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Broker recommendations and Australian small-cap equity fund management

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Abstract

This study examines whether the abnormal performance of active Australian small-cap equity fund managers is associated with broker recommendations. Our evidence supports the investment value of broker recommendations, showing significant abnormal returns (ARs) both pre- and post-broker recommendations. We find that when a factor-mimicking portfolio based on broker recommendations is added to a Carhart (1997) model, annual alphas are reduced by 48 basis points. Using transaction-level data, buy trades following broker recommendations earn significant cumulative ARs of 1.56 per cent after 60 days. Overall, we find that broker recommendations account for an economically significant component of alphas.

Key words: Active small-cap fund management; Broker recommendations; Alpha

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1. Introduction

The recent abnormal performance by Australian small-cap equity fund managers (see Chen *et al.*, 2010; Gallagher and Looi, 2006) prompts the question of whether small-cap managers are genuinely well-informed.[1] Our paper is primarily empirical, although its theoretical motivation derives from information economics. Active equity fund managers are known to conduct in-house research and establish relationships with company management in attempts to beat the benchmark index. While these research and relationship-building activities are costly, they potentially give small-cap managers an information advantage over other investors. Grossman and Stiglitz (1980) argue that market prices must be sufficiently noisy to allow traders and investors who engage in costly information search to recover these costs, otherwise there is no incentive to become informed. This 'internally generated' information advantage might contribute to the significant alphas their portfolios have achieved in recent years. In a seminal paper, Wermers (2000) shows that active equity mutual funds generated excess returns (1.3 per cent p.a.) that were almost sufficient to cover their expenses and trading costs (1.6 per cent), which is broadly consistent with the Grossman–Stiglitz equilibrium.[2]

In addition to fund managers' own research, they also rely on their broker panels for timely access to valuable information and trade execution services. Thus, their observed alphas may be partly derived by trading on the basis of 'externally generated' broker recommendations, which are also known to possess information content. Broker recommendations provide an important alternative information source that enable fund managers to exploit valuable private information in a timely manner.

This study explores the extent to which small-cap equity fund outperformance is attributable to 'internally generated' information versus fund managers following the external recommendations of brokers, as well as the extent to which broker recommendations influence the investment decisions of Australian funds trading in small-cap stocks. Our research has important practical implications for active portfolio management because it is very much in the spirit of the alpha

[1] Chen *et al*. (2010) find evidence of small-cap managers' stock selection ability with risk-adjusted abnormal returns (ARs) of between 59.6 and 76.1 basis points per month. Furthermore, Gallagher and Looi (2006) find evidence that fund managers are better at exploiting potential mispricing for the most liquid of small-cap stocks (ranked 101st to 150th in market capitalisation) on the Australian Stock Exchange (ASX).

[2] Wermers (2000) provides a decomposition of portfolio holdings performance and compares this to reported net returns. The research documents a 2.3 per cent p.a. difference between portfolio holdings returns and net returns, where the difference 0.7 per cent p.a. is explained owing to returns from non-stock holdings and remaining 1.6 per cent p.a. is explained by trading costs and management expenses. The study reports that for stock holdings, mutual funds generate excess returns above the market (i.e., 1.3 per cent p.a).

capture hedge fund strategies developed by Marshall Wace in 2002 (the Trade Optimized Portfolio System), which uses computer algorithms for analysing and evaluating brokers' best tips.

We make a number of contributions to the empirical literature. First, we extend the work of Chan *et al.* (2006), through the use of robust methods to compute ARs, with a focus on short-term horizons for returns around broker recommendation dates. This is in the light of findings by Kothari and Warner (2006) that misspecification is common in long-horizon event studies. Furthermore, we use a large and representative sample of broker recommendations to confirm the findings of Chan *et al.* (2006) that broker recommendations possess information content within the Australian market. Second, we provide a link between broker recommendations and the value derived by small-cap equity fund managers. There exists an extensive literature on the investment value of broker recommendations, including Womack (1996) and Barber *et al.* (2001). However, no study to our knowledge tests whether internally and externally produced recommendations are one of the drivers of small-cap equity fund outperformance. We test this by using broker recommendations as a proxy for valuable information and investigate the extent to which these recommendations affect the investment decisions of small-cap equity fund managers. Third, our research extends the widely adopted four-factor Carhart (1997) model applied to mutual funds, using a fifth factor controlling for information asymmetry available from connections to the brokerage industry. It should of course be noted that three of the four factors in the Carhart model (size, book-to-market and momentum) are primarily based on empirical anomalies to the predictions of asset pricing theory. The remaining factor, the return on the market, is theory-driven.

Initially, performance is analysed through returns-based models using a representative dataset of 34 active institutional Australian small-cap equity funds. We also extend the traditional factor models of Jensen (1968), Fama and French (1992) and Carhart (1997) to incorporate broker recommendations as an additional factor.[3] This factor model extension confirms that a component of the significant alphas documented in Chen *et al.* (2010) can be attributed to an investment strategy based on broker recommendations. In addition to returns-based performance models, transaction-based measures are used to determine the extent to which equity fund managers trade in small-cap stocks on the basis of recommendation levels. This approach represents a significant improvement to holdings-inferred trades observed over quarterly or monthly intervals (for example, see Chen *et al.* (2000) for the US and Pinnuck (2003), for Australia). We also use a number of innovative approaches to analyse the

[3] Chan and Faff (2003) test the importance of liquidity, in addition to factors for the market return, size, book-to-market and momentum, in explaining Australian equity returns. They find that stocks with lower liquidity have higher returns.

transaction-based performance of small-cap equity managers, including their performance sensitivity around recommendation levels, research coverage levels and timing factors.

The findings on returns-based performance models are consistent with those of Chen *et al*. (2010) in that small-cap equity managers possess stock selection ability. Using a Carhart (1997) model, we show small-cap managers earn economically and statistically significant alphas of 58 basis points a month. Furthermore, the addition of a broker recommendation mimicking factor portfolio to the Carhart (1997) model reduces alpha by 48 basis points per annum (i.e., from 58 to 54 basis points a month), although it continues to be statistically significant. This is important also from an economic perspective; it is approximately half the average management expenses of small-cap funds (i.e., 100 basis points per annum).

The remainder of the study is structured as follows. Section 2 provides a brief review of theoretical motivation and empirical literature and develops our hypotheses. Section 3 outlines the data used in this study, while Section 4 provides an outline of the research design. This is followed by the empirical results as well as a number of robustness tests in Section 5. Section 6 concludes.

2. Background and hypotheses

Our study investigates whether costly investment in developing an information advantage is recovered through superior portfolio returns, and it is thus grounded in a costly information economics' view of the efficient markets hypothesis. One source of information for small-cap fund managers is internally generated investment recommendations. Further, prior empirical evidence shows that small-cap fund managers generate exceptional performance (Chen *et al*., 2010). This outperformance is consistent with the theoretical arguments in Grossman and Stiglitz (1980) that, in order that there is an incentive to engage in costly information search, market prices must be sufficiently noisy (i.e., inefficient) to allow informed investors to recover the costs of information production. However, small-cap managers might also rely on externally generated investment recommendations made by analysts in broking firms. These recommendations are also costly to produce, and accordingly, they should have some investment value. Indeed, Chan *et al*. (2006) show that this is the case. We are interested in empirically decomposing the documented outperformance of small-cap fund managers into that part associated with following externally produced investment recommendations of analysts. Accordingly, our empirical investigation has its theoretical foundation in information economics. The theory suggests that markets must be sufficiently noisy to allow the recovery of information search costs.

Brokerage houses publish information and recommendations on stocks. Sell-side analysts are also known to develop strong relationships with the management of the companies they cover. In spite of regulation that prohibits the selective disclosure of material information by sell-side analysts,[4] research analysts are often perceived to have an information advantage over other investors given their perceived proximity and access to company management. This may be attributed to either their superior ability in analysing and processing public information or by acquiring private information before other market participants. The significant stock price reaction upon the announcement of a recommendation is interpreted as recommendations having information content.

Broker research coverage has been documented to explain information asymmetries. Arbel *et al.* (1983) first discovered a 'neglected firm effect' where firms with minimal research coverage experience higher returns. These returns persist after controlling for stock size, which is important given that smaller firms tend to have lower analyst coverage. Dhiensiri and Sayrak (2005) find that the value of a recommendation revision is inversely related to the number of analysts following a firm, which is also similarly supported by Kelly and Ljungqvist (2007). This notion that stocks with lower research coverage possess a greater degree of information asymmetry potentially provides opportunities for small-cap equity managers to earn excess returns.

An 'Initiating' recommendation on a stock represents the first coverage of that stock by a broker. Given a lack of prior information, Chan *et al.* (2006) posit that 'Initiating' recommendations have greater information content and price response upon their announcement. Demiroglu and Ryngaert (2008) find that 'neglected' stocks with no prior research coverage in the past year experience ARs of up to 4.82 per cent upon announcement. Although these authors acknowledge their result is partially attributed to an initiation with favourable information content, it suggests an information asymmetry for firms prior to their first analyst coverage. Similarly, Irvine (2003) finds that the incremental price impact of an initiation of coverage is 1.02 per cent greater than the price reaction for a recommendation on a stock that is already covered. There is also evidence of this in the Australian market by Chan *et al.* (2006), which shows that returns on initiating buy (sell) recommendations are significantly greater (less) than zero over the 6 months following their release.

