031	-0.23
LRG MgrSell(t-1:t-10)	-0.000175	-0.53	-0.000463	-1.38	0.000293	1.76
SharesBuy(t)	-0.002194	-1.05	-0.002684	-1.29	0.000511	0.52
SharesBuy(t-1:t-5)	-0.006189	-1.60	-0.004138	-1.08	-0.001340	-0.69
SharesBuy(t-1:t-10)	**-0.011010**	-2.26	-0.005770	-1.20	-0.004389	-1.90
SharesSell(t)	**0.003888**	2.66	**0.003729**	2.50	0.000341	0.47
SharesSell(t-1:t-5)	0.002629	0.96	0.001629	0.57	-0.000258	-0.20
SharesSell(t-1:t-10)	0.005046	1.34	**0.008256**	2.14	**-0.003679**	-2.40

Standard errors are calculated using White's heteroskedasticity consistent estimators
Bolded coefficients are statistically significant at the 5 percent level or better

Table VIII
Institutional Trading, Past Stock Returns and Investment Style

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{j=1}^{j=10} b_j R_{s,t-j} + \sum_{k=1}^{k=10} b_k NeutBuy_{t-k} + \sum_{l=1}^{l=10} b_l NeutSell_{t-l} + \sum_{m=1}^{m=10} b_l SharesBuy_{t-m} + \sum_{n=1}^{n=10} b_l SharesSell_{t-n} + \sum_{k=1}^{k=10} b_k GroBuy_{t-k} + \sum_{l=1}^{l=10} b_l GroSell_{t-l}$$
$$\sum_{k=1}^{k=10} b_k ValBuy_{t-k} + \sum_{l=1}^{l=10} b_l ValSell_{t-l} + \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.Size_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t}$$

The dependent variable y is one of six variables, NeutBuy, NeutSell, GroBuy, GroSell, ValBuy and ValSell. NeutBuy is the standardized number of neutral managers purchasing stock ‘s’ on day ‘t’, although we leave out the subscripts. NeutSell is the standardized number of neutral managers selling stock ‘s’ on day ‘t’. GroBuy is the standardized number of growth managers purchasing stock ‘s’ on day ‘t’. GroSell is the standardized number of growth managers selling stock ‘s’ on day ‘t’. ValBuy is the standardized number of value managers purchasing stock ‘s’ on day ‘t’. ValSell is the standardized number of value managers selling stock ‘s’ on day ‘t’. We standardize by subtracting the mean and dividing by the standard deviation of the institutional trading variable particular to each stock over the sample period. R(t) is the return on stock ‘s’ on day ‘t’, *SharesBuy* is the total number of shares bought by managers in stock ‘s’ on day ‘t’ divided by the mean daily volume calculated over the prior 20 days. *SharesSell* is the total number of shares sold by managers in stock ‘s’ on day ‘t’ divided by the mean daily volume calculated over the prior 20 days. *Market* is the return on the value weighted portfolio of all stocks listed on the ASX300 (the largest 300 stocks on the exchange) on day ‘t’. *Size*, is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by market capitalisation) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *BMRatio* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by book to market ratio) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *Momentum* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by stock return calculated over the last 130 days) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. d is an indicator variable for each stock. These results are for the sample period 2 January 2000 to 31 December 2001. Only trades in the top 50 stocks as ranked by manager trading activity are included. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period. We report the sum of the lagged coefficients as follows, (t-1:t-10) is the sum of the lags from t-1 to t-10.

