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CONNECTIONS, INSIDER INFORMATION AND INSTITUTIONAL TRADES

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An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
In Business
2011

Abstract

CONNECTIONS, INSIDER INFORMATION AND INSTITUTIONAL TRADES

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This dissertation explores the channels that institutional funds and managers use to obtain informational advantage. The first essay ("Business connections and informed trading of mutual fund managers") explores the hypothesis that investors gain information advantages through business connections made during prior employment. Using hand-collected data, I find that mutual fund managers who previously worked as sell-side analysts put significantly more weight on the stocks they previously covered, and those stocks perform significantly better than the other stocks in their portfolio. Holdings of stocks that the fund managers covered previously outperform their other holdings by 18 percent annually. The abnormal returns are concentrated around earnings announcements and fund managers' trades of covered stocks predict subsequent earnings surprises. However, the superior performance of covered stocks decreases significantly after the implementation of Regulation-FD, which prohibits selective disclosure by company management. Also, after executive changes at the covered companies, fund managers place less weight on covered stocks, and they no longer earn abnormal returns on them. The results indicate that fund managers have access to inside information through the business connections they made while working as analysts. In the second essay ("Institutional trades around takeover announcements: skill vs. inside information" – co-authored with Narasimhan Jegadeesh), we examine the pattern and profitability of institutional trades around takeover announcements. We find that the trades of funds as a group, either before or after takeover announcements, are not profitable. However, funds whose main broker is also a target advisor are net buyers of target shares before announcements and their pre-announcement trades are significantly profitable. Therefore, leakage of inside information from brokerages that advise the target is a significant source of funds' informational advantage. We also find that a subset of funds is skilled at privately gathering information even when they do not trade through target advisors.

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Acknowledgements

I am indebted to my dissertation committee members: Tarun Chordia, Clifton Green, Jay Shanken, and, in particular, my advisor, Narasimhan Jegadeesh. Their strong understanding of empirical research methodologies and excellent economic intuition has made them invaluable resources in the development of my dissertation. In addition, their experience publishing research has been extremely helpful in making my research accessible and interesting to a broad audience.

I would also like to thank Byoung-Hyoun Hwang, Seoyoung Kim, Narayan Naik, Jay Ritter, Kelsey Wei, and seminar participants at Emory, Drexel, University of Florida, LBS, Baruch College, DFA, Georgia State University, University of Texas at Dallas, WFA meetings 2010, CICF meetings 2010 and AFA meetings 2011 for helpful comments on parts of my dissertation.

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First Essay: Business Connections and Informed Trading of Mutual Fund Managers

I. Introduction

A recent article in the *Wall Street Journal* asserts that "information flows these days are increasingly about networks." [1] The observation about network communication raises an important question: Do investors gain informational advantage through their network connections? One network that can potentially serve as an information conduit is the connections formed through business interactions. Ubiquitous business connections seem to be a natural channel for the flow of business-related information. Therefore, this paper examines whether fund managers collect important information through their business connections that affects their investment decisions and performance.

Business connections are the most frequently used relationships in financial markets. Money managers advertise that their business networks help their investments by "allowing them to gain rapid and high-level access to senior management in companies" (AIG investment Web page). Despite the awareness of the significance of business relationships in financial markets, researchers have not examined whether business connections can form a direct channel for some investors to obtain information advantages—primarily because business connections are difficult to quantify. To overcome the challenges in studying these relationships, this paper focuses on business connections formed during previous employment. Specifically, I look at mutual fund managers who have previously worked as financial analysts. The paper tests whether their prior work connections—formed while working as analysts—provide them with an information advantage on the stocks they covered as analysts.

The fact that sell-side analysts build connections with the management teams of those companies for which they provide research coverage is hardly a secret—it is documented both in

[1] Wall Street Journal, October 26, 2009, "'Outsider Trading' and Too Much Information".

research and the media. Easy access to management may help build these connections. Companies traditionally provide analysts with easy access not only to gain publicity, but also to attract analyst attention and coverage (Healy, Hutton and Palepu (1999)). Analyst coverage has been shown to increase firm value (Chung and Jo (1996)) while lack of analyst coverage may lead to lack of liquidity[2] and increased volatility in stock price (Schutte and Unlu (2007)). A 2008 *Institutional Investor Magazine* survey[3] reveals that institutional investors view management access as one of the most important analyst attributes[4]. Furthermore, through such frequent communications as company visits or conference calls, analysts may build closer relationships with companies' management teams over time. Lim (2001) offers evidence that analysts provide optimistic forecasts in order to build favorable relationships with management. In return, these relationships grant analysts better access to a firm's information[5].

