Institutional Trading and Share Returns*

F. Douglas Foster
David R. Gallagher
Adrian Looi [†]

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School of Banking and Finance, The University of New South Wales,
Sydney, N.S.W. 2052 AUSTRALIA

ABSTRACT

Using a unique database of daily transactions from Australian equity managers, we investigate the relation between institutional trading and share returns. Our sample of institutional investors exhibit 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 growth-oriented managers are momentum traders, while style neutral and value managers are contrarian. Further, the contemporaneous relation between institutional trading and returns depends on relative trade size, broker use, 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. The manner in which brokerage is employed by the fund manager can provide insights on the motivation for the trade.

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[†] Corresponding author. E-mail: adrianlooi@yahoo.com. Postal address: P.O. Box H58, Australia Square, Sydney N.S.W. 1215, Australia.

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Institutional Trading and Share 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 large 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.[1]

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, Australian fund managers have, as a group, consistently beaten passive benchmark indices over the past several years.[2] 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 fund managers, as a group, at times possess particular expertise or insights that allow them to predict or anticipate future price changes.[3] This would make active portfolio managers comparable to informed traders in most microstructure models (see for example Kyle (1985) and Glosten and Milgrom (1985)). As we are using daily data, we

[1] Market impact studies documenting the effect of trade activity on stock prices include Chan and Lakonishok (1995), Keim and Madhavan (1995), Chakravarty (2001) and Chiyachantana, Jain, Jiang and Wood (2004). Research has also considered the effects of order imbalance on security prices in an intermediated market (e.g. Chordia and Subrahmanyam (2004)).

[2] Evidence of superior manager ability in Australian equities is documented in Mercer Investment Consulting surveys and from academic studies examining fund performance (e.g. Gallagher, 2003).

[3] More recent studies have also documented significant ability exhibited by other institutional participants. These include persistence in stock picking skill by security analysts (Mikhail, Walther and Willis (2004)) and profitable recommendations from professional market timers (Chance and Hemler (2001)).

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 wholly due to investor contributions / redemptions, portfolio rebalancing, index changes, *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. Indeed, Edelen (1999) documents mutual funds trade a substantial size of their portfolio as uninformed, liquidity-motivated activity that is provided to their clients at virtually no cost.[4] As sophisticated investors, we expect institutional managers 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*. 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 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.

[4] The effect on portfolio returns arising from flow-induced trading has been shown by Edelen (1999) to downward bias the risk-adjusted (α) performance estimates of active mutual funds.

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.

If unanticipated institutional trading volume has been skilfully allocated to times when the market is likely to more easily absorb the orders, this 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, institutional investors 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 is 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. trading with temporal urgency, as opposed to trading with a high degree of discretion), we argue that it is more likely that the 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 further explore the implications of informed versus discretionary liquidity motives for trading, we also incorporate information about the "style" of the institutional investor. Our entire sample of institutional equity 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 self-stated expertise, which we proxy according to their investment style. We use the institutional investors' reported style with the well-known categories of value, growth, and neutral. We find that investment style is particularly relevant in understanding the contemporaneous link between trading and share returns, with the contrarian actions of value managers being especially striking.

Finally, we are also able to observe the manner in which they choose to process their trades. For example, we know which broker (using an established broker ID through the Exchange) was used to facilitate and route the order. The technique used for order submission provides corroborating evidence on our breakdown of liquidity and information-related trades. We argue that when a single fund manager splits their order across many brokers, they are more likely doing so because they have an informed basis for their trade and there are likely to be longer-term price consequences for this transaction. When a single broker manages a number of similar orders from a range of fund managers, we argue that this is a result of the broker soliciting liquidity to offset a prior trade. If this is the case, we would expect transitory price reactions to these trades as the liquidity need is met. Both of these views are confirmed by our data.

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

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.

A common view of market efficiency is that historical stock returns should not be a predictor of future returns, so historical returns should not provide systematic ways to build portfolios that out-perform a passive benchmark. However, a number of empirical studies document significant abnormal returns to both contrarian and momentum trading. For example, 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)). At the same time, empirical research documents positive autocorrelation over a medium-term investment horizon. This evidence is consistent with the use of 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). For the Finnish market, Grinblatt and Keloharju (2000) find that institutional traders execute momentum-based trading strategies, and that investor sophistication is directly related to trade performance over both short and intermediate intervals. More recent analysis also documents a strong momentum anomaly that persists over the long run, and which is based on a stock's 52-week high (i.e. a price level indicator). George and Hwang

(2004) show that for stocks trading near their 52-week high, this public information represents significant predictive power in security returns.[5]

In this study 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 (see for example Gompers and Metrick (2001) and Cohen, Gompers and Vuolteenaho (2002)) and “momentum” investors are likely to focus on positive autocorrelation in returns (see for example Grinblatt, Titman and Wermers (1995), Nosfinger and Sias (1999), Pinnuck (2003), Griffin, Harris and Topaloglu (2003) (for institutional investors), and Cai and Zheng (2004)). 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. 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 growth oriented investment managers (growth managers and growth-at-a-reasonable-price (GARP) managers) are momentum traders, while style neutral and value managers are contrarian.

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 much of the current

[5] A number of recent studies have also considered the impact of trading costs in the execution of momentum-based strategies. Lesmond, Schill and Zhou (2004) find that momentum-based investing cannot be economically exploited in a successful manner because such activity is typically required in smaller and less liquid stocks. In the case of Korajczyk and Sadka (2004), their study documents diminishing abnormal returns to scale, due to the impact of trade costs. Boudoukh, Richardson and Whitelaw (1994) consider serial correlation in small stocks and observe that non-synchronous trading is a major driver of observed autocorrelations.

empirical research 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 possess superior private information (as evidenced by Grinblatt and Titman (1989), Daniel, Grinblatt, Titman and Wermers (1997), Wermers (2000), Cesari and Panetta (2002), Gallagher (2003), 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. We are able to analyse information motives more closely than prior studies by using information about which broker is used to facilitate an institution's trades.

