Investment Manager Skill in Small-Cap Equities*

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Abstract:

This study presents evidence of significant stock selection skill on a risk-adjusted basis for small-cap equity managers. Our results are robust across three distinct observation units – total fund return, portfolio holdings and daily trades. More importantly, the magnitude of performance generated by managers in our sample indicates superior managerial ability, from both a statistical and economic perspective (even after controlling for transaction costs). The average monthly alphas range between 59.6 and 76.1 basis points, while the cumulative abnormal returns (CARs) over a one-month period for holdings-based and transactions-based metrics are 59.7 and 64.1 basis points, respectively. Our research provides important out-of-sample evidence concerning the value of active management, in a market segment which exhibits both lower liquidity and analyst coverage.

Keywords: SMALL-CAP EQUITY FUNDS; TRADING ACTIVITY; INVESTMENT PERFORMANCE; ACTIVE PORTFOLIO MANAGEMENT.

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1. Introduction

Do active managers have the requisite skills to successfully outperform the market? This question has been rigorously debated in both academic and practitioner communities for a number of decades. Despite a large number of empirical studies showing that the average active mutual fund does not provide investors with superior risk-adjusted returns to a passive investment strategy (even before management costs are considered), more recent evidence suggests the existence of some value in active management. [1, 2] In the small-cap industry, a number of studies report alphas which are both economically and statistically significant. These include U.S. evidence by Keim (1999), Christopherson *et al.* (2002) and Gorman (2003), and European evidence by Otten and Bams (2002), Dahlquist *et al.* (2000) and Engstrom (2004). The range of outperformance reported across these studies is documented to be between 1.65 and 3.2 percent per annum.

Recent research has investigated investment manager skill using a trade-level analysis of fund performance, observed from changes in monthly or quarterly portfolio holdings. These studies suggest active funds earn abnormal returns that at least partially account for the investment expenses incurred in active management. In particular, Wermers' (2000) evidence for U.S. mutual funds provides support for the Grossman and Stiglitz (1980) informational efficiency equilibrium. In Australia, both Gallagher and Looi (2005) and Pinnuck (2003) document superior stock selection ability for active managers. Gallagher and Looi (2005) also report that managers' stock picking ability is stronger across the universe of medium to small companies. The opportunities for exploiting private information in these companies may be higher due to the fact that that these stocks are less liquid, and analyst coverage is lower compared to larger stocks.

Given the recent evidence documenting active funds' ability, on average, this study examines an important and growing segment of the active investment industry – the small-cap equities universe.

[1] For example, see Jensen (1968), Malkiel (1995), Gruber (1996), and Ferson and Schadt (1996).
[2] Studies include Grinblatt and Titman (1989), Daniel, Grinblatt, Titman and Wermers (1997), Wermers (2000), and Cesari and Panetta (2002)).

The Australian case is interesting in a number of respects. First, it represents a market where active managers have been spectacularly successful in beating the market across the investment universe.[3] Second, the Australian small-cap industry has approximately doubled in size in the two-year period to June 2004, with assets under management exceeding $A4 billion. Third, our study has access to a unique and proprietary dataset comprising the daily trades and monthly portfolio holdings of a large and representative sample of small-cap equity managers. Utilising a unique dataset of monthly stockholdings and the daily transactions of active small-cap equity managers in Australia, we provide new evidence on the extent to which market efficiency prevails for stocks that have lower levels of information flow and analyst coverage, as well as significant institutional participation. Further motivation for an examination of small-cap management is the work of Bennett *et al.* (2003), who document that in recent times institutional investors in the U.S. have increased their preference toward small-cap stocks as a strategy of chasing perceived mispricing in these securities relative to large stocks. Our research therefore provides further examination of small-cap fund management ability.

Our research extends the literature by considering three different units of observation in evaluating manager skill - returns-based measures, portfolio holdings and daily transactions. This unification of various performance metrics represents a significant contribution to the performance evaluation literature. Indeed, Kothari and Warner (2001) and Pastor and Stambaugh (2002a, 2002b) identify potential biases arising from returns-based measures, and Gallagher and Looi (2005) argue that there are possible limitations from inferring trades from quarterly or monthly portfolio holdings because such a measure does not capture intra-period trading. To our knowledge, only Gallagher and Looi (2005) have employed finer data in performance evaluation through the use of daily trade data, although their research examines active funds which are more oriented towards larger-cap equities. In addition, our analysis controls for a new variable in risk models that can be applied to performance evaluation studies examining funds with lower liquidity.

[3] Source: Mercer Investment Consulting Performance Surveys of Australian Small-cap Equity Managers.

A unique feature of the small-cap equities industry is that firms have lower levels of liquidity, and trading by institutions in this market segment will have more significant transaction cost implications on fund returns. Since the seminal work of Banz (1981), a number of studies have since argued that the return premium from small stocks is due to the lower liquidity offered by such securities, and this risk proxy has also been considered in a number of asset pricing models.[4] This has led to a number of researchers, including Stoll and Whaley (1983), Fouse (1989), Sinquefield (1991), and Aitken and Ferris (1991) calling into question whether the small-firm premium is an exploitable strategy, given that smaller companies have lower liquidity, wider bid/ask spreads, and therefore significantly greater transaction costs which can substantially erode returns. Other studies have sought to solve the premium puzzle by considering the role of measurement and statistical errors (e.g. Roll, 1981, 1983; Reinganum, 1981, 1982; Blume and Stambaugh, 1983) tax loss selling (e.g. Roll, 1983; Brown *et al.*, 1983) and informational asymmetries (e.g. Klein and Bawa, 1977; Banz, 1981). In addition, market impact costs incurred by institutions have been shown to vary according to factors such as trade size, investment style and market conditions (e.g. Chan and Lakonishok, 1995; Keim and Madhavan, 1997 and Chiyachantana *et al.*, 2004). A recent study of price impact costs by Comerton-Forde *et al.* (2004) for actively managed small-cap equity funds in Australia reports round-trip costs of 69 basis points, which is more than twice the magnitude for funds trading in larger-cap equity securities in Australia (e.g. Gallagher and Looi, 2005). Keim (1999) provides an interesting examination of Dimensional Fund Advisor's small-cap index fund. Keim (1999) demonstrates that this fund outperforms the benchmark by an economically significant 2.2 percent per annum. This is achieved by sacrificing tracking error accuracy using a trading strategy that has a lower demand for immediacy.

We find out-of-sample evidence in Australia which is consistent with active small-cap equity managers exhibiting superior stock picking skill. Managerial skill in active management is also

[4] For example, Ahimud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia and Subrahmanyam (1998), Chordia, Subrahmanyam and Anshuman (2001), Ahimud (2002), Jones (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2003), Chan and Faff (2003).

consistent with Australian research documented by Gallagher and Looi (2005) and Pinnuck (2003) for larger-cap oriented funds. We report the magnitude of outperformance by small-cap equity funds is between 59.6 and 76.1 basis points per annum, which is both statistically and economically significant even after considering management expenses of only 8.4 basis points per annum. Our findings indicate that active managers have been able to exploit information advantages successfully and almost consistently across all institutional providers. Our evidence is therefore not consistent with an efficient capital market, and demonstrates the value of active management in small-cap equities.

The remainder of the paper is organised as follows. Section 2 provides a description of the data and a summary of daily trading activities of the active small-cap equity managers in our sample. Section 3 outlines the research design. Section 4 provides the empirical results examining the performance of active small-cap managers. Section 5 concludes the study and provides suggestions for future research.

2. Data and Institutional Background

Data is obtained from three sources: Mercer Investment Consulting, Portfolio Analytics, and the Securities Industry Research Centre of Asia-Pacific (SIRCA). The Mercer Manager Performance Analytics (Mercer) database provides pre-expense monthly-returns of 40 active Australian small-cap equity funds, both surviving and non-surviving, over the period 1991 to 2004. These funds are benchmarked to the S&P/ASX Small Ordinaries Accumulation Index. Funds from the Mercer database are included providing each fund has a minimum of 12 consecutive monthly returns between January 1991 to March 2004.[5] The resulting sample contains 34 active small-cap funds. The additional observations are required to accommodate the increased number of independent

[5] This requirement is necessary to ensure the results are both accurate and robust.

variables employed in the conditional based regression analysis.[6] The reduced conditional sample contains 25 active small-cap funds. Table 1 provides summary performance data for the funds examined in this study.

<<INSERT TABLE 1>>

This study also performs analysis on a subset of managers in the Mercer universe, using both the month-end portfolio holdings and daily transactions data. This confidential information is sourced from the *Portfolio Analytics Database*. This sub-sample comprises the individual month-end portfolio holdings (daily transactions) of 13 (12) active Australian small-cap equity funds. The number of unique institutions contributing portfolio holdings data (trading data) is 11 (10). The period of analysis using more granular data is January 1998 to March 2004. Table 2 presents summary statistics showing the trade frequency for purchases (Panel A) and sales (Panel B) over time by trade package and by order value. Trade packages represent aggregated daily trades in the same stock and where trades occur in the same direction, yet are executed over multiple days (following the method of Chan and Lakonishok, 1995). The trade level analysis illustrates that packages are executed over more than one day, and that trade package duration is a positive function of trade size. Purchases and sales are executed at approximately the same rate by trade frequency and package value. What is also noteworthy is that a significant component of the total package value remains incomplete two weeks after trading commenced (17.1 percent for buys and 17.4 percent for sells), which means that small-cap managers still trade a material quantity of their orders beyond the second week. Table 2 (Panel C) documents information on fund trading activity and portfolio turnover. What is evident here is that active small-cap managers indeed engage in a high degree of portfolio turnover (where turnover is defined as the quotient of all trading divided by average annual fund size). These results illustrate that small-cap managers turnover their portfolios between 102 percent and 237 percent per annum over the sample period.

[6] Restriction on the availability of data necessary to calculate the conditional variables meant the evaluation period for conditional-based analysis had to be reduced. (For example, dividend yield from the Small Ordinaries Accumulation Index was only available between the period January 1995 to March 2004)

<<INSERT TABLE 2>>

ASX stock information is procured from the Stock Exchange Automated Trading System (SEATS) through the Securities Industry Research Centre of Asia-Pacific (SIRCA). In addition, the ASPECT Financial database is also used to source accounting-related information to determine book-to-market equity ratios. In terms of the risk-adjusted performance techniques outlined in the research design, characteristic-matched benchmark portfolios are formed with reference to stocks comprising the S&P/ASX Small Ordinaries Index.