In the Chan *et al.* (2006) study, recommendations are classified as 'Initiating' if a particular broker has not published a recommendation in the past 1, 2 or 3 years,[5] and 'Continuing' if otherwise. Furthermore, 'Virgin' recommendations

[4] Such regulations include Regulation Fair Disclosure (Regulation FD) in the United States and the Continuous Disclosure requirements in Australia. In addition, the Securities Exchange Commission in 2003 undertook enforcement action with respect to ten investment banks that led to the Global Settlement. The SEC actions were brought with respect to the investment banking entities having improper influence on securities research in the brokerage divisions of these firms.

[5] Chan *et al.* (2006) use three different periods of time to determine whether a recommendation is initiating, namely whether there was a recommendation by the same broker in the previous 1, 2 or 3 years.

are a subset of 'Initiating' recommendations and are the first coverage of that stock by any broker. Chan *et al*. (2006) expect 'Virgin' recommendations to have the greatest information content. However, their finding differs to Irvine (2003), as the share price reactions of 'Virgin' recommendations are not significantly different from 'Continuing' or 'Initiating' recommendations.

The literature generally finds that broker recommendations have investment value. Beneish (1991) and Stickel (1995) find significantly positive (negative) stock price reactions to buy (sell) recommendations. Broker recommendations are also found to have predictive power with respect to stock returns (see Elton *et al*., 1986; Womack, 1996; and Barber *et al*., 2001). Australian evidence also indicates that brokers have stock-picking ability (see Aitken *et al*., 2000).

The literature has also investigated changes, rather than the absolute level of analyst recommendations, and their impact on stock returns (see Elton *et al*., 1986; and Womack, 1996). Jegadeesh *et al*. (2004) find that the quarterly change in consensus recommendation level is also a robust predictor of returns. Research on investment strategies, formed around recommendations, has also documented ARs (Barber *et al*., 2001).

There is limited literature on the value of broker recommendations with respect to equity funds. Industry surveys reveal that most funds employ their own in-house analysts to provide private research coverage of stocks. In addition, funds themselves have access to company management in the same way that sell-side research analysts do. The ability of equity fund managers to conduct their own private research, and possibly obtain information from company management, suggests that fund managers may be informed. However, a study by Brown *et al*. (2008) examines the extent of recommendation-motivated trades and finds that mutual funds 'herd' into (out of) stocks with consensus upgrades (downgrades). Similarly, Chan *et al*. (2005) finds that the extent of such herding is greater with increased information uncertainty, which is proxied by the dispersion in analyst forecasts. These two studies provide evidence that mutual funds rely heavily on the public information provided through broker recommendations.

An alternative view proposed by Irvine *et al*. (2007) is that sell-side analysts 'tip' their institutional clients prior to recommendation release. Their joint finding that (i) institutional trading increases significantly in the days prior to recommendation date and that (ii) these trades earn positive ARs provides some support for the tipping hypothesis. However, given the gap in the literature linking broker recommendations and equity funds, it is appropriate to test how public information, such as broker recommendations, is used in the investment decisions of Australian small-cap funds, in the light of recent evidence demonstrating outperformance.

In this study, we empirically investigate five hypotheses:

Hypothesis 1: Broker recommendations are short-term predictors of stock returns and possess information content. Initiating recommendations have greater information content and share price reactions upon announcement than continuing recommendations.

Hypothesis 2: Small-cap equity managers mimic broker recommendations in their investment decisions; hence, the alpha earned by these managers can be (partly) attributed to the information contained in recommendations.

Hypothesis 3: Active Australian small-cap equity managers trade on the basis of recommendation levels and subsequently earn significant ARs on these trades.

Hypothesis 4: Active Australian small-cap equity managers build up positions in stocks with upcoming recommendations and earn subsequent ARs from these positions.

Hypothesis 5: Research coverage levels are inversely related to the level of ARs earned from small-cap equity manager trades.

3. Data

Small-cap funds in Australia generally target stocks that are constituents of the S&P/ASX 300 Index (hereafter ASX 300) but lie outside of the S&P/ASX 100 Index (hereafter ASX 100). These stocks comprise the S&P/ASX Small Ordinaries Index (hereafter Small Ordinaries). Based on ASSIRT estimates, the total funds under management of the small-cap funds industry at 30 April 2007 is approximately A$4561 million, or approximately 7 per cent of the total Australian small-cap equity market capitalisation.

In the period 1994–2008, broker coverage has increased over time. The total number of brokers in the market has increased, as too has the mean number of brokers following a Small Ordinaries Index stock, which increased from 2.54 in 1994 to 5.13 in 2008. A total of 650 stocks were at some stage included in the Small Ordinaries Index during our sample period. The average number of unique brokers that issued a recommendation on these 650 stocks at some stage during the 15-year period was 7.76. Small-cap stocks are generally associated with lower research analyst coverage levels than large-cap stocks.

Broker recommendations are sourced from the IBES database. We include stocks ranked between 101st and 300th in market capitalisation between November 1993 and December 2008 in our recommendation database, resulting in a sample of 801 ‘small caps’. Of these, 762 unique stocks had recommendations in IBES, with a total of 21 231 unique recommendations. This forms the full recommendation sample, in which a total of 64 unique brokers provide recommendations. Most brokers use an expanded classification system with recommendations such as underweight, overweight, underperform and outperform. For consistency, the IBES database converts these to a five-point classification system, which we use in this study. The categories are Strong Buy, Buy, Hold, Underperform and Sell.

Consistent with the literature, considerable asymmetry exists in the number of buy and sell recommendations, with Strong Buys and Buys combined outnumbering Sells and Underperforms by a factor of 2.8 in the full sample. This asymmetry is even greater in Virgin recommendations, where the buy/sell ratio is 4.2. The direction of this bias to recommend stocks as buys is in line with economic incentives that exist for analysts to issue favourable recommendations. It is also consistent with the notion that a self-selection bias exists, where firms tend to initiate coverage on firms with favourable prospects as a mechanism to generate trading commissions.

The Mercer Manager Performance Analytics (Mercer) database includes the monthly returns of 40 active Australian small-cap equity funds on a pre-expense basis. Following Chen *et al.* (2010), each fund in our sample is required to have a minimum of 12 consecutive monthly returns between January 1991 and March 2004 to allow model estimation. The resulting subsample of 34 active small-cap funds has consecutive returns that range from 14 to 158 months.

We also use the Portfolio Analytics (PA) database, which includes month-end portfolio holdings and daily transactions of a subset of the small-cap equity fund managers. The PA database was constructed using an 'invitation' approach to the largest equity investment managers (on the basis of funds under management) in Australia. Each manager was requested to provide, on a confidential basis, information on their largest pooled active Australian equity funds that were open to institutional investors.

The PA database includes month-end portfolio holdings of 13 active Australian small-cap equity funds, which are managed by 11 separate managers. The holdings are from March 1995 to June 2004. This represents a sample of 38 261 individual holdings of stocks by the small-cap fund managers. As at the end of the sample period in 2004, the PA funds had a total of A$0.76 billion in funds under management. Hence, the PA database accounts for approximately 16.7 per cent of the entire small-cap fund universe (by funds under management). Furthermore, the mean monthly fund size by net asset value (NAV) throughout the sample period is A$78.5 million. The daily transaction data for the small-cap fund managers include the aggregate daily trades of 12 active Australian small-cap equity funds, which are managed by ten unique fund managers. On a transaction level, the full sample is made up of 43 700 aggregated daily trades over a 7-year period spanning February 1997 to June 2004.

Rather than analysing each trade separately, we follow Chan and Lakonishok (1995) and group individual trades into trade packages.

Table 1 provides summary statistics for the trade packages formed from the daily transactions of the small-cap fund managers in the PA database. Of the 43 700 aggregated daily trades comprising the full sample, 15 060 trade packages are formed using the 5-day definition. Of these, buy packages outnumber sell packages, with 8525 buy packages compared to 6535 sell packages. Within the full sample, 52 (51) per cent of the buy (sell) packages are executed within a single day and approximately 76 per cent of all trade packages (i.e., both buy and sell trades) are executed within 4 days.

Table 1
Summary statistics for transactions data – full sample

Summary statistics for trade packages full sample – February 1997 to June 2004

Panel A: Buys

	1 day	2–4 days	5–8 days	> 8 days	Total buy packs
Number of packages	4452	1984	1206	883	8525
% of buys	52	23	14	10	100
Mean pack value $	201 480	321 056	497 848	1 088 375	363 097
SD pack value	390 549	452 681	602 517	1 258 422	643 128
Q1	35 844	94 242	150 449	308 446	60 789
Median	92 428	186 114	313 254	640 422	159 540
Q3	202 500	371 431	581 005	1 370 171	385 700

Panel B: Sells

	1 day	2–5 days	5–8 days	> 8 days	Total sell packs
Number of packages	3336	1633	844	722	6535
% of sells	51	25	13	11	100
Mean pack value $	227 940	339 028	505 967	895 512	365 361
SD pack value	488 489	563 481	639 539	1 140 198	663 890
Q1	35 866	71 589	117 374	241 349	59 409
Median	107 128	167 538	290 685	548 596	156 860
Q3	238 354	363 440	658 340	1 099 648	389 961

Trade packages are defined as a fund manager's successive trades in a particular stock within the same direction (i.e., only a buy or sell in one package) until no trades are executed for a period of five consecutive days. Panel A reports summary statistics for all buy trade packages, with a breakdown for the number of days it took to execute the entire trade package. Panel B reports summary statistics for sell trade packages with a similar breakdown. The sample is also split into quartiles based on trade package value.