A fund manager has a strong incentive 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).[6] This being the case we would generally expect there to be relatively small share price impact from professional trades, irrespective of their underlying motive. However, there may be times when an investor trading on a special insight or analysis may not have wide flexibility in timing trades. In particular, the information may be firm or industry specific, mandating trade in a single stock (or a select list of stocks). Further, the information that institutional traders have may be relatively short-lived; it can be announced by the firm, or by a research provider to the general market, or by a news reporter. Finally, there may be other fund managers who have the same (or similar) views, and they have an incentive to trade quickly so as to anticipate other investors with an information motive.

[6] 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 matches a basic prediction of Foster and Viswanathan (1990).

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 see 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 studies 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 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 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. We find growth and growth-at-a-reasonable-price (GARP) managers to be momentum traders, while value managers are 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 consultations with Mercer Investment Consulting, who provided a comprehensive list of the largest Australian equity managers as well as 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. These funds are benchmarked against the S&P/ASX 200 and 300 Accumulation Index.[7] 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. In addition, we can also motivate the sourcing of data for the largest pooled institutional equity fund for each institution, as these products represent the manager's single largest revenue source from the fund family, given that fund revenue is determined as a fixed percentage of assets under management, and that fee variations are relatively small within common asset classes.

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 Financial 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

[7] The correlation between these indexes is very high, and approximately 0.98. The additional stocks included in the S&P/ASX 300 only increases total market capitalisation by around 1 percent.

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 gross 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.[8] 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. In terms of representativeness, according to the March 2002 Mercers Australian Shares Specialist Survey, our sample includes 'flagship' funds from 25 of the 35 managers with funds under management exceeding AUD 200 Million. While each manager may have a number of investment products available (including private equity funds, retail and wholesale funds), discussions with fund managers reveal that investment decision making is uniform across almost all fund products. Therefore we reduce collinearity induced by related funds under the same product family by only including 'flagship' funds.

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

[8] According to the Mercer Wholesale Investment Fee Survey, mean management expense ratios for 2000 and 2001 were 0.74 and 0.8 percent respectively indicating that active Australian equity managers were able to outperform on both a gross and net of fees basis.

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 attractive long term earnings 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 together 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 and 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 1.52 and 1.54 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 total 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 market capitalisation at the start of the sample period. This restriction is in place in order to maintain a reasonable number of manager trades per day per stock.[9] 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

[9] We have also repeated all analysis using the 50 most active stocks (by manager trading) over the sample period and obtain very similar results. 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

stocks are 1.07 and 0.82, respectively. As a percentage of mean daily trading volume, the average number of shares purchased per day in the 15 largest stocks in the database is 2.8 and 2.4 percent, respectively. As we consider lower capitalization shares, the relative size of manager trades rises, while the number of managers active in the market falls, consistent with diminished liquidity in the lower capitalization stocks. For the purpose of further analysis, we standardize manager trading activity with the sample mean and standard deviation of manager trading in each stock. Table II also provides statistics on the weight of the portfolio invested in stocks included in our sample. The sum of weights gives the mean and standard deviation of the total weight in the portfolio invested in stocks within the corresponding stock rank bucket. On average, over 65 percent of the portfolio weight is allocated to just these top 50 stocks, indicating that our sample covers much of the manager's investible universe by market capitalisation.

[INSERT TABLE II ABOUT HERE]

III. Research Design

To understand the relation between institutional trading and stock returns, we examine these 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 past 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 prices and their returns. As a consequence, a rational stock trading strategy might not rely on 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), Griffin *et al.* (2003), and Cai and Zheng (2004)). 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 changes in price are not accompanied with changes 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)). Indeed, Fong, Gallagher, Gardner and Swan (2005) show that followers imitate the trades of leaders, and that such activity leads to significant profits for the leader and early followers. 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, stock size and price 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:

$$\begin{aligned} y_{s,t} &= \sum_{z=1}^{z=10} \beta_{j,z} R_{s,t-z} + \beta_k MgrBuy_{t-1} + \beta_l MgrSell_{t-1} + \beta_m SharesBuy_{t-1} + \beta_n SharesSell_{t-1} + \\ &+ \sum_{s=1}^{S} \beta_{a,s} .\delta_s + \sum_{s=1}^{S} \beta_{b,s} .\delta_s Market_t + \sum_{s=1}^{S} \beta_{c,s} .\delta_s .SIZE_t + \\ &+ \sum_{s=1}^{S} \beta_{d,s} .\delta_s .BMRatio_t + \sum_{s=1}^{S} \beta_{e,s} .\delta_s .Momentum_t + \varepsilon_{s,t} \end{aligned} \tag{1}$$

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*'. *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[10].

[10] In unreported regressions we re-estimate our results using alternative measures of volume traded by managers, including the number of shares purchased / sold divided by the number of shares outstanding and find very similar results to those reported.

Explanatory variables include lags of the dependent variables as well as risk control variables. *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 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. δ is an indicator variable for each stock.

Since lagged values of the dependent variable in expression (1) are included as explanatory variables, ordinary least squares estimates are inefficient and inconsistent, we therefore employ a two-step procedure suggested by Hatanaka (1974) to compute our estimates.