Thus, the connections made as an analyst may provide fund managers with an information advantage for their covered stocks in numerous ways. These connections could lower fund managers' cost or increase the speed of gathering information—it might take either fewer phone calls to reach the management or people might be more forthcoming when discussing the company. Frequent interaction with the management may also help fund managers better assess management quality (Previts, Bricker, Robinson and Young (1994)). Finally, connections may also help fund managers obtain information that is not usually available to the public.

To test whether business relationships made during previous employment as analysts provide fund managers with information advantages on their once-covered stocks, I compare both the holdings and returns of these covered stocks with those of the stocks not covered by fund managers when they were previously employed. I predict that, if managers have information

[2] "The Art of the Analyst Conference Call and Earnings Forecasts — To Guide or Not to Guide", 2007 National Directors Institute.
[3] http://www.iimagazinerankings.com/rankingsEqtyTeamAmerica08/whatInvestorsWant.asp
[4] Buy side fund managers often do not have easy access to the management. They usually ask analysts to arrange meetings with the management of the companies they want to evaluate for investment.
[5] See also Chen and Matsumoto (2006)

advantages in the stocks they have previously covered, one should observe that those managers place larger bets on the previously covered stocks and earn higher abnormal returns on them. Through the use of a hand-collected list of mutual fund managers in the United States who have previously been employed as sell-side financial analysts, the results of this study strongly confirm this prediction. Fund managers place more than double weights on the stocks they once covered than they do on the average stocks in their portfolios. The calendar portfolio, which mimics the aggregate holdings of the funds on covered stocks, significantly outperforms the portfolio on non-covered stocks. The strategy of buying covered holdings and selling non-covered holdings earns a risk-adjusted return of 18% annually. I also find that the covered stocks that fund managers chose not to hold underperform the covered stocks they chose to hold by 16.6% annually. This finding confirms that fund managers do have an information advantage on their covered stocks and that rather than hold some because of familiarity, the managers' actively select stocks from those they previously covered.

This research also examines the persistence of abnormal returns on the covered stocks. If the abnormal returns are due to fund managers' superior information, the returns should diminish over time as such information gradually disseminates through the market and is incorporated into prices. Consistent with this, the abnormal returns appear to decrease monotonically over time and disappear four months after portfolio formation. Fund managers also typically hold covered stocks for a shorter time than non-covered stocks, consistent with the concept of information-driven buying. The abnormal return persists three months after the portfolio formation, suggesting a potential profitable replicating strategy if an uninformed investor can get timely access (within three months) to the reported holdings of the funds.

Furthermore, I look at the returns of covered holdings around corporate earnings announcements. If the higher returns are due to fund managers' superior information that they have obtained through their business connections, the returns would be mostly concentrated around events such as earnings announcements when the information is eventually released to the public and incorporated into prices. Consistent with this, the evidence indicates that fund managers' covered holdings realize a disproportionally larger amount of positive returns around earnings announcements. Almost the entire difference in returns between covered holdings and non-covered holdings is concentrated around earnings announcements. In addition, fund managers' trades of covered stocks predict their subsequent earnings surprises, while their trades on non-covered stocks do not. This indicates that fund managers possess information beyond what is publicly available on covered stocks; this information potentially helps them better predict the firms' earnings.

While business connections may be the most easily recognizable source of fund managers' information advantages, there are other possible interpretations of the results. The superior performance of investments in covered stocks might be due to fund managers' knowledge or skills gained as analysts. Providing research coverage may endow analysts with valuable knowledge about companies, including its fundamentals, operations, and profitability (Lev and Thiagarajan (1993)). In addition, analysts, through experience, may develop skill in better interpreting the firm's public information (Maines, McDaniel and Harris (1997)), for example, being able to identify significant details in a report that might otherwise be ignored by those without the analyst's experience.

