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Buy-side trades and sell-side recommendations: Interactions and information content ☆

Jeffrey A. Busse, T. Clifton Green, Narasimhan Jegadeesh*

Goizueta Business School, Emory University, 1300 Clifton Road, Atlanta, GA 30322, Unites States

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Abstract

We examine the performance of buy-side institutional investor trades and sell-side brokerage analyst stock recommendations, as well as their interactions. Buy-side trades follow sell-side analyst recommendations but not the other way around. While buy-side purchases significantly outperform their sales, the difference in performance is largely concentrated on the day of the transaction. Following recommendation changes, buy-side trades in the same direction as the recommendation change earn the same returns as trades in the opposite direction. Therefore, institutional investors do not exhibit special skills in discerning the quality of recommendations.

JEL classification: G14

Keywords: Analyst recommendations; Institutional trading

1. Introduction

Timely and accurate dissemination of information is critical for capital markets to function efficiently. Not surprisingly, enormous resources are spent collecting and analyzing market and stock-specific information. The agents involved in these tasks could be compensated for their role, broadly, in two ways. Skilled information producers could set up mutual funds to actively invest in stocks and collect fees from their investors, or,

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*Corresponding author.
E-mail addresses: Jeff_Busse@bus.emory.edu (J.A. Busse), Clifton_Green@bus.emory.edu (T.C. Green), Narasimhan_Jegadeesh@bus.emory.edu (N. Jegadeesh).

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alternatively, they could sell their information to investors through research reports, as typically done by sell-side analysts in brokerage firms.

In practice, however, active mutual funds and brokerage analysts who communicate directly with investors coexist. Mutual funds reveal their information through their trades, and sell-side analysts reveal their investment opinion through recommendations. Besides issuing recommendations, sell-side analysts also provide additional services such as helping generate trade commissions for their employer or assisting with investment banking activities.

Sell-side analysts' multi-faceted role potentially exposes them to conflicts of interest. Concerns about such conflicts led to close scrutiny of analysts' activities, which resulted in the 2003 Global Analyst Research Settlement between ten large brokerage houses and the SEC and state regulators, which curtailed their activities in the area of investment banking. While this settlement reduced their involvement in investment banking activities, other potential conflicts remain. For example, Irvine (2001, 2004) finds evidence that trading commissions are an important determinant for the types of information that are released by brokerage analysts. In addition, surveys of institutional investors indicate that providing management access to information is an important service offered by brokerage analysts. As a result, the desire to stay in the good graces of firm management may color the opinions of brokerage firm analysts.

Mutual funds do not face these types of conflicts of interest. Their fees depend on the amount of assets under management, and investors choose funds based primarily on their past performance (Warther, 1995; Sirri and Tufano, 1998). Therefore, one might expect the mutual fund set-up to be the optimal mechanism to deliver the value of stock research to investors in the presence of agency conflicts.

We present a comparative analysis of the performance of stocks recommended by brokerage analysts and stocks that are traded by mutual funds and investigate the relative information content. Several papers in the literature present evidence of the stock-picking skills of mutual funds (e.g., Daniel, Grinblatt, Titman, and Wermers, 1997; Chen, Jegadeesh, and Wermers, 2000; Wermers, 2000, 2004) and sell-side analysts (e.g., Womack, 1996; Barber, Lehavy, McNichols, and Trueman, 2001; Jegadeesh, Kim, Krische, and Lee, 2004; Jegadeesh and Kim, 2006). Our study is the first to investigate the relative information content of active funds' trades and brokerage recommendations using the same sample of stocks and the same sample period.

We also investigate the relation between sell-side analysts' recommendations and mutual fund trades, addressing several issues that have been of interest both in the academic literature and in the popular media. Academic studies often suggest that institutions are sophisticated investors who can sort through recommendations potentially tainted by analysts' incentives. For instance, Malmendier and Shanthikumar (2007) argue that institutions take into account the fact that sell-side analysts tilt their recommendations towards buy ratings but individual investors trade naively and "follow recommendations literally."

The media and many investors also share such perceptions. For instance, a *New York Times* article asserts that "For years, Wall Street's dirty little secret was that its research was devised expressly for two key constituencies: its institutional investors and its corporate clients. If the individual investor wanted to join the party, well, caveat emptor."[1]

[1] *The New York Times*, December 23, 2002, "Can settlements actually level the playing field for investors?"

Recent reports that "analysts at Goldman sometimes shared with traders and key clients short-term trading tips that sometimes differed from the firm's long-term research"[2] add support to such perceptions.

Other media reports suggest that institutional investors are able to see through any inherent biases in sell-side recommendations due to conflicts of interest, although these recommendations may mislead retail investors. For example, a *Euromoney* article about the Global settlement reports that "The managers attribute all the fuss to the lack of sophistication among retail investors, who were too witless or ill-informed to translate the Wall Street language of buy, strong buy, and hold. They didn't seem to realize, a common argument goes, that you had to call analysts to get their private views, not merely read their reports."[3]

The relation between mutual fund trades and sell-side analysts' recommendations will shed light on whether institutional investors are indeed able to differentiate between good recommendations and bad recommendations, as well as if these investors are a "key constituency" for sell-side analysts. If mutual funds use analyst recommendations as an input for their trading decisions, then we expect fund trades to be correlated with the direction of analyst recommendations. Moreover, if institutional investors have special access to analysts' private views or if they have superior abilities to understand recommendations, then we expect analyst recommendations that are accompanied by mutual fund trades in the same direction to outperform those that are accompanied by trades in the opposite direction.

In related work, Malmendier and Shanthikumar (2007) examine whether small investors are naïve about analysts' conflicts of interest when they make recommendations, and they compare the patterns of large trades and small trades around recommendation revisions. Malmendier and Shanthikumar's dataset does not report the identity of the trader. Therefore they classify trades as those by institutions or individuals based on trade size, and they attribute large trades to institutions and small trades to individuals. However, institutions typically break up their trades into small orders, and hence trades that are classified as individual trades may well be parts of a larger institutional trade. In contrast, we use institutional trade datasets from Plexus and Abel/Noser in which we know that the trades are executed by institutions, and we also know the direction (buy or sell) of each trade.

Goldstein, Irvine, Kandel, and Wiener (2009) also use the Abel/Noser dataset to examine institutional trades around recommendations. They focus on whether trades by institutional clients of the brokerage that employs the analyst issuing recommendations differ from those by other institutions. However, they do not examine the incremental information content of institutional trades, nor do they investigate whether institutions are able to differentiate between good recommendations and bad recommendations. It is critically important to investigate whether institutions are able to differentiate between good and bad recommendations to understand whether institutional investors have special insights that individual investors lack.

We find that sell-side analysts' recommendations are informative, which is consistent with earlier findings in the literature. Although mutual fund purchases significantly outperform their sales, the difference in performance is largely concentrated on the day of

[2]See "Regulators Examine Goldman's Trade Tips," August 25, 2009, http://online.wsj.com/article/SB125115914476055403.html.

[3]Euromoney.com, February 1, 2003, "Where is all the buy-side outrage?"

the trade. In direct comparisons, we find that sell-side analysts' recommendations show superior stock-selection skills compared with mutual fund trades.

We also find that mutual funds tend to trade in the direction of recommendation revisions.[4] However, mutual fund trades are not incrementally informative. Specifically, the performance of analyst recommendations that are accompanied by mutual fund trades in the same direction is the same as those accompanied by trades in the opposite direction.

In related work, a recent paper by Irvine, Lipson, and Puckett (2007) finds that analysts tip institutional investors before they initiate recommendations with Buy or Strong Buy ratings. Initiations are relatively rare compared with the number of upgrades and downgrades that analysts issue. We examine here whether institutional trading prior to recommendation revisions indicates that they were tipped about impending revisions.

We find that institutions are not net buyers prior to upgrades, but they are net sellers prior to upgrades. Therefore, contrary to the findings in Irvine, Lipson, and Puckett (2007) for initiations, analysts do not seem to be tipping investors prior to regular upgrades. However, we find that institutions are significant net sellers over the five-day period prior to downgrades.[5] This finding indicates that analysts potentially tip their clients prior to downgrades but not for upgrades.

When we compare the performance of analysts' recommendations with mutual fund trades, we have to account for the fact that sell-side analysts publicly announce their recommendations, while mutual fund trades are not public information. Therefore, the impact of recommendations would be quickly incorporated in prices, whereas the value of the signals on which mutual funds base their trades would only be reflected in prices over time. Moreover, mutual funds have access to sell-side analysts' recommendations when they make their trades. We develop a model that allows us to make direct comparisons of the relative information content of analyst recommendations and mutual fund trades that take these factors into account.

The paper proceeds as follows. Section 2 describes the data on fund trades and analyst recommendations. Section 3 examines the performance of trades and recommendations, and Section 4 investigates the empirical relations between them. Section 5 concludes.

2. Data

2.1. Institutional trading

We use institutional funds' trades to evaluate their stock-selection skills. We obtain institutional trading data from two sources: the Plexus Group (now owned by Investment Technology Group) and Abel/Noser Corporation.[6] Both companies are consulting firms that help institutional investors monitor and manage their transaction costs. Their clients include both pension-plan sponsors and money managers, and the databases identify each client by a numeric code.

[4]Recent work by Brown, Wei, and Wermers (2007) examines, using quarterly data, whether fund trades in the same direction as revisions lead to price pressure. Our findings indicate that the frequency of fund trades and revisions that occur in the same direction is fairly small.