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

We expect the contemporaneous relation between institutional trading and share returns to be influenced by liquidity and information effects. If institutional trades are small, or do not require the provision of additional liquidity, then we expect no contemporaneous link between institutional trade and 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 the volume of 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).

$$\begin{aligned} y_{s,t} = & \sum_{z=0}^{z=10} \beta_{k,z} MgrBuy_{t-z} + \sum_{z=0}^{z=10} \beta_{l,z} MgrSell_{t-z} + \sum_{z=0}^{z=10} \beta_{m,z} SharesBuy_{t-z} + \sum_{z=0}^{z=10} \beta_{n,z} SharesSell_{t-z} + \\ & + \sum_{s=1}^{S} \beta_{a,s} .\delta_s + \sum_{s=1}^{S} \beta_{b,s} .\delta_s Market_t + \sum_{s=1}^{S} \beta_{c,s} .\delta_s .SIZE_t + \\ & + \sum_{s=1}^{S} \beta_{d,s} .\delta_s .BMRatio_t + \sum_{s=1}^{S} \beta_{e,s} .\delta_s .Momentum_t + \varepsilon_{s,t} \end{aligned} \quad (2)$$

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

Past studies examining 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 of institutional trades as many as 10 trading days previous on current returns.[11] 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. Such evidence would be inconsistent with the efficient markets hypothesis.

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. However, we note that daily stock returns are likely to be autocorrelated, and therefore we correct for an AR(1) process by estimating the autocorrelation parameter for each security with OLS, and then transforming the dependent and independent variables accordingly. This allows us clean autocorrelation effects prior to estimation of expressions (1) and (2). We also note that each stock is likely to have a different residual variance inducing heteroskedasticity. We therefore estimate the residual variance for each stock individually, and transform the variables in the regression accordingly.[12]

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[11] 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.

[12] In unreported results, we test the robustness of our standard error estimates by conducting a boot-strap experiment. We form numeric standard errors by randomly reconstructing the independent variables in order to build a distribution for the coefficients. For example, for each stock, we divide the manager buying variable into blocks of 4 (in order to retain any autocorrelation structures present in the manager buying variable) and

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 institutions are contrarian traders (although in later sections we investigate the role of investment style on the relation between historical stock returns and institutional trading). 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-1*' to '*t-10*' is -2.6908 and 0.8793 for purchases and sales respectively, indicating that a fall (rise) in price over the last 10 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 20 percent fall in the price of BHP (over and above any autocorrelation effects) over 10 days, the model predicts that on average, one manager will be induced to buy (-2.6908 * -0.2 * 1.47 = 0.79 managers).

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randomly reassign the order of the blocks. We then re-run the regression with the randomly assigned blocks and note the coefficient of manager buying. We conduct this trial 500,000 times in order to build up a distribution for the coefficient of manager buying. Our results show that the reported regression results using OLS give similar results to the numerically generated estimates. We also find similar results when we use heteroskedasticity consistent estimators on the 'raw' unweighted data.

[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 (2002), however it is inconsistent with Grinblatt, Titman and Wermers (1995), Nosfinger and Sias (1999), Pinnuck (2003) and Cai and Zheng (2004). 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. 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)). 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, highly significant coefficients on lagged institutional trading show 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 (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*0.5193 = 1.04) over the next day. 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.

[INSERT TABLE IV ABOUT HERE]

We test these hypotheses using equation 2, and the results are reported in the column headed "Basic" in Table IV. The results indicate that there is no significant contemporaneous effect. The coefficient of manager buying from our estimate of equation 2 is -0.0002, while that of selling is 0.0001, 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, if managers are adept at hiding the information content of their trades, then we should see that the contemporaneous effect of manager trading volume should not be statistically significant. We find no evidence of a contemporaneous effect for purchases, or sales. One should note however, that while 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.

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 Table IV shows that lagged values of the number of institutions purchasing (selling) are significantly related to 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. In unreported computations, we have found these results to be 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 significance, the predictive power of institutional trading can be significant. For example, according to Table IV, "Basic", 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 0.42 percent over the following 10 days (0.0014 * 3 = 0.0042). The effect for sales is not quite as strong, with the sum of the lag coefficient of manager selling being -0.0011 (although still statistically different from zero at the 1 percent level) as compared to 0.0014 for purchases. While these figures may seem small in magnitude, they should be compared to an annual alpha of say two percent, which is approximately 0.08 percent over 10 trading days.

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

In Section B, 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. There may be a number of reasons why we do not find a contemporaneous effect, one possibility is that we may be aggregating many different types of trades in the *MgrBuy* variable that have very different contemporaneous effects. Another possibility is that the investment philosophy of the manager may cause them to trade in very different circumstances leading to different contemporaneous effects.

Trade Characteristics

Perhaps the most obvious trade characteristic is trade size. Large trades relative to funds under management (FUM) should be indicative of high information content. 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 for greater market impact than small trades, and hence we expect the contemporaneous effect of large trades to exceed that of other trades. Small trades are more likely to be liquidity motivated, perhaps motivated by redemptions or applications. Edelen (1999) shows mutual funds do engage in a material volume of uninformed or liquidity-motivated trading.

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

$$Tradesize = \frac{price \times quantity}{bmkweight \times FUM} \tag{3}$$

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 two groups outlined above.

We form two variables (and their lags) of institutional trading corresponding to the number of manager purchases and sales made on day '*t*' in each stock '*s*' and the number of group 1 (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.

Another factor that may be causing our finding of a zero contemporaneous effect for manager trading is that managers may be hiding or masking their trades in order to reduce their market visibility. One such tactic is to use multiple brokers to trade on the same day. Trades made on days where a manager has used multiple brokers are not likely to induce a positive contemporaneous effect due to trade masking. However, the converse, multiple managers using the same broker, may be indicative of a broker providing price and time sensitive information to many managers at the same time, and therefore we would expect days where many managers use the same broker to exhibit a positive contemporaneous effect.