To differentiate from the explanations based on knowledge or skill, I perform three tests. First, I explore a regulation change that occurred during the sample period: Regulation FD; this prohibits firms from selectively disclosing corporate information to a subset of market participants as opposed to the general public. Such selective disclosure (Bowen, Davis and Matsumoto (2002); Gintschel and Markov (2004)) represents exactly the type of privileged information that fund managers might have obtained through their previous work connections. The results reveal that fund managers' performance on covered stocks decreases significantly after Regulation FD—a finding consistent with the idea that fund managers' information is mostly connection-based. Second, I examine the fund managers' performance on the industries they covered previously as analysts; that position might help fund managers gain extensive knowledge and skills in analyzing their specialized industries[6] (Clement (1999); Jacob, Lys and Neale (1999)). While knowledge and skills may more easily be generalized to industries, relationships are more company-specific and, therefore, not easily replicable to other companies in the industry. The study finds that fund managers' holdings in their covered industries do not outperform, nor do their stock picks within their covered industries. This result indicates that connections—rather than knowledge or skills—play a major role in helping fund managers obtain information advantages. Third, I explore a natural experiment when company executives leave a firm. If fund managers obtain information advantage through their relationships with company management, executive change will cause an exogenous break in the fund manager's information channel. The results reveal that fund managers put less weight on their covered stocks after executive changes, and no longer earn any abnormal returns. This provides further evidence to support the importance of relationships.

Given these findings, it is natural for one to ask when the information advantage from business connections is strongest. This paper explores two factors to answer this question: first, the length of time since managers left their previous analyst job, and second, the number of analysts covering the stock. Fund managers should lose their information advantages as their connections naturally loosen over time. Consistent with this, I find that fund managers earn higher abnormal returns on stocks they hold shortly after providing coverage, and no abnormal returns on stocks they hold long after they left their analyst positions. Fund managers' information advantage could also be affected by the number of analysts covering the stock, as a stronger or more personal relationship can be built when fewer analysts provided coverage on the company. With less competition while building relationships, for example, an analyst might have more chances to ask questions, more time to interact with the management, and greater access to

[6] An *Institutional Investor Magazine* survey in 2009 shows that industry knowledge is the most important factor institutional investors consider when evaluating analysts.

other opportunities. The evidence supports this hypothesis—the holdings of covered stocks with lower analyst coverage earn 21% more returns than those stocks with higher analyst coverage.

My paper contributes to the literature in several dimensions. First, it adds to the growing literature studying how investors acquire information beyond traditional paid information gathering, such as equity research and investment advising, by identifying another important channel—business connections built from prior employment. Coval and Moskowitz (2001) find that fund managers are more informed about geographically proximate companies. Hong, Kubik and Stein (2005) show that fund managers obtain information through word-of-mouth communication with neighboring managers in the same city. Related to my paper is also the study by Cohen, Frazzini and Malloy (2008) with whom we share the basic theme that networks help mutual fund managers obtain information. However, the key distinction is that this paper focuses on prior work connections, whereas Cohen et al. focus on the shared education networks in a social network setting. While social ties are informal and relies on homophily (an affinity for similar others) to facilitate interactions (Marsden (1987); McPherson, Smith-Lovin and Cook (2001)), business connections are direct, stronger and allow agents to pursue repeated, enduring exchange relations (Rauch (2001)[7]). Therefore the potential information advantage investors get from business connections can be significant.

This paper also adds to the debate on whether mutual fund managers have stock-picking abilities (Jensen (1968); Carhart (1997); Daniel, Grinblatt, Titman and Wermers (1997); Chen, Jegadeesh and Wermers (2000)) and whether managers' characteristics matter (Chevalier and Ellison (1999)). Rather than using their entire portfolios to evaluate performances, this paper emphasizes managers' information advantages on some stocks and the channels through which they acquire such information.

[7] Rauch (2001) shows two definitions of economic networks used in the sociological literature. The first, based on Podolny and Page (1998), defines an economic network as a group of agents that pursue repeated, enduring exchange relations with one another. The second, weaker definition is based on the work of Granovetter (1973), (1983): a set of actors who know each other's relevant characteristics or can learn them through referral.

It also relates to papers in analyst literature that evaluate the investment value of analyst research in a broader setting (Elton, Gruber and Grossman (1986); Stickel (1995); Womack (1996); Barber, Lehavy, McNichols and Trueman (2001); Jegadeesh, Kim, Krische and Lee (2004)). Recently, however, the possible biases in analysts' forecasts and recommendations have been called into question (Dugar and Nathan (1995); Irvine (2004). By identifying those analysts who trade on the information themselves later on as fund managers, this paper avoids the contamination of biases in analysts' reports and presents a more focused and powerful test for such investment values.