[5]Irvine, Lipson, and Puckett (2007) do not examine trading patterns prior to initiations with negative ratings such as Sell or Strong Sell.

[6]Keim and Madhavan (1995), Conrad, Johnson, and Wahal (2002), and Irvine, Lipson, and Puckett (2007) are some of the papers that use Plexus data; Hu (2009), Goldstein, Irvine, Kandel, and Wiener (2009) are some of the studies that use Abel/Noser data.

Table 1 presents a data summary. The Plexus sample covers the period from September 1993 through December 2001. This dataset contains over 1.9 million transactions for 10,737 different stocks. The Abel/Noser sample begins in 1997, ends in 2005, and contains about 5.1 million transactions for 10,905 different stocks. Together, these two datasets contain trades by 908 different institutional investors.[7] About 55% of the trades are buys, and 45% are sells. The larger proportion of buys reflects the overall growth in assets under management by institutions.

2.2. Analyst recommendations

We obtain analyst recommendations from the Institutional Brokers' Estimate System (I/B/E/S) for the period from 1993 to 2005. The data consist of a ticker to identify the recommended stock, the date of the recommendation, the broker, and the analyst's recommendation.[8] I/B/E/S codes analyst recommendations using a 1–5 scale, with 1 signifying a strong buy, 2 a buy, 3 a hold, 4 a sell, and 5 a strong sell. Analysts routinely change their recommendations based on any new information that they get, as well as on stock price movements relative to their target prices.

We follow the prior literature and use price changes following revisions in analysts' recommendations as a measure of the value of analysts' information. Table 1 presents summary statistics for our recommendation change sample over our 1993–2005 sample period. There are about 55% downgrades and about 45% upgrades during this period. Overall, there are 135,652 recommendation revisions in the sample, covering 8,174 different stocks.

We obtain individual stock returns, prices, volume of trades, shares outstanding, and exchange listings from the Daily and Monthly Stock files of the Center for Research in Security Prices (CRSP). Finally, we obtain financial statement data from Compustat. We use the CRSP and Compustat data to characterize the types of stocks that institutions trade and analysts follow and to evaluate the performance of their stock picks.

3. Performance of institutional trades and recommendation changes

3.1. Institutional trades

We first evaluate the stock selection skills of analysts and funds. To measure skill, we compute abnormal returns following trades and revisions on the event dates and for holding periods of one to four weeks and for two months and three months. Since analysts publicly announce their revisions, stock prices would react to the information content on

[7]When aggregating trading across institutions, we assume clients are unique across data providers, but the results are not sensitive to this assumption. For the period when the samples overlap, we find similar results when we use either source alone.

[8]Recent work by Ljungqvist, Malloy, and Marston (2009) suggests that I/B/E/S has periodically modified its database in non-random ways. Such modifications naturally can affect inference based on its historical record. Ljungqvist, Malloy, and Marston (2009) indicate that many of the modifications have been reversed in recent versions of the database. We base our analysis on a version of the database that appeared several months after Ljungqvist, Malloy, and Marston (2009) indicate the issues were somewhat corrected. Furthermore, using alternative databases such as Zacks and Thomson Financial's First Call, numerous papers find evidence of price patterns following analyst recommendations similar to our findings (e.g., Barber, Lehavy, and Trueman, 2007).

Table 1
Sample description.

	Panel A: Institutional transactions									Panel B: Analyst		
	Plexus			Abel/Noser			Merged sample			Recommendation changes		
	No. of trades	No. of stocks	% Buys	No. of trades	No. of stocks	% Buys	No. of trades	No. of stocks	% Buys	No. of changes	No. of stocks	% Upgrade
1993	5,348	158	0.542				5,348	158	0.542	545	399	0.519
1994	10,553	1,045	0.536				10,553	1,045	0.536	9,829	2,193	0.489
1995	39,712	4,245	0.759				39,712	4,245	0.759	10,063	2,290	0.441
1996	435,910	6,738	0.560				435,910	6,738	0.560	9,124	2,483	0.479
1997	515,601	6,780	0.543	4,225	595	0.507	516,620	6,790	0.543	8,541	2,662	0.444
1998	127,692	5,684	0.535	34,840	2,705	0.534	158,804	5,998	0.535	10,443	2,902	0.435
1999	20,794	2,912	0.562	631,452	7,252	0.547	635,153	7,299	0.547	10,645	2,859	0.494
2000	633,172	7,499	0.537	670,557	7,097	0.555	832,038	7,956	0.543	9,511	2,658	0.427
2001	148,200	5,076	0.593	640,765	6,324	0.558	673,766	6,553	0.562	10,507	2,549	0.422
2002				712,316	6,017	0.532	712,316	6,017	0.532	17,079	2,976	0.348
2003				745,132	6,196	0.544	745,132	6,196	0.544	15,319	3,001	0.459
2004				766,625	6,455	0.572	766,625	6,455	0.572	12,674	2,947	0.479
2005				882,472	6,647	0.550	882,472	6,647	0.550	11,372	3,038	0.515
Full sample	1,936,982	10,737	0.552	5,088,384	10,905	0.551	6,414,449	13,169	0.551	135,652	8,174	0.449

The table shows the number of observations in our sample of institutional transactions and analyst recommendation changes. The transaction data are from the Plexus Group and Abel/Noser Corp. The analyst recommendation data are from I/B/E/S. No. of stocks refers to the number of stocks traded or recommended.

the announcement date. However, funds do not publicly announce their trades. Therefore, any private information underlying their trades would be reflected in stock prices only over time as the market learns that information through various channels.

In addition to computing raw returns over various holding periods, we also compute DGTW-adjusted abnormal returns because trades and revisions are tilted towards various characteristics as Chen, Jegadeesh, and Wermers (2000) and Jegadeesh, Kim, Krische, and Lee (2004) report. Similar to the findings in earlier studies, we find in unreported results that both analysts and funds tilt their trades and revisions towards high momentum stocks, and funds exhibit a more significant momentum tilt than analysts. However, in our sample, we find that funds and analysts exhibit a preference for value stocks over growth stocks while earlier studies report a preference for growth stocks.

We compute abnormal returns over various holding periods as:

$$AR_{i,t}(H) = \prod_{\tau=t}^{t+H}(1 + r_{i,\tau}) - \prod_{\tau=t}^{t+H}(1 + r_{dgtw,\tau}), \tag{1}$$

where $r_{i,\tau}$ is the daily return for stock i, and $r_{dgtw,\tau}$ is the daily benchmark return from one of 125 portfolios matched on size, book-to-market, and return momentum. H is the return horizon and varies from 0 to 62 days.

We take a transaction dollar-weighted mean of these returns within the month and then average across months.[9] We compute Fama and MacBeth (1973) standard errors, taking into account autocorrelations over overlapping intervals for various holding periods, as in Jegadeesh and Karceski (2009). Specifically, we compute standard errors allowing for first-order serial correlation for holding periods up to four weeks, up to second-order serial correlation for two-month holding periods, and up to third-order serial correlation for three-month holding periods.

Table 2 reports the results for raw returns (Panel A) and DGTW-adjusted returns (Panels B, C, and D). Panels C and D examine large and small cap subsets respectively. The raw return results in Panel A show large transaction-day ("one day") effects, with returns on purchases of 0.57% and sales of −0.36%. Over time, the cumulative returns of purchases steadily increase, which, by itself, is not surprising, since the stock market increased during this sample period. Sales also show positive returns following the first day.[10] Consequently, the differences between purchases and sales in the last two columns are the most relevant metrics for raw returns.

Panel B of Table 2 presents the DGTW-benchmark adjusted abnormal returns for institutional trades. The first day abnormal returns are positive for purchases (0.45%) and negative for sales (−0.39%). The abnormal return difference is 0.85% on day 1. The point estimates of abnormal return difference falls to 0.70% at the end of one week but increases marginally subsequently.

The pattern of change in abnormal returns over time is different for purchases and sales. In the case of purchases, abnormal returns increase from 0.45% on day 1 to 0.74% three months from the event date. Therefore, the price impact on day 1 reflects funds' information, and as time progresses, more of their information gets reflected in prices. However, in the case of sales, abnormal returns increase from −0.39% on day 1 to −0.11% at the end of three months. Therefore, the day 1 return for sales is a temporary

[9] Weighting the transactions equally within the month produces similar results.

[10] We use the terminology "purchases" and "sales" to refer to institutional trades rather than the terms "buys" and "sells" to avoid any confusion with recommendation levels.

Table 2
Performance of institutional investors' trades.