We regress the midpoint close-to-close return on the standardized number of institutions purchasing and selling in the large trade size category and the non-large trade size category as well as the number of managers trading multiplied by two sets of indicator variables; (1) MultiBKR, set to one if a manager has used more than one broker to trade, and (2) if the same broker has purchased or sold for many managers. We also include the risk control variables for market, stock size, book-to-market and momentum. The trade characteristics results are presented in the column headed "TradeCharacteristics" in Table IV.

We find that the contemporaneous return effect of the number of managers for large trades is significantly larger than that for non-large trades. The coefficient for large purchases is 0.0002, and is significant at the 10 percent level. This result lends support to the information hypothesis of price impact. A significant permanent effect is however non-existent for large sized trades. The additional contemporaneous return effect (through the number of managers) of a large sale is larger in magnitude and more significant than that found for a large purchase.

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 mean daily trading volume).

When we consider the masking effect of using multiple brokers, we find evidence of statistically significant incremental information content. When managers use many brokers to purchase, over the next five days, autocorrelation adjusted stock returns rise by 0.25 percent (significant at the 5 percent level) per standard deviation of manager buying. We find that this incremental information advantage however, is short-lived, dissipating to 0.17 percent (not significant) over 10 days. Interestingly, we find that this incremental information does not come at an increased contemporaneous effect cost. We find no evidence of a significant difference between the contemporaneous effect of manager buying (selling) and manager buying (selling) on days when a manager has used multiple brokers. This indicates that managers are able to benefit from the higher information content of their purchases if they mask their trades by using many brokers without causing undue changes to stock prices on the day they trade.[13]

However, when we examine the effect of multiple managers using the same broker we find that purchases exhibit a positive incremental contemporaneous effect (statistically significant at the 1 percent level). This suggests that when brokers provide information to many of their clients, prices adjust on the same day. Furthermore, we find no evidence of an incremental information effect over the following 5 or 10 days, suggesting that the information revealed by brokers are fully accounted in prices on the same day. Hence, such information may be about temporary liquidity needs in the market, rather than long-term valuation shifts in the company.

Investment Philosophy

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 they may behave as price stabilizers, purchasing or selling when prices deviate from fundamentals.

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 V.

[INSERT TABLE V ABOUT HERE]

[13] There may be other reasons for using multiple brokers, for example, a manager with a large time critical order may employ several brokers to ensure the order is filled quickly, however we control for the impact of large trades by including the trade size variable. Therefore, the coefficient of the broker variables should capture the incremental effect of using multiple brokers over and above any effect due to time critical large trades.

The results in Table V show that investment style has a profound impact on the relation between past stock returns and institutional trading. Style neutral purchasing (selling) is negatively (positively) related to past stock returns. We find 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 5 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.

We investigate the influence of investment style on the contemporaneous effect and the forecasting ability of institutional trading by regressing 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 VI.

[INSERT TABLE VI ABOUT HERE]

In terms of the ability of managers to forecast future stock returns, the results reported in Table VI confirm that lagged values of the number of institutions purchasing are positively correlated with stock returns, and vice versa for sales, robust to varying degrees, over investment manager style. Consistent with prior studies we find that value managers have superior forecasting ability relative to growth managers.

The results also show that the contemporaneous effect of institutional trading depends on investment style. Style neutral purchasing and selling has a statistically significant impact, however growth manager selling does not. The contemporaneous effect of value managers is however, much stronger than style neutral or growth manager results and is of the opposite sign. 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. For example, during a supply shock (many investors wishing to sell for liquidity reasons), value managers may provide liquidity to the market, stabilizing prices, and requiring a discount for the service they provide as counterparty purchases.

If value managers are stabilizing prices, then the extent of this activity should be correlated with a measure of stock price instability. To test this, we proxy instability with lagged intra-day volatility and investigate the interaction effect between lagged volatility and value manager trading activity. We use the lag of volatility since value managers cannot observe the current level of price instability directly, and instead must infer instability from historical data. In unreported results, we confirm that volatility is highly serially correlated; suggesting that information about lagged instability is useful in determining current instability.[14]

If value managers are stabilizing prices, then the negative contemporaneous effect should be 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 lagged intra-day volatility, lagged intra-day volatility, aggregate manager trading volume, and control variables for risk factors.

$$y_{s,t} = \sum_{z=1}^{z=10} \beta_{k,z} NonValueBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{l,z} NonValueSell_{t-z} + \sum_{z=1}^{z=10} \beta_{m,z} SharesBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{n,z} SharesSell_{t-z}$$
$$+ \sum_{z=1}^{z=10} \beta_{o,z} ValueBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{p,z} ValueSell_{t-z} + \sum_{z=0}^{z=10} \beta_{q} .Volatility_{t-z-1} +$$

[14] Ideally, we would use the volatility of prices immediately prior to value manager trades, however we do not know the exact time when the manager trades, so we use the one day lag of volatility as a viable alternative.

$$\sum_{z=1}^{z=10} \beta_{r,z} Volatility_{t-z-1} * ValueBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{u,z} Volatility_{t-z-1} * ValueSell_{t-z} + \varepsilon_{s,t}$$

(4)

Intra-day volatility is calculated as follows:

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

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

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

In our regressions, we use standardized intra-day volatility to ensure our results do not reflect cross-sectional variation in volatility.

The results for the value manager regressions are reported in the columns of Table VII headed ‘Value’. We also replicate the results using growth oriented managers in order to confirm whether there is any degree of symmetry between value and growth oriented managers, and these results are reported in the columns headed ‘Growth’. The variable name *style* in the column of variable names, refers to either value or growth corresponding to the ‘Value’ and ‘Growth’ column headings.