The paper is organized as follows: Section 2 describes the data and the process of collecting the fund managers. Section 3 shows the results, and Section 4 offers conclusions.

II. Data

This study uses data from several sources. The CRSP survivor-bias-free mutual fund database, which started collecting fund manager names in 1993, provided mutual fund manager names. The database lists fund manager names and the start and end dates of managers, and it notes whether the fund is team managed. It also contains the basic fund information such as fund names, management companies, fund advisors, self-declared investment objectives, and total assets under management. I supplemented CRSP fund manager data with the Morningstar mutual fund monthly disc. Besides offering similar fund information to CRSP, Morningstar provides a short biography of managers, including managers' start dates, previous positions held, and the employers of those positions. Both managers' current and previous employment information is helpful in identifying the matches with analysts to ensure that each manager is matched accurately.

Identifying those managers who were formerly employed as analysts involves several steps. First, I obtained brokerage firm analyst information from the Institutional Brokers' Estimate

System (I/B/E/S). I/B/E/S provides analysts' earnings forecasts and recommendations. The data includes the analyst's identity code, the brokerage house to which the analyst belongs, the security identity, and the research report date. This study uses the I/B/E/S Broker Translation File to translate analyst codes into last names and initials of first names. To get analysts' full names, I hand collect data from the corresponding annual edition of *Nelson's Directory of Investment Research,* which contains analysts' full names, brokerage firms, and contact information. The last name and the initial of the first name are the main matching links. When the match is not unique, the analysts' employing brokerage firms and employment period[8] are also used to help find a unique match. Second, match mutual fund manager names are matched with analyst names to generate a potential list of managers with analyst backgrounds. Third, to ensure that the name-matched manager and analyst are the same person, the manager's employment history from Morningstar's manager biography is used to discern whether the manager indeed worked at the same brokerage firm as the name-matched analyst. If managers' employment histories are not available from Morningstar, resumes from Zoominfo[9] and Google search are used as well. Other sources, including contacting the companies to verify the identity and employment history of the managers, are used to ensure data accuracy. Both fund managers' previous employment information and current employers (fund management companies or advisors) are helpful in identifying the matches with analysts to ensure that each manager is matched accurately.

Mutual fund holdings data from the Thomson Financial CDA/Spectrum Mutual Funds database is used to study the trading decisions of mutual fund managers. This data contains portfolio holdings of all registered mutual funds from their filings with the Securities and Exchange Commission (SEC) at quarterly or semiannual frequency. To link the fund managers from CRSP to their holdings, the funds in the CRSP database are compared to CDA Funds—primarily by their names. Investment objectives, management company names, and total net

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[8] Both the employing brokerage firm and employment time can be inferred from the I/B/E/S detail file.

[9] Www.zoominfo.com is a search engine specializing in collecting and indexing biographical and employment data from publicly available documents through the Web.

assets are also used to help make comparisons between the databases.[10] This study focuses specifically on managers of actively managed U.S. equity funds with the investment objectives of aggressive growth, growth, or growth and income. A conservative method of selecting samples has been employed in this study. Team-managed funds are excluded from the sample because the trading of such funds may not reflect the decision of a single manager.

Table 1 shows the summary statistics of the sample. The above procedure identifies 152 mutual fund managers who previously worked as financial analysts. These individuals managed 199 mutual funds[11] between 1993 and 2006. The fund net asset values range from $660,000 to $16 billion, with an average value of $590 million. In terms of total assets under management, they represent, on average, 5.88% of the active equity fund universe over the sample period. Fund holdings are reasonably diversified, with an average of 84 stocks held at one time.

In addition, Table 1 illustrates the characteristics of managers' holdings related to their previous analyst jobs. Managers covered an average of 25 stocks in their analyst careers.[12] On average, fund managers hold 2.59 covered stocks at one time and 4.47 of them over their tenures. They hold their covered stocks for about six months, two-months shorter than non-covered stocks.[13] This is more consistent with information-driven buying, as opposed to the valuation-driven long term buy-and-hold. A different characteristic, the number of analysts who followed the fund managers' covered stocks, ranges widely. The fund manager could have been the only analyst providing coverage, or one out of 61 analysts. Another interesting variable is the length of time between a manager's last coverage of a stock and when she begins managing the fund. These periods range from one month to nearly twenty years, with an average length of about four years.