To examine the behaviour and performance of small-cap fund managers around broker recommendations, we form a recommendation subsample of trade packages, based on stocks with data from our recommendations file. In forming the subsample, we require stocks to be continuously traded over the past year, as momentum characteristics are required to calculate Daniel, Grinblatt, Titman and Wermers (1997) (hereafter DGTW) adjusted daily ARs around trade packages. This results in a 'recommendation subsample' of 2800 trade packages, 1572 buys and 1228 sells. The sample size is considerably smaller than the full sample; hence, we also calculated descriptive statistics for this set to ensure no selection bias has occurred. The results are quantitatively similar to those in Table 1, although in general the value of the packages for this reduced set of recommendations is somewhat larger than those for the full sample.[6]

[6] These results are available from the corresponding author on request.

In addition to analyst recommendations and fund manager data, stock-specific information such as price, dividend and capitalisation change data is needed to calculate returns. For this, ASX daily price data are sourced from the Securities Industry Research Centre of Asia-Pacific (SIRCA). These include daily opening and closing prices, daily high and low prices and also daily trading volumes and values. In addition, a daily dilution factor is included for each stock to take into account changes in shares outstanding owing to events such as dividends, rights issues or stock splits. Accounting information such as book-to-market ratios for multi-factor models is sourced from the Aspect Financial database.

4. Research design

In this section, we outline our research design used to test whether broker recommendations have information content and investment value, as proposed in Hypothesis 1. After classifying recommendations by level and type, we conduct an event study to investigate the share price reaction and the presence of statistically significant ARs around the recommendation date. For robustness, two approaches are used to compute ARs – the traditional market model as well as a control-firm approach first developed by Daniel *et al.* (1997).

4.1. Classifying recommendations by level and type

Initially, recommendations are grouped into three categories by level. These are (i) Strong Buys or Buys, (ii) Holds and (iii) Underperform or Sell. The IBES classification system is used to group recommendations by level.

Following this, recommendations are classified according to their type, as per Chan *et al.* (2006). An Initiating recommendation is the first recommendation made on a stock by a particular broker, where other brokers currently cover the stock. A Virgin recommendation is the first recommendation made on a stock by *any* broker. Thus, Virgin recommendations are a subset of Initiating recommendations. As the IBES database commences in 1993 for Australian stocks, we use 1993 as a ‘holdout’ year and classify Virgin or Initiating stocks if no prior recommendations were issued during that year. The remaining recommendations are classified as Continuing.

4.2. Abnormal returns around recommendation date – market model

An event study methodology with a short-horizon window is used to compute the ARs around recommendation date. While Chan *et al.* (2006) focus on 6-month returns following recommendation, we focus on the ARs in the 2 weeks around a stock’s recommendation date. We estimate the familiar market model during a 180-day ‘estimation period’ prior to each recommendation date, using the Small Ordinaries Index values to calculate the market return. Abnormal returns on a stock for the 10 days around a recommendation date are computed as the difference between the actual return and the expected return as predicted by the market model.[7] Based on the entire sample of recommendations, mean daily ARs are computed by averaging across recommendations in the sample and the ARs are then summed to form cumulative abnormal returns (CARs).

4.3. DGTW-adjusted abnormal returns

A DGTW control-firm approach to benchmark stock returns is adopted as an additional robustness check. This approach is motivated by the characteristics of the underlying stocks held in fund portfolios examined in Daniel *et al*. (1997). These include well-known market anomalies such as size, book-to-market and momentum. Although the DGTW method was developed to measure mutual fund performance, this benchmarking approach can also be applied to computing ARs on individual stocks.

To compute ARs around recommendation date, we use daily DGTW-adjusted alphas constructed by Fong *et al*. (2008) based on the Pinnuck (2003) approach. The Pinnuck (2003) approach modifies the Daniel *et al*. (1997) approach for an Australian context and is constructed on a stock universe consistent with our benchmark specification. The daily DGTW-adjusted alphas can be expressed algebraically as:

$$\mathrm{AR}_{i,t} = r_{i,t} - r_t^{\mathrm{DGTW}(i)} \tag{1}$$

where $\mathrm{AR}_{i,t}$ is the AR on the underlying stock of recommendation i at time t, $r_{i,t}$ is the actual return on underlying stock of recommendation i on day t and $r_t^{\mathrm{DGTW}(i)}$ is the return of a characteristic matched benchmark portfolio assigned to the underlying stock of recommendation i across the characteristics of size, book-to-market and momentum.[8]

Following this, the mean AR is computed based on daily ARs averaged across all recommendations in the sample, and CARs around recommendation date are calculated.

4.4. Returns-based performance measures

Returns-based performance measures are used to determine whether small-cap equity managers have the ability to outperform passively selected

[7] Following the event study approach suggested by MacKinlay (1997), we include a separation between the estimation ($t = -200$ to $t = -20$) and event windows ($t = -10$ to $t = +10$), which prevents event-related activity in the stock price from influencing the estimated market model parameters.

[8] The factors included in the DGTW benchmark portfolio of size, book-to-market and momentum are based on empirically documented anomalies of asset pricing theory.

benchmark portfolios. The literature has proposed a number of factor models in risk-adjusting the returns of mutual funds, including the approaches advocated by Jensen (1968), Fama and French (1992) and Carhart (1997). While the inclusion of a market factor has theoretical motivation, the other factors in the Fama–French and Carhart models (i.e., size, book-to-market and momentum) are based on empirical regularities. The purpose of these multi-factor models is to control for strategies that are known to generate alpha (i.e., these anomalies are well-known) in capital markets. The reliance on multi-factor risk models is therefore an attempt to measure the true value of services rendered by active fund managers and thereby account for alpha that is otherwise delivered from well-known risk factors shown to explain stock returns in the cross-section. Studies by Chen and Knez (1996) and Admati and Pfleiderer (1997) argue the importance of accurately benchmarking performance in the compensation of investment managers. Indeed, in the Australian literature, asset pricing tests by Chan and Faff (2003) and Gharghori *et al.* (2007) are recent examples that propose extensions to the Fama–French three-factor model with respect to liquidity (proxied by trade volume) and default risk, respectively.

A number of commonly used single and multi-factor models are employed in our study, namely the Jensen approach, Fama–French, Carhart and our new model that further accounts for asymmetries related to broker recommendations (a test of Hypothesis 2). Further details of these models are outlined in Chen *et al.* (2010). An innovation in this study is that it is the first to account for broker recommendations as a potential source of alpha generation by active small-cap equity funds.

In constructing a broker recommendation factor BMS or 'Buy minus Sell', mimicking portfolios are formed on a monthly basis, which take a long position in stocks with newly issued Strong Buy or Buy recommendations during the month and a short position in stocks with newly issued Underperform or Sell recommendations in the month.

In addition, BMS is formed from a recommendation sample whose stocks were members of the Small Ordinaries Index *in the month* of recommendation. This is to ensure that only pure 'small-cap' stocks that fall under the investment mandate of small-cap managers are included.

In any month, it is possible for several brokers to issue *conflicting* recommendation levels on a stock. It is also possible for a single broker to revise the recommendation level on a stock from a buy to a sell and vice versa. For stocks that had 'conflicting' recommendations, the consensus recommendation for that month is used to classify the stock. Within our sample of 4770 buy or sell recommendation/months, we identified only 160 instances of 'conflicting' recommendation/months and applied the monthly consensus recommendation level to these cases.

The five-factor model used in this study is thus specified as follows:

$$r_{i,t} = a_i + b_{i\mathrm{SO}} r_{m,t} + b_{i\mathrm{HML}_t}\mathrm{HML}_t + b_{i\mathrm{SMB}}\mathrm{SMB}_t + b_{i\mathrm{PR1YR}}\mathrm{PR1YR}_t + b_{i\mathrm{BMS}}\mathrm{BMS}_t + e_{i,t}. \tag{2}$$

The HML, SMB and PR1YR factors are constructed as per the Carhart (1997) four-factor model. BMS represents a 'Buy minus Sell' broker recommendation factor, and $b_{i\mathrm{BMS}}$ is its corresponding loading coefficient.

4.5. Justification of market benchmarks specified

Specification of an appropriate benchmark and model is extremely important in the light of recent studies that suggest that inferences of abnormal performance are highly sensitive to choice of benchmarks and models, such as Kothari and Warner (2001).[9] In particular, the chosen market portfolio should adequately reflect the investment styles of the fund managers in the sample. Typically, small-cap fund managers are benchmarked against the Small Ordinaries Index. Indeed, an analysis of their holdings shows that over 70 per cent of funds are invested in the Small Ordinaries Index constituent stocks. Further, Lehmann and Modest (1987) also stress the importance of a consistent approach when constructing benchmark factors. The broker recommendation factor BMS has been constructed using Small Ordinaries stocks, as this appropriately reflects the underlying stocks small-cap equity managers invest in. Based on both an analysis of the holdings and the way BMS was constructed, the Small Ordinaries Index is initially used as the market risk factor in returns-based performance evaluation models.