	Purchases		Sales		Difference	
	Returns	*t*-stat	Returns	*t*-stat	Returns	*t*-stat
Panel A: Raw returns						
1 day	0.0057	12.31	−0.0036	−7.03	0.0094	14.81
1 week	0.0085	6.28	0.0002	0.15	0.0083	7.13
2 weeks	0.0106	4.73	0.0023	0.93	0.0083	5.87
3 weeks	0.0128	3.88	0.0043	1.26	0.0085	5.01
4 weeks	0.0155	3.61	0.0065	1.54	0.0089	5.01
2 months	0.0262	3.00	0.0168	1.99	0.0093	3.70
3 months	0.0367	2.82	0.0270	2.19	0.0097	3.53
Panel B: Abnormal returns						
1 day	0.0045	13.57	−0.0039	−9.69	0.0085	15.42
1 week	0.0047	6.85	−0.0023	−3.32	0.0070	7.40
2 weeks	0.0048	6.15	−0.0027	−2.46	0.0075	6.68
3 weeks	0.0050	4.58	−0.0027	−1.90	0.0077	5.50
4 weeks	0.0055	4.57	−0.0023	−1.47	0.0078	5.16
2 months	0.0061	3.21	−0.0015	−0.77	0.0076	5.15
3 months	0.0074	2.27	−0.0011	−0.44	0.0084	4.43

The table reports the performance of stocks bought or sold by institutional investors beginning with the day of the transaction. Returns over each horizon are averaged by month and then across months. Standard errors are adjusted for autocorrelation. Panel A reports the return results. Panel B reports abnormal returns which are measured relative to DGTW benchmark portfolios matched on size, book-to-market, and recent return momentum. The institutional transaction data are from Plexus and Abel/Noser. The sample period covers 1993 though 2005.

price impact, and it does not reflect any information. Overall, these results indicate that fund purchases contain information. Fund sales are by and large uninformative, and any price impact on day 1 is temporary.

When we measure funds' skills, a question that arises is whether funds' skills are better captured by abnormal returns of purchases or by the difference between the abnormal returns of purchases and sales. One may argue that a fund's purchases are more reflective of its skills because, eventually, a fund's performance depends on the stocks it purchases and not by the stocks it sells. However, at any point in time when funds turn over their positions, they always have the choice of keeping the stocks they sell rather than making new purchases. Therefore, although we report the performance of purchases and sales separately, we use the difference between purchase and sales abnormal returns as the primary measure of fund skills.[11]

We find significant difference between returns for purchases and sales on day 1. However, the holding period abnormal returns after day 1 are not statistically different

[11]Our findings are different from the results in Chen, Jegadeesh, and Wermers (2000), who report that for mutual funds, purchases outperform sales by 1.24–4.69% in the first four quarters after the trade over a sample period from 1975 to 1995. We used the same data source and methodology as Chen, Jegadeesh, and Wermers (2000) in our 1993–2005 sample period, and we find the difference between the holding-period returns of purchases and sales range from 0.82% for one quarter to −0.76% for four quarters. Therefore, the differences between the results here and those in Chen, Jegadeesh, and Wermers (2000) are due to the fact that our paper covers a more recent time period.

from day 1 returns. In unreported tests, we also examine returns for up to one year after the trades and find no evidence of any drift. This finding is quite surprising since fund managers presumably trade based on their private information that is not reflected in market prices. However, any information that they may have is reflected in prices on the day they trade. Therefore, they do not seem to have any value-relevant information that is not already reflected in prices on the day of the trade.

The evidence that the difference between abnormal returns on purchases and sales is almost entirely due to the difference on the day of the trade indicates that price changes may be due to the impact of their trades. The information content of trades depends on whether the price impact is permanent or temporary. For instance, in Kyle's (1985) model, trades convey the traders' private information, and hence the accompanying price impact is permanent. However, price impact would be temporary if the trade is not informative and the price eventually reverts to pre-trade levels. Thus, the pattern of returns in the days subsequent to a trade would reveal whether trades do indeed reveal funds' value-relevant private information.

The abnormal returns over time in Table 2 indicate that the difference between purchase and sales return remains at about the same level as on Day 1 over the next three months.[12] For instance, the abnormal return difference on Day 1 is 0.85%, and it is 0.84% after three months. Therefore, the price change observed on the day of purchase and sales is permanent.

The evidence that the price impact is permanent indicates that the trades bring new information to the market. Our results indicate that the value of funds' private information is roughly 1%. A related issue is whether funds are able to fully profit from this information. To investigate this issue, one should not only take into account the price impact but also all costs related to gathering the information and brokerage commissions. Our focus is on evaluating the information that funds bring to the market through their trades rather than the magnitude of their profits net of all costs.

It is possible that funds buy and sell stocks for a variety of reasons, and not all trades may be informationally motivated. For example, funds frequently experience inflows and outflows from clients, and their trades to accommodate flows could be less informative than trades motivated solely by their informational advantage. When funds trade to accommodate flows, unless they have specific information about particular stocks, they are likely to spread their trades across multiple stocks and trade relatively small quantities of each stock. However, if funds attempt to exploit their informational advantage about specific stocks, they are likely to trade larger quantities of those stocks. More generally, the size of fund trades would be determined by the perceived strength of funds' information. We investigate whether funds' informational advantage is more evident in their larger trades by partitioning trades into large and small trade subsamples. Specifically, we group aggregate net order flow into two groups based on whether the absolute net order flow is above or below the median calculated within each NYSE market capitalization decile over the previous calendar year.

Table 3 reports abnormal returns for small and large trades. On the trade date, the abnormal return differences for small and large trades are 0.24% and 0.91%, respectively. The difference between these abnormal returns is statistically significant, indicating that large trades convey more information to the market. For small trades, the abnormal return difference continues to increase to 0.8% by the end of three months. However, for large

[12]In unreported tests, we find no evidence of any return reversals up to six months.

Table 3
Transaction size and trade performance.

	Small-sized Trades		Large-sized Trades		Large−small	
	Returns	*t*-stat	Returns	*t*-stat	Returns	*t*-stat
Panel A: Purchases						
1 day	0.0017	8.27	0.0049	11.83	0.0032	8.03
1 week	0.0019	4.37	0.0051	7.30	0.0032	6.11
2 weeks	0.0022	3.14	0.0053	7.00	0.0031	4.00
3 weeks	0.0031	2.85	0.0054	4.84	0.0022	1.60
4 weeks	0.0037	2.50	0.0060	4.81	0.0022	1.30
2 months	0.0052	1.91	0.0067	3.24	0.0015	0.49
3 months	0.0074	2.11	0.0072	2.32	−0.0001	−0.04
Panel B: Sales						
1 day	−0.0007	−3.18	−0.0041	−8.59	0.0035	7.10
1 week	−0.0012	−2.26	−0.0019	−2.26	0.0008	0.86
2 weeks	−0.0014	−1.34	−0.0022	−1.82	0.0011	0.89
3 weeks	−0.0017	−1.23	−0.0020	−1.25	0.0005	0.34
4 weeks	−0.0018	−1.20	−0.0016	−0.89	−0.0001	−0.06
2 months	−0.0006	−0.18	−0.0005	−0.31	0.0005	0.18
3 months	−0.0006	−0.16	0.0006	0.25	−0.0005	−0.14
Panel C: Purchase—sales						
1 day	0.0024	7.76	0.0091	14.44	0.0067	11.75
1 week	0.0032	4.63	0.0070	6.32	0.0040	3.81
2 weeks	0.0036	3.48	0.0075	6.10	0.0042	3.17
3 weeks	0.0048	3.71	0.0074	4.33	0.0028	1.26
4 weeks	0.0055	4.02	0.0075	4.03	0.0021	0.88
2 months	0.0057	2.34	0.0072	4.18	0.0021	0.59
3 months	0.0080	2.92	0.0067	3.55	−0.0006	−0.20

The table reports the performance of stocks bought or sold by institutional investors beginning with the day of the transaction. Returns over each horizon are averaged by month and then across months. Standard errors are adjusted for autocorrelation. The columns report abnormal returns for trades of different sizes, where trades are classified as small or large relative to median absolute net order flow within each NYSE size quintile. Abnormal returns are measured relative to DGTW benchmark portfolios matched on size, book-to-market, and recent return momentum. The institutional transaction data are from Plexus and Abel/Noser. The sample period covers 1993 though 2005.

trades the abnormal returns decline to 0.6% by the end of three months. The abnormal return difference for large trades and small trades are not statistically significant beyond two weeks.

The patterns of returns for large and small trades present an interesting contrast. The first day returns for large trades include a temporary component that eventually reverts. However, for small trades, prices continue to drift in the direction of trades after the day of trade, indicating that the funds' information is not fully reflected in prices on the trade date.

The evidence that the abnormal return differences for large trades and small trades are about equal indicates that the value of the best ideas of funds, as reflected by the trade size, is not different from the ideas that the funds did not deem worthy of large trades. In unreported tests, we also examined the performance of small and large trades when we partitioned the sample into trade size deciles rather than into two groups. On the date of the transaction, we found that abnormal return differences between buys and sells generally increased with trade size (e.g., 0.21% for decile 1, 0.24% for decile 2, up to 1.35% for decile 10). However, the abnormal return differences were not meaningfully different across deciles beyond one month, with the exception of small return differences for decile 1. For example, the abnormal return difference after three months was 0.18% for decile 1 compared to 0.80% and 0.75% for deciles 2 and 10, respectively. Perhaps the smallest trades are uninformative because they are driven primarily by fund flows or diversification motives. Nevertheless, the important finding from our analysis here is that the value of funds' information for even their best ideas as reflected by their trade size is about 1%.

It is possible that funds of different sizes exhibit different levels of stock selection skill. For instance, large funds may have the benefit of their own skilled analysts, but small funds may rely relatively more on outside sources. Our next set of tests examines the relation between stock selection skill and fund size. Our dataset does not directly report fund size, and it only identifies funds by ID numbers and not by name. We determine the annual dollar trade volume for each fund and use this measure as a proxy for fund size.