[10] For detailed procedure, see Wermers (2000).
[11] Funds with different share classes are counted as one.
[12] Only stocks that managers had once covered as a single analyst—not as a team member—are considered because how much they had been involved and had contributed to the research as a team member is unclear and difficult to discern.
[13] Because managers report holdings only quarterly, the calculated holding time is in 3 month increments. The minimum holding time is calculated to be 3 months.

III. Results

1. Holdings of Covered Stocks

This subsection reviews the portfolio choices of mutual fund managers. Fund managers may put more weights on certain stocks for many reasons. They may prefer stocks in accordance with their funds' investment styles, or follow such trading strategies as value or momentum investing. Fund managers might also place large concentrated bets on certain stocks because of their comparative advantage in collecting information about those stocks. In order to test if fund managers acquire information advantages in certain stocks through their business connections, the weights they choose to put on the stocks they covered previously as analysts are compared to those on the stocks they did not cover.

Table 2 reports the pooled OLS regressions[14] of stock portfolio weights on the coverage dummy variable and control variables. The dependent variable is the dollar weight (in percentage) of a given stock in its fund portfolio. The coverage dummy is equal to 1 if the fund manager has provided analyst coverage on the stock before, and 0 otherwise. Stock size (ME), book-to-market (BM), and past 12-month return (R12) are included as control variables, as they have implications for cross-sectional stock returns and represent stock characteristics that may be preferred by some managers. These control variables are in percentiles for easier comparison of the coefficients. Following Cohen, Frazzini and Malloy (2008), I also include %STYLE, the percentage of the fund's total net assets invested in the style corresponding to the stock in question, where style is defined in Daniel, Grinblatt, Titman and Wermers (1997) (hereafter DGTW) as one of the 125 portfolios formed by sorting CRSP stocks into size, book-to-market, and past 12-month return quintiles. The regression is conducted on quarterly holdings of all stocks by all managers. As ME, BM, and R12 control the stock characteristic preferences across managers, %STYLE will capture

[14] As portfolio weights are limited by 0 and 100 bound, the regression has censored dependent variable. OLS may not be appropriate in this case. When the Tobit regression with lower and upper bounds is run, the results are similar.

such preferences within a manager. Standard errors are adjusted for clustering at the fund-stock level.

The results listed in Table 2 indicate that fund managers place larger bets on stocks they covered previously as analysts. As seen from the univariate regression result in column 1, they put an additional 101 basis-point weight on stocks they covered before—more than double the weight of 89 basis points they put on other stocks. The multivariate regression (in column 2) indicates that fund managers place larger weights on large size stocks, low book-to-market stocks and past winners among the stocks in their portfolios. Yet these effects are dwarfed by the coverage effect. For example, the weight of the stocks in a higher size percentile is only 1.5 basis points more. Since this is a pooled regression with the stock-fund-quarter as the unit of observation, this study also considers possible fixed effects. For example, some stocks might become attractive at certain times for reasons that may or may not correlate with other characteristics; therefore the regression includes quarter fixed effects. Weights on a stock may also be due to reasons related to the firm, its industry, the fund, or the fund's investment objective. So in other specifications I also include fixed effects for industry, firm, fund, and fund investment objective code. In all specifications, the results consistently reveal that fund managers place larger than normal bets on stocks that they have covered when employed as analysts.

2. Returns on Covered Stocks

2.1. Covered Stock Holdings

The larger bets that fund managers place on their covered stocks may not necessarily mean that such bets are profitable. Fund managers could have information about these stocks, or they could merely be over-confident—believing that they know more about these stocks because they have followed these firms closely as analysts. To test whether fund managers' business connections provide them with information advantages on their covered stocks, this subsection examines the performance of their covered stock holdings versus their non-covered stock holdings.

I construct calendar time portfolios based on fund managers' holdings in covered stocks and non-covered stocks. At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned to one of the two portfolios: covered and non-covered, based on whether the fund manager has provided research coverage for the stock as an analyst. For each portfolio, value-weighted monthly returns are computed, weighting stocks by their actual dollar weights in the fund. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report.[15] Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. This results in the calendar-time returns of two portfolios: covered stocks and non-covered stocks. The portfolios represent the investing strategy on covered and non-covered stocks based on the actual weights mutual fund managers chose.