However, an issue that arises is that the Carhart (1997) mimicking factors that we have access to are constructed from stocks within the All Ordinaries Index. To incorporate the use of a wider benchmark and to ensure consistency in benchmark construction, the All Ordinaries Index is also used as a robustness test. The holdings data also show approximately 13 per cent of holdings by value are micro-caps and approximately 4 per cent of holdings are large-cap stocks in the ASX 100. For this reason, we also create a customised 'Balanced Index', which accurately reflects the proportionate holdings of small-cap equity managers in the sample. The Balanced Index is constructed using the weighted returns on the ASX 100, Small Ordinaries and micro-cap stocks (defined as stocks outside of the ASX 300 but within the All Ordinaries indices) with weights of 4/90, 73/90 and 13/90, respectively.

In summary, three key market benchmark specifications are used:

1 Small Ordinaries Index
2 All Ordinaries Index
3 A Self-constructed Balanced Index.

[9] See also Lehmann and Modest (1987) and Grinblatt and Titman (1993).

4.6. Broker recommendations and small-cap manager trades

Previous studies have examined fund manager trades by focussing on trades inferred from quarterly or monthly portfolio holdings. However, as pointed out by Gallagher and Looi (2006), this approach fails to capture trading activity during the month. Furthermore, Chen *et al.* (2000) argue that trades are more likely to signal private information over the passive decision of holding a stock.

Thus, we use a refined level of data, the daily transactions of small-cap equity managers to test Hypothesis 3 that broker recommendations influence fund manager trades, as well as Hypothesis 4 that small-cap managers are informed and build up positions in stocks with an upcoming recommendation. As mentioned earlier, consistent with the approach of previous small-cap equity fund studies, such as Gallagher and Looi (2006), Comerton-Forde *et al.* (2010) and Chen *et al.* (2010), trades are grouped based on the trade package methodology of Chan and Lakonishok (1995). This is motivated by the fact that fund managers tend to split up large trades to minimise transaction costs through price impact and to disguise the execution of their trades.

4.6.1. Trades on the basis of recommendation level

Under the assumption that there is information content in broker recommendations, we propose in Hypothesis 3 that broker recommendations influence the trades of small-cap equity fund managers in two ways. First, small-cap equity managers trade on the basis of recommendation levels. That is, managers should be more likely to execute a buy trade on stocks with a Buy recommendation or execute a sell trade on stocks with a Sell recommendation. Second, we expect significant ARs to be earned on trades in which a recommendation direction is followed.

To test the extent that small-cap managers trade on the basis of recommendation levels, a database of trade packages that have taken place around a recommendation date is constructed. A trade that had a Strong Buy or Buy (hereafter Buy), or an Underperform or Sell (hereafter Sell) recommendation in the same month is included in this database. Following this, we partition trade packages on the basis of recommendation level and trade type.

Using the holdings data from the PA database, we further split the full sample based on whether a fund manager had an 'existing position' in the stock when the trade occurred or whether the trade package represented a 'new position' in the stock for a particular fund manager. This is motivated by the idea that managers are more likely to rely on the information content of broker recommendations if they do not have a prior position in the stock.

4.6.2. Returns around trade packages

Following the partitioning, we examine the ARs earned on trades that have followed the recommendation direction using the DGTW approach outlined in section 4.3. First, daily DGTW-adjusted ARs are computed in the 60 days before and after the trade package date. The mean daily DGTW-adjusted ARs and the CARs are then calculated for the sample.

4.6.3. The information advantage of small-cap fund managers

If recommendations possess information content and if small-cap fund managers are informed as proposed in Hypothesis 4, then we expect to observe trading activity prior to the release of a recommendation. That is, we expect fund managers to have built up positions in stocks where information is due to be released to investors through a recommendation. We also expect that small-cap fund managers earn significant ARs from these positions. Again, we use the trade package methodology of Chan and Lakonishok (1995).

First, instances of managers taking a position prior to recommendation release are identified. Accordingly, a trade package is flagged if the last day of the package occurs in a 10-day period prior to either a Buy or Sell recommendation. Hold recommendations are omitted from this analysis, given the expectation that they do not contain the same level of information as a Buy or Sell recommendation. We initially define a 10-day period as an indication of managers taking a prior position; however, other time periods are also used in robustness checks.

After identifying instances of prior positions by small-cap equity managers, a number of trade-related metrics are constructed to analyse the relative magnitude of these trade packages. This is to ensure that small-cap fund managers take substantial positions in stocks with an upcoming recommendation.

Transaction weight: Within the sample, the small-cap equity funds vary substantially in NAV, which has implications in the size of the trades executed. Hence, it is more meaningful to examine the relative weight of the trade as a proportion of NAV rather than the absolute value of the trade package. The transaction weight is defined as

$$\text{Transaction Weight}_{ijt} = \frac{\text{Trade Package Value}_{ijt}}{\text{NAV}_{jt}} \tag{3}$$

where Trade Package Value_{ijt} is the dollar value of the trade package i made by fund manager j in month t and NAV_{jt} is the net asset value of fund manager j during month t.

Relative position – prior and post-trade: Fund managers are likely to have existing positions in the stocks in which they trade. For this reason, we are also interested in the relative weight of the overall position in a stock both prior to and following a trade, rather than the weight of the trade package alone. The relative weight of the overall position, both prior to trade and post-trade, can be defined as

$$\text{Relative Position (Prior)}_{ijt} = \frac{\text{Holding Value}_{ijt-1}}{\text{NAV}_{jt}} \tag{4}$$

$$\text{Relative Position (Post)}_{ijt} = \frac{\text{Trade Package Value}_{ijt} + \text{Holding Value}_{ijt-1}}{\text{NAV}_{jt}} \tag{5}$$

where Trade Package Value$_{ijt}$ is defined as in equation (3) and Holding Value$_{ijt-1}$ is the value of fund manager j's holding in the stock underlying trade package i during month $t-1$, given that holdings in the PA database are month-end values.

Overweight position: Position weights in a stock may also vary across different stocks, depending on their market capitalisation. For instance, it is expected that positions will be greater in smaller stocks. Hence, we also examine the size of a trade package in the context of a stock's weight in the index. We define an overweight (relative to the index) metric as

$$\text{Overweight}_{ijt} = \text{Relative Position (Post)}_{ijt} - \text{Weight}_{it\text{XSO}} \tag{6}$$

where Relative Position (Post)$_{ijt}$ is as per equation (5) and Weight$_{it\text{XSO}}$ is the weight of a stock within the Small Ordinaries Index in the corresponding month t.

After analysing a number of trade-related metrics, we compute mean daily DGTW-adjusted ARs around each prior position trade and average these across the N trade packages in which a prior position was taken, rather than the entire sample. We also compute CARs for the 30- and 60-day periods, again using the last day of a trade package as the reference date.

4.7. Impact of coverage levels on transaction-based performance

In this section, we outline our approach in testing the information advantage of small-cap equity managers by examining research coverage levels in conjunction with transaction-based performance measures. This is motivated by the 'neglected firm effect' first documented by Arbel *et al*. (1983) and more recently by Irvine (2003).

If small-cap equity managers are genuinely informed, then we would expect coverage levels to be inversely related to the ARs earned from their trades, as proposed in Hypothesis 5. This is based on the notion that managers are better able to exploit information asymmetry and potential mispricing in stocks with less publicly available information.

Motivated by the approach of Dhiensiri and Sayrak (2005), we initially define sell-side research coverage levels for all the underlying stocks of the trade packages of small-cap funds. Based on the recommendations sample, the frequency of issued recommendations varies between different brokers. However, as suggested by Kecskes and Womack (2007), an analyst will at least provide a yearly earnings forecast for the stocks they cover. Given this, we define the 'coverage level' as the total number of brokers issuing a recommendation on a stock within the same year.

Following this, we analyse the performance of trade packages with a split around coverage levels. We use the trade packaging methodology and methods for computing mean daily and CARs, consistent with the approach detailed above.

5. Empirical results

5.1. Value of brokers' recommendations

Table 2 presents the CARs around recommendation date based on a market model approach. All Continuing recommendations earn statistically significant post-recommendation CARs that are consistent with the direction of their forecast, regardless of recommendation level (assuming that a hold recommendation is a disappointment). Initiating and Virgin recommendations are expected to contain greater information content, given there is limited prior information on a stock. Thus, a greater price reaction is expected, as proposed in Hypothesis 1. Consistent with this, Initiating hold and underperform/sell recommendations are more negative in the period following the recommendation than those of the Continuing group. Virgin recommendations are however entirely inconsistent with expectations. Virgin buy recommendations have CARs after 10 days of −1.55 per cent, while the hold and underperform groups have positive, albeit insignificant, returns. Interestingly, there is some evidence of statistically significant negative returns prior to Initiating and Continuing sell recommendations' release, with CARs in the 10 days before the recommendation date of −0.97 per cent and −1.59 per cent, respectively. This finding supports the notion of sell-side analysts 'tipping' institutional clients, consistent with Irvine *et al.* (2007). Overall, our findings based on the market model approach are consistent with those of a previous Australian study by Chan *et al.* (2006).