Table 4 presents abnormal returns for funds categorized based on size. We assign funds to small, medium, and large categories based on their trading volume. Each year we sort institutions into three equal groups based on their total dollar trading volume. We then examine each group's trading activity over the following year. The difference in abnormal return for purchases less sales on the trade date is monotonically related to fund size (0.52%, 0.69%, and 1.00%), and the results for large funds are significantly different than small- and medium-sized funds. However, the abnormal return differences for the three categories converge over time. By the end of three months, the point estimates of abnormal return differences are roughly the same for all three categories, and they are not statistically different. Therefore, the differences we observe on the trade date are related to differences in price pressure across trades that are temporary and not to differences in information content across funds of different sizes. Therefore, there is no evidence that funds of different sizes exhibit different levels of skill.

3.2. *Analyst recommendations*

We next examine the performance of stocks recommended by analysts. In particular, we focus on the performance of stocks recently upgraded or downgraded. Table 4 presents the performance of recommendation revisions. Panel A reports raw returns, and Panel B reports returns net of their DGTW benchmark.

The stock price reaction for recommendation revision dates is much stronger than the stock price reaction for trade dates in Table 2. For instance, the average abnormal returns on upgrades and downgrades are 1.98% and −2.83%, compared with 0.64% and −0.54% for purchases and sales, respectively. This result *per se* is not surprising, since analysts publicly announce their recommendations, leading to a large announcement effect, whereas institutions seek secrecy to minimize the impact of their trades on prices.

Upgrades and downgrades continue to drift in the direction of revisions over the next three months. For example, the abnormal returns for upgrades increase to 4.05% and those of the downgrades decline to −3.50% by the end of month 3. The differences in the last set of columns in Table 2 show a large one-day effect followed by additional gains through three months, though much of the total cumulative return occurs during the first month (6.46% after four weeks and 7.55% after three months). The performance following recommendation changes is generally consistent with the literature on the value of analysts' recommendation (e.g., Womack, 1996; Green, 2006).

Table 4
Institution size and trade performance.

	Small Institutions		Medium Institutions		Large Institutions		Large−small	
	Returns	*t*-stat	Returns	*t*-stat	Returns	*t*-stat	Returns	*t*-stat
Panel A: Purchases								
1 day	−0.0005	−0.61	0.0020	5.53	0.0048	15.28	0.0052	6.40
1 week	−0.0016	−0.96	0.0020	3.67	0.0055	9.28	0.0068	5.61
2 weeks	0.0007	0.27	0.0027	3.81	0.0055	6.95	0.0068	4.77
3 weeks	0.0009	0.37	0.0029	3.49	0.0055	4.33	0.0060	3.33
4 weeks	0.0018	0.50	0.0027	2.45	0.0057	3.61	0.0057	2.68
2 months	0.0019	0.35	0.0021	0.96	0.0052	2.36	0.0036	1.22
3 months	0.0025	0.33	0.0036	1.36	0.0064	1.92	0.0060	1.91
Panel B: Sales								
1 day	−0.0057	−5.52	−0.0049	−10.96	−0.0051	−15.54	0.0026	2.96
1 week	−0.0059	−3.39	−0.0038	−6.14	−0.0041	−8.28	0.0032	3.33
2 weeks	−0.0064	−2.86	−0.0034	−3.91	−0.0037	−6.75	0.0035	3.07
3 weeks	−0.0064	−2.19	−0.0030	−3.15	−0.0039	−5.54	0.0026	1.87
4 weeks	−0.0061	−1.72	−0.0028	−2.17	−0.0035	−3.85	0.0027	1.69
2 months	−0.0074	−1.93	−0.0036	−1.44	−0.0019	−1.32	0.0025	1.28
3 months	−0.0033	−0.66	−0.0018	−0.53	−0.0006	−0.23	0.0031	1.43
Panel C: Purchase—sales								
1 day	0.0052	3.98	0.0069	13.55	0.0100	21.32	0.0026	2.29
1 week	0.0044	1.92	0.0058	9.63	0.0096	15.96	0.0036	3.89
2 weeks	0.0071	2.60	0.0061	9.12	0.0092	12.05	0.0032	2.15
3 weeks	0.0073	2.56	0.0059	7.44	0.0094	8.41	0.0034	1.81
4 weeks	0.0079	1.93	0.0054	4.44	0.0091	6.06	0.0030	1.23
2 months	0.0093	1.75	0.0057	2.53	0.0071	3.69	0.0011	0.35
3 months	0.0058	1.25	0.0054	2.24	0.0069	2.68	0.0028	0.83

A comparison of abnormal returns in Tables 2 and 5 indicates that analyst recommendation changes convey more valuable information than institutional trades. Interestingly, although recommendation revisions are publicly announced, stock prices continue to drift in the direction of the revision in the days following revisions. However, although institutional trades are not publicly announced, their trades by themselves convey virtually all information on the trade date. We observe very little drift in the days following trades.

Overall, our results indicate that sell-side analysts are more skilled than buy-side analysts. Admati and Pfleiderer (1990) present a theoretical model that concludes that the optimal mechanism for selling valuable private information is a mutual fund that pays the fund managers based on performance. Intuitively, their result follows from the fact that a mutual fund set-up allows the information producer to exploit monopolistically his or her private information by directly trading based on the information, while selling information to multiple investors dilutes its value as these investors compete with one another to exploit the information.

Our findings, however, imply that the more skilled analysts convey their information to the market through sell-side research. Why do our findings conflict with theory? The theoretical model makes a number of simplifying assumptions that diverge from reality.

Table 5
Performance of brokerage firm analysts' stock picks.

	Upgrades		Downgrades		Difference	
	Returns	*t*-stat	Returns	*t*-stat	Returns	*t*-stat
Panel A: Raw returns						
1 day	0.0198	22.54	−0.0283	−19.54	0.0481	24.06
1 week	0.0287	13.48	−0.0319	−10.93	0.0607	15.18
2 weeks	0.0354	11.54	−0.0309	−8.05	0.0664	15.61
3 weeks	0.0402	10.20	−0.0293	−6.25	0.0695	16.44
4 weeks	0.0454	9.06	−0.0276	−4.89	0.0730	16.45
2 months	0.0610	6.28	−0.0198	−1.94	0.0809	13.99
3 months	0.0749	5.42	−0.0133	−0.92	0.0882	12.00
Panel B: Abnormal returns						
1 day	0.0184	22.37	−0.0257	−20.10	0.0440	23.09
1 week	0.0249	14.59	−0.0305	−13.80	0.0554	15.00
2 weeks	0.0281	14.97	−0.0316	−13.27	0.0597	15.61
3 weeks	0.0302	14.69	−0.0322	−12.97	0.0623	16.04
4 weeks	0.0322	13.92	−0.0324	−12.80	0.0646	16.26
2 months	0.0361	10.22	−0.0343	−10.03	0.0705	14.12
3 months	0.0405	8.46	−0.0350	−7.75	0.0755	11.62

The table reports the performance of stocks upgraded or downgrades by brokerage firm analysts beginning with the day of the recommendation change. Returns over each horizon are averaged by month and then across months. Standard errors are adjusted for autocorrelation. Panel A reports the return results. Panel B reports abnormal returns, measured relative to DGTW benchmark portfolios matched on size, book-to-market, and recent return momentum. Panels C and D report the results for large and small stocks, designated relative to the NYSE median. The analyst recommendation data are from I/B/E/S. The sample period covers 1993 though 2005.

For instance, the primary responsibility of the information producer in the model is to analyze stocks, which fits the job description of buy-side analysts. However, sell-side analysts have a multitude of responsibilities, including client service, support with generating trades, and raising the profile of their employers, activities which, in turn, help them get investment banking business.

These additional responsibilities of sell-side analysts have been widely blamed for conflicts of interest and poor investment advice, and one may expect that they would adversely affect the stock-selection skills of sell-side analysts. However, there may be a positive side to the story as well. Because of these responsibilities, sell-side analysts add value to their employers on multiple dimensions, and as a result they are able to command higher compensation. Perhaps this higher compensation attracts more skilled analysts.

It is also possible that since sell-side analysts follow fewer stocks, they are able to specialize their skills to analyze the investment prospects of these stocks.[13] They may be able to develop close relationships with the mangers of stocks they follow and may have access to private information. A recent paper by Tang (2009) sheds some light on this

[13]Green, Jegadeesh, and Tang (2009) report that sell-side analysts follow roughly ten stocks on average. In comparison, Tang (2009) reports that analysts who later become fund managers hold roughly 260 stocks in their funds. These statistics provide an indication of the large disparity between the number of stocks that sell-side and buy-side analysts follow. The disparity may well be larger given that funds typically do not hold all stocks that they follow.

possibility. Tang examines the holdings of a sample of sell-side analysts who switched to the buy side and finds that their holdings of stocks that they used to follow significantly outperform the market, but their other holdings do not. His findings provide support for the idea that specialization helps.

4. Institutional trades and recommendation revisions—interactions

Since many institutions pay brokerages soft dollar commissions for their research, it is quite likely that they use their recommendations as inputs for their trading decisions. Additionally, it is also possible that analysts become aware of their clients' trades after they are executed and may use the information in trades as inputs for their recommendations. This section examines the interactions between institutional trades using recommendation revisions. The first set of tests examines the lead-lag relation between trades and revisions. The second set of tests examines whether institutional trades are able to differentiate between more- and less-informative recommendation revisions.

4.1. Institutional trades and recommendation revisions—lead-lag relation

Analysts announce their recommendations revisions publicly, and the information is immediately available both to the brokerages' customers, as well as to subscribers of various information providers. Thus, analyst recommendations are typically available to institutions when they make their trades. The converse is not necessarily true because institutions generally do not disclose their individual trades. However, analysts are likely to be aware of institutional clients' general interest in particular trades because funds often contact sell-side analysts for information about stocks that they actively evaluate. Also, when information flows from analysts flow to brokerage clients through events such as the Goldman Huddle, it is possible that information about clients' trades flow to analysts as well.