[INSERT TABLE VII ABOUT HERE]

The results show that the value manager contemporaneous effect of purchasing is made less negative during periods of low intra-day volatility, as evidenced by the statistically significant negative coefficient of *StyleMgrBUY*Volatility*. Thus, when prices are relatively stable, value manager trading is not due to any price stabilizing behaviour and therefore should yield a positive (or less negative) contemporaneous effect. Conversely, when prices are relatively unstable, a portion of value manager trading is made due to their price stabilizing behaviour and hence they are able to transact with a negative contemporaneous effect.

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 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 growth-oriented managers are momentum traders while style neutral and value managers are contrarian. This is consistent with the 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 strongly positively correlated with lagged value manager purchasing, but is weakly 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 autocorrelation within investment styles, we conclude that institutional traders may either engage in information-based 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, use 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. We find that trade characteristics such as size and broker use can affect the contemporaneous effect of manager trading. We also find that the investment philosophy of managers has a profound effect on the measured contemporaneous effect. For example, value managers behave in a price stabilizing fashion, purchasing during periods of price instability, thereby causing their measured contemporaneous effect to be negative.

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, broker use, 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

	Growth	Value	GARP	Neutral
Number of managers	3	9	8	14
Number of Trade day observations	4551	7428	6142	12372
Number of Purchase day observations	2907	4435	2790	6337
Number of Sale day observations	1644	2993	3352	6035

Panel B - Distribution of Trade Size (Purchases)

	Mean	Stdev	25th	50th	75th
Dollar Trade Value ('000's)	544	1,307	83	219	582
Trade Size relative to Volume	4.92	20.35	0.46	1.52	4.59
Trade Size relative to SharesOutstanding	0.0080	0.0247	0.0008	0.0027	0.0081

Panel C - Distribution of Trade Size (Sales)

Dollar Trade Value	557	1,062	570	208	72
Trade Size relative to Volume	5.55	15.55	5.04	1.54	0.46
Trade Size relative to SharesOutstanding	0.0101	0.0319	0.0095	0.0029	0.0009

Table II
Institutional Trading Activity

This table reports descriptive statistics for the trading activity and portfolio weights for the largest 50 stocks in our sample. We select the largest stocks based on market capitalizations on the first day of our 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. The mean sum of weights is the sum of the portfolio weights for all stocks in the corresponding stock size bucket, averaged over all the managers in the sample. The Weights of stocks is the average weight allocated by the average manager to stocks in that stock size bucket. Managers with zero holdings are included in the calculation of these figures. All figures are in percent.

Panel A - Distribution of Trades Partitioned by Stock Rank

	3rd Largest Rank 35 to 50		2nd Largest Rank 16 to 34		1st Largest Rank 1 to 15	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
Number of Purchasing Managers	0.34	0.58	0.59	0.77	1.07	1.04
Number of Selling Managers	0.34	0.60	0.53	0.73	0.82	0.99
Trade Size relative to Volume (purchases)	4.52	18.18	3.57	10.50	2.83	6.16
Trade Size relative to Volume (sales)	4.14	16.22	4.03	11.33	2.45	6.88
Trade Size relative to SharesOutstanding (purchases)	0.0073	0.0250	0.0059	0.0189	0.0047	0.0100
Trade Size relative to SharesOutstanding (sales)	0.0093	0.0378	0.0065	0.0175	0.0038	0.0091

Panel B - Distribution of Manager Weights and Overweights

Sum of Weights of stocks within rank bucket	6.1534	4.7010	14.8020	6.0730	44.4080	11.9710
Weights of stocks within rank bucket	0.3846	0.9132	0.7791	1.3342	2.9605	2.7364
Sum of Overweights of stocks within rank bucket	1.2744	4.7010	3.2452	6.0730	5.4511	11.9710
Overweights of stocks within rank bucket	0.0797	0.9132	0.1708	1.3342	0.3634	2.7364

Table III
Institutional Trading and Past Stock Returns

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{z=1}^{z=10} \beta_{j,z} R_{s,t-z} + \beta_k MgrBuy_{t-1} + \beta_l MgrSell_{t-1} + \beta_m SharesBuy_{t-1} + \beta_n SharesSell_{t-1} +$$

$$+ \sum_{s=1}^{S} \beta_{a,s} .\delta_s + \sum_{s=1}^{S} \beta_{b,s} .\delta_s Market_t + \sum_{s=1}^{S} \beta_{c,s} .\delta_s .SIZE_t + \sum_{s=1}^{S} \beta_{d,s} .\delta_s .BMRatio_t + \sum_{s=1}^{S} \beta_{e,s} .\delta_s .Momentum_t + \varepsilon_{s,t}$$

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. δ 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 largest 50 stocks (based on market capitalizations on the first day of our sample period) are included. 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 - R-Squared

R-Squared	0.1371	0.1392	0.1097	0.1120
R-Bar	0.1271	0.1293	0.0994	0.1017

Panel B - Regression Estimates

	MgrBuy		MgrSell		SharesBuy		SharesSell	
Variable	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
MgrBuy(t-1)	0.5193	35.53 ***	0.0155	2.16 **	0.0025	7.61 ***	0.0000	-0.07
MgrSell(t-1)	-0.0001	-0.01	0.4753	33.83 ***	-0.0006	-1.82 *	0.0020	6.27 ***
Ret(t-1:t-5)	-2.0298	-3.15 ***	1.3350	2.12 ***	-0.0603	-2.41 ***	-0.0130	-0.42
Ret(t-1:t-10)	-2.6908	-2.88 ***	0.8793	0.96	-0.0978	-2.63 ***	-0.0685	-1.50
SharesBuy(t-1)	0.5336	6.58 ***	-0.2803	-3.34 ***	0.3836	25.34 ***	-0.0057	-0.92
SharesSell(t-1)	-0.0951	-1.18	0.7748	9.81 ***	-0.0066	-1.26	0.4103	28.68 ***