As a robustness check, CARs around recommendation date are also computed based on DGTW-adjusted daily alphas. These results are very similar to those for the market model; hence, they are not reported in detail.[10] The minor differences are that the negative CARs in the period after the Strong Buy/Buy Virgin recommendations are less significantly negative under the DGTW approach, while some Initiating Strong Buy or Buy recommendations have significantly positive CARs (at the 5 per cent level) in the period after the recommendation.[11]

[10] These results are available from the corresponding author on request.

[11] We also estimated the statistical significance of the results presented in Table 2 recognising that the standard errors might be biased owing to clustering, as suggested by Petersen (2009). Our statistical tests are essentially identical under either approach.

Table 2
Returns around recommendation date – market model cumulative abnormal returns (CARs)

Panel A: Virgin recommendations				*Panel B: Initiating recommendations*				*Panel C: Continuing recommendations*			
Event	Strong buy/buy	Hold	Underperform/ sell	Event	Strong buy/buy	Hold	Underperform/ sell	Event	Strong buy/buy	Hold	Underperform/ sell
CAR [−10;0]	0.0108	−0.0074	−0.0158	CAR [−10;0]	−0.0014	−0.0004	−0.0084*	CAR [−10;0]	0.0026**	−0.0022	−0.0160***
CAR [−9;0]	0.0098	−0.0095	−0.0102	CAR [−9;0]	−0.0016	0.0002	−0.0068	CAR [−9;0]	0.0029**	−0.0023*	−0.0160***
CAR [−8;0]	0.0101	−0.0083	−0.0090	CAR [−8;0]	−0.0013	0.0006	−0.0056	CAR [−8;0]	0.0035***	−0.0023*	−0.0163***
CAR [−7;0]	0.0106	−0.0064	−0.0071	CAR [−7;0]	−0.0011	0.0000	−0.0043	CAR [−7;0]	0.0045***	−0.0024*	−0.0164***
CAR [−6;0]	0.0106	−0.0056	−0.006	CAR [−6;0]	−0.0016	0.0004	−0.0024	CAR [−6;0]	0.0050***	−0.0016	−0.0168***
CAR [−5;0]	0.0051	−0.0037	0.0034	CAR [−5;0]	−0.0007	0.0006	−0.0027	CAR [−5;0]	0.0052***	−0.0018	−0.0157***
CAR [−4;0]	0.0006	−0.0015	0.0076	CAR [−4;0]	0.0002	0.0006	−0.0041*	CAR [−4;0]	0.0047***	−0.0023**	−0.0151***
CAR [−3;0]	0.0016	0.0014	0.0018	CAR [−3;0]	0.0003	0.0000	−0.0037	CAR [−3;0]	0.0043***	−0.0020**	−0.0118***
CAR [−2;0]	0.0061	−0.0026	−0.0033	CAR [−2;0]	0.0012	−0.0002	−0.0028	CAR [−2;0]	0.0032***	−0.0013*	−0.0087***
CAR [−1;0]	0.002	−0.0003	−0.0024	CAR [−1;0]	0.0003	−0.0001	−0.0021*	CAR [−1;0]	0.0027***	−0.0011**	−0.0041***
CAR [0; + 1]	−0.0004	0.0021	0.0018	CAR [0; + 1]	0.0011*	−0.0017**	0.0021	CAR [0; + 1]	0.0014***	−0.0013***	−0.0038***
CAR [0; + 2]	0.0013	0.0002	−0.0023	CAR [0; + 2]	0.0013	−0.0021**	0.0008	CAR [0; + 2]	0.0023***	−0.0025***	−0.0060***
CAR [0; + 3]	−0.0059	0.0036	0.0051	CAR [0; + 3]	0.0008	−0.0033***	−0.0011	CAR [0; + 3]	0.0034***	−0.0029***	−0.0064***
CAR [0; + 4]	−0.0133***	0.0007	0.0105	CAR [0; + 4]	−0.0011	−0.0050***	−0.0035	CAR [0; + 4]	0.0033***	−0.0032***	−0.0074***
CAR [0; + 5]	−0.0108**	0.0035	0.0081	CAR [0; + 5]	−0.0004	−0.0062***	−0.0042	CAR [0; + 5]	0.0030***	−0.0037***	−0.0085***
CAR [0; + 6]	−0.0140**	0.0016	0.0221	CAR [0; + 6]	−0.0009	−0.0059***	−0.0080**	CAR [0; + 6]	0.0036***	−0.0041***	−0.0090***
CAR [0; + 7]	−0.0118	0.0015	0.0171	CAR [0; + 7]	−0.0014	−0.0062***	−0.0100**	CAR [0; + 7]	0.0036***	−0.0042***	−0.0097***
CAR [0; + 8]	−0.0130*	0.0040	0.0052	CAR [0; + 8]	−0.0025	−0.0063***	−0.0093**	CAR [0; + 8]	0.0032***	−0.0041***	−0.0099***
CAR [0; + 9]	−0.0143*	0.0024	0.0075	CAR [0; + 9]	−0.0034*	−0.0067***	−0.0100**	CAR [0; + 9]	0.0034***	−0.0044***	−0.0108***
CAR [0; + 10]	−0.0155*	0.0048	0.0103	CAR [0; + 10]	−0.0038*	−0.0074***	−0.0129***	CAR [0; + 10]	0.0036***	−0.0049***	−0.0109***

Table 2 presents the CARs around recommendation date, with a breakdown for Virgin, Initiating and Continuing recommendations, as well as by recommendation levels. The returns for the 180-day period from $t = -200$ to $t = -20$ prior to each recommendation date are regressed against the return on the Small Ordinaries Index. The mean daily abnormal returns (ARs) are computed by averaging across recommendations, and CAR $[t,T]$ is the sum of mean daily ARs between days t and T. All t-statistics and significance levels are calculated using Newey and West (1987) standard errors which adjust for heteroskedasticity and autocorrelation in the residuals. ***, ** and * indicate significance at the 1 per cent, 5 per cent and 10 per cent (two-tail) levels, respectively. H_0: CAR $[t,T] = 0$ and H_1: CAR $[t,T] \neq 0$.

5.2. Returns-based performance measures

Single and multi-factor models are used to evaluate small-cap fund manager performance. Each model involves a regression of monthly pre-expense returns of a fund in excess of the monthly risk-free rate against one or more factors. Table 3 reports the results of a number of returns-based performance evaluation models. The magnitude of Jensen's alpha provides an estimate of the level of fund manager skill with respect to stock selection ability after controlling for market risk. Panel A indicates that small-cap equity funds outperform the Small Ordinaries Index by 82 basis points a month, or 9.8 per cent annually. In addition, the beta on the market factor indicates that small-cap fund manager returns are highly sensitive to the Small Ordinaries Index. This is not surprising, given that fund managers hold diversified portfolios of stocks, the majority of which are constituents of the Small Ordinaries.

The results from the Fama and French (1992) model in Panel B and the Carhart (1997) model in Panel C show that the coefficient on the SMB 'small minus big' size factor is significantly positive, indicating the presence of a small-firm return anomaly, which partly explains the alphas reported in Panel A. Taken together, the SMB and the HML factors (i.e., the Fama–French factors) cause small-cap equity manager returns to drop from 82 to 69 basis points per month. Similarly, Panel C suggests that small-cap equity managers also adopt momentum strategies, buying (selling) stocks with positive (negative) past 6-month returns, which also contributes to alphas earned.

After controlling for the additional factor based on the Carhart (1997) four-factor model (i.e., momentum), alpha drops by 11 basis points to 0.58 per cent a month, although it remains economically (i.e., 7.0 per cent per annum) and statistically significant. Our results are consistent with Chen *et al.* (2010), indicating a pronounced level of stock selection ability among small-cap equity fund managers, even after controlling for market anomalies such as size, book-to-market ratio and momentum.

Panel D presents results for a five-factor model where the BMS broker recommendation factor is introduced. Overall, the findings in Panel D confirm Hypothesis 2, i.e., broker recommendations play a role in the investment decisions of small-cap equity managers and contribute to their alphas. The excess return of 58 basis points per month in the Carhart (1997) model is reduced to 54 basis points per month when the BMS factor is added. In summary, the BMS factor explains 7 per cent of the excess return in the Carhart model.

The loading coefficient on the Small Ordinaries market factor is reduced from 0.8781 to 0.8132 with the introduction of the BMS factor. This can be explained by the correlation that exists between the BMS factor and the Small Ordinaries market factor.[12] The addition of the BMS factor also causes an increase in the coefficient on the size, book-to-market and momentum factor in Panel C.[13]

5.3. Transaction-based performance measures

We now turn to an analysis of fund manager data at the trade level to ascertain the impact of broker recommendations on the trading behaviour and performance of small-cap equity managers. Based on Hypothesis 3, it is expected that small-cap equity managers trade on the basis of broker recommendations. That is, managers should be more likely to execute a buy trade on stocks with a Buy recommendation or execute a sell on stocks with a Sell recommendation.