The Australian small-cap equity market accounts for a small fraction (less than 6%) of the total market capitalisation of Australian stocks listed on ASX. Small-cap stocks are often characterised as exhibiting relatively lower trade volume and trade frequency compared to larger stocks. Table 3 presents a comparison of ASX trading for small-cap stocks, large-cap equities and micro-caps. [7] Table 3 shows that the current level of liquidity in the Australian small-cap equity market is sufficient for institutional managers to actively participate in this segment of the market. Interestingly, liquidity has been increasing for small-cap stocks (relative to larger stocks) over time.

<<INSERT TABLE 3>>

The institutional small-cap equity fund market in Australia has grown substantially over recent years. The size of the market at 30 June 2004 was $A4 billion, and has almost doubled in size in the last two years (see Figure 1).

<<INSERT FIGURE 1>>

3. Research Design

[7] Note: micro-cap stocks are defined in this study as stocks that are constituents of the S&P/ASX All Ordinaries Index but are outside the S&P/ASX 300 Index.

This study examines the performance of small-cap equity managers using different performance metrics across three distinct units of observation: aggregate fund returns, month-end portfolio holdings, and daily transactions.

3.1 Holdings-Based Performance Measures

Holdings-based performance estimates are constructed to evaluate whether managers own stocks that generate returns in excess of an appropriate characteristic-matched benchmark portfolio. The abnormal return generated by manager *j* in month *t* is defined as follows;

$$AR_{jt} = \sum_{t=1}^{N} w_{i,t-1}(r_{i,t} - r_t^{DGTW(i),t-1}) \tag{1}$$

where $w_{i,t-1}$ is the portfolio weight for stock *i* at the end of month *t – 1*, $r_{i,t}$ is the month *t* return of stock *i* and $r_t^{DGTW(i),t-1}$ is the month *t* return of the characteristic matched benchmark portfolio that is assigned to stock *i* in month *t*. Characteristic benchmark portfolios are formed using the All Ordinaries index through a triple-sort across the dimension of 'size', 'book-to-market', and 'momentum'.[8] This study follows the approach outlined in Daniel *et al.* (1997) in constructing the characteristic-benchmark portfolios. Using the S&P/ASX All Ordinaries Index as the reference index, 24 benchmark portfolios are constructed on a monthly basis.[9] The All Ordinaries Index is selected as the referencing index, to ensure that benchmark portfolios reflect both the actual holdings and trading activities of underlying managers.[10] This approach is motivated by the findings of Elton

[8] Due to the results derived from the market liquidity model, this study elected to omit a sort across a fourth 'illiquidity' risk dimension when forming the characteristic benchmark portfolios. Moreover, it is arguable that an added risk dimension will have an adverse effect on the benchmark portfolios formed, in that, the added dimension will increase the concentration of the benchmark portfolios, thus making it more prone to mis-specification errors.

[9] On each formation date, the universe of stocks in the All Ords are first sorted into quartiles based on each stock's market-capitalisation immediately prior to the formation date. Then the stocks within each size quartile are further partitioned into three individual portfolios based on their respective book-to-market ratio. This ratio is calculated using the book-value of the underlying stock at the end of the firm's financial year during the calendar year preceding the formation date, and the market value (i.e., market-capitalisation) of the stock at the end of the preceding December. Finally, the stocks within each of the 12 portfolios (partitioned by size and book-to-market) are then further divided into two more portfolios based on the stocks' prior twelve-month return, giving a total of 24 characteristics benchmark portfolios.

[10] Preliminary tests found that around 35% of the actual stocks held by the small-cap managers in this sample are outside the Small Ordinaries Index and moreover approximately 30% of stocks bought by small-cap managers in this sample are also outside the Small Ordinaries Index.

et al. (1993) which reports that 'spurious' inferences of performance can arise due to mis-specified benchmarks.[11]

Motivated by Chen *et al*. (2000) and Pinnuck (2003), our study also examines the performance of inferred trades executed by managers by considering the changes in portfolio holdings between successive months. These authors argue that one will normally expect active trades to better represent the existence of private information compared to their aggregate holdings at period end. A positive (negative) trade value represents a 'purchase' ('sale') trade. Algebraically, inferred trades can be identified using the following equation;

$$IT_{ijt} = w_{ijt} - w_{ijt-1} \tag{2}$$

where IT_{ijt} refers to the inferred trade measure for stock *i* of manager *j* at time *t*, and w_{ijt} and w_{ijt-1} refer to the portfolio weight for stock *i* at the end of month *t* and *t – 1* respectively.[12]

3.2 Transactions-Based Performance Measures

Gallagher and Looi (2005) report evidence that inferred trades from monthly or quarterly holdings do not perfectly account for a manager's total trading intra period. To overcome this issue, Gallagher and Looi (2005) examine performance using a more refined level of data – the daily transactions of small-cap institutions. This study follows the approach outlined in Gallagher and Looi (2005) to examine the value of short-term information represented by the actual trading decisions of small-cap equity funds. Because daily trades are expected to be executed over several days, we proxy for an institution's orders by aggregating trades into trade packages using Chan and Lakonishok's (1995) trade packaging methodology.

A similar approach to the method outlined in Section 3.1 is adopted to calculate the daily abnormal returns generated by the underlying stocks in each trade package. The mean daily abnormal return

[11] In a similar vein, Gruber (1996), when discussing multi-factor models, argues that selected factors employed in multi-factor regression models should be reflective of the major type of assets held by the funds under examination, and warns that failure to do so can lead to substantially biased performance measures.
[12] This approach is consistent with the method used by Pinnuck (2003).

across the entire evaluation period is calculated using the individual daily abnormal returns generated by the underlying stocks across all trade packages. Cumulative abnormal returns (CARs) are then formulated as the sum of the mean daily abnormal returns across the accumulation period, where the reference dates for the CARs are procured from both the start and end dates of the respective trade packages. Algebraically, abnormal returns are calculated as follows;

$$\overline{AR_t} = \sum_{j=1}^{L} \sum_{t=1}^{D_j} (r_{ij,t} - r_t^{DGTW(ij),t-1}) \Big/ N \tag{3}$$

where $\overline{AR_t}$ is the mean daily abnormal return for day *t*, $r_{ij,t}$ is the day *t* return of stock *i* for manager *j*, $r_t^{DGTW(ij),t-1}$ is the day *t* return of the characteristic-matched benchmark portfolio that is assigned to stock *i* for manager *j* on day *t*, *L* represents the total number of underlying stocks traded across the entire sample, D_j represents the number of multiple trade packages in the same stock across different time periods and managers, and *N* is the total number of trade packages in the entire sample. Hence, algebraically, CARs are calculated as follows;

$$CAR_T = \sum_{t=1}^{T} \overline{AR}_t \tag{4}$$

where CAR_T is the cumulative abnormal return between day *t* and day *T*, inclusive. Adjustments to the test statistics for the CARs are made following the approach outlined in Gregory, Matatko, Tonks and Purkis (1994). Their procedure makes corrections for the understated standard errors induced as a result of estimating the CARs across overlapping periods.

3.3 Returns-Based Performance Measures

In this study, returns-based estimates are calculated using traditional risk models. The performance estimates are risk-adjusted returns based on the pre-expense performance of the funds in the sample.

3.3.1 Unconditional Models

The single factor model measures the risk-adjusted return due to the stock-selection ability of managers, where the level of skill is reflected by the magnitude of the alpha. The single-factor regression model is specified as follows;

$$r_{i,t} = \alpha_i + \beta_{iSO}(r_{m,t}) + \varepsilon_{i,t} \tag{5}$$

where $r_{i,t}$ and $r_{m,t}$ are the pre-expense monthly-return of fund *i* the S&P/ASX Small Ordinaries Accumulation Index (in excess of the monthly RBA risk-free rate), respectively. α_i is the unconditional alpha for the model and β_{iSO} is the systematic risk factor.

In order to ensure the robustness of our results, this study also examines performance using unconditional multi-factor models. The four-factor model uses similarly specified factors to those outlined in Elton *et al.* (1996), Gruber (1996) and Carhart (1997), and is expressed as;

$$r_{i,t} = \alpha_i + \beta_{iSO} r_{m,t} + \beta_{iSML} SML_t + \beta_{iGMV} GMV_t + \beta_{iPR1YR} PR1YR_t + \varepsilon_{it} \tag{6}$$

where *SML*, *GMV* and *PR1YR* are zero net investment, factor-mimicking portfolios designed to capture 'size', 'growth versus value' and 'momentum' effects respectively. The β_i's are the estimated sensitivities to the respective factors. The *SML* factor is constructed as the difference between returns of the S&P/ASX Small Ordinaries Accumulation Index and S&P/ASX 100 Accumulation Index. The *GMV* factor is the return difference between a portfolio of growth-stocks and a portfolio of value-stocks based on the Citigroup Global Markets Australian Small-cap Growth and Value indices. The *PR1YR* factor is constructed as the return difference between an equally-weighted portfolio of stocks performing in the top 20% and bottom 20% of the S&P/ASX Small Ordinaries Index in the previous 11 months, lagged one-month. All factors are re-formed on a monthly basis.

We also contribute to the literature by considering the importance of liquidity as a risk factor in performance models. Controlling for liquidity is motivated given that smaller stocks trade less frequently than larger securities, as well as giving consideration to the seminal work of Amihud and Mendelson (1986). More recently, Chan and Faff (2003) present evidence showing turnover (a proxy for market liquidity) is negatively related to stock returns in the Australian market. Accordingly, we include a market liquidity factor as a fifth risk control variable to improve estimates of risk-adjusted performance for small-cap equity funds. The five factor model is specified as follows;

$$r_{i,t} = \alpha_i + \beta_{iSO} r_{m,t} + \beta_{iSML} SML_t + \beta_{iGMV} GMV_t + \beta_{iPR1YR} PR1YR_t + \beta_{iIML} IML_t + \varepsilon_{it} \qquad (7)$$

where *IML* is the zero investment, factor-mimicking portfolio designed to capture the 'illiquidity' effect of smaller stocks, and β_{iIML} is the factor loading on the liquidity variable (*IML*). The *IML* factor is constructed as the difference in returns between the equally-weighted portfolio of stocks comprising the top 20% and bottom 20% of the S&P/ASX Small Ordinaries Index, ranked by their average daily turnover in the previous month. All factors are re-formed on a monthly basis.