Table 3 lists the excess returns of the two portfolios (over Treasury bill returns). Covered holdings earn an annualized excess return of 29.28%, compared to 8.45% for non-covered holdings. A strategy of buying covered holdings and shorting non-covered holdings earns 19.35% per year—statistically significant with a t-statistic of 3.08. The higher returns from covered holdings do not seem to be solely explained by increased risk, as their Sharpe Ratio equals 1.07, compared to 0.46 for non-covered holdings.

Next, the risk-adjusted returns of the two calendar-time portfolios are reviewed. Characteristic-adjusted returns and factor regression alphas are calculated as the abnormal returns. Following DGTW, the characteristic-adjusted return is calculated by subtracting from the raw return the return on a value-weighted portfolio of CRSP stocks in the same size, book-to-

[15] This follows the common practice in the mutual fund literature using quarterly holdings data; see, for example, Grinblatt and Titman (1989), Daniel, Grinblatt, Titman and Wermers (1997) and Chen, Jegadeesh and Wermers (2000). Recent papers show such omissions of intra-quarter trades may obscure some abnormal performance of the manager (Elton, Gruber, Krasny and Ozelge (2006); Puckett and Yan (2008)). However, this omission would only bias this paper against finding any results.

market, and 12-month past return quintile. Factor regression alpha is the intercept of the regression of monthly excess returns on the Fama and French (1993) three factors and the Carhart (1997) momentum factor.

Table 4 details the results. Although both covered holdings and non-covered holdings earn significant raw returns, the risk-adjusted returns reveal the differences. Non-covered holdings earn a small DGTW-adjusted return of 0.19%—not significantly different from 0. In contrast, covered holdings earn a DGTW-adjusted return of 18.29%—both statistically (t-statistic=3.2) and economically significant. Factor regression alphas indicate similar results. The alpha of covered holdings is 18.49% (t-statistic=2.73), compared to that of non-covered holdings—only -0.08% and, thus, not significant. The long-short portfolio of buying covered holdings and shorting non-covered holdings earns more than an 18% DGTW risk-adjusted return per year, and has a factor alpha of 18.58% per year—both are significant at the 1% level. The results are consistent with the hypothesis that fund managers have information advantages on the stocks they covered through the business connections they built up when previously employed as analysts, and the fund managers earn abnormal returns by holding them.

It should be noted that, although covered holdings earn large abnormal returns, they represent only a small portion of the funds' total assets. This implies that the return of the overall holdings attributable to covered holdings is small. Subsection 6 of this paper investigates why, despite their high returns, fund managers do not increase their holdings of covered stocks.

2.2. Covered Held vs. Covered Non-held

In addition to examining the returns on the fund managers' holdings of covered stocks, I also look at the returns on those stocks that fund managers covered when employed as an analyst but chose not to hold as a manager. Because mutual funds are often restricted from short selling, fund managers' portfolio allocations may not reflect their full information advantage. The stocks that managers hold do not reveal to outside observers what, if any, information managers may possess about those covered stocks they have chosen not to hold. In other words, one cannot make an inference about the reasons why a fund manager bets against a stock they do not hold. However, comparing the returns of the covered stocks they hold with the returns of the covered stocks they do not hold does aid the researcher in ruling out familiarity-based explanations. [16] If fund managers hold covered stocks simply because they are familiar with them, but not because they have information, one would observe that the covered stocks they hold and those they do not hold perform comparably. If, on the other hand, they possess better or more information about their covered stocks, the stocks they choose should outperform those they do not choose.

The value-weighted return of covered stocks that managers choose not to hold is computed using the same portfolio approach. Table 5 indicates that the previously covered stocks not held by fund managers earn an insignificant DGTW-adjusted return of 1.04% per year, compared to those previously covered stocks that managers choose to hold, which earn a statistically significant DGTW-adjusted return of 18.29%. If managers held all the stocks they covered previously, the abnormal return would have been reduced to 6.05%, and becoming statistically insignificant. The risk-adjusted return of a long-short portfolio buying the covered, held stocks and shorting the covered, non-held stocks is 16.6% per year (t-statistic=2.51). The results for factor regression alphas are largely similar. The results are also consistent with the hypothesis that fund managers have an information advantage for their covered stocks. They engage in actively selecting from them, rather than holding them because of simple familiarity.