Table 4 (Panel A) presents the results on transaction-based performance measures, partitioned on the basis of recommendation levels. Consistent with Hypothesis 3, an examination of the CARs reveals that small-cap fund managers earn highly significant CARs on purchases where the underlying stock had a buy recommendation. For example, a buy trade package on a stock with a Buy recommendation earns a CAR of 1.56 per cent in the 60-day period following the last day of the buy trade package. The pattern of the CARs for this set of securities suggests that broker Buy recommendations are for stocks with positive momentum or that fund managers become aware of the recommendation prior to its publication in the IBES database, because the pre-recommendation CARs are a significantly positive 4.37 per cent. In contrast, the stocks sold by small-cap fund managers after a broker Sell recommendation experienced insignificant positive CARs in the order of 0.47 per cent in the 60-day period following the last day of the sell trade package.

We investigate whether taking a prior position in a stock occurs by examining the daily trades of small-cap equity managers prior to recommendation date.

We calculate a number of trade-related metrics to analyse the relative magnitude of the trade packages. The aim is to test whether managers take substantial positions in stocks prior to a recommendation.

[12] We confirm that multicollinearity is not an issue in the model by conducting further analysis to control for the correlation between BMS and the market factor. Our findings indicate that BMS continues to be statistically significant after accounting for its correlation with the market factor. These results are available from the corresponding author on request.

[13] We also estimated the returns-based factor models using a ‘balanced index’ as the market factor. The ‘balanced index’ comprises stocks, which reflect the underlying holdings of small-cap equity managers, as detailed in Table 3. Under this benchmark specification, essentially the same results detailed in Table 3 are encountered. The various models have high explanatory power, and the alphas are statistically and economically significant across all model specifications. These results are available from the corresponding author on request.

Table 3
Returns-based performance measures – multi-factor models

Returns-based performance evaluation – multi-factor models – March 1995 to March 2004							
	Mean	Median	Min.	Max.	SD	Positive significance	Negative significance
Panel A: Single factor model (Jensen's Alpha)							
α	0.0082	0.0072	−0.0025	0.0260	0.0063	8***	0
β_{SO}	0.8669	0.8450	0.5516	1.4315	0.2081	14	0
Adjusted R^2	0.7068	0.6986	0.3527	0.9371	0.1547		
Number of months	50.6429	38	13	114	33.9652		
Panel B: Three-factor model (Fama and French, 1992)							
α	0.0069	0.0075	−0.0044	0.0209	0.0069	6***	0
β_{SO}	0.8465	0.8478	0.5105	1.3616	0.1982	14	0
β_{HML}	0.0595	−0.0058	−0.1271	0.6764	0.2186	3	0
β_{SMB}	0.0301	0.0077	−0.0808	0.2360	0.1033	3	1
Adjusted R^2	0.7098	0.6979	0.4037	0.9529	0.1525		
Number of months	50.6429	38	13	114	33.9652		
Panel C: Four-factor model (Carhart, 1997)							
α	0.0058	0.0052	−0.005	0.0189	0.0064	6***	0
β_{SO}	0.8781	0.8572	0.5129	1.3617	0.2133	14	0
β_{HML}	0.0556	−0.0051	−0.13	0.6848	0.2147	2	0
β_{SMB}	0.0977	0.0928	−0.071	0.3617	0.1317	4	1
β_{MOM}	0.1003	0.0501	−0.0588	0.3909	0.1355	3	0
Adjusted R^2	0.7185	0.7179	0.3555	0.9517	0.1671		
Number of months	50.6429	38	13	114	33.9652		
Panel D: Five-factor model							
α	0.0054	0.0050	−0.0135	0.0172	0.0072	5***	0
β_{SO}	0.8132	0.7648	0.4934	1.2704	0.2375	13	0
β_{HML}	0.0737	0.0526	−0.123	0.7286	0.2233	2	0
β_{SMB}	0.1133	0.1146	−0.0609	0.3875	0.1365	5	1
β_{MOM}	0.1108	0.0705	−0.0516	0.3849	0.1285	3	0
β_{BMS}	0.0791	0.1403	−0.8183	0.6962	0.3425	3	0
Adjusted R^2	0.7223	0.7178	0.4044	0.9518	0.1612		
Number of months	50.6429	38	13	114	33.9652		

Table 3 presents the results derived from returns-based models, where βs represent the loading coefficient on their corresponding factor. The results for a single-factor model are presented in Panel A, Panel B reports the results derived from a three-factor Fama and French (1992) model, Panel C reports results derived from a four-factor Carhart (1997) model, Panel D reports results derived from our five-factor Broker Recommendation model, specified as follows:

$$r_{i,t} = a_i + b_{iSO} r_{m,t} + b_{iHML_t}\mathrm{HML}_t + b_{iSMB}\mathrm{SMB}_t + b_{iPR1YR}\mathrm{PR1YR}_t + b_{iBMS}\mathrm{BMS}_t + e_{i,t} \quad (2)$$

T-tests: H_0 coefficient = 0. All t-statistics and significance levels are calculated using Newey and West (1987) standard errors which adjust for heteroskedasticity and autocorrelation in the residuals of panel data. Note: Alpha estimates are reported in decimal form. ***Significance at the 1 per cent (two-tail) level, respectively, based on a Binomial test.

Table 4
Results from transaction-based measures – cumulative abnormal returns (CARs) around transactions

Transaction-based performance measures – February 1997 to June 2004

CARs around transactions by recommendation level and trade type

	Buy pack		Sell pack	
Event day	Buy	Sell	Buy	Sell
N	1248	324	1003	225
CAR [−60;0]	0.0437*** (0.0069)	0.0355*** (0.0096)	0.0389*** (0.0079)	0.0085 (0.0106)
CAR [−50;0]	0.0351*** (0.0058)	0.0261*** (0.0094)	0.0296*** (0.0069)	0.0058 (0.0108)
CAR [−40;0]	0.0276*** (0.0050)	0.0193** (0.0086)	0.0261*** (0.0056)	−0.0060 (0.0088)
CAR [−30;0]	0.0196*** (0.0042)	0.0115 (0.0074)	0.0152*** (0.0044)	−0.0050 (0.0082)
CAR [−20;0]	0.0097*** (0.0031)	0.0126** (0.0054)	0.0080** (0.0034)	−0.0097 (0.0068)
CAR [−10;0]	0.0025 (0.0022)	0.0029 (0.0032)	0.0035 (0.0023)	0.0013 (0.0031)
CAR [0;10]	0.0045*** (0.0017)	0.0024 (0.004)	0.0072*** (0.0020)	−0.0021 (0.0033)
CAR [0;20]	0.0055** (0.0024)	−0.0031 (0.0044)	0.0059** (0.0029)	0.0026 (0.0058)
CAR [0;30]	0.0051 (0.0033)	−0.0008 (0.0051)	0.0032 (0.0036)	0.0033 (0.0072)
CAR [0;40]	0.0091** (0.0040)	0.0020 (0.0061)	0.0012 (0.0042)	0.0063 (0.0082)
CAR [0;50]	0.0121*** (0.0046)	0.0089 (0.0071)	0.0027 (0.0046)	0.0030 (0.0092)
CAR [0;60]	0.0156*** (0.0052)	0.0082 (0.0076)	0.0025 (0.0053)	0.0047 (0.0096)

Table 4 presents CARs calculated using the last day of the trade package as the reference date. Abnormal returns (ARs) are computed based on DGTW-adjusted daily alphas, and the mean daily AR and CARs are then computed. All t-statistics and significance levels are calculated using Newey and West (1987) standard errors, which adjust for heteroskedasticity and autocorrelation in the residuals of panel data. ***, ** and * indicate significance at the 1 per cent, 5 per cent and 10 per cent (two-tail) levels, respectively, based on T-tests.

Table 5 shows trade packages partitioned by their type (i.e., buy or sell) as well as the recommendation level on the underlying stock. The trade-related metrics are similar across all groups, with the vast majority of trades taking place in stocks for which the manager has an existing position. For example, over 96 per cent (98 per cent) of the sell trade packages following buy (sell) recommendations have an existing position in the stock, indicating that very few of the sell trade packages are indeed short sales. Further, 85 per cent (90 per cent) of the buy trade packages following a Buy (Sell) recommendation have an existing position in the stock, while the mean transaction weight as a proportion of NAV is approximately 0.43 (0.32) per cent. Given that the average number of stocks held by each manager is approximately 46 (and therefore that most of the existing positions will, by definition, be overweight relative to the weights in the small-cap index) and the majority of trade packages already have an existing position in the stock, the magnitude of the trades alone as a proportion of NAV is substantial. Following the trade, the overweight position for buy trades, for which there is a Buy recommendation (1.03), is greater (as expected) than the overweight position for a sell trade following a sell recommendation (0.73). Buy

Table 5
Results from transaction-based performance measures

Transaction-based performance measures – February 1997 to June 2004

Panel A: All trade packages in recommendation subsample

Recommendation level	Buy transactions: Strong buy/buy	Buy transactions: Underperform/sell	Sell transactions: Strong buy/buy	Sell transactions: Underperform/sell
N	1111	302	854	190
N with existing stock position	948	272	823	187
% transactions with existing position	85.33	90.07	96.37	98.42
Mean trade package size $	344 624	249 453	325 623	313 774
Mean transaction weight (% NAV)	0.43	0.32	0.34	0.28
Relative position – prior to trade (% NAV)	1.55	1.63	2.16	2.03
Relative position – post-trade (% NAV)	1.98	1.95	1.82	1.75
Overweight relative to index – post-trade position	1.03	0.87	0.87	0.73