To investigate the interactions between institutional trades and analyst recommendations, we first examine the pattern of trades around recommendation revisions. Fig. 1 presents daily abnormal order flows from 10 trading days before to 63 trading days after recommendation changes. We create abnormal order imbalance by subtracting the average net trading for that stock during the three-month period prior to the recommendation change (trading days -73 to -11).[14] The bars in the figure denote abnormal order flows, and the lines denote confidence intervals that are two-standard errors away from the mean estimates. Standard errors are computed using the cross-section of abnormal order flows at each date.

For upgrades, the order flow significantly increases on the day of recommendation revisions. The order flow remains significant over the next 30 days. Interestingly, order flows are negative in the days preceding an upgrade. Therefore, there is no evidence that analysts tip funds ahead of upgrades.

The order flows are negative following downgrades, and the order flows remain significantly negative for the next two months. Funds sell with a much greater intensity following downgrades than they buy following upgrades. For example, funds in our sample sell -0.02% of the shares outstanding on the day of downgrades, and in comparison buy

[14]Using a six-month interval (126 trading days) for the benchmark period produces similar results.

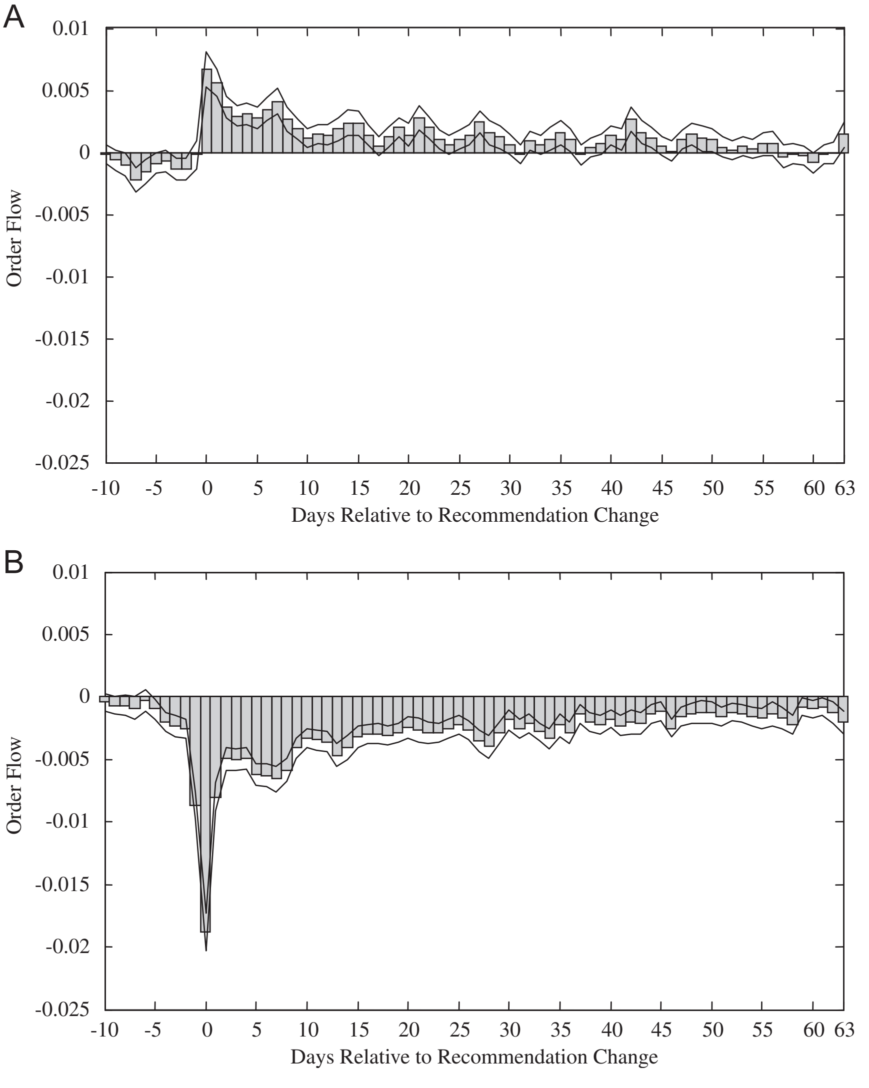

Fig. 1. **Institutional abnormal order imbalance following analyst recommendations**. The plots show abnormal net order imbalance for institutional trades, as a fraction of shares outstanding (multiplied by 100), for 10 trading days before to 63 trading days after recommendation changes. We create abnormal order imbalance by subtracting the average net trading for that stock during the three months before the recommendation change. Panel A shows imbalances for upgrades while Panel B shows imbalances for downgrades. The institutional transaction data are from Plexus and Abel/Noser, and the analyst recommendation data are from I/B/E/S. The sample period covers 1993 though 2005.

only 0.005% following upgrades. The higher selling intensity continues over the next two months.

We also note an interesting contrast in the pattern of order flows during the week before downgrades. The order flow is significantly negative during this period, indicating that analysts likely tipped funds prior to downgrades. The results in a contemporaneous paper by Juergens and Lindsey (2009) are consistent with our findings. Juergens and Lindsey find that sell volume through brokerages whose analysts downgrade a particular stock are significantly larger than that through other brokerages on days −2 and −1 relative to the downgrade date. They do not find any significant increase in buy volumes prior to upgrades, which is consistent with our results. While Juergens and Lindsey examine trading volume through brokerages that employ the analysts and other brokerages, we directly examine the trades of institutional investors and find evidence of information leakage prior to downgrades.

One potential explanation for the observation that analysts tip funds prior to downgrades but not upgrades is that funds attach asymmetric values to obtaining information prior to recommendation changes. In the event of downgrades, funds would incur losses on their current holdings. Funds may therefore feel that they are caught unawares if their broker does not warn them about impending downgrades. On the other hand, a lack of warning prior to upgrades represents potential opportunity losses that may not be resented by these funds.

The pattern of order flows following recommendation revisions indicates that funds incorporate analyst revisions as one of their trading signals. In fact, funds use revisions for their trading strategies even when they are quite stale, particularly for downgrades. The evidence that funds use stale signals is somewhat surprising since the results in Table 5 indicate that most of the price drift occurs during the first four weeks after revisions and any strategy that uses stale signals misses most of this run-up. However, it is likely that funds trade at preset calendar times, and hence use revisions as signals when they do trade, but they generally do not alter their trading schedule because of recommendation revisions.

To further examine the interactions between institutional trades and analyst recommendations, we fit the following regressions:

$$NetBuy_{i,t} = \alpha + a_1 Size_{i,t} + a_2 Turnover_{i,t} + a_3 BookToMkt_{i,t} + a_4 Mom_{i,t} + \sum_{l=0}^{4} b_l NetRevision_{i,t-l} + \sum_{l=1}^{4} c_l NetBuy_{i,t-l} \tag{2}$$

and

$$NetRevision_{i,t} = \alpha + a_1 Size_{i,t} + a_2 Turnover_{i,t} + a_3 BookToMkt_{i,t} + a_4 Mom_{i,t} + \sum_{l=0}^{4} b_l NetBuy_{i,t-l} + \sum_{l=1}^{4} b_l NetRevision_{i,t-l}, \tag{3}$$

where $NetBuy_{i,t}$ is the aggregate number of shares of stock i bought by funds in week t divided by the number of shares outstanding, and $NetRevision_{i,t}$ is the number of upgrades (where double upgrades count as two) minus the number of downgrades divided by the number of recommendation changes.[15]

We also include the following control variables in the regressions: *Size* is the market capitalization decile using NYSE breakpoints; *Turnover* is the average daily share turnover as a fraction of shares outstanding over the six months prior to the trading week; *BookToMkt* is the ratio of book value to market value of equity, where book value is from

[15]If there are no recommendation revisions in week t, $NetRevision_{i,t}$ equals zero.

Table 6
Interaction between analyst recommendations and institutional trading.

	Institutional Net trading		Number of Rec. changes	
Constant	0.011	3.06	−0.209	−6.88
Size	−0.001	−2.68	0.018	5.97
Share Turnover	−0.013	−0.10	0.153	0.18
Book-to-Market	−0.006	−2.18	0.062	2.77
Return Momentum	0.163	7.95	0.667	4.99
Institutional Trading	–	–	0.135	3.98
Institutional Trading (1-wk lag)	0.336	58.17	0.062	0.79
Institutional Trading (2-wk lag)	0.056	14.14	0.320	1.38
Institutional Trading (3-wk lag)	0.043	11.10	−0.107	−1.07
Institutional Trading (4-wk lag)	0.031	5.26	0.485	1.05
Recommendation Changes	0.036	11.96	–	–
Recommendation Changes (1-wk lag)	0.021	8.64	0.047	2.42
Recommendation Changes (2-wk lag)	0.007	3.68	0.008	0.39
Recommendation Changes (3-wk lag)	0.009	5.09	−0.031	−1.56
Recommendation Changes (4-wk lag)	0.005	2.74	−0.043	−2.21
Average R-Squared	0.173		0.161	

The table reports the results of regressions of institutional trading and analyst recommendations on lags and firm characteristics. Institutional trading and analyst recommendation changes are aggregated to the weekly level. In the first two columns, the dependent variable is the net fraction of shares outstanding traded by institutions over the previous week. In the second two columns, the dependent variable is the number of upgrades (where double upgrades count as two) minus the number of downgrades all over the number of recommendation changes. Size is the market capitalization decile using NYSE breakpoints. Share Turnover is the average daily share turnover as a fraction of shares outstanding over the six months prior to the trading week. Book-to-Market is the ratio of book value to market value of equity, where accounting data is from the most recent fiscal year ending at least three months prior to the trade. Return Momentum is the six-month return of the stock prior to the transaction week, skipping one month. Cross-sectional regressions are run each week and the coefficients are averaged over time. t-statistics are calculated using Newey-West standard errors with four lags. The institutional transaction data are from Plexus and Abel/Noser, and the analyst recommendation data are from I/B/E/S. The sample period covers 1993 though 2005.

the most recent fiscal year ending at least three months prior to the trade; and *Mom*is six-month return of the stock prior to the transaction week, skipping one month.