Panel A - Adjusted R-Squared

Adjusted R-Squared (BUYS)	0.0428	0.1565	0.0686
Adjusted R-Squared (SELLS)	0.0375	0.1435	0.0945

Panel B - Regression Estimates (BUYS)

	Neutral		Growth		Value	
	Coefficient	*t-stat*	Coefficient	*t-stat*	Coefficient	*t-stat*
Ret(t-1:t-5)	**2.426839**	2.56	0.241206	0.27	**-7.994400**	-8.59
Ret(t-1:t-10)	**2.552040**	1.81	1.633882	1.24	**-8.470800**	-5.95
NeutralMgrBuy(t-1:t-5)	**0.300278**	14.53	0.027857	1.76	-0.031327	-1.85
NeutralMgrBuy(t-1:t-10)	**0.363496**	14.67	0.009444	0.43	-0.040041	-1.90
NeutralMgrSell(t-1:t-5)	-0.001201	-0.07	0.011787	0.78	-0.001934	-0.12
NeutralMgrSell(t-1:t-10)	-0.007090	-0.34	0.016432	0.82	-0.002152	-0.11
GrowthMgrBuy(t-1:t-5)	**-0.070468**	-3.95	**0.486371**	24.31	-0.026012	-1.62
GrowthMgrBuy(t-1:t-10)	**-0.060624**	-3.03	**0.591951**	26.88	**-0.041736**	-2.16
GrowthMgrSell(t-1:t-5)	0.026422	1.64	-0.026101	-1.80	-0.006429	-0.41
GrowthMgrSell(t-1:t-10)	**0.051798**	2.86	-0.020347	-1.24	0.000738	0.04
ValueMgrBuy(t-1:t-5)	0.014666	0.87	-0.022456	-1.57	**0.304200**	13.56
ValueMgrBuy(t-1:t-10)	0.009422	0.45	**-0.045376**	-2.64	**0.420120**	16.94
ValueMgrSell(t-1:t-5)	0.021354	1.50	0.025804	1.88	**-0.053738**	-4.58
ValueMgrSell(t-1:t-10)	**0.049285**	2.82	-0.006088	-0.37	**-0.071738**	-4.91
SharesBuy(t-1:t-5)	0.218488	0.85	**0.961305**	3.90	0.186890	0.87
SharesBuy(t-1:t-10)	0.583535	1.86	0.448930	1.49	0.288380	1.05
SharesSell(t-1:t-5)	0.071783	0.49	-0.132054	-0.99	0.034906	0.24
SharesSell(t-1:t-10)	0.047652	0.27	-0.101714	-0.59	-0.067599	-0.39

Panel C - Regression Estimates (SELLS)

Ret(t-1:t-5)	0.841279	0.84	**-1.917846**	-2.22	**4.630600**	4.92
Ret(t-1:t-10)	2.054522	1.40	**-2.264225**	-1.79	**7.214800**	5.10
NeutralMgrBuy(t-1:t-5)	-0.012413	-0.77	0.019104	1.21	0.010037	0.66
NeutralMgrBuy(t-1:t-10)	-0.014707	-0.71	**0.052973**	2.67	0.008684	0.43
NeutralMgrSell(t-1:t-5)	**0.217276**	10.86	**0.064396**	3.83	-0.004962	-0.29
NeutralMgrSell(t-1:t-10)	**0.274397**	10.87	0.039376	1.79	0.032854	1.43
GrowthMgrBuy(t-1:t-5)	0.018500	1.10	-0.015656	-1.03	**0.055234**	3.28
GrowthMgrBuy(t-1:t-10)	0.033371	1.68	0.003468	0.20	**0.075855**	3.91
GrowthMgrSell(t-1:t-5)	**-0.094704**	-5.21	**0.465013**	22.04	-0.005677	-0.34
GrowthMgrSell(t-1:t-10)	**-0.113569**	-5.66	**0.610393**	26.75	0.014891	0.80
ValueMgrBuy(t-1:t-5)	0.014831	0.95	0.012882	0.86	0.010307	0.70
ValueMgrBuy(t-1:t-10)	0.007787	0.41	0.014758	0.80	0.010324	0.55
ValueMgrSell(t-1:t-5)	**-0.033063**	-2.04	0.014345	1.03	**0.394510**	17.65
ValueMgrSell(t-1:t-10)	-0.035709	-1.92	0.018154	1.03	**0.461440**	17.34
SharesBuy(t-1:t-5)	-0.309655	-1.42	0.245264	1.21	**-0.652710**	-3.48
SharesBuy(t-1:t-10)	-0.512464	-1.77	0.080682	0.30	**-0.951240**	-3.64
SharesSell(t-1:t-5)	**0.424963**	2.16	0.179361	1.02	0.295890	1.44
SharesSell(t-1:t-10)	0.207344	0.94	0.178130	0.82	0.473230	1.87