*****,**,*, indicate statistical significance at the 1, 5, and 10 percent levels respectively.**

Table IV
Institutional Trading, Contemporaneous Effect, Forecasting, and Trade Characteristics

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{z=1}^{z=10}\beta_{k,z}MgrBuy_{t-z} + \sum_{z=1}^{z=10}\beta_{l,z}MgrSell_{t-z} + \sum_{z=1}^{z=10}\beta_{m,z}SharesBuy_{t-z} + \sum_{z=1}^{z=10}\beta_{n,z}SharesSell_{t-z} +$$
$$+ \sum_{z=1}^{z=10}\beta_{o,z}LRGMgrBuy_{t-z} + \sum_{z=1}^{z=10}\beta_{p,z}LRGMgrSell_{t-z} + \sum_{z=1}^{z=10}\beta_{q,z}MultiBKR * MgrBuy_{t-q} + \sum_{z=1}^{z=10}\beta_{r,z}MultiMGR * MgrSell_{t-z}$$
$$+ \sum_{s=1}^{S}\beta_{a,s}.\delta_s + \sum_{s=1}^{S}\beta_{b,s}.\delta_s Market_t + \sum_{s=1}^{S}\beta_{c,s}.\delta_s.SIZE_t + \sum_{s=1}^{S}\beta_{d,s}.\delta_s.BMRatio_t + \sum_{s=1}^{S}\beta_{e,s}.\delta_s.Momentum_t + \varepsilon_{s,t}$$

The dependent variable y is the return stock ‘s’ on day ‘t’. *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. Large sized trades are those larger than the 75^{th} percentile of trade ranked by relative trade size. *MultiBKR* is an indicator variable set to unity when a manager on day ‘t’ uses more than one broker to purchase or sell stock ‘s’. MultiMgr is an indicator variable set to unity when a broker on day ‘t’ services more than one manager to purchase or sell stock ‘s’. 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. δ 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 largest 50 stocks (based on market capitalizations on the first day of our sample period) are included. 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 - R-Squared

R-Squared	0.1455	0.1505
R-Bar	0.1340	0.1364

Panel B - Regression Estimates

	Basic		TradeCharacteristics	
Variable	Coefficient	*t* -stat	Coefficient	*t* -stat
MgrBuy(t)	-0.0002	-1.13	-0.0003	-2.33 ***
MgrBuy(t-1:t-5)	0.0011	4.60 ***	0.0010	3.69 ***
MgrBuy(t-1:t-10)	0.0014	4.89 ***	0.0013	3.84 ***
MgrSell(t)	0.0001	1.04	0.0003	2.09 ***
MgrSell(t-1:t-5)	-0.0011	-4.30 ***	-0.0013	-4.66 ***
MgrSell(t-1:t-10)	-0.0011	-3.73 ***	-0.0013	-4.16 ***
MgrBuyLRG(t)			0.0002	1.79 *
MgrBuyLRG(t-1:t-5)			-0.0001	-0.56
MgrBuyLRG(t-1:t-10)			0.0002	0.45
MgrSellLRG(t)			-0.0003	-2.44 ***
MgrSellLRG(t-1:t-5)			0.0003	1.21
MgrSellLRG(t-1:t-10)			0.0004	1.11
MgrBuy*MultiBroker(t)			0.0008	1.28
MgrBuy*MultiBroker(t-1:t-5)			0.0025	1.97 **
MgrBuy*MultiBroker(t-1:t-10)			0.0017	0.98
MgrSell*MultiBroker(t)			-0.0005	-0.86
MgrSell*MultiBroker(t-1:t-5)			0.0004	0.27
MgrSell*MultiBroker(t-1:t-10)			0.0021	1.12
MgrBuy*MultiMgr(t)			0.0014	2.24 ***
MgrBuy*MultiMgr(t-1:t-5)			0.0016	1.14
MgrBuy*MultiMgr(t-1:t-10)			0.0002	0.12
MgrSell*MultiMgr(t)			-0.0007	-1.12
MgrSell*MultiMgr(t-1:t-5)			0.0002	0.17
MgrSell*MultiMgr(t-1:t-10)			0.0004	0.20
SharesBuy(t)	-0.0022	-1.42	-0.0027	-1.62
SharesBuy(t-1:t-5)	-0.0008	-0.29	-0.0006	-0.20
SharesBuy(t-1:t-10)	-0.0031	-0.88	-0.0035	-0.99
SharesSell(t)	-0.0025	-1.48	-0.0030	-1.75 *
SharesSell(t-1:t-5)	-0.0036	-1.13	-0.0034	-1.03
SharesSell(t-1:t-10)	-0.0046	-1.19	-0.0040	-0.99

*****,**,*, indicate statistical significance at the 1, 5, and 10 percent levels respectively.**

Table V
Institutional Trading, Past Stock Returns and Investment Style

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{z=1}^{z=10}\beta_j R_{s,t-z} + \beta_k NeutralBuy_{t-1} + \beta_l NeutralBuy_{t-1} + \beta_m GrowthBuy_{t-1} + \beta_n GrowthBuy_{t-1} + \beta_o ValueBuy_{t-1} + \beta_p ValueBuy_{t-1}$$

$$+ \sum_{s=1}^{S}\beta_{a,s}.\delta_s + \sum_{s=1}^{S}\beta_{b,s}.\delta_s Market_t + \sum_{s=1}^{S}\beta_{c,s}.\delta_s.SIZE_t + \sum_{s=1}^{S}\beta_{d,s}.\delta_s.BMRatio_t + \sum_{s=1}^{S}\beta_{e,s}.\delta_s.Momentum_t + \varepsilon_{s,t}$$