Earlier studies document that both institutional trades and analyst revisions are related to these stock characteristics (Chen, Jegadeesh, and Wermers, 2000; Jegadeesh, Kim, Krische, and Lee, 2004). Since both trades and recommendations generally tilt in the same direction along these characteristics, it is important to control for them to ensure that any relation between trades and recommendations is not driven solely by these characteristics. We fit the cross-sectional regressions each week and report coefficients averaged over time. We compute the t-statistics based on Newey-West standard errors with four lags.[16] Table 6 presents the estimates of Regressions (2) and (3).

[16]Peterson (2009) shows that this approach yields consistent estimates of standard errors. However, if the error terms are serially correlated, the coefficient estimates may be biased due to the inclusion of lagged values of the dependent variables as independent variables [e.g., Chapter 13 of Greene (2000)]. We find that the average serial correlation of the error terms across all stocks in the sample is about −0.04, which indicates that any bias due to serial correlation is likely to be small. In a univariate context, negative serial correlation biases a positive slope coefficient towards zero, which would understate the significance of the coefficients.

The results in Table 6 indicate that institutional trades are significantly related to trades in the prior four weeks. The slope coefficients gradually decline from 0.336 for one-week lagged trades to 0.031 for four-week lagged trades.[17] Our findings indicate that when institutions are net buyers of a stock in one week, then they are also on average net buyers of that stock over the next four weeks. This result is consistent with the findings of institutional herding in Sias (2004).

We also find that institutional trades are significantly correlated with contemporaneous as well as lagged recommendation revisions. On the other hand, when fitting Regression (3), we find recommendation revisions are not correlated with lagged trades. There are two possible interpretations of the correlation between trades and revisions. First, it is possible that institutions use recommendation revisions in their trading decisions, and vice versa. Alternatively, it is possible that both revisions and trades reflect common information, but there is no causal relation between them.

The result that both trades and revisions are positively related contemporaneously suggests that the relation may be driven by common information, rather than by any causal effect. For instance, both revisions and trades may be triggered by earnings announcements.[18] However, in the case of lagged variables, trades are related to past revisions but not the other way around. Taken together, the findings do not support the common information hypothesis. It appears likely that at least some institutions use recommendation revisions in their trading decisions.

4.2. Do trades differentiate between good and bad recommendations?

As we discuss in the Introduction, the academic literature and the popular press claim that analysts' recommendations are tainted by conflicts of interest. Media reports and papers by Malmendier and Shanthikumar (2007) and others suggest that, while individual investors are apparently fooled, institutional investors can either see through biases in recommendations or they have special access to analysts' private views. This view implies that institutions selectively use only the good recommendations and ignore the bad recommendations. Under this hypothesis, upgrades that institutions purchase should outperform upgrades they sell, and downgrades that institutions purchase should outperform downgrades they sell as well.

We examine the ability of institutions to differentiate between good and bad analyst recommendations as follows. For each institutional trade observation, we examine whether any analyst changed his recommendation for that stock within the preceding week. If there were no recommendation changes in the preceding week, we discard the observation. We then compare the performance of recommendation revisions when institutions trade in the same direction as revisions with those cases in which institutions trade in the opposite direction.

In Table 6, Panels A and B report the upgrade results. Panel A examines raw returns while Panel B examines abnormal returns (returns net of the DGTW benchmark). The first two columns of Panel A report the performance of institutional purchases. The pattern evident in Panel A is similar to the analyst upgrade results in Table 4 and consistent with analyst skill in upgrading stocks. The returns are positive and significant for most horizons.

[17]In unreported results, we find that the slope coefficients on institutional trades lagged five weeks or more were not reliably different from zero.

[18]We find similar results after excluding earnings announcement dates from the sample.

The returns here are somewhat smaller than in Table 4, however, because Table 4 measures returns beginning the day of the recommendation change, while the results here exclude price changes up to one week from the date of upgrade. The next two columns, which report the results for stocks upgraded but sold by institutions, show a less dramatic pattern with positive and, in most cases, statistically significant returns. The last set of columns in Panel A reports the performance difference between purchases and sales. At the one-week horizon, purchases significantly outperform sales by 1.29%. This difference diminishes over the following weeks and is statistically insignificant at the three-month horizon. Panel B reports the abnormal return results, which are generally similar to the results in Panel A.

In Table 6, Panel C (raw returns) and Panel D (abnormal returns) report the downgrade results. Similar to Panels A and B, the return pattern here differs from the downgrade return pattern in Table 4 because we miss up to one week of the return following the downgrade. Again, institutional purchases outperform their sales, but the performance is largely concentrated on the day of the trade.

At first glance, abnormal return differences between fund purchases and sales may seem to suggest that funds are able to differentiate between good and bad revisions. However, the entire return difference occurs on the day of trade. As Table 2 reports, fund purchases also outperform fund sales on the day of trade even without conditioning on recommendation revisions on the trade date. Therefore, if funds are able to differentiate between good recommendations and bad recommendations, we would expect purchases to outperform sales around revisions by a larger magnitude than unconditionally.

The unconditional abnormal return difference on day 0 between purchases and sales on the trade date is 0.85% in Table 2. In comparison, the corresponding abnormal returns difference on the recommendation date in Table 6 is 0.8%. This return difference is close to zero, and not statistically significant. In effect, any additional information that the trade of a fund conveys about revisions is orthogonal to the information in revisions.

Our results indicate funds are not able to differentiate between good and bad recommendations. Therefore, the concern expressed in the media that institutional investors may be able to "call analysts to get their private views"[19] and are hence at an advantage to trade based on recommendations is not supported by empirical evidence.

Our next set of tests examines the relative information content of revisions and trades in a head-to-head test. Any direct test of the relative information content should account for the fact that analyst revisions are publicly announced, and their information content is readily observable. Trades, however, are not publicly announced, and the information underlying trades becomes publicly known only gradually over time. Moreover, funds observe revisions, and hence they can use this information in trades.

We incorporate these factors in a model and show in the Appendix that, if funds optimally use the information in revisions in their trades, then their trades should subsume the information content of revisions. Specifically, consider the following regression:

$$R_{i,t} = a + b_1 BtSd_{i,t-1} + b_2 UpDn_{i,t-1} + e_t, \tag{4}$$

where $R_{i,t}$ is the return for stock i over holding periods from one week to three months, and $BtSd_{i,t-1}$ and $UpDn_{i,t-1}$ are indicator variables for net bought/sold and upgrade/downgrade

[19]See Euromoney.com, February 1, 2003, "Where is all the buy-side outrage?"

for the one-week period before the return period. The Appendix shows that b_1 will be greater than zero and b_2 will equal zero if funds optimally use the information in revisions in their trades.[20] If b_1 is less than b_2, then funds do not use the information optimally, and sell-side analysts exhibit better stock-picking skills than funds.

We estimate the regression each week, and then take the mean of the coefficients each month and then across months. We compute t-statistics Fama-Macbeth style with a correction for autocorrelation, as in Jegadeesh and Karceski (2009). We only include observations when both of the regressors are not zero. Similar to much of our earlier analysis, we examine several alternative return horizons: those at one week, two weeks, three weeks, four weeks, two months, and three months.

Table 8 reports the cross-sectional regression results. As before, Panel A reports the results associated with raw returns while Panel B reports the results for DGTW-adjusted returns. The upgrade/downgrade columns in Panel A indicate a strong relation between future returns and past analyst recommendation changes, as the recommendation change coefficients are positive and statistically significant at all horizons. The results are consistent with positive returns following upgrades and/or negative returns following downgrades. In contrast, the purchase/sale columns indicate that, after controlling for recommendation changes, no relation exists between future returns and past institutional trades. In fact, the institutional trade variables are negative for all horizons but are not statistically significant.

The abnormal return results in Panel B of Table 8 mirror the raw return results in Panel A. The coefficient on the upgrade/downgrade indicator variable is positive and strongly statistically significant regardless of horizon, and the coefficient on the purchase/sale indicator is not significantly positive at any horizon. The size of the coefficients is also consistent with the patterns evident in Tables 5 and 7, where the abnormal returns increase with the horizon.

Overall, the results in Table 8 indicate a strong correspondence between analyst recommendation changes and future stock returns. When an analyst changes his recommendation on a stock on the week that an institution buys or sells that stock, more often than not the recommendation change, rather than the institutional transaction, predicts the future return of the stock. After controlling for the recommendation change, no evidence exists of any relation between institutional trades and stock returns.