Standard errors are calculated using White's heteroskedasticity consistent estimators
Bolded coefficients are statistically significant at the 5 percent level or better

Table IX
Institutional Trading, Contemporaneous Effect, Forecasting, and Investment Style

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{k=1}^{k=10} b_k NeutBuy_{t-k} + \sum_{l=1}^{l=10} b_l NeutSell_{t-l} + \sum_{m=1}^{m=10} b_l SharesBuy_{t-m} + \sum_{n=1}^{n=10} b_l SharesSell_{t-n} + \sum_{k=1}^{k=10} b_k GroBuy_{t-k} + \sum_{l=1}^{l=10} b_l GroSell_{t-l}$$

$$\sum_{k=1}^{k=10} b_k ValBuy_{t-k} + \sum_{l=1}^{l=10} b_l ValSell_{t-l} + \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.Size_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t}$$

The dependent variable y is close-to-close, open-to-close or last close-to-open return stock 's' on day 't', although we leave out the subscripts. *NeutBuy* and *NeutSell* is the standardized number of style neutral managers purchasing and selling stock 's' on day 't' respectively. *GroBuy* and *GroSell* is the standardized number of growth managers purchasing and selling stock 's' on day 't' respectively. *ValBuy* and *ValSell* is the standardized number of value managers purchasing and selling stock 's' on day 't' respectively. We standardize by subtracting the mean and dividing by the standard deviation of the institutional trading variable particular to each stock over the sample period. R(t) is the return on stock 's' on day 't'. *SharesBuy* is the total number of shares bought by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *SharesSell* is the total number of shares sold by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *Market* is the return on the value weighted portfolio of all stocks listed on the ASX300 (the largest 300 stocks on the exchange) on day 't'. *Size*, is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by market capitalisation) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *BMRatio* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by book to market ratio) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *Momentum* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by stock return calculated over the last 130 days) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. d is an indicator variable for each stock. These results are for the sample period 2 January 2000 to 31 December 2001. Only trades in the top 50 stocks as ranked by manager trading activity are included. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period. We report the sum of the lagged coefficients as follows, (t-1:t-10) is the sum of the lags from t-1 to t-10.

Panel A - Adjusted R-Squared

Adjusted R-Squared	0.11967	0.071553	0.10201

Panel B - Estimated Coefficients

	Return		Open to Close		Last Close to Open	
	Coefficient	*t-stat*	Coefficient	*t-stat*	Coefficient	*t-stat*
Neutral MgrBuy(t)	**0.000331**	2.25	**0.000445**	2.99	-0.000092	-1.33
Neutral MgrBuy(t-1:t-5)	0.000110	0.40	0.000196	0.70	-0.000067	-0.49
Neutral MgrBuy(t-1:t-10)	0.000414	1.21	0.000553	1.60	-0.000138	-0.81
Neutral MgrSell(t)	-0.000056	-0.37	-0.000132	-0.88	0.000100	1.47
Neutral MgrSell(t-1:t-5)	-0.000166	-0.59	-0.000034	-0.12	-0.000101	-0.73
Neutral MgrSell(t-1:t-10)	-0.000094	-0.25	0.000192	0.51	-0.000273	-1.49
Growth MgrBuy(t)	0.000049	0.29	0.000169	1.00	-0.000078	-1.00
Growth MgrBuy(t-1:t-5)	0.000372	1.32	0.000302	1.06	0.000052	0.37
Growth MgrBuy(t-1:t-10)	0.000616	1.93	**0.000961**	3.00	**-0.000362**	-2.33
Growth MgrSell(t)	-0.000190	-1.18	**-0.000416**	-2.57	**0.000282**	3.67
Growth MgrSell(t-1:t-5)	**-0.000744**	-2.71	**-0.000946**	-3.41	0.000197	1.48
Growth MgrSell(t-1:t-10)	**-0.000672**	-2.08	**-0.001226**	-3.78	**0.000511**	3.23
Value MgrBuy(t)	**-0.000729**	-4.86	**-0.000522**	-3.51	**-0.000167**	-2.41
Value MgrBuy(t-1:t-5)	**0.001308**	4.95	**0.000615**	2.28	**0.000667**	4.94
Value MgrBuy(t-1:t-10)	**0.001441**	4.38	0.000526	1.57	**0.000897**	5.31
Value MgrSell(t)	**0.000989**	6.22	**0.000680**	4.36	**0.000351**	4.80
Value MgrSell(t-1:t-5)	**-0.001450**	-6.10	**-0.001121**	-4.68	**-0.000322**	-2.59
Value MgrSell(t-1:t-10)	**-0.001246**	-4.13	**-0.001195**	-3.93	-0.000070	-0.46
SharesBuy(t)	0.001743	0.87	0.001110	0.56	0.000809	0.87
SharesBuy(t-1:t-5)	-0.003925	-1.05	-0.001940	-0.53	-0.001324	-0.74
SharesBuy(t-1:t-10)	-0.005210	-1.11	-0.001391	-0.30	-0.003252	-1.50
SharesSell(t)	0.001289	0.89	0.001684	1.16	-0.000143	-0.21
SharesSell(t-1:t-5)	0.003438	1.27	0.002649	0.95	-0.000356	-0.29
SharesSell(t-1:t-10)	0.006903	1.91	**0.009860**	2.65	**-0.003391**	-2.21