The dependent variable y is one of six variables, NeutralBuy, NeutralSell, GrowthBuy, GrowthSell, ValueBuy and ValueSell. NeutralBuy is the standardized number of neutral managers purchasing stock 's' on day 't', although we leave out the subscripts. NeutralSell is the standardized number of neutral managers selling stock 's' on day 't'. GrowthBuy is the standardized number of growth managers purchasing stock 's' on day 't'. GrowthSell is the standardized number of growth managers selling stock 's' on day 't'. ValueBuy is the standardized number of value managers purchasing stock 's' on day 't'. ValueSell 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. δ 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 largest 50 stocks (based on market capitalizations on the first day of our sample period) are included. 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 - R-Squared

R-Squared (BUYS)	0.1286	0.0608	0.1313
R-Bar (BUYS)	0.1184	0.0498	0.1211
R-Squared (SELL)	0.1062	0.0693	0.1488
R-Bar (SELLS)	0.0957	0.0584	0.1388

Panel B - Regression Estimates (BUYS)

	Neutral			Value			Growth		
Variable	Coefficient	*t*-stat		Coefficient	*t*-stat		Coefficient	*t*-stat	
NeutralMgrBuy(t-1)	0.5087	37.25	***	-0.0026	-0.39		-0.0039	-0.59	
NeutralMgrSell(t-1)	0.0066	1.02		0.0007	0.11		0.0130	2.00	**
ValueMgrBuy(t-1)	-0.0034	-0.52		0.3914	21.52	***	-0.0006	-0.10	
ValueMgrSell(t-1)	-0.0169	-2.55	**	-0.0247	-3.61	***	0.0158	2.37	***
GrowthMgrBuy(t-1)	0.0013	0.19		-0.0061	-0.85		0.5620	39.07	***
GrowthMgrSell(t-1)	0.0070	0.98		0.0059	0.81		-0.0100	-1.44	
Ret(t-1:t-5)	-0.0930	-0.14		-4.9891	-7.12	***	0.5412	0.81	
Ret(t-1:t-10)	-0.2437	-0.25		-6.4709	-6.33	***	0.8226	0.85	
SharesBuy(t-1)	0.3254	3.98	***	0.2711	3.10	***	0.4646	5.50	***
SharesSell(t-1)	-0.0256	-0.32		-0.0840	-1.00		-0.1147	-1.43	

Panel B - Regression Estimates (SELLS)

NeutralMgrBuy(t-1)	0.0029	0.44		0.0122	1.86	**	0.0175	2.72	***
NeutralMgrSell(t-1)	0.4292	29.35	***	0.0071	1.09		0.0000	0.00	
ValueMgrBuy(t-1)	0.0007	0.11		-0.0228	-3.43	***	-0.0112	-1.73	*
ValueMgrSell(t-1)	0.0006	0.08		0.4015	24.17	***	-0.0103	-1.59	
GrowthMgrBuy(t-1)	0.0212	3.03	***	0.0281	4.00	***	-0.0116	-1.71	*
GrowthMgrSell(t-1)	-0.0189	-2.65	***	0.0095	1.33		0.5236	39.09	***
Ret(t-1:t-5)	1.7002	2.58	***	3.8728	5.70	***	-2.1673	-3.31	***
Ret(t-1:t-10)	2.0555	2.14	***	5.0408	5.10	***	-3.6719	-3.84	***
SharesBuy(t-1)	-0.1833	-2.24	***	-0.1425	-1.67	*	-0.0324	-0.39	
SharesSell(t-1)	0.3843	4.70	***	0.0464	0.57		0.7794	9.85	***

*****,**,*, indicate statistical significance at the 1, 5, and 10 percent levels respectively.**

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

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{z=1}^{z=10} \beta_{k,z} NeutralBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{l,z} NeutralSell_{t-z} + \sum_{z=1}^{z=10} \beta_{m,z} SharesBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{n,z} SharesSell_{t-z} +$$
$$+ \sum_{z=1}^{z=10} \beta_{o,z} GrowthBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{p,z} GrowthSell_{t-z} + \sum_{z=1}^{z=10} \beta_{q,z} ValueBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{r,z} ValueSell_{t-z} +$$
$$+ \sum_{s=1}^{S} \beta_{a,s} .\delta_s + \sum_{s=1}^{S} \beta_{b,s} .\delta_s Market_t + \sum_{s=1}^{S} \beta_{c,s} .\delta_s .SIZE_t + \sum_{s=1}^{S} \beta_{d,s} .\delta_s .BMRatio_t + \sum_{s=1}^{S} \beta_{e,s} .\delta_s .Momentum_t + \varepsilon_{s,t}$$

The dependent variable y is the return stock ‘s’ on day ‘t’. *NeutralBuy* and *NeutralSell* is the standardized number of style neutral managers purchasing and selling stock ‘s’ on day ‘t’ respectively. *GrowthBuy* and *GrowthSell* is the standardized number of growth managers purchasing and selling stock ‘s’ on day ‘t’ respectively. *ValueBuy* and *ValueSell* 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. δ 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 largest 50 stocks (based on market capitalizations on the first day of our sample period) are included. 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 - R-Squared