3.3.2 Conditional Models

Ferson and Schadt (1996) demonstrate the inability of unconditional performance measures to control for the time-variation in expected risk and return. They motivate the use of conditional models which account for a manager's reliance on public information variables. Consistent with Ferson and Schadt (1996), this study employs the following conditional regression model;

$$r_{i,t} = \alpha_i + \beta_{iSO}(r_{m,t}) + \beta_i' z_{t-1}(r_{m,t}) + \varepsilon_{i,t} \qquad (8)$$

where Z_{t-1} is a vector of pre-determined public information variables, $z_{t-1} = Z_{t-1} - E(Z)$ is a vector of the deviations of Z_{t-1} from their unconditional mean, and β_i' is the vector of factor loadings on the respective public information variables Z_{t-1} on a monthly basis. The four conditional variables used are the 30-day Treasury bill (TB) yield, dividend yield (DY) on the ASX Small Ordinaries Index, term structure of interest rates (TS) measured as the difference in yield between 30-day bills and 10-year Commonwealth government bond, and a dummy variable for the month of January.

3.3.3 Market-Timing Models

Market-timing measures the ability of active investment managers to forecast future price movements in the market. We examine market timing using the Treynor and Mazuy (1966) approach;

$$r_{i,t} = \alpha_i + \beta_{iSO}(r_{m,t}) + \gamma_i (r_{m,t})^2 + \varepsilon_{i,t} \tag{9}$$

where γ_i (gamma) is the estimate of market timing skill using a quadratic term that extends (5).

4. Empirical Results

4.1 Performance using Holdings-Based Data

This section examines small-cap equity managers' skill utilising monthly portfolio holdings data. Table 4 presents the mean abnormal returns, which are estimated at an aggregate holdings level across the respective evaluation periods. The results demonstrate that, on average, funds in the sample generate positive mean abnormal returns over the six-month period, of which the mean abnormal return over the first three months is also significantly positive. More importantly, the mean abnormal returns are also economically significant. For example, the mean abnormal return earned over the first month is more than 38 basis points, which is equivalent to an annualised return of more than 5 percent. These results are consistent with previous literature in finding that the stocks held by managers generate subsequent outperformance.[13] Overall, the results reveal that managers indeed possess stock picking talent.

<<INSERT TABLE 4>>

We next examine fund performance by testing more informative trade-based estimates. Specifically, trades are inferred from changes in the level of holdings across consecutive holding periods, whereby

[13] See for example Daniel *et al.* (1997), Chen, Jegadeesh and Wermers (2000) and Pinnuck (2003). Although the magnitude of abnormal returns is slightly higher in this study, the difference is most likely explained by the difference in the investment universes being examined.

a positive (negative) change implies a ‘buy’ (‘sell’) trade. Table 5 (Panel A) documents that the mean abnormal returns for stocks purchased are consistently positive across all six evaluation periods, with the first period also exhibiting a significantly positive mean abnormal return. In contrast, the results for ‘sell’ trades demonstrate that most of the subsequent mean abnormal returns generated by stocks are negative. Although, the mean abnormal return is only significantly negative in the second period, the lack of statistical significance in the abnormal return for first month may be caused by the fact that investment managers sell securities well prior to deterioration in a stock’s price.

<<INSERT TABLE 5>>

Interestingly, when comparing the results in Table 5 (Panel A) with that of the mean abnormal return formulated based on aggregate holdings for buy trades (60 basis points) is significantly larger than the mean abnormal return for stocks held in Table 4 (39 basis points). Consistent with the literature, this finding suggests that small-cap managers have a tendency to hold onto stocks beyond the timeframe for which they maximise profitability. Chen *et al*. (2000) argue that this behaviour reflects the need of managers to consider other factors (including transaction costs) in addition to the future profitability of the stock when making a sell decision.

We next examine the relative performance on the basis of a manager’s trade package size in Table 5 (Panel B). This analysis is motivated given that medium-sized trades are more likely to reflect information (on average) held by the manager, whereas smaller trades are more likely to be liquidity motivated. Indeed, Chakravarty (2001) finds a disproportionate number of informed trades are associated medium-sized trades. We define a ‘Large’ trade as trade packages with an underlying dollar value greater than A$1,000,000. A ‘Medium’ trade is defined as a package value between

A$100,000 and A$1,000,000, and a 'Small' package less than A$100,000.[14] If managers hold valuable private information, we would expect medium size trades to generate higher abnormal returns compared to smaller trades. Interestingly, the results in Panel B show the mean abnormal return 'Medium' buy trades is comparatively larger than 'Large' buy trades. One potential explanation for this finding relates to the relative size and illiquid nature of the Australian small-cap equity market. It is arguable that due to the characteristics of the small-cap market it becomes increasingly difficult for managers operating in this market to execute large trades, without being adversely affected by price impact.[15] Overall, the results presented in Table 5 (Panel B) indicates that small-cap managers are successful at undertaking both 'Small' and 'Medium' sized trade packages. This is supported by the finding that stocks purchased in both categorises generate mostly positive mean abnormal returns in subsequent evaluation periods (particularly over the initial four months), while the stocks sold in both categories generate mostly negative mean abnormal returns (particularly over the first two months).

4.2 Results of Transactions-Based Estimation

This section reports the results derived from employing the performance evaluation procedure outlined in Gallagher and Looi (2005). The use of daily transaction data facilitates the examination of the value of short-term information content that is associated with each decision to trade. However, there is a major issue concerning the use of individual transactions as the basis for formulating performance estimates. This issue arises because, for institutional investors, a moderately sized position in a stock (relative to the market) can represent a significant portion of the stock's total daily trading volume (this applies especially to small-cap stocks). Therefore, it is normal practice amongst investment managers to split orders into smaller parcels. The concern for performance studies is therefore the need to aggregate individual daily transactions in a meaningful

[14] These values are selected by giving consideration to the market in which small-cap managers operate. In addition, we also conduct tests on a relative trade size basis.
[15] Especially since most studies find, buy side trades incur a significantly higher level of price impact. For example, see Chan and Lakonishok (1993 and 1995).

manner that will enable the identification of the aggregated order. We follow the approach outlined in Chan and Lakonishok (1995) to group trades into 'packages' which reflects the desired order quantity to be traded given a common information signal.

Performance using trade data is examined across two separate event windows. The first window utilises the starting date of each trade-package as its reference date, and ends 60 days before the start of each trade-package (hereafter referred to as [Day (-60 to 0)]). The second window utilises the end date of each trade-package as the reference date and ends 60 days after the end of each trade-package (hereafter referred to as [Day (0 to +60)]). Adjustments to fund performance with respect to 'priced' risk factors is undertaken using Daniel *et al.* (1997) characteristic-benchmark portfolios formed along the risk dimensions of 'size', 'book-to-market' and 'momentum'. In the spirit of CAPM, and the type of portfolio holdings of small-cap managers, we reference the broader S&P/ASX All Ordinaries Index as being an important reference portfolio in constructing these characteristic-portfolios. Abnormal returns are calculated on a daily basis as the difference between the buy-and-hold returns of the underlying stocks and that of the corresponding characteristic-matched benchmark portfolios. Individual daily abnormal returns are then aggregated over respective accumulation periods to formulate the CARs.

Table 6 presents summary statistics concerning the daily abnormal returns generated by stocks traded by active Australian small-cap equity managers. The results for the window [Day (0 to +60] demonstrate that, on average, abnormal returns for stocks purchased are positive for 42 days (out of the 60 days event window), of which 16 days also exhibit statistical significance. Comparatively, none of the 18 days exhibit negative abnormal returns. Given the mean daily abnormal return is also highly economically significant (i.e., 2.1 basis points per-day is equivalent to more than 46 basis points per-months), these results corroborate our earlier finding that active small-cap equity managers are capable of identifying and exploiting mispriced securities.[16]

[16] This is assuming that there are 22 trading days in a month.

<<INSERT TABLE 6>>

Table 7 reports the CARs over selected accumulation periods. This new performance metric enables a more detailed analysis of the timeframe during which the private information possessed by active small-cap managers is generated in the market. The results for the period [Day (0 to +60)] report a positive and increasing trend for the CARs accumulated over varying periods subsequent to the end of 'buy' trade-packages. In particular the CARs accrued over the initial 10 day period exhibits both statistical and economical significance. In contrast, CARs accumulated over periods subsequent to the end of 'sell' trade-packages are always negative. Overall, these results provide further confirmation that collectively, active Australian small-cap equity managers are successful stock pickers. The first 10 days subsequent to the end of 'buy' trade-packages is the most significant period over which private information possessed by small-cap managers is released to the market. Thus, there is a clear indication that abnormal returns earned as result of superior stock-selection ability is mostly concentrated over a short period of time. These findings provide further motivation for the use of trading data in performance evaluation.

<<INSERT TABLE 7>>

Next, we extend Table 7 to examine abnormal returns from daily trading data according to absolute trade size.[17] Similar to Table 5, the results in Table 8 report that buy trades with the largest underlying values are not the ones generating the highest CARs. Comparatively, both 'Medium' and 'Small' size trade packages accumulate relatively higher levels of abnormal returns than 'Large' size packages (with 154, 110 and 65 basis points being the respective CARs accumulated over the 60 day evaluation period subsequent to the end of 'buy' trade-packages for 'Small', 'Medium' and 'Large'

[17] The definition of trade size is outlined on page 14.

size trades respectively). The CARs for stocks sold in 'Small' and 'Medium' trade partitions are always consistently negative over the initial five-day period subsequent to the end of the trade packages. In contrast, the results for 'Large' size trade packages suggest that active Australian small-cap equity managers are selling too early, since the CARs accumulated over periods subsequent to the end of 'sell' trade packages are both positive and large in magnitude. There are two possible explanations for this behaviour. First, managers do not necessarily rely on negative information alone to execute a sell decision. Rather, a number of factors may contribute to the overall decision making process, including exogenous liquidity demands on a manager. Second, because the Australian small-cap equity market is smaller and less liquid than S&P/ASX 100 stocks, managers will need to trade more patiently, and larger orders will likely be executed using smaller-sized trades over a longer period of time. Consequently, this practice may force managers to initiate sell orders at a stage earlier than perhaps the information they possess demands of them (Chan and Lakonishok (1995) report the existence of such behaviour).

<<INSERT TABLE 8>>

Table 2 reports that the 'Large' sell trade packages are over represented by trade-packages that are formed across longer time horizons. For example, almost 57 percent of trade-packages categorised into the 'Large' sell category are executed over a period of more than four-trading days. In comparison, only 26 percent of the trade-packages in the complete uncategorised 'sell' sample are formed over a period consisting of more than four-trading days. This finding clearly illustrates that small-cap managers take significantly longer periods of time to complete 'Large' sell orders. Managers also appear to attempt to minimise price impact, where active Australian small-cap equity managers initiate their sell orders at a stage much earlier than perhaps demanded by the private information held by these managers.