Standard errors are calculated using White's heteroskedasticity consistent estimators
Bolded coefficients are statistically significant at the 5 percent level or better

Table X
Institutional Trading, Investment Style, and Intra-day Volatility

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{k=0}^{k=10} b_k NonValMgrBuy_{t-k} + \sum_{l=0}^{l=10} b_l NonValMgrSell_{t-l} + \sum_{m=0}^{m=10} b_l SharesBuy_{t-m} + \sum_{n=0}^{n=10} b_l SharesSell_{t-n} + \sum_{k=1}^{k=10} b_k ValBuy_{t-k} + \sum_{l=1}^{l=10} b_l ValSell_{t-l}$$
$$+ \sum_{k=0}^{k=10} b_m .Volatility_{t-k} * ValBuy_{t-k} + \sum_{l=0}^{l=10} b_n .Volatility_{t-k} ValSell_{t-l} + \sum_{l=0}^{l=10} b_o .Volatility_{t-k}$$
$$+ \sum_{s=1}^{S} b_s d + \sum_{s=1}^{S} b_s d.Market_t + \sum_{s=1}^{S} b_s d.Size_t + \sum_{s=1}^{S} b_s d.BMRatio_t + \sum_{s=1}^{S} b_s d.Momentum_t + e_{s,t}$$

The dependent variable y is close-to-close, open-to-close or last close-to-open return stock 's' on day 't', although we leave out the subscripts. *NonValMgrBuy* is the standardized number of non-value managers purchasing stock 's' on day 't'. *NonValMgrSell* is the standardized number of non-value managers selling stock 's' on day 't'. *ValMgrBuy* is the standardized number of value managers purchasing stock 's' on day 't'. *ValMgrSell* is the standardized number of managers selling stock 's' on day 't'. We standardize by subtracting the mean and dividing by the standard deviation of the institutional trading variable particular to each stock over the sample period. R(t) is the return on stock 's' on day 't'. *SharesBuy* is the total number of shares bought by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *SharesSell* is the total number of shares sold by managers in stock 's' on day 't' divided by the mean share trading volume calculated over the prior 20 days. *Market* is the return on the value weighted portfolio of all stocks listed on the ASX300 (the largest 300 stocks on the exchange) on day 't'. *Size*, is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by market capitalisation) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *BMRatio* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by book to market ratio) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. *Momentum* is the value weighted return on a portfolio of stocks comprised of the largest quintile of stocks (as ranked by stock return calculated over the last 130 days) in the ASX300 less the value weighted return on a portfolio of stocks comprised of the smallest quintile of stocks in the ASX300. d is an indicator variable for each stock. These results are for the sample period 2 January 2000 to 31 December 2001. Only trades in the top 50 stocks as ranked by manager trading activity are included. Manager trading activity is defined as the number of purchases plus the number of sales made by our sample group in the sample period. We report the sum of the lagged coefficients as follows, (t-1:t-10) is the sum of the lags from t-1 to t-10. Volatility is defined in expression (4) and (5).