R-Squared	0.1555
R-Bar	0.1424

Panel B - Regression Estimates

	Basic		
Variable	Coefficient	*t*-stat	
NeutralMgrBuy(t)	0.0007	5.54	***
NeutralMgrBuy(t-1:t-5)	0.0003	1.16	
NeutralMgrBuy(t-1:t-10)	0.0005	1.90	
NeutralMgrSell(t)	-0.0005	-4.19	***
NeutralMgrSell(t-1:t-5)	-0.0001	-0.69	
NeutralMgrSell(t-1:t-10)	-0.0001	-0.28	
ValueMgrBuy(t)	-0.0009	-8.02	***
ValueMgrBuy(t-1:t-5)	0.0010	4.54	***
ValueMgrBuy(t-1:t-10)	0.0014	5.27	***
ValueMgrSell(t)	0.0010	8.86	***
ValueMgrSell(t-1:t-5)	-0.0011	-4.98	***
ValueMgrSell(t-1:t-10)	-0.0010	-3.88	***
GrowthMgrBuy(t)	0.0000	-0.17	
GrowthMgrBuy(t-1:t-5)	0.0004	1.83	*
GrowthMgrBuy(t-1:t-10)	0.0004	1.42	
GrowthMgrSell(t)	-0.0001	-0.96	
GrowthMgrSell(t-1:t-5)	-0.0009	-3.83	***
GrowthMgrSell(t-1:t-10)	-0.0009	-3.39	***
SharesBuy(t)	-0.0017	-1.06	
SharesBuy(t-1:t-5)	-0.0005	-0.19	
SharesBuy(t-1:t-10)	-0.0024	-0.69	
SharesSell(t)	-0.0021	-1.30	
SharesSell(t-1:t-5)	-0.0056	-1.79	*
SharesSell(t-1:t-10)	-0.0064	-1.70	*

*****,**,*, indicate statistical significance at the 1, 5, and 10 percent levels respectively.**

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

This table reports regression estimates of the following regression equation:

$$y_{s,t} = \sum_{z=1}^{z=10} \beta_{k,z} NonStyleBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{l,z} NonStyleSell_{t-z} + \sum_{z=1}^{z=10} \beta_{m,z} SharesBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{n,z} SharesSell_{t-z} +$$
$$+ \sum_{z=1}^{z=10} \beta_{o,z} StyleBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{p,z} StyleSell_{t-z} + \sum_{z=0}^{z=10} \beta_{q} .Volatility_{t-z} +$$
$$\sum_{z=1}^{z=10} \beta_{r,z} Volatility_{t-z} * StyleBuy_{t-z} + \sum_{z=1}^{z=10} \beta_{u,z} Volatility_{t-z} * StyleSell_{t-z} + \varepsilon_{s,t}$$

The dependent variable y is the return stock 's' on day 't'. *NonStyleBuy* is the standardized number of non-value or non-growth managers purchasing stock 's' on day 't'. *NonStyleSell* is the standardized number of non-value or non-growth managers selling stock 's' on day 't'. *StyleBuy* is the standardized number of value or growth managers purchasing stock 's' on day 't'. *StyleSell* is the standardized number of value or growth 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. δ 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 largest 50 stocks (based on market capitalizations on the first day of our sample period) are included. 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).

0.1573	0.1499
0.1438	0.1363

Panel A - R-Squared

R-Squared	0.1573	0.1499
Adjusted R-Squared	0.1438	0.1363

Panel B - Regression Estimates

	Value			Growth		
Variable	Coefficient	*t-stat*		Coefficient	*t-stat*	
NonStyleMgrBuy(t)	0.0005	3.82	***	-0.0001	-0.63	
NonStyleMgrBuy(t-1:t-5)	0.0004	1.95	**	0.0009	4.11	***
NonStyleMgrBuy(t-1:t-10)	0.0006	2.36	***	0.0013	4.83	***
NonStyleMgrSell(t)	-0.0005	-4.02	***	0.0002	1.94	*
NonStyleMgrSell(t-1:t-5)	-0.0005	-2.36	***	-0.0008	-3.34	***
NonStyleMgrSell(t-1:t-10)	-0.0005	-1.80	*	-0.0008	-2.74	***
SharesBuy(t)	-0.0020	-1.26		-0.0025	-1.59	
SharesBuy(t-1:t-5)	-0.0004	-0.16		-0.0009	-0.30	
SharesBuy(t-1:t-10)	-0.0028	-0.82		-0.0032	-0.92	
SharesSell(t)	-0.0026	-1.59		-0.0035	-2.17	**
SharesSell(t-1:t-5)	-0.0039	-1.26		-0.0041	-1.31	
SharesSell(t-1:t-10)	-0.0047	-1.25		-0.0049	-1.29	
StyleMgrBuy(t)	-0.0009	-7.83	***	0.0000	-0.08	
StyleMgrBuy(t-1:t-5)	0.0010	4.49	***	0.0005	2.14	**
StyleMgrBuy(t-1:t-10)	0.0013	4.99	***	0.0005	1.81	*
StyleMgrSell(t)	0.0010	8.55	***	-0.0002	-1.62	
StyleMgrSell(t-1:t-5)	-0.0010	-4.89	***	-0.0008	-3.49	***
StyleMgrSell(t-1:t-10)	-0.0010	-3.71	***	-0.0008	-3.01	***
StyleMgrBuy*Volatility(t)	-0.0003	-2.95	***	0.0001	1.02	
StyleMgrBuy*Volatility(t-1:t-5)	0.0001	0.27		0.0002	0.78	
StyleMgrBuy*Volatility(t-1:t-10)	0.0005	1.98	**	0.0002	0.56	
StyleMgrSell*Volatility(t)	0.0003	2.95	***	-0.0001	-0.99	
StyleMgrSell*Volatility(t-1:t-5)	-0.0005	-2.60	***	0.0004	1.82	
StyleMgrSell*Volatility(t-1:t-10)	-0.0009	-3.39	***	0.0004	1.61	
Volatility(t)	0.0000	-0.26		-0.0001	-0.62	
Volatility(t-1:t-5)	0.0003	1.14		0.0002	1.05	
Volatility(t-1:t-10)	0.0003	1.62		0.0004	1.82	*

*****,**,*, indicate statistical significance at the 1, 5, and 10 percent levels respectively.**