Finally, we examine abnormal returns from daily trading data according to relative trade size. As the absolute trade size definition fails to control for the size of the funds undertaking the trade, we also conduct a relative trade size test measured as the ratio of a fund's trade package and month *t-1* total fund assets. The results in Table 9 are slightly different to those presented in Table 8. Both the 'Medium' and 'Large' trade categories generated the highest abnormal returns over the 60 day evaluation period, equal to 127 and 120 basis points, respectively, while the 'Small' trade category accumulated 87 basis points. However, the CARs over the initial 10 days illustrates that 'Small' and 'Medium' size trades significantly outperforms 'Large' size trades. The CARs for stocks sold in both the 'Small' and 'Medium' trade partitions are almost always consistently negative, whereas, the results for the sale of the 'Large' trade partition are always positive, (and therefore suggests that active small-cap equity managers are perhaps selling prematurely).

<<INSERT TABLE 8>>

4.3 Results of Returns-Based Estimations

This section reports the results derived from employing returns-based analysis for a larger sample of institutional funds captured in the Mercer Investment Consulting universe of managers. Our motivation for these tests is to provide comparisons to the measures of performance documented above, as well as to also consider performance metrics that have been used extensively in the literature (including small-cap performance studies published overseas).

4.3.1 Conditional/Unconditional Single-Factor and Market-Timing Measures

Table 10 (Panel A) presents the performance estimates from both the conditional/unconditional single-factor models. Consistent with our earlier findings, active Australian small-cap equity funds exhibit superior stock-selection ability. The magnitude of the alphas from the unconditional model is also highly economically significant, with small-cap equity managers, on average, outperforming their respective benchmark by more than 76 basis points per-month (or 9 percent per annum). Even after accounting for monthly fund management expenses, which are approximately 9 basis points per-month, the average alpha remains economically significant at more than 67 basis points per-month (or 8 percent per annum).[18]

<<INSERT TABLE 10>>

We next evaluate returns-based performance with a Ferson and Schadt (1996) conditional model which accounts for the time-variation in expected return and risk. Consistent with Ferson and Schadt (1996), we document a reduction in the magnitude of alphas. However, there still remains a significant component of excess returns generated by managers which is robust to controls on public information variables. Table 10 (Panel B) presents the results estimated using both the conditional/unconditional Treynor and Mazuy models that enables a performance decomposition between market timing and stock picking. Overall, the results are consistent with prior research that managers do not exhibit superior market-timing ability.[19, 20]

4.3.2 Multi-Factor Model Performance Measures

Table 11 presents the regression estimates derived from a four-factor model that accounts for the small companies' market proxy, stock size, book-to-market ratio and price momentum. We provide the results of these additional returns-based performance tests to determine whether manager skill is explained by a fund's exposure to factor loadings on stock size, book-to-market, momentum and liquidity. Our results provide further support that active Australian small-cap equity managers collectively possess superior stock-selection ability. Small-cap managers on average outperform the benchmark by an economically significant 68 basis points per month (or 8 percent per-annum) for

[18] Monthly expenses are estimated using the current population of active Australian small-cap equity funds.
[19] Results obtained from the Henriksson and Merton model (unreported) are consistent with that of the Treynor and Mazuy model, in showing a lack of superior market-timing ability.
[20] See for example, Treynor and Mazuy (1966), Kon (1983), Chang and Lewellen (1984), Henriksson (1984), Lee and Rahman (1990), Coggin et al. (1993), Ferson and Schadt (1996), Becker, Ferson, Myers and Schill (1999), Hallahan and Faff (1999), Sawicki and Ong (2000), Gallagher (2001), and Bollen and Busse (2001).

the four-factor model, which declines to 59.6 basis points when we consider a five-factor model controlling for market liquidity.[21]

<<INSERT TABLE 11>>

4.3.3 Multi-Factor Model Fund Flow Measures

Table 12 presents the regression estimate used to control for the effects of fund flow. Using the five-factor model as the base model, we control for fund flow using three different proxies for the fund flow variable. The results from the different tests are both consistent with each other and with the results previously discussed. Moreover, the results demonstrate that after controlling for fund flow, active small-cap managers still exhibit superior stock selection ability (ranging between 54.2 basis points to 62.6 basis points).

<<INSERT TABLE 12>>

4.4 Further Robustness Test

To further analyse the robustness of our results, whereby active Australian small-cap managers successfully identify and exploit mis-priced securities, this section examines the frequency distribution of the CARs (formulated on a stock level) for both holdings and transaction-based performance estimates. This analysis is motivated in terms of better understanding the reliance of managers on individual stock selection bets. In other words, skilful managers should be expected to generate abnormal returns across their portfolio holdings, rather than relying on outperformance being generated from a small, concentrated number of stocks held.

[21] In unreported results, different versions of the 'illiquidity' factor as well as different definitions of liquidity (i.e., in this study active bid-ask spread is also used to proxy for liquidity) are tested to ensure that the results reported are robust. The results from unreported tests are consistent with the results discussed, in the sense that they also fail to report any conclusive evidence to suggest that active Australian small-cap equity funds are exposed to an 'illiquidity' factor.

Figure 2 shows that the histograms for the CARs, across all three distinct performance metrics, are relatively normally distributed, and where stock positions contribute to overall fund performance.

<<INSERT FIGURE 2>>

4.5 Transaction Cost Considerations

Overall, there is overwhelming evidence to support the proposition that active Australian small-cap equity managers possess superior skill in identifying and exploiting mis-priced securities. However, all the performance estimates discussed thus far have being calculated on a pre-expense basis. While explicit costs charged by investment managers still leads us to conclude that the alphas are economically significant, analysis of the size of implicit costs is also of significant interest. It is important to note that the performance results presented in this study already account for price impact, as the returns generated are those actually achieved by the fund managers after market effects. While the measurement and analysis of transaction costs are beyond the scope of this study, recent research by Comerton-Forde *et al.* (2004) finds that transaction costs are indeed significant, with total price impact (on a principal-weighted basis) averaging 0.37 percent for purchases, and -0.32 percent for sales on a principal-weighted basis. When analysis is constrained to S&P/ASX Small-Ords stocks only, costs approximately double in size. On a principal-weighted basis, total price impact averaged 0.65 percent for purchases and -0.63 percent for sales, implying a round-trip transaction cost of 1.27 percent. This suggests that the overall transactions costs incurred by small-cap managers are reduced by the fact that they trade stocks outside their specified investment universe.

5. Conclusion and Suggestions for Future Research

Our study examines actively managed small-cap equity management in Australia using a unique database of portfolio holdings and transactions. Our study is the first to examine active portfolio management in smaller stocks within the Australian market. Consistent with the international evidence, we find evidence of superior stock selection ability in the Australian small-cap equity market. Interestingly, the magnitude of abnormal returns remains economically significant, even after accounting for transaction costs. Monthly performance estimates, after transaction costs, range between 51.2 and 67.7 basis points. Performance is also found to be relatively consistent across various risk models, including our research design which relies on finer measures of performance sourced from portfolio holdings and transactions data.

In our study, the comparatively lower levels of efficiency in the Australian small-cap equity market may well help us to explain the size of the alphas generated by small-cap managers. Small-cap equities exhibit a lower number of analysts following stocks, and limited coverage market may result in these securities having lower levels of market efficiency. Alternatively, some may link the success of the industry to significant funds flowing into the Australian small-cap equity market over the last few years. Indeed, Warther (1995) finds that monthly fund returns are strongly correlated with concurrent unexpected fund flows, which suggests there is a positive relationship between fund inflows and the subsequent returns generated by portfolios. In addition, larger market participants may also exercise increasing influence over the performance of stocks given their relative size on the register of smaller companies, which may lead to price inflation concerns similar to those documented by Carhart, Kaniel, Musto and Reed (2002). Their research suggests that price inflation around quarter-end is around two percent per year for small-cap stocks. Future research is warranted concerning the drivers of outperformance in small-cap equity management. This is the subject of current research.

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Table 1

Cross-Sample Comparisons

Panel A reports the mean gross-return generated by sub-sample sets of funds. Panel B presents the non-risk adjusted returns-based performance estimates, calculated as the difference between the gross returns generated by small-cap equity funds and the benchmark return (S&P/ASX Small-Ordinaries Accumulation Index). Panel C presents the risk-adjusted performance estimates using the single factor model:

$$r_{i,t} = \alpha_i + \beta_{iSO}(r_{m,t}) + \varepsilon_{i,t}$$

where $r_{i,t}$ and $r_{m,t}$ are the raw monthly excess-returns of fund *i* and the ASX/S&P Small Ordinaries Accumulation Index, respectively, over the one-month risk-free rate from the Reserve Bank of Australia (RBA). α_i is the unconditional Jensen alpha and β_i's are the factor loadings. All return metrics are calculated on a monthly-basis and expressed in percentages.

Cross-Sample Comparison of Monthly Fund Performance				
Panel A: Gross-Return				
	Complete	Unconditional	Conditional	Holdings/ Transactions[22]
Mean Return	1.808	1.565	1.498	1.693
Std. Dev	0.882	0.647	0.633	0.690
t-statistics	-	1.331	1.531	0.416
No. Sign and Pos	32	27	23	10
Total No. of Funds	40	34	25	12
Panel B: Gross Minus Benchmark (Non-risk adjusted)				
	Complete	Unconditional	Conditional	Holdings/ Transactions
Mean Return	0.781	0.679	0.804	0.959
Std. Dev	0.647	0.617	0.466	0.658
t-statistics	-	0.692	-0.148	-0.831
No. Sign and Pos	28	23	22	9
Total No. of Funds	40	34	25	12
Panel C: Jensen's Alpha (Risk-adjusted)				
		Unconditional	Conditional	Holdings/ Transactions
Alpha (α)	-	0.761	0.814	1.010
Std. Dev	-	0.594	0.459	0.630
t-statistics	-	-	-0.489	-1.315
No. Sign and Pos	-	26	21	9
Total No. of Funds	-	34	25	12

[22] Fund data provided by one of the institutions was not complete, and accordingly was not included here.

Table 2

Summary Statistics for Transactions-Based Data

Trade packages are defined as either a series of purchases or sales made by managers in the same stock, where the number of trading days between consecutive trades is no more than four days. Panel A and Panel B presents the frequency distribution of both trade packages and their associated market value. 'Packs' refers to the percentage of trade packages completed within the indicated number of days, and 'Value' refers to the ratio of total trading activity to the underlying dollar value of trades completed in the period. Panel C provides annual summary statistics of the daily trading activities of 11 active Australian small-cap equity managers over the period January 1998 to March 2004. Turnover refers to the average turnover of all funds in the sample for the respective year, where turnover for a specific fund (*i*) is defined as [sum of all trades of fund (*i*) in year *t*/average size of fund (*i*) in year *t*].