Table 5 presents descriptive statistics of the trade-related metrics used in analysing transaction-based performance. The mean transaction weight is the total value of the trade package divided by the fund's Net Asset Value (NAV), averaged across the number of trade packages. This can be expressed as:

$$\text{Transaction Weight}_{ijt} = \frac{\text{Trade Package Value}_{ijt}}{\text{NAV}_{jt}} \tag{3}$$

where N is the number of trade packages, L is the total number of managers, NAV_{jt} is fund j's NAV in time t, Trade Package Value_{ijt} is the dollar value of the trade package i made by fund j at time t. Relative Position (Prior) to trade is defined as a fund's holding in a stock in the prior month as a proportion of NAV in the current month. This is expressed as:

$$\text{Relative Position (Prior)}_{ijt} = \frac{\text{Holding Value}_{ijt-1}}{\text{NAV}_{jt}}. \tag{4}$$

Similarly, Relative Position (Post) trade is defined as the sum of a fund's existing holding in a stock and the trade package value as a proportion of NAV. This is expressed as:

$$\text{Relative Position (Post)}_{ijt} = \frac{\text{Trade Package Value}_{ijt} + \text{Holding Value}_{ijt-1}}{\text{NAV}_{jt}}. \tag{5}$$

Overweight relative to index is weight of the stock underlying trade package i within the Small Ordinaries Index subtracted from Relative Position (Post) computed as per equation (5).

$$\text{Overweight}_{ijt} = \text{Relative Position (Post)}_{ijt} - \text{Weight}_{it\text{XSO}}. \tag{6}$$

trades following a Buy recommendation are larger, as expected, than buy trades following a Sell recommendation. However, in contrast, managers sell smaller quantities of stock following a Sell recommendation than they do following a Buy recommendation. This finding is perhaps because small-cap fund managers have a smaller proportion of NAV invested in stocks that receive unfavourable Sell recommendations.

Table 6
Coverage levels and transaction-based performance

Transaction-based performance by coverage level – February 1997 to June 2004

Panel A: Transaction-based CARs by coverage level for buy packs

Trade type	Buy packs				
Coverage level (no. of brokers)	0	1–3	4–6	7–9	> 9
N	559	1596	2107	1371	101
CAR [−60;0]	0.0486***	0.0269***	0.0274***	0.0215***	0.0466**
CAR [−30;0]	0.0253***	0.0117**	0.0089***	0.0090*	0.0307*
CAR [−10;0]	0.0032	0.0020	−0.0013	−0.0005	0.0074
CAR [0;10]	0.0013	0.0009	0.0064***	0.0024	0.0040
CAR [0;30]	0.0071	−0.0049	0.0088***	0.0042	0.0081
CAR [0;60]	0.0044	−0.0062	0.0141***	0.0126*	0.0428**

Panel B: Transaction-based CARs by coverage level for sell packs

Trade type	Sell packs				
Coverage level (no. of brokers)	0	1–3	4–6	7–9	> 9
N	356	1139	1686	1106	106
CAR [−60;0]	0.0163	0.0119	0.0197***	−0.0019	0.0217
CAR [−30;0]	−0.0098	0.0024	0.0064*	−0.0024	0.0204
CAR [−10;0]	0.0018	0.0049	0.0000	−0.0007	0.0171***
CAR [0;10]	−0.0023	−0.0034	0.0030*	0.0015	0.0042
CAR [0;30]	−0.0038	−0.0092	0.0044	−0.0020	−0.0022
CAR [0;60]	−0.0264*	−0.0113	0.0047	0.0026	0.0099

CARs, cumulative abnormal returns. Table 6 (Panel A) presents the CARs from the last day of a buy trade package, with a split around broker coverage levels. *N* refers to the total number of brokers following the underlying stock of a particular trade package, defined as the number of unique brokers who have issued a recommendation within the same year. Similarly, Panel B presents the results for sell packs. Abnormal returns (ARs) are computed based on DGTW-adjusted daily alphas. The mean daily AR and CARs between day t and T, denoted as CAR $[t,T]$, are computed by summing the mean daily ARs from days t to T. All t-statistics and significance levels are calculated using Newey and West (1987) standard errors, which adjust for heteroskedasticity and autocorrelation in the residuals of panel data. ***, ** and * indicate significance at the 1 per cent, 5 per cent and 10 per cent (two-tail) levels, respectively, based on T-tests with Newey–West standard errors.

5.4. Coverage levels and transaction-based performance

Table 6 presents the CARs earned around trade packages with a split based on coverage levels. Specifically, Panel A reports the CARs around buy packs for the respective coverage level groups, and Panel B reports CARs for the sell packs. Consistent with Hypothesis 5, sell trades in stocks with lower coverage generated significant CARs post-trade. For the 356 sell trades made in stocks with a zero coverage level, the CARs are a significantly negative (−2.64) per cent after 60 days. In contrast, the CARs are an insignificant 0.99 per cent after 60 days on a sell trade where the stock had more than nine brokers following it. Overall, the CARs follow a decreasing trend as the number of brokers decreases.

This result is consistent with Dhiensiri and Sayrak (2005), who find that recommendations are less informative as the number of analysts following a firm increases. Our findings on sell trades support the notion that small-cap equity fund managers exploit the lower levels of information available on stocks with low research coverage, thereby earning statistically significant ARs.

In contrast, and inconsistent with expectations, Panel A reports the performance of buy packs through an analysis of the CARs around the last date of a buy trade package. For buy trades, the magnitude of the CAR following the trade is positively related to broker coverage. Where there are more than nine brokers covering a stock, the post-trade CAR is significantly positive (4.28 per cent), while buy packs for which there is low analyst coverage have insignificant returns. A possible explanation for this finding is that there needs to be a strong consensus among several brokers in relation to buys, before market participants follow the recommendation, given the propensity for a buy imbalance in broker recommendations. In contrast, sell transactions are more informative when there is low coverage.

5.5. *Robustness tests*

To strengthen the validity of the findings in this study, a number of robustness tests are conducted. These involve altering the research design to ensure that our results are robust to differences in methodology, as well as alternative econometric techniques.

5.5.1. *Controlling for the correlation between BMS and the market factor*

We control for the correlation between the BMS broker recommendation factor and the market risk factor in the following manner. Firstly, the Small Ordinaries Index is regressed on the BMS factor, and the residuals from this regression, which represent the portion of BMS that is uncorrelated with the Small Ordinaries market factor (which we term BMS*), are used in a five-factor model in which BMS* is used in place of BMS in equation (2).

We also repeat the process, substituting the All Ordinaries Index and a Balanced Index in place of the Small Ordinaries Index. The regression results[14] indicate that across all the two benchmark specifications, the coefficient on the BMS factor continues to be significant. Hence, after controlling for the correlation

[14] These results are available from the corresponding author on request.

between BMS and the market factor, broker recommendations continue to play a significant role in the investment decisions of small-cap managers.

5.5.2. Long-only portfolios in five-factor model

The broker recommendation factor BMS is formed on the assumption that fund managers are equally able to take short and long positions in stocks. However, an analysis of the holdings data reveals that short positions are rare or non-existent. For instance, Saar (2001) observes that funds generally do not short sell, to avoid risking unlimited losses if the stock price goes up. Furthermore, the charters of many funds restrict the usage of short sales.

Based on this, we reconstruct the BMS factor using long-only portfolios that better reflect the actual portfolio allocation decisions of small-cap funds.

To construct a long-only BMS factor, a long position is taken in newly issued buy recommendations each month. For stocks with both buy and sell recommendations, the consensus recommendation is applied for that month and a long position is taken if its consensus recommendation is a buy. Following this, returns-based factor models are estimated. These results confirm the robustness of our findings, as the significance of the BMS factor and the results as a whole remains unchanged.[15]

5.5.3. Changing risk owing to the technology boom and bust

The sample period used in the returns-based performance regressions encompasses both the technology boom and its subsequent bust in 2001. As a robustness test, we control for possible differences in the risk and levels of information asymmetry attributable to this event. Given that the bust occurred in 2001, we divide the sample in half to capture the lead-up ‘boom’ period prior to and excluding 2001, as well as its subsequent ‘bust’ from 2001 onwards. This approach is chosen over a regression with calendar year dummies as it prevents over-specification of the models. The results indicate that the magnitude and significance of alpha is highly sensitive to this event.[16] Furthermore, the results suggest that small-cap managers invested in the technology boom, with a tilt towards growth stocks prior to 2001, as observed by a statistically significant negative coefficient on the HML factor. This is observed across all model specifications. They also profited from this, given the statistically significant alpha of 53 basis points per month prior to 2001 from the five-factor model. Interestingly, we observe that the BMS factor is statistically significant prior to the boom, but not after. This suggests that post-2001, small-cap managers were perhaps more cautious and did not rely as much on the information provided by brokers for

[15] These results are available from the corresponding author on request.

[16] These results are available from the corresponding author on request.

their investments. Further, alpha is not statistically different to zero in the bust period.