5. Conclusion

This paper evaluates the stock-selection skills of buy-side funds and sell-side analysts and examines their interactions. We find that stocks that funds buy significantly outperform stocks that they sell, but the difference in performance is largely concentrated on the day of the trade. Therefore, any superior information that funds may possess seems to be fully revealed to the market through their trades. Consistent with earlier findings, we also find that sell-side analysts' recommendations are informative.

Fund trades are related to past recommendation revisions, indicating that funds do use analysts' recommendations as factors in their trading decisions. In fact, fund trades are

[20]The model in the Appendix assumes the independent variables are continuous variables rather than binary variables. Using continuous measures of recommendation changes and institutional trading (e.g., changes in consensus recommendation or changes in fractional ownership of the firm) produces similar results.

Table 7
Performance of institutional investors' trades following recommendation changes.

	Purchases		Sales		Difference	
	Returns	*t*-stat	Returns	*t*-stat	Returns	*t*-stat
Panel A: Performance of transactions following upgrades in the previous week						
1 week	0.0096	4.58	0.0006	0.32	0.0090	4.51
2 weeks	0.0132	4.41	0.0049	1.69	0.0083	3.68
3 weeks	0.0159	3.80	0.0072	1.97	0.0087	2.52
4 weeks	0.0179	3.40	0.0101	2.16	0.0078	1.96
2 months	0.0366	3.48	0.0275	2.95	0.0091	1.61
3 months	0.0481	2.97	0.0400	2.97	0.0080	0.98
Panel B: Abnormal performance of transactions following upgrades in the previous week						
1 week	0.0047	3.90	−0.0033	−2.29	0.0080	4.37
2 weeks	0.0054	2.92	−0.0020	−0.95	0.0073	2.92
3 weeks	0.0054	2.24	−0.0005	−0.20	0.0059	1.71
4 weeks	0.0049	1.90	0.0006	0.21	0.0042	1.13
2 months	0.0120	3.33	0.0047	1.22	0.0073	1.47
3 months	0.0111	2.46	0.0073	2.17	0.0039	0.81
Panel C: Performance of transactions following downgrades in the previous week						
1 week	0.0061	3.73	−0.0027	−1.38	0.0087	6.30
2 weeks	0.0096	2.74	−0.0020	−0.68	0.0115	5.04
3 weeks	0.0103	2.03	0.0003	0.08	0.0100	3.05
4 weeks	0.0153	2.52	0.0026	0.49	0.0127	3.81
2 months	0.0259	2.17	0.0149	1.52	0.0110	1.72
3 months	0.0337	1.94	0.0257	1.89	0.0081	1.13
Panel D: Abnormal performance of transactions following downgrades in the previous week						
1 week	0.0025	2.21	−0.0046	−3.64	0.0071	4.62
2 weeks	0.0040	2.21	−0.0054	−3.83	0.0094	4.57
3 weeks	0.0034	1.42	−0.0058	−2.76	0.0091	3.38
4 weeks	0.0062	2.25	−0.0055	−2.06	0.0117	4.06
2 months	0.0049	0.93	−0.0034	−0.79	0.0083	1.28
3 months	0.0066	1.01	−0.0015	−0.31	0.0081	1.27

The table reports the performance of stocks bought or sold by institutional investors that were also upgraded or downgraded by analysts over the previous week. Returns over each horizon are averaged by month and then across months. Standard errors are adjusted for autocorrelation. Panels A and B report the performance results that were bought and sold following upgrades, and Panels C and D show the results following downgrades. Abnormal returns are measured relative to DGTW benchmark portfolios matched on size, book-to-market, and recent return momentum. The institutional transaction data are from Plexus and Abel/Noser, and the analyst recommendation data are from I/B/E/S. The sample period covers 1993 though 2005.

related to revisions as far back as four weeks. Sell-side recommendations, however, are not related to past trades.

We also investigate whether funds are able to differentiate between good recommendations and bad recommendations. We find that whether funds trade in the same direction as recommendation revisions or in the opposite direction does not contain incremental information. Our findings indicate that the empirical evidence is not consistent with the notion widely expressed in the media and in some academic studies that institutional investors are able to see through any inherent biases in recommendations due to sell-side analysts' conflicts of interest.

Table 8
Institutional investors and brokerage firm analysts: a performance horse race.

	Constant		Purchase/Sale		Upgrade/Downgrade	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Panel A: Returns						
1 week	0.0044	2.26	0.0007	1.41	0.0049	7.92
2 weeks	0.0087	2.30	−0.0003	−0.67	0.0071	7.62
3 weeks	0.0122	2.15	−0.0002	−0.38	0.0086	7.13
4 weeks	0.0171	2.37	−0.0007	−0.96	0.0088	6.63
2 months	0.0330	2.94	0.0003	0.21	0.0129	10.66
3 months	0.0503	3.48	0.0018	0.95	0.0135	6.61
Panel B: Abnormal returns						
1 week	0.0015	2.14	0.0004	0.92	0.0045	7.82
2 weeks	0.0026	1.91	−0.0005	−1.15	0.0067	8.51
3 weeks	0.0029	1.45	−0.0003	−0.46	0.0078	7.80
4 weeks	0.0042	1.70	−0.0004	−0.66	0.0079	7.44
2 months	0.0062	1.60	0.0011	0.79	0.0114	13.77
3 months	0.0083	1.60	0.0023	1.26	0.0119	5.80

The table reports average coefficients from cross-sectional regressions of stock returns on measures of institutional trading and analyst recommendations. Trading and Recommendation changes are aggregated to the weekly level. Purchase/Sale is an indicator variable that is 1 (−1) if institutions were net buyers (sellers) of the stock over the previous week, and Upgrade/Downgrade is 1 (−1) if the stock was upgraded (downgraded) by analysts over the previous week. Cross-sectional regressions for each return horizon are estimated each week. Coefficients are averaged by month and then across months. Standard errors are adjusted for autocorrelation. Panel A reports the return results. Panel B reports abnormal returns which are measured relative to DGTW benchmark portfolios matched on size, book-to-market, and recent return momentum. The institutional transaction data is from Plexus and Abel/Noser. The sample period covers 1993 though 2005.

Appendix A. Theoretical regression coefficients

A.1. Unbiased analyst forecasts

Consider a setting in which analysts make forecasts of stock returns. Fund managers observe an analyst's forecast and combine it with a privately observed signal. What happens when we regress the returns on their two information signals? Let $a_t = r_t + \varepsilon_t$ reflect the analyst's estimate of return, and $s_t = r_t + u_t$ reflect a fund manager's private signal of value, where r_t denotes returns at time t, and ε_t and u_t are uncorrelated and normally distributed mean-zero forecast errors with variances equal to V_ε and V_u. Fund managers combine the analyst's signal and their private signal according to Bayes' rule as follows:

$$m_t = \left(\frac{1/V_\varepsilon}{1/V_\varepsilon + 1/V_u}\right)a_t + \left(\frac{1/V_u}{1/V_\varepsilon + 1/V_u}\right)s_t.$$

If returns are normally distributed with variance V_r, then regressing them on the two information signals according to the specification, $r_t = \alpha + \beta_1 a_t + \beta_2 m_t$, produces the following regression coefficients:

$$\beta_1 = 0,$$

$$\beta_2 = \frac{V_r}{\left(V_r + \frac{1}{((1/V_\varepsilon)+(1/V_u))}\right)}.$$

Thus, when fund managers observe analysts' return forecasts, the managers' signal incorporates the information and drives out the usefulness of the analysts' signal in the return regression.

The coefficients can be derived as follows. From basic statistics, the coefficients will be:

$$\beta_1 = \frac{\mathrm{Cov}_{r,a}\mathrm{Var}_m - \mathrm{Cov}_{a,m}\mathrm{Cov}_{r,m}}{\mathrm{Var}_a\mathrm{Var}_m - \mathrm{Cov}_{a,m}^2}$$

and

$$\beta_2 = \frac{\mathrm{Cov}_{r,m}\mathrm{Var}_a - \mathrm{Cov}_{a,m}\mathrm{Cov}_{r,a}}{\mathrm{Var}_a\mathrm{Var}_m - \mathrm{Cov}_{a,m}^2}.$$