Statistics for Trade Packages in the Period January 1998 to March 2004										
Size Quartiles	1 Day		2-3 Days		4-6 Days		7-10 Days		>11 Days	
	Packs	Value	Packs	Value	Packs	Value	Packs	Value	Packs	Value
Panel A: Buys										
Q1 (%)	15.85	9.56	2.95	3.29	3.42	5.00	2.22	4.02	1.16	3.63
Q2 (%)	30.72	18.82	10.43	9.71	7.42	9.94	2.07	4.96	2.58	10.75
Q3 (%)	9.96	5.84	2.76	2.64	2.14	2.72	1.47	3.69	0.43	2.28
Q4 (%)	3.50	1.74	0.40	0.28	0.35	0.63	0.08	0.04	0.08	0.46
Total	60.03	35.96	16.54	15.92	13.33	18.30	5.84	12.71	4.26	17.11
Panel B: Sells										
Q1 (%)	12.99	8.45	2.20	1.65	3.54	4.21	0.28	0.35	0.78	1.74
Q2 (%)	29.41	20.57	12.82	10.48	7.30	8.98	4.48	7.93	4.18	11.95
Q3 (%)	9.27	6.78	3.26	3.92	2.28	3.40	0.96	1.46	1.04	3.07
Q4 (%)	3.39	1.98	0.45	0.41	0.56	0.61	0.74	1.42	0.08	0.63
Total	55.06	37.78	18.72	16.47	13.68	17.21	6.46	11.15	6.08	17.39

Panel C: Summary Statistics								
	1998	1999	2000	2001	2002	2003	2004 (to March)	Years 1998-2003
Total Dollar Value of Buy Packs (A$,000)	15,146	35,147	132,152	497,467	748,795	1,068,031	215,992	2,496,738
Total Dollar Value of Sell Packs (A$,000)	4,044	12,173	83,874	349,811	643,553	853,429	214,784	1,946,884
Average Value of Buy Packs (A$,000)	72	106	210	362	317	342	382	235
Average Value of Sell Packs (A$,000)	81	112	319	459	391	324	362	281
Std. Dev of the Value of Buy Packs (A$,000)	353	163	486	631	500	588	607	454
Std. Dev of the Value of Sell Packs (A$,000)	328	120	442	951	568	572	860	497
No. of Buy Packs	209	333	629	1375	2365	3120	566	8031
No. of Sell Packs	50	109	263	762	1644	2630	594	5458
No. of Buy Trades	271	478	1062	2995	5786	8470	1534	19062
No. of Sell Trades	59	156	490	1584	4623	8101	1690	15013
Turnover (%) p.a. = ($\sum$buys + sells)/average fund size	136.51	102.03	126.02	164.41	172.25	237.04	n/a	156.38

Table 3

The Relative Trading Activity of Small-Cap Stocks on the Australian Stock Exchange (ASX)

Table 1 reports the average daily trading activity for a typical stock included in the S&P/ASX 100 Index, S&P/ASX Small Ordinaries Index, and micro-cap stocks (ex-S&P/ASX 300) listed on the Australian Stock Exchange. The reported variables include the average daily value traded, the average daily trade volume, the average daily trade frequency and the average daily off-market volume for a typical stock in each category. In addition, a comparison of the proportion of trading activity is also provided. Results are reported for the last four years and the last 12 months to 30 June 2004.

Daily Average Trading Activities for a Typical Stock in the Respective Sectors				
Panel A: 4 Years to 30 June 2004				
Indices	Avg. Daily Value	Avg. Daily Trade Volume	Avg. Daily Trade Frequency	Off-Market Volume
S&P/ASX 100	13,104,576	2,110,604	353	763,445
S&P/ASX Small Ordinaries	543,784	470,263	58	161,513
Micro-Cap	181,111	259,298	16	38,144
Small Ordinaries/ASX100 (%)	4.14	22.28	16.43	21.16
Micro-Caps/ASX100 (%)	1.38	12.29	4.53	5.00
Panel B: 12 Months to 30 June 2004				
S&P/ASX 100	15,967,542	2,671,994	402	924,851
S&P/ASX Small Ordinaries	803,995	690,594	70	214,260
Micro-Cap	264,405	461,919	22	66,913
Small Ordinaries/ASX100 (%)	5.04	25.85	17.41	23.17
Micro-Caps/ASX100 (%)	1.66	17.29	5.47	7.23

Table 4

Holdings-Based Performance Measures

This table presents the performance of small-cap equity funds using holdings-based measures. The mean abnormal return is the average of the monthly abnormal returns generated by small-cap managers in the sample, whereby the monthly abnormal returns of individual managers are calculated on a value-weighted basis using the individual abnormal returns generated by the underlying stocks held by the managers. The weights assigned is determined by the relative value, in dollar terms, of the underlying position in each stock relative to the aggregate portfolio as at the end of the month. This weight then remains constant throughout subsequent evaluation periods. Adjustment for risk is made using characteristic-matched benchmark portfolios. The abnormal return for a particular stock in a particular month is calculated as the monthly difference between the buy-and-hold return of the underlying stock and the buy-and-hold return of a value-weighted portfolio of stocks having similar characteristics across the risk dimensions of 'size', 'book-to-market' and 'momentum'. Algebraically, the abnormal-return for manager *j* in month *t* is defined as follows;

$$AR_{jt} = \sum_{t=1}^{N} w_{i,t-1}(r_{i,t} - r_t^{DGTW(i),t-1}) \tag{6.11}$$

where $w_{i,t-1}$ is the portfolio weight for stock *i* at the end of month *t – 1*, $r_{i,t}$ is the month *t* return of stock *i,* and $r_t^{DGTW(i),t-1}$ is the month *t* return of the characteristic-matched benchmark portfolio that is assigned to stock *i* during month *t – 1.* All returns related measures are expressed in percentages.

Holdings-Based Performance Estimates									
	Event Time								
	AR+1		AR+2		AR+3		AR+4	AR+5	AR+6
Mean	0.384		0.275		0.280		0.165	0.212	0.101
t-statistics	2.46	**	1.81	*	1.82	*	1.05	1.40	0.64
Std. Dev	3.528		3.437		3.468		3.524	3.390	3.492
Maximum	20.257		19.171		18.372		17.068	15.566	16.719
Minimum	-25.177		-25.108		-20.410		-23.064	-19.602	-22.213
No. Positive (%)	60.27		57.48		57.22		54.69	54.52	51.62
No. Negative (%)	39.73		42.52		42.78		45.31	45.47	48.38
Total Observations [a]	511		508		505		501	497	492
CAR	0.384		0.659		0.939		1.104	1.316	1.417

***, **, and * indicates significance at the 1%, 5% and 10% (two-tail) level, respectively.

[a] The reason for the drop-off in the number of observations occurs due to not all stocks in the sample having trading prices for the entire six-month period. This is because some of the stocks were delisted during the evaluation period.

Table 5

Holdings-Based Inferred Trade Performance Measures

This table presents the results derived from inferred trade measures. Trade is inferred from changes in the level of portfolio holdings between consecutive months, where a positive change implies a purchase trade and a negative change implies a sell trade. Algebraically, inferred trade can be computed using the following equation:

$$IT_{ijt} = w_{ijt} - w_{ijt-1}$$

where IT_{ijt} refers to the inferred trade measure for stock *i* of manager *j* at time *t*, and w_{ijt} and w_{ijt-1} refer to the portfolio weight for stock *i* at the end of month *t* and *t – 1* respectively. Using the trade metric value, inferred trades are further partitioned into sub-samples of 'buy' and 'sell' trades. Once the sub-samples are formed, the procedure outlined in Table 3 is then applied to arrive at the estimated values presented in Panel A. Panel B presents the results derived from holdings-based inferred trade performance measures decomposed according to trade size. Three different categories of trade size are employed - 'Large' trade is defined as a trade that has an underlying dollar value that is greater than A$1,000,000, a 'Medium' trade is defined as a trade with an underlying dollar value between A$100,000 and A$1,000,000 and a 'Small' trade is a trade with a value less than A$100,000. Once the sub-samples are partitioned, the estimation procedure outlined in Table 3 is then applied to arrive at the estimated values presented in Panel B. 'Weight' refers to the percentage of stocks categorised into each respective trade size category. All returns related measures are expressed in percentages.

		Event Time						
		AR+1	AR +2	AR +3	AR +4	AR +5	AR +6	Weight (%)
Panel A: Holdings-Based Inferred Trade Performance Estimates								
Buys								
Mean		0.597	0.238	0.369	0.163	0.279	0.167	-
t-statistics		2.28 **	0.79	1.09	0.57	1.12	0.63	-
Std. Dev		5.761	6.582	7.430	6.195	5.417	5.671	-
Maximum		27.989	41.494	42.689	23.241	20.706	20.025	-
Minimum		-28.181	-59.411	-81.694	-35.974	-25.513	-45.428	-
No. Positive (%)		56.28	56.96	55.02	54.01	51.70	54.83	-
CAR		0.597	0.835	1.204	1.367	1.646	1.813	-
Sells								
Mean		-0.141	-0.709	-0.081	0.022	-0.353	-0.084	-
t-statistics		-0.37	-1.65 *	-0.26	0.07	-0.99	-0.29	-
Std. Dev		7.750	8.784	6.248	5.960	7.165	5.849	-
Maximum		28.827	26.524	19.774	45.541	31.068	26.280	-
Minimum		-55.814	-87.568	-33.935	-24.944	-39.946	-20.410	-
No. Positive (%)		50.00	49.40	48.66	46.56	44.19	50.75	-
CAR		-0.141	-0.850	-0.931	-0.909	-1.262	-1.346	-
Panel B: Holdings-Based Inferred Trade Performance Estimates - Trade Level Breakdown								
Buys								
Large	Mean	-0.184	0.599	1.180	-0.422	-0.021	0.125	17.01
	t-statistics	-0.44	1.34	2.11 **	-0.72	-0.05	-0.27	
Medium	Mean	1.254	-0.096	0.071	0.506	0.219	0.097	55.96
	t-statistics	3.12 ***	-0.30	0.21	1.91 *	0.88	0.38	
Small	Mean	0.386	0.107	0.185	0.430	-0.093	-0.945	27.03
	t-statistics	0.79	0.24	0.32	0.87	-0.23	-1.48	
Sells								
Large	Mean	0.240	0.776	-0.702	0.296	-0.886	-0.444	18.31
	t-statistics	0.55	1.38	-1.45	0.70	-1.79 *	-0.50	
Medium	Mean	-0.223	-0.963	0.008	0.288	-0.093	-0.139	54.98
	t-statistics	-0.55	-2.30 **	0.02	0.35	-0.25	-0.44	
Small	Mean	-0.967	-0.883	-0.607	-0.726	-1.236	-0.062	26.71
	t-statistics	-1.88 *	-1.57	-0.73	-0.89	-1.70 *	-0.12	