Panel A - Adjusted R-Squared

Adjusted R-Squared	0.1220	0.0734	0.1070

Panel B - Regression Estimates

	Return		Open to Close		Last Close to Open	
	Coefficient	*t-stat*	Coefficient	*t-stat*	Coefficient	*t-stat*
NonValMgrBuy(t)	**0.000596**	3.81	**0.000650**	4.14	0.000005	0.08
NonValMgrBuy(t-1:t-5)	**0.000449**	1.67	0.000391	1.44	0.000025	0.18
NonValMgrBuy(t-1:t-10)	**0.000888**	2.78	**0.000968**	3.01	-0.000131	-0.83
NonValMgrSell(t)	**-0.000576**	-3.89	**-0.000742**	-4.99	**0.000230**	3.37
NonValMgrSell(t-1:t-5)	-0.000514	-1.95	**-0.000650**	-2.47	0.000150	1.16
NonValMgrSell(t-1:t-10)	-0.000193	-0.63	**-0.000811**	-2.66	**0.000576**	3.79
SharesBuy(t)	-0.001863	-0.91	-0.002379	-1.16	0.000559	0.58
SharesBuy(t-1:t-5)	-0.006423	-1.68	-0.004135	-1.09	-0.001579	-0.82
SharesBuy(t-1:t-10)	**-0.010884**	-2.25	-0.005325	-1.11	**-0.004770**	-2.06
SharesSell(t)	**0.002953**	2.06	**0.003146**	2.16	-0.000017	-0.02
SharesSell(t-1:t-5)	0.003548	1.31	0.002358	0.83	-0.000043	-0.03
SharesSell(t-1:t-10)	0.005782	1.57	**0.008520**	2.25	**-0.003176**	-2.08
ValMgrBuy(t)	**-0.000765**	-5.33	**-0.000586**	-4.11	**-0.000141**	-2.13
ValMgrBuy(t-1:t-5)	**0.001281**	5.23	**0.000594**	2.38	**0.000655**	5.21
ValMgrBuy(t-1:t-10)	**0.001340**	4.46	0.000439	1.43	**0.000878**	5.65
ValMgrSell(t)	**0.000876**	5.92	**0.000625**	4.32	**0.000290**	4.19
ValMgrSell(t-1:t-5)	**-0.001387**	-6.13	**-0.001012**	-4.43	**-0.000371**	-3.16
ValMgrSell(t-1:t-10)	**-0.001180**	-4.20	**-0.001111**	-3.91	-0.000086	-0.60
ValMgr*VolatilityBuy(t)	**-0.000483**	-2.95	**-0.000445**	-2.66	-0.000004	-0.06
ValMgr*VolatilityBuy(t-1:t-5)	0.000163	0.65	0.000086	0.36	0.000064	0.46
ValMgr*VolatilityBuy(t-1:t-10)	0.000336	1.00	0.000100	0.30	0.000224	1.24
ValMgr*VolatilitySell(t)	0.000391	1.90	0.000240	1.13	0.000174	1.84
ValMgr*VolatilitySell(t-1:t-5)	-0.000250	-1.03	-0.000120	-0.49	-0.000161	-1.20
ValMgr*VolatilitySell(t-1:t-10)	-0.000422	-1.35	0.000009	0.03	**-0.000470**	-2.80
Volatility(t)	**0.000584**	2.54	0.000453	1.95	0.000019	0.18
Volatility(t-1:t-5)	0.000140	0.48	-0.000377	-1.26	**0.000482**	3.23
Volatility(t-1:t-10)	0.000351	1.45	**-0.000699**	-2.83	**0.001033**	8.30