6. Conclusion

The Grossman and Stiglitz (1980) informational equilibrium asserts that markets are informationally efficient when investors generate ARs that compensate them for the costs of becoming informed. Such activities suggest that financial market researchers and analysts will only decide to incur costs when they can be compensated for doing so. The study of Wermers (2000) is one of the first mutual fund studies to show that active mutual fund managers in the US conform to Grossman–Stiglitz equilibrium and therefore represents one important yardstick in comparing whether the alphas generated by fund managers are economically significant. A second barometer in assessing economic significance relates to the management expenses charged in providing asset management services and whether the services rendered are commensurate with performance generated (e.g. Admati and Pfleiderer, 1997).

In a recent study, Chen *et al.* (2010) find evidence of the stock selection ability of Australian small-cap equity managers, as they earn risk-adjusted ARs of between 60 and 76 basis points per month. The large magnitude of the alphas earned inevitably prompts the question of whether these returns can be explained through the information advantage of small-cap funds.

Our present study contributes to the literature by jointly exploring the areas of broker recommendations and small-cap equity funds to determine how valuable the recommendations are in the fund management process. Given that the outperformance of these fund managers has been confirmed, this study is unique in that it seeks to understand the drivers behind such outperformance, such as the information asymmetry between managers and investors in the market.

Initially, we confirm the findings of Chan *et al.* (2006) in that broker recommendations possess investment value. We also show that the price reaction around Initiating recommendations is not significantly different from 'Continuing' recommendations. These findings are confirmed using two approaches of estimating ARs, a traditional market model approach and a DGTW approach motivated by Daniel *et al.* (1997).

The findings on returns-based performance models are consistent with those of Chen *et al.* (2010) in that small-cap equity managers possess stock selection ability. Using a Carhart (1997) model, we show small-cap managers earn economically and statistically significant alphas of 58 basis points a month. Furthermore, the addition of a broker recommendation mimicking factor portfolio to the Carhart (1997) model reduces alpha by 48 basis points per annum (i.e., from 58 to 54 basis points a month), although it continues to be statistically significant. We additionally test the robustness of alpha across alternative benchmark specifications of the market factor. Our transaction-based performance measures involve the examination of DGTW-adjusted

CARs around trades. We find that small-cap equity managers earn statistically significant ARs on trades that follow broker recommendations. Furthermore, managers have a greater likelihood of trading on the basis of recommendation levels if they do not have an existing position in a stock prior to the trade, presumably because of a lack of information and company relationships on these stocks.

Further, we find that the ARs following small-cap equity manager sell trades are inversely related to the number of analysts following a stock, whereas results are reversed for buy trades. This confirms findings in the literature that sell trades are motivated by information and allow managers to exploit mispricing when there are lower coverage levels, whereas buy trades are informative only when there is a strong buy consensus recommendation among several brokers.

In terms of economic significance, our results show that small-cap fund managers generate ARs that exceed their costs. Indeed, increasing the benchmark hurdle by moving from a four-factor to a five-factor model (that controls for externally produced research from analysts) does not alter the overall conclusions concerning managerial ability.

Finally, it is known that brokers and fund managers alike may have expertise in a particular industry, which could result in an information advantage over market participants. For example, Boni and Womack (2006) take an industry perspective when analysing broker recommendation value and find that an analyst's industry expertise provides incremental investment value. With this in mind, it would be interesting to take industry expertise into account when examining the impact of broker recommendations on small-cap funds.

References

Admati, A., and P. Pfleiderer, 1997, Does it all add up? Benchmarks and the compensation of active portfolio managers, *Journal of Business* 70, 323–350.

Aitken, M., K. Wong, and J. Muthuswamy, 2000, The impact of brokers' recommendations: Australian evidence, Paper presented at the PACAP/FMA conference, Melbourne.

Arbel, A., S. Carvell, and P. Strebel, 1983, Giraffes, institutions and neglected firms, *Financial Analysts Journal* 39, 57–63.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman, 2001, Can investors profit from the prophets? Security analyst recommendations and stock returns, *Journal of Finance* 56, 531–563.

Beneish, M. D., 1991, Stock prices and the dissemination of analysts' recommendations, *Journal of Business* 64, 393–416.

Boni, L., and K. Womack, 2006, Analysts, industries and price momentum, *Journal of Financial and Quantitative Analysis* 41, 85–109.

Brown, N. C., K. D. Wei, and R. R. Wermers, 2008, Analyst recommendations, mutual fund herding, and overreaction in stock prices, working paper (University of Maryland, Maryland).

Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chan, H., and R. Faff, 2003, An investigation into the role of liquidity in asset pricing: Australian evidence, *Pacific-Basin Finance Journal* 11, 555–572.

Chan, L. K. C., and J. Lakonishok, 1995, The behavior of stock prices around institutional trades, *Journal of Finance* 50, 1147–1174.
Chan, K., C. Y. Hwang, and G. M. Mian, 2005, Mutual fund herding and dispersion of analysts' earnings forecasts, working paper (Hong Kong University of Science and Technology, Hong Kong).
Chan, H., R. Brown, and Y. K. Ho, 2006, Initiation of brokers' recommendations, market predictors and stock returns, *Journal of Multinational Financial Management* 16, 213–231.
Chen, Z., and P. Knez, 1996, Portfolio performance measurement: theory and applications, *Review of Financial Studies* 9, 511–555.
Chen, H.-L., N. Jegadeesh, and R. Wermers, 2000, The value of active mutual fund management: an examination of the stockholdings and trades of fund managers, *Journal of Financial and Quantitative Analysis* 35, 343–368.
Chen, C., C. Comerton-Forde, D. R. Gallagher, and T. S. Walter, 2010, Investment manager skill in small-cap equities, *Australian Journal of Management* 35, 23–49.
Comerton-Forde, C., D. R. Gallagher, J. Nahhas, and T. S. Walter, 2010, Transaction costs and institutional trading in small-cap equity funds, *Australian Journal of Management* (forthcoming).
Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.
Demiroglu, C., and M. D. Ryngaert, 2008, The first analyst coverage of neglected stocks, working paper (University of Florida, Florida).
Dhiensiri, N., and A. Sayrak, 2005, The value effects of analysts coverage initiations, working paper (University of New Hampshire, New Hampshire).
Elton, E. J., M. J. Gruber, and S. Grossman, 1986, Discrete expectational data and portfolio performance, *Journal of Finance* 41, 699–713.
Fama, E., and K. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.
Fong, K., D. R. Gallagher, and A. D. Lee, 2008, Benchmarking benchmarks: measuring characteristic selectivity using portfolio holdings data, *Accounting and Finance* 48, 761–781.
Gallagher, D. R., and A. Looi, 2006, Trading behaviour and the performance of daily institutional trades, *Accounting and Finance* 46, 125–147.
Gharghori, P., H. Chan, and R. Faff, 2007, Are the Fama-French factors proxying default risk? *Australian Journal of Management* 32, 223–249.
Grinblatt, M., and S. Titman, 1993, Performance measurement without benchmarks: an examination of mutual fund returns, *Journal of Business* 66, 47–68.
Grossman, S. J., and J. E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393–408.
Irvine, P., 2003, The incremental impact of analyst initiation of coverage, *Journal of Corporate Finance* 9, 431–451.
Irvine, P., M. Lipson, and A. Puckett, 2007, Tipping, *Review of Financial Studies* 20, 741–768.
Jegadeesh, N., K. Joonghyuk, S. D. Krische, and C. M. C. Lee, 2004, Analyzing the analysts: when do recommendations add value? *Journal of Finance* 59, 1083–1124.
Jensen, M. C., 1968, The performance of mutual funds in the period 1945–1964, *Journal of Finance* 23, 389–416.
Kecskes, A., and K. L. Womack, 2007, Adds and drops of analyst coverage: does the stock market overreact? working paper (Dartmouth College, New Hampshire).
Kelly, B., and A. Ljungqvist, 2007, The value of research, working paper (Stern School of Business, New York).

Kothari, S. P., and J. B. Warner, 2001, Evaluating mutual fund performance, *Journal of Finance* 56, 1985–2010.

Kothari, S. P., and J. B. Warner, 2006, Econometrics of event studies, in: B. E. Eckbo, ed., *Handbook of Empirical Corporate Finance* (Elsevier North-Holland, The Netherlands), 4–36.

Lehmann, B. N., and D. M. Modest, 1987, Mutual fund performance evaluation: a comparison of benchmarks and benchmark comparisons, *Journal of Finance* 42, 233–265.

MacKinlay, A. C., 1997, Event studies in economics and finance, *Journal of Economic Literature* 35, 13–39.

Newey, W. K., and K. D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Petersen, M. A., 2009, Estimating standard errors in finance data sets: comparing approaches, *Review of Financial Studies* 22, 435–480.

Pinnuck, M., 2003, An examination of the performance of the trades and stock holdings of fund managers: further evidence, *Journal of Financial and Quantitative Analysis* 38, 811–828.

Saar, G., 2001, Price impact asymmetry of block trades: an institutional trading explanation, *Review of Financial Studies* 14, 1153–1181.

Stickel, S., 1995, The anatomy of the performance of buy and sell recommendations, *Financial Analysts Journal* 51, 25–39.

Wermers, R., 2000, Mutual fund performance: an empirical decomposition into stock-picking talent, style, transaction costs, and expenses, *Journal of Finance* 55, 1655–1695.

Womack, K. L., 1996, Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51, 137–167.