***, **, and * indicates significance at the 1%, 5% and 10% (one-tail) level, respectively.

Table 6

Transactions-Based Performance Measures (Abnormal Returns)

This table presents the results derived from transactions-based performance measures. Specifically, this table reports the average of the mean daily abnormal returns for the respective evaluation periods. The mean abnormal return for a particular day is calculated on an equally-weighted basis as the average of the daily abnormal returns for all trade-packages in the sample for that day. The daily abnormal return for a single trade-package is calculated as the difference between the one-day buy-and-hold return of the underlying stock in the package and the one-day buy-and-hold return of a value-weighted portfolio of stocks having similar characteristics across the risk dimensions of 'size', 'book-to-market' and 'momentum' as the stock under examination. Algebraically, the mean daily abnormal return for day *t* is calculated as follows;

$$\overline{AR_t} = \sum_{j=1}^{L} \sum_{t=1}^{D_j} (r_{ij,t} - r_t^{DGTW(ij),t-1}) \Big/ N$$

where $\overline{AR_t}$ is the mean daily abnormal return for day *t*, $r_{ij,t}$ is the day *t* return of stock *ij*, $r_t^{DGTW(ij),t-1}$ is the day *t* return of the characteristic matched benchmark portfolio that is assigned to stock *i* for manager *j* on day *t*, *L* represents the total number of underlying stocks traded across the entire sample, D_j represents the number of multiple trade-packages in the same stock across different time periods and managers, and *N* is the total number of trade-packages in the entire sample. Note the daily abnormal returns calculated over the window [Day (-60 to 0)] utilises the start date of a trade-package as the reference date, while the daily abnormal returns calculated over the window [Day (0 to +60)] utilises the end date of a trade-package as the reference date. All returns related measures are expressed in percentages.

Summary Statistics of Mean Daily Abnormal Returns Over the Event Window [Day (-60 to +60)]				
	Day (-60 to 0)		Day (0 to +60)	
	Buy	Sell	Buy	Sell
Mean Abnormal Returns	0.042	0.027	0.021	-0.006
Std. Dev	0.044	0.037	0.036	0.044
Maximum	0.142	0.120	0.192	0.094
Minimum	-0.103	-0.101	-0.039	-0.153
No. of Days with Positive Abnormal Returns	54	48	42	32
No. of Days with Negative Abnormal Returns	6	12	18	28
No. of Days with Significant and Positive Abnormal Returns	29	18	16	2
No. of Days with Significant and Negative Abnormal Returns	2	2	0	5

Table 7

Transactions-Based Performance Measures (CARs)

This table presents the results derived from transactions-based performance measures. Cumulative abnormal returns are calculated as the sum of individual daily mean abnormal returns over corresponding accumulation periods, whereby the mean daily abnormal returns are calculated on an equally weighted basis using the procedure outlined in Table 5. The CARs calculated over the period [Day (-60 to 0)] utilises the start date of a trade-package as the reference date, while the CARs calculated over the period [Day (0 to +60)] utilises the end date of a trade-package as the reference date. Algebraically, the CARs are calculated as follows;

$$CAR_T = \sum_{t=1}^{T} \overline{AR}_t$$

where CAR_T is the cumulative abnormal return measured between day t and day T inclusive and $\overline{AR}_t$ is the mean daily abnormal return for day t. Further the *Z-statistics* for the CARs are calculated using an approach consistent with Gregory *et al*. (1994), which provides correction to the understated standard errors induced as a result of estimating the CARs across overlapping periods.

Transactions-Based Performance Estimates											
	Buys		Sells		Buy - Sell		Buys		Sells		Buy - Sell
AR [-60] [a]	0.036		0.013		0.023	AR [+1] [a]	0.192	***	-0.034		0.226
CAR [-59; -60]	0.154	***	0.045	***	0.109	CAR [0; +2]	0.309	***	-0.131	***	0.440
CAR [-58; -60]	0.157	***	0.054	*	0.103	CAR [0; +3]	0.390	***	-0.116	*	0.506
CAR [-57; -60]	0.237	***	0.101	*	0.136	CAR [0; +4]	0.414	***	-0.165	*	0.579
CAR [-56; -60]	0.292	***	0.174	*	0.118	CAR [0; +5]	0.465	***	-0.071		0.536
CAR [-51; -60]	0.496	**	0.428		0.069	CAR [0; +10]	0.576	**	-0.040		0.616
CAR [-46; -60]	0.832	*	0.673		0.159	CAR [0; +15]	0.621		-0.211		0.832
CAR [-41; -60]	1.034		0.604		0.429	CAR [0; +20]	0.641		-0.201		0.842
CAR [-31; -60]	1.597		0.903		0.695	CAR [0; +30]	0.866		-0.183		1.049
CAR [-21; -60]	2.044		1.111		0.933	CAR [0; +40]	1.016		-0.441		1.457
CAR [-11; -60]	2.449		1.342		1.107	CAR [0; +50]	1.099		-0.358		1.457
CAR [-1; -60]	2.499		1.606		0.892	CAR [0; +60]	1.248		-0.380		1.628

***, **, and * indicates significance at the 1%, 5% and 10% (two-tail) level, respectively.

[a] The statistical significance for abnormal return series (i.e. AR -60 and AR +1) are calculated using standard *t*-tests.

Table 8

Transactions-Based Performance Measures by Absolute Trade Size (CARs)

This table presents the results derived from transactions-based performance measures decomposed by trade size. Three different categories of trade size are employed - a 'Large' trade is defined as a trade that has an underlying dollar value that is greater than A$1,000,000, a 'Medium' trade is defined as a trade with an underlying dollar value between A$100,000 and A$1,000,000 and a 'Small' trade is a trade with a value less than A$100,000. Once the sub-samples are partitioned, the estimation procedure outlined in Table 6 is applied to compute the estimated values presented in the table. Further, the *Z-statistics* for the CARs are calculated using an approach consistent with Gregory *et al*. (1994), which provides a correction for the understated standard errors induced as a result of estimating the CARs across overlapping periods.

Transactions-Based Performance Estimates - Trade Size Decomposition												
	Buys						Sells					
	Small Trade		Medium Trade		Large Trade		Small Trade		Medium Trade		Large Trade	
AR [-60] [a]	0.049		0.024		0.052		-0.044		0.028		0.176	*
CAR [-59; -60]	0.173	***	0.111	**	0.375	***	-0.006		0.041	**	0.308	**
CAR [-58; -60]	0.130	***	0.135	***	0.495	**	-0.028		0.043	*	0.511	*
CAR [-57; -60]	0.187	***	0.240	***	0.523	*	0.027		0.082	*	0.572	*
CAR [-56; -60]	0.190	***	0.332	***	0.610		0.129		0.115		0.773	*
CAR [-51; -60]	0.298		0.570	**	1.132		0.366		0.385		0.995	
CAR [-41; -60]	0.825		1.140		1.487		0.444		0.617		1.261	
CAR [-31; -60]	1.359		1.722		2.088		0.578		1.038		1.500	
CAR [-21; -60]	1.861		2.142		2.395		0.651		1.273		2.152	
CAR [-11; -60]	2.160		2.626		2.839		0.930		1.500		2.189	
CAR [-1; -60]	1.977		2.742		3.791		1.328		1.694		2.307	
AR [+1] [a]	0.202	***	0.183	***	0.195	*	-0.176	***	0.041		0.115	
CAR [0; +2]	0.362	***	0.272	***	0.279	***	-0.275	***	-0.062		0.073	
CAR [0; +3]	0.476	***	0.331	***	0.322	***	-0.276	***	-0.065		0.279	
CAR [0; +4]	0.545	***	0.331	***	0.268		-0.324	**	-0.119		0.269	
CAR [0; +5]	0.604	***	0.386	***	0.233		-0.183		-0.067		0.417	
CAR [0; +10]	0.641	*	0.553	*	0.362		-0.368		0.089		0.609	
CAR [0; +20]	0.628		0.694		0.31		-0.882		0.132		0.719	
CAR [0; +30]	0.717		1.059		0.277		-1.06		0.229		1.112	
CAR [0; +40]	1.085		1.039		0.418		-1.593		0.067		1.481	
CAR [0; +50]	1.303		1.022		0.449		-1.468		0.148		1.384	
CAR [0; +60]	1.544		1.093		0.644		-1.534		0.191		1.135	

***, **, and * indicates significance at the 1%, 5% and 10% (two-tail) level, respectively.

[a] The statistical significance for abnormal return series (i.e. AR -60 and AR +1) are calculated using standard *t*-tests.

Table 9

Transactions-Based Performance Measure by Relative Trade Size (CARs)

This table presents the results derived from transactions-based performance measures decomposed by relative trade size, whereby relative trade size is measured using actual trade value divide by fund size. Three different categories of trade size are employed – the 'Large' category contains the largest 33% of relative trade packages in the sample, the 'Medium' category contains the next 33% of trade packages in the sample and the 'Small' contains the remaining 33% of trade packages in the sample. Once the sub-samples are partitioned, the estimation procedure outlined in Table 6 is applied to compute the estimated values presented in the table. Further, the *Z-statistics* for the CARs are calculated using an approach consistent with Gregory *et al*. (1994), which provides a correction for the understated standard errors induced as a result of estimating the CARs across overlapping periods.