According to our assumptions, the variances and covariances are:

$$\mathrm{Var}_a = V_r + V_\varepsilon, \quad \mathrm{Cov}(r+\varepsilon, r+u) = V_r, \mathrm{Cov}(r,a) = \mathrm{Cov}(r, r+\varepsilon) = V_r,$$

$$\begin{aligned}\mathrm{Var}_m &= V_r + \left(\frac{1/V_\varepsilon}{(1/V_\varepsilon)+(1/V_u)}\right)^2 V_\varepsilon + \left(\frac{1/V_u}{(1/V_\varepsilon)+(1/V_u)}\right)^2 V_u \\ &= V_r + \frac{1}{((1/V_\varepsilon)+(1/V_u))},\end{aligned}$$

$$\mathrm{Cov}(r,m) = \mathrm{Cov}\left(r, r + \left(\frac{1/V_\varepsilon}{(1/V_\varepsilon)+(1/V_u)}\right)\varepsilon + \left(\frac{1/V_u}{(1/V_\varepsilon)+(1/V_u)}\right)u\right) = V_r,$$

and

$$\begin{aligned}\mathrm{Cov}(a,m) &= \mathrm{Cov}\left(r+\varepsilon, r + \left(\frac{1/V_\varepsilon}{(1/V_\varepsilon)+(1/V_u)}\right)\varepsilon + \left(\frac{1/V_u}{(1/V_\varepsilon)+(1/V_u)}\right)u\right) \\ &= V_r + \left(\frac{1}{(1/V_\varepsilon)+(1/V_u)}\right),\end{aligned}$$

which makes the coefficients simplify as follows:

$$\beta_1 = \frac{\mathrm{Cov}_{r,a}\mathrm{Var}_m - \mathrm{Cov}_{a,m}\mathrm{Cov}_{r,m}}{\mathrm{Var}_a\mathrm{Var}_m - \mathrm{Cov}_{a,m}^2} = \frac{V_r\left(V_r + \frac{1}{((1/V_\varepsilon)/(1/V_u))}\right) - \left(V_r + \frac{1}{((1/V_\varepsilon)/(1/V_u))}\right)V_r}{(V_r + V_\varepsilon)\left(V_r + \frac{1}{((1/V_\varepsilon)/(1/V_u))}\right) - \left(V_r + \frac{1}{((1/V_\varepsilon)/(1/V_u))}\right)^2} = 0$$

and

$$\beta_2 = \frac{\mathrm{Cov}_{r,m}\mathrm{Var}_a - \mathrm{Cov}_{a,m}\mathrm{Cov}_{r,a}}{\mathrm{Var}_a\mathrm{Var}_m - \mathrm{Cov}_{a,m}^2}$$

$$= \frac{V_r(V_r + V_\varepsilon) - \left(V_r + \frac{1}{((1/V_\varepsilon)+(1/V_u))}\right)V_r}{(V_r + V_\varepsilon)\left(V_r + \frac{1}{((1/V_\varepsilon)+(1/V_u))}\right) - \left(V_r + \frac{1}{((1/V_\varepsilon)+(1/V_u))}\right)^2} = \frac{V_r}{\left(V_r + \frac{1}{((1/V_\varepsilon)+(1/V_u))}\right)}.$$

A.2. Biased analyst forecasts

We now consider a setting in which analysts purposefully add a bias to their signals of value as a side effect of the other services they provide for their brokerage firms. We assume that a fund manager's skill involves deciphering recommendations to uncover the useful investment advice. Let $a_t = r_t + \varepsilon_t + \mu_t$ reflect analysts' estimate of return with added bias $\mu \sim N(0, V_\mu)$. Fund managers separate out the bias to create their private signal of value $m_t = a_t - \mu_t$, which is not observed by the overall market. In this setting, regressing returns on the two information signals according to the specification, $r_t = \alpha + \beta_1 a_t + \beta_2 m_t$, produces the following regression coefficients:

$$\beta_1 = 0,$$

$$\beta_2 = \frac{V_r}{(V_r + V_e)}.$$

Thus, when fund managers are able to observe analysts' return forecasts and "see through" the bias, the fund manager's signal incorporates the information and drives out the usefulness of analysts' signals in the return regression.

The coefficients are derived as follows. From basic statistics the coefficients will be;

$$\beta_1 = \frac{\mathrm{Cov}_{r,a}\mathrm{Var}_m - \mathrm{Cov}_{a,m}\mathrm{Cov}_{r,m}}{\mathrm{Var}_a\mathrm{Var}_m - \mathrm{Cov}_{a,m}^2} \quad \text{and} \quad \beta_2 = \frac{\mathrm{Cov}_{r,m}\mathrm{Var}_a - \mathrm{Cov}_{a,m}\mathrm{Cov}_{r,a}}{\mathrm{Var}_a\mathrm{Var}_m - \mathrm{Cov}_{a,m}^2}.$$

Under our assumptions, the variances and covariances are:

$$\mathrm{Var}_a = V_r + V_\varepsilon + V_\mu,$$

$$\mathrm{Var}_m = V_r + V_\varepsilon,$$

$$\mathrm{Cov}_{r,a} = E[(r - E_r)(a - E_a)] = E[(r - E_r)(r - E_r + \varepsilon - E_\varepsilon + \mu - E_\mu)]$$
$$= E[(r - E_r)^2] + E[(r - E_r)(\varepsilon - E_\varepsilon)] + E[(r - E_r)(\mu - E_\mu)] = V_r + 0 + 0,$$

$$\mathrm{Cov}_{r,m} = E[(r - E_r)(m - E_m)] = E[(r - E_r)(r - E_r + \varepsilon - E_\varepsilon)] = E[(r - E_r)^2]$$
$$+ E[(r - E_r)(\varepsilon - E_\varepsilon)] = V_r + 0,$$

and

$$\mathrm{Cov}_{a,m} = E[(a - E_a)(m - E_m)] = E[(r - E_r + \varepsilon - E_\varepsilon + \mu - E_\mu)(r - E_r + \varepsilon - E_\varepsilon)] = V_r + V_e$$

and the coefficients simplify to:

$$\beta_1 = \frac{\mathrm{Cov}_{r,a}\mathrm{Var}_m - \mathrm{Cov}_{a,m}\mathrm{Cov}_{r,m}}{\mathrm{Var}_a\mathrm{Var}_m - \mathrm{Cov}_{a,m}^2} = \frac{V_r(V_r + V_e) - (V_r + V_e)V_r}{(V_r + V_e + V_\mu)(V_r + V_e) - (V_r + V_e)^2} = 0,$$

and

$$\beta_2 = \frac{\mathrm{Cov}_{r,m}\mathrm{Var}_a - \mathrm{Cov}_{a,m}\mathrm{Cov}_{r,a}}{\mathrm{Var}_a\mathrm{Var}_m - \mathrm{Cov}_{a,m}^2} = \frac{V_r(V_r + V_e + V_\mu) - (V_r + V_e)V_r}{(V_r + V_e + V_\mu)(V_r + V_e) - (V_r + V_e)^2}$$
$$= \frac{V_r V_\mu}{(V_r + V_e)V_u} = \frac{V_r}{(V_r + V_e)}.$$

References

Admati, A.R., Pfleiderer, P., 1990. Direct and indirect sale of information. Econometrica 58, 901–928.

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

Barber, B.M., Lehavy, R., Trueman, B., 2007. Ratings Changes, Ratings Levels, and the Predictive Value of Analysts' Recommendations. Working Paper, University of California, Davis.

Brown, N.C., Wei, K.D., and Wermers, R., 2007. Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices. Working Paper, University of Southern California.

Chen, H., Jegadeesh, N., Wermers, R., 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.

Conrad, J.S., Johnson, K.M., Wahal, S., 2002. Institutional trading and soft dollars. Journal of Finance 56, 397–416.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035–1058.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.

Goldstein, M.A., Irvine, P.J., Kandel, E., Wiener, Z., 2009. Brokerage commissions and institutional trading patterns. Review of Financial Studies 22, 5175–5212.

Green, T.C., 2006. The value of client access to analyst recommendations. Journal of Financial and Quantitative Analysis 41, 1–24.

Green, T.C., Jegadeesh, N., Tang, Y., 2009. Gender and job performance: evidence from Wall Street. Financial Analysts Journal 65, 65–78.

Greene, W.H., 2000. Econometric Analysis. Prentice-Hall, Upper Saddle River, NJ.

Hu, G., 2009. Measures of implicit trading costs and buy–sell asymmetry. Journal of Financial Markets 12, 418–437.

Irvine, P.J., 2004. Analysts' forecasts and brokerage-firm trading. The Accounting Review 79, 125–149.

Irvine, P.J., 2001. Do analysts generate trade for their firms? Evidence from the Toronto Stock Exchange. Journal of Accounting and Economics 30, 209–226.

Irvine, P.J., Lipson, M.L., Puckett, A., 2007. Tipping. The Review of Financial Studies 20, 741–768.

Jegadeesh, N., Karceski, J., 2009. Long-run performance evaluation: correlation and heteroskedasticity-consistent tests. Journal of Empirical Finance 16, 101–111.

Jegadeesh, N., Kim, J., Krische, S.D., Lee, C.M.C., 2004. Analyzing the analysts: when do recommendations add value? Journal of Finance 59, 1083–1124.

Jegadeesh, N., Kim, W., 2006. Value of analyst recommendations: international evidence. Journal of Financial Markets 9, 274–309.

Juergens, J.L., Lindsey, L., 2009. Getting out early: an analysis of market making activity at the recommending analyst's firm. Journal of Finance 64, 2327–2359.

Keim, D.B., Madhavan, A., 1995. Anatomy of the trading process: empirical evidence on the motivations for and execution of institutional equity trades. Journal of Financial Economics 37, 371–398.

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.

Ljungqvist, A., Malloy, C.J., Marston, F.C., 2009. Rewriting history. Journal of Finance 64, 1935–1960.

Malmendier, U., Shanthikumar, D.M., 2007. Are investors naïve about incentives? Journal of Financial Economics 85, 457–489.

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

Sias, R.W., 2004. Institutional herding. Review of Financial Studies 17, 165–206.

Sirri, E.R., Tufano, P., 1998. Costly search and mutual fund flows. Journal of Finance 53, 1589–1622.
Tang, Y., 2009. Prior Employment and Informed Trading of Mutual Fund Managers. Working Paper, Emory University.
Warther, V.A., 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 39, 209–235.
Wermers, R., 2000. Mutual fund performance: an empirical decomposition into stock-picking talent, style, transactions costs, and expenses. Journal of Finance 55, 1655–1695.
Wermers, R., 2004. Is Money Really 'smart'? New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence. Working Paper, University of Maryland.
Womack, Kent L., 1996. Do brokerage analysts' recommendations have investment value? Journal of Finance 51, 137–167.