Transaction Based Performance Estimates - Relative Trade Size Decomposition												
	Buys						Sells					
	Small Trade		Medium Trade		Large Trade		Small Trade		Medium Trade		Large Trade	
AR[-60] [a]	0.016		0.010		0.061		-0.020		0.038		0.026	
CAR [-59;-60]	0.157	***	0.110	*	0.183	***	0.006	***	0.103	***	0.035	
CAR [-58;-60]	0.159	***	0.102		0.212	*	-0.002	***	0.122	***	0.043	
CAR [-57;-60]	0.166	***	0.278		0.280		0.065	***	0.085	***	0.143	
CAR [-56;-60]	0.186	***	0.389		0.332		0.155	**	0.154	**	0.200	
CAR [-51;-60]	0.077		0.773		0.696		0.424		0.398		0.405	
CAR [-41;-60]	0.576		1.588		1.099		0.287		0.818		0.622	
CAR [-31;-60]	1.068		2.226		1.741		0.556		0.799		1.226	
CAR [-21;-60]	1.439		2.583		2.478		0.599		1.040		1.538	
CAR [-11;-60]	1.554		3.118		3.104		0.710		1.299		1.744	
CAR [-1;-60]	0.960		3.354		3.723		0.977		1.559		1.966	
AR[+1] [a]	0.240	***	0.215	***	0.107	**	-0.212	***	0.032		0.073	
CAR [0;+2]	0.484	***	0.254	***	0.145	***	-0.350	***	-0.169	***	0.121	***
CAR [0;+3]	0.564	***	0.355	***	0.190	***	-0.407	***	-0.135		0.176	**
CAR [0;+4]	0.631	***	0.381	***	0.187	**	-0.478	***	-0.155		0.115	
CAR [0;+5]	0.679	***	0.499	***	0.161		-0.341		-0.020		0.124	
CAR [0;+10]	0.591		0.669		0.382		-0.490		0.080		0.259	
CAR [0;+20]	0.324		0.924		0.466		-0.866		-0.328		0.545	
CAR [0;+30]	0.315		1.164		0.767		-0.960		-0.438		0.817	
CAR [0;+40]	0.494		1.296		0.865		-1.669		-0.361		0.672	
CAR [0;+50]	0.629		1.227		0.974		-1.517		-0.247		0.648	
CAR [0;+60]	0.865		1.265		1.208		-1.409		-0.238		0.461	

***, **, and * indicates significance at the 1%, 5% and 10% (two-tail) level, respectively.

[a] The statistical significance for abnormal return series (i.e. AR -60 and AR +1) are calculated using standard *t*-tests.

Table 10

Conditional and Unconditional Single-Factor and Market-Timing Performance Measures

Panel A reports performance estimates from the conditional and unconditional single-factor models over the period March 1995 to March 2004 and January 1991 to March 2004, respectively. Panel B reports results estimated from the conditional and unconditional Treynor and Mazuy models over the same respective periods. The dependent variables in these regressions are the time-series of monthly pre-expense excess-return of the funds over the one-month risk-free rate retrieved from the RBA. The independent variables are the monthly return of the Small Ordinaries Accumulation Index over the one-month risk free rate retrieved from the RBA, and the squared value of the excess-return on the Small Ordinaries Index over the one-month risk-free rate (from the RBA, which applies only to the Treynor and Mazuy model). The four conditional variables are the yield of the 30-day Treasury bill (*TB*), the dividend yield on the Small Ordinaries Index (*DY)*, the difference in yield between short and long-term interest rates (*TS*), and a dummy variable that takes the value of unity if the corresponding month at $t - 1$ is January and zero otherwise (*Jan*). α_i is a measure of stock-selection ability, γ_i is a measure of market-timing ability and β_i's are the respective factor loadings. Statistical significance is calculated at the 90% level and the *t-statistics* are calculated using White (1980) heteroskedastic-consistent standard errors.

Panel A: Summary Statistics for Returns-Based Performance Estimates														
	α_i		β_{SO}	γ	*Adj* R^2	α_i		β_{SO}	γ	β_{TB}	β_{DY}	β_{TS}	β_{Jan}	*Adj* R^2
	Unconditional Single-Factor Measure					Conditional Single-Factor Measure								
Mean	0.761	***	0.879	-	0.724	0.726	***	0.747	-	-267.47	-31.00	-13.39	0.181	0.745
Std. Dev	0.594		0.157	-	-	0.479		0.369	-	509.79	41.02	32.22	0.257	-
Maximum	2.395		1.152	-	0.949	2.294		1.385	-	670.95	58.38	31.33	0.738	0.969
Minimum	-1.07		0.507	-	0.416	-0.076		-0.065	-	-1553.73	-137.01	-89.88	-0.3	0.396
No. Pos	32		34	-	-	23		24	-	6	4	13	19	-
No. Sig and Pos	26		34	-	-	19		19	-	6	0	0	3	-
No. Sig and Neg	0		0	-	-	0		0	-	1	7	3	1	-
No. of Managers	34		34	-	-	25		25	-	25	25	25	25	-
Panel B: Performance Estimates Derived from the Treynor and Mazuy Model														
	Unconditional Treynor and Mazuy Measure					Conditional Treynor and Mazuy Measure								
Mean	0.718	***	0.865	0.49	0.716	0.774	***	0.764	0.048	-198.33	-29.14	-10.36	0.21	0.748
Std. Dev	0.699		0.146	2.685	-	0.599		0.412	2.545	573.35	39.44	36.08	0.247	-
Maximum	2.186		1.098	7.983	0.954	2.346		2.066	8.94	1552.01	51.94	90.69	0.717	0.973
Minimum	-1.329		0.51	-7.668	0.406	-0.364		-0.144	-3.432	-1664.97	-130.98	-88.66	-0.302	0.389
No. Pos	32		34	19	-	23		24	10	10	4	11	20	-
No. Sig & Pos	20		34	4	-	16		21	3	1	0	1	5	-
No. Sig & Neg	1		0	2	-	0		0	3	2	8	1	1	-
No. of Funds	34		34	34	-	25		25	25	25	25	25	25	-

***, **, and * indicates significance at the 1%, 5% and 10% (two-tail) level, respectively.

Table 11

Unconditional Multi-Factor Performance Measures

This table reports results estimated from the five-, four- and three-factor models over the period March 1995 to March 2004, March 1995 to March 2004 and June 1992 to March 2004, respectively. The dependent variables of these regressions are the time-series of monthly pre-expense excess-returns of the funds (over the one-month risk-free rate sourced from the RBA). The five independent variables are the monthly return of the Small Ordinaries Accumulation Index over the one-month risk free rate, the *SML* factor which is calculated as the difference in returns between the Small Ordinaries Index and the S&P/ASX 100 Index, the *GMV* factor which is obtained from the difference in return between a growth and a value portfolio of stocks based on the Citigroup Global Markets Australian small-cap growth and value indices, the *PR1YR* factor which is constructed as the difference between the equally-weighted returns of two portfolios formed from either the top 20% or the bottom 20% of stocks on the Small Ordinaries Index ranked by their previous eleven-month returns lagged one-month. All factors are re-calculated on a monthly basis. The *IML* factor is constructed as the difference between the equally-weighted returns of two portfolios formed from either the top 20% or the bottom 20% of stocks on the Small Ordinaries Index ranked by their average daily turnover in the previous month. All factors are re-calculated on a monthly basis. All returns-related measures are expressed in percentages. α_i is a measure of stock-selection ability and β_i's are the factor loadings for the respective factors. Statistical significance is calculated at the 90% level and the *t-statistics* are calculated using White (1980) heteroskedastic-consistent standard errors.

	α		β_{SO}	β_{SML}	β_{GMV}	β_{PR1YR}	β_{IML}	$Adj\ R^2$
Panel A: Five-Factor Model								
Mean	0.596	***	0.89	-0.017	0.086	-0.028	-0.028	0.785
Std. Dev	0.519		0.202	0.166	0.376	0.24	0.094	-
Maximum	1.398		1.443	0.428	0.784	0.251	0.14	0.963
Minimum	-0.754		0.509	-0.352	-1.025	-1.344	-0.303	0.47
No. Positive	29		34	14	25	19	12	-
No. Significant and Positive	18		34	1	10	6	2	-
No. Significant and Negative	0		0	0	2	2	6	-
No. of Managers in the Sample	34		34	34	34	34	34	34
Panel B: Four-Factor Model								
Mean	0.68	***	0.885	-0.038	0.118	-0.038	-	0.735
Std. Dev	0.493		0.201	0.174	0.373	0.242	-	-
Maximum	1.947		1.407	0.402	0.983	0.156	-	0.939
Minimum	-0.357		0.486	-0.526	-0.882	-1.374	-	0.339
No. Positive	32		34	11	25	17	-	-
No. Significant and Positive	19		34	2	11	5	-	-
No. Significant and Negative	0		0	0	0	2	-	-
No. of Managers in the Sample	34		34	34	34	34	-	-
Panel C: Three-Factor Model								
Mean	0.638	***	0.902	-0.032	0.042	-	-	0.729
Std. Dev	0.589		0.167	0.127	0.311	-	-	-
Maximum	1.938		1.246	0.226	0.748	-	-	0.941
Minimum	-1.33		0.527	-0.273	-0.579	-	-	0.385
No. Positive	30		34	13	23	-	-	-
No. Significant and Positive	20		34	0	11	-	-	-
No. Significant and Negative	0		0	2	2	-	-	-
No. of Managers in the Sample	34		34	34	34	-	-	34

***, **, and * indicates significance at the 1%, 5% and 10% (two-tail) level, respectively.

Table 12

Unconditional Multi-Factor Fund Flow Measure

This table reports estimated fund flow measure, using the five factor model as the base model, over the period March 1995 to March 2004. Both independent and dependent variables are consistent with the five-factor model are as defined above. There are three different proxies for the fund flow variable. In Panel A the fund flow variable (β_{FF}) is proxied using the mean dollar value of resources flowing into the funds in the Aspect Financial Database, over the respective evaluation period. In Panel B the fund flow variable (β_{FF}) is proxied using the lagged mean dollar value of resources flowing into the funds in the Aspect Financial Database, over the respective evaluation period. In Panel C the relative fund flow variable (β_{RFF}) is proxied using the mean dollar value of resources flowing into the funds in the Aspect Financial Database, divided by the mean total assets of those funds at (*t -1*), over the respective evaluation period.

Panel A: Fund Flow at Time *t*

	α	β_{SO}	β_{SML}	β_{GMV}	β_{PR1YR}	β_{IML}	β_{FF}	*Adj* R^2
Mean	0.554	0.854	-0.030	0.079	-0.007	-0.059	0.0001615	0.793
Std. Dev	0.551	0.258	0.199	0.329	0.222	0.117	0.0009416	-
Maximum	2.138	1.490	0.437	1.018	0.301	0.098	0.0054905	0.973
Minimum	-0.697	0.005	-0.720	-0.876	-1.176	-0.530	-7.55E-09	0.482
No. Positive	30	34	14	24	22	10	30	-
No. Significant and Positive	19	34	1	7	8	0	9	-
No. Significant and Negative	0	0	1	1	2	6	0	-
No. of Managers in the Sample	34	34	34	34	34	34	34	34

Panel B: Fund Flow at Time *t+1*

	α	β_{SO}	β_{SML}	β_{GMV}	β_{PR1YR}	β_{IML}	β_{FF}	*Adj* R^2
Mean	0.626	0.869	-0.051	0.171	-0.009	-0.074	1.026E-10	0.800
Std. Dev	0.600	0.189	0.176	0.362	0.261	0.101	1.534E-09	-
Maximum	2.334	1.332	0.427	1.297	0.312	0.119	2.54E-09	0.964
Minimum	-0.532	0.430	-0.483	-0.893	-1.405	-0.317	-5.94E-09	0.473
No. Positive	29	34	11	27	24	8	21	-
No. Significant and Positive	17	34	2	9	8	0	6	-
No. Significant and Negative	0	0	1	1	2	10	4	-
No. of Managers in the Sample	34	34	34	34	34	34	34	34

Panel C: Relative Fund Flow

	α	β_{SO}	β_{SML}	β_{GMV}	β_{PR1YR}	β_{IML}	β_{RFF}	*Adj* R^2
Mean	0.542	0.881	-0.025	0.083	-0.005	-0.058	0.110	0.794
Std. Dev	0.545	0.210	0.198	0.329	0.224	0.114	0.168	-
Maximum	2.127	1.495	0.431	1.012	0.300	0.097	0.615	0.974
Minimum	-0.705	0.485	-0.697	-0.883	-1.190	-0.517	-0.497	0.484
No. Positive	30	34	14	24	23	8	28	-
No. Significant and Positive	16	34	1	8	8	0	13	-
No. Significant and Negative	0	0	1	1	2	5	0	-
No. of Managers in the Sample	34	34	34	34	34	34	34	34

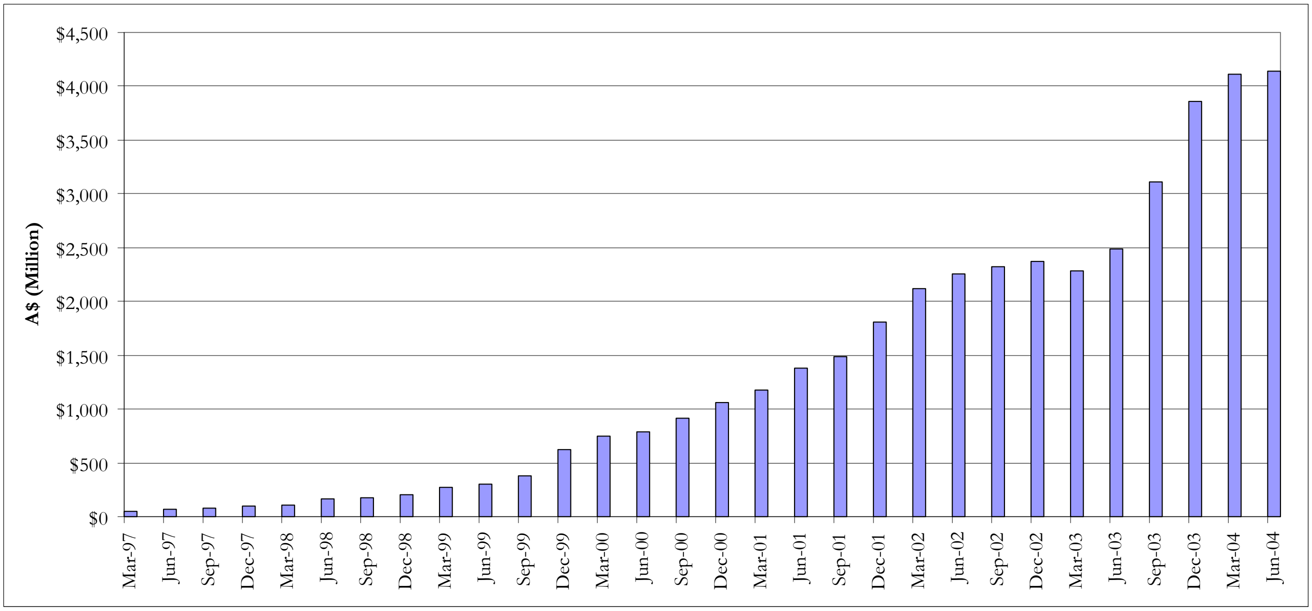
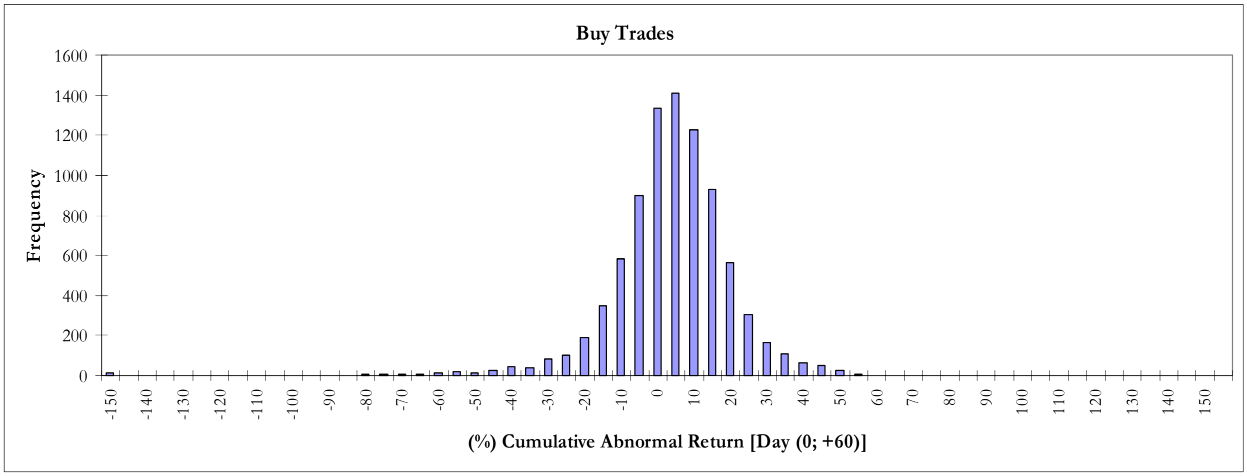
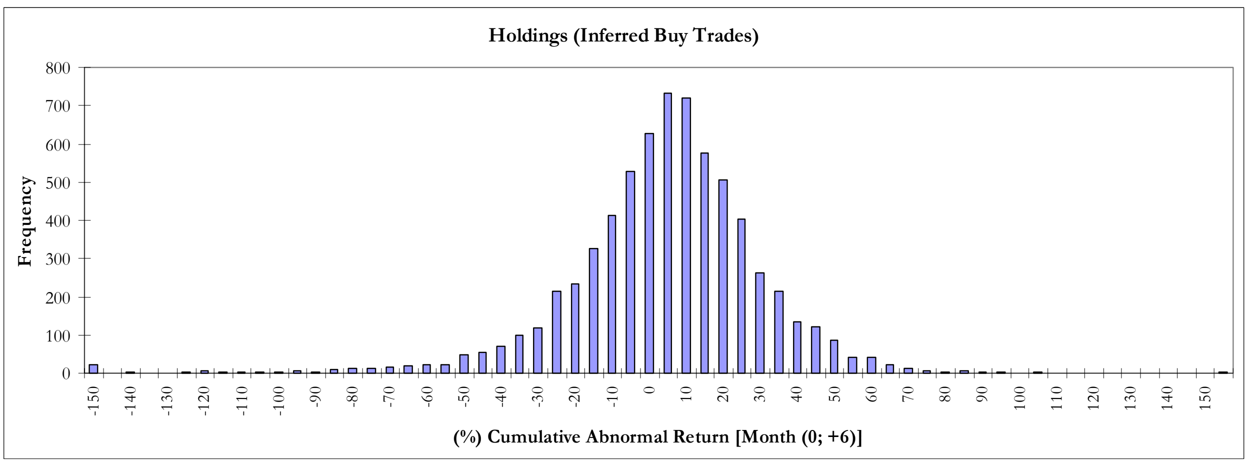


Figure 1. Time-Series of the Value of Assets Managed by the Current Universe of Active Australian Small-Cap Equity Funds.[23]

[23] This information was retrieved from http://www.investorweb.com.au on 27/10/04.





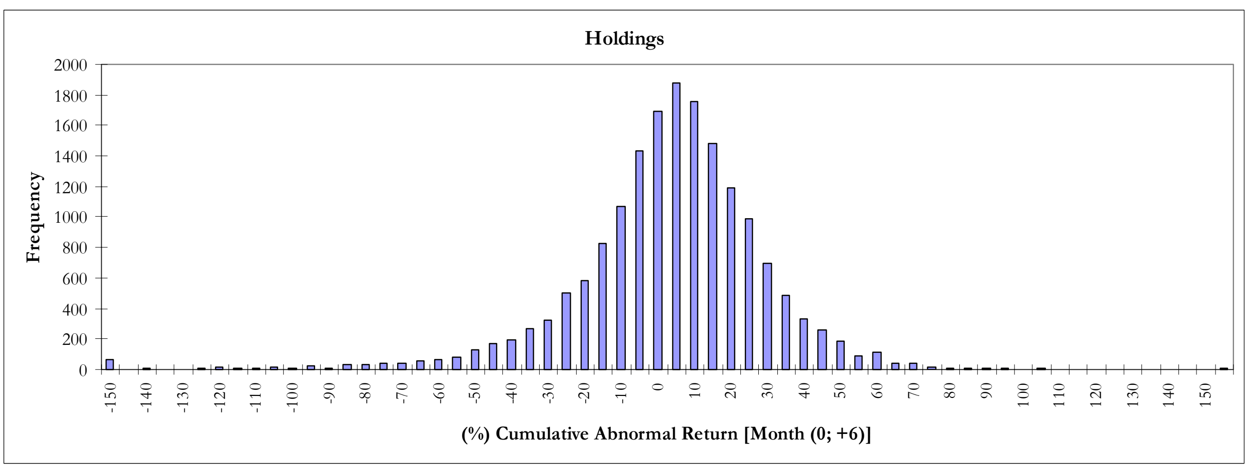


Figure 2. Frequency Distribution of the CARs (Formulated on a Stock Level) for Both Holdings and Transactions-Based Performance Estimates. The histograms represent the frequency distribution of the CARs (formulated on a stock level) for the respective holdings/transactions based performance estimates. The CARs in Figure 2.b and 2.c represents only the stocks with available abnormal return estimates over the entire six-month event window. All the CARs are expressed in percentages.