2.3. The Persistence of Covered Holding Performance

This subsection explores how long the information advantages and the better performances of fund managers in those covered stocks are able to persist. In particular, the previous portfolio strategy is repeated, using various lags between the reported fund holdings and the returns. That is, the portfolios are constructed using the reported fund holdings; however, this calculation waits

[16] See Grinblatt and Keloharju (2001) for a discussion on familiarity based portfolio choice.

one to four months before starting to measure its returns. This may also represent the replicating portfolio returns that investors can earn if they do not have timely access to the SEC holdings data.[17]

The DGTW-adjusted returns in Table 6 indicate that covered holdings continue to outperform non-covered holdings three months after the portfolio formation. The long-short portfolios earn a risk-adjusted return of 15.6% (t=2.89) with a one-month lag between reported holdings and risk-adjusted returns, a return of 10.63% (t=1.96) with two-month lags, and a return of 8.88% (t=1.68) with a three-month lag. If uninformed investors can obtain SEC holdings data used in constructing the portfolio within three months after the filing, they could likely implement a profitable trading strategy. In addition, the return difference between the covered stocks that managers choose to hold and those that managers choose not to hold is 15.57% (t=2.50) with one-month lag, and becomes insignificant with lags greater than one month. This suggests that managers' picks within covered stocks between held and non-held can forecast stock returns in a shorter horizon than their picks between covered and non-covered stocks.

Table 6 also indicates a clear trend that the abnormal returns managers earn on their covered stocks decrease with time and eventually disappear. This serves as further evidence that the abnormal returns on covered stocks are due to managers' information advantages (versus some spurious reasons), and these abnormal returns diminish as the information disseminates through the market. This is also consistent with managers' trading behavior in that they hold covered stocks for shorter periods of time. Managers buy covered stocks based on their special information about those firms. After the information disseminates and no more abnormal return can be realized, managers move out of these stocks quickly.

[17] The SEC requires funds to file their holdings within 60 days after the end of each fiscal period, although the average time that funds actually take is typically much less.

3. Returns around Earnings Announcements and Earnings Surprise Prediction

In this subsection, I first examine the returns of covered holdings around corporate earnings announcements. If the abnormal returns of covered holdings are due to fund managers' superior information that they have obtained through their business connections, the returns would be mostly concentrated around events such as earnings announcements when the information is eventually released to the public and incorporated into prices. To test this, I separate monthly stock returns into two parts: first, the compounded returns of a three trading-day window (-1, 0, 1) around earnings announcements, and, second, the returns of the remaining days in the month. Earnings announcement returns and returns of other periods for covered holdings, non-covered holdings, and the long-short portfolio are then computed using the same calendar portfolio approach as in the previous subsection.

Panel A of Table 7 shows the annualized returns. Covered holdings earn a statistically significant return of 19.17% during the three-day earnings announcement periods, but only 8.80% (not significant) in the other periods. For non-covered holdings, the average earnings announcement return is 4.79%[18], while the average other-period return is 10.95%. Given that the earnings announcement windows only represent about 14% of the total trading days in a month, both the covered and the non-covered holdings have their returns concentrated disproportionally around earnings announcement. However, this disproportionality is greater for the covered holdings. The average earnings announcement returns for covered holdings represent 69% of their corresponding total monthly returns[19], compared to 30% for the non-covered holdings. The long-short portfolio of buying the covered holdings and shorting the non-covered holdings earns an annualized return of 13.78% (t-statistic=2.69) during earnings announcement periods,

[18] Baker, Litov, Wachter and Wurgler (2007) report that the average earnings announcement period return of mutual fund holdings is 3.48%.

[19] The concentration of returns around earnings announcement is much higher than what can be explained by earnings announcement premium---the fact that stocks on average earn positive returns around earnings announcements. The premium was first documented in Beaver (1968) and has since been studied by Ball and Kothari (1991), Cohen, Dey, Lys and Sunder (2007) and Frazzini and Lamont (2007), among others.

compared to -1.95% (t-statistic=-0.27) on other days. This means that almost the entire difference in returns between covered holdings and non-covered holdings is concentrated around earnings announcements. The result is consistent with the hypothesis that managers have superior information about covered firms and the information helps managers predict the firms' earnings better than members of the general public. When such information is released to the public in earnings announcements, the covered holdings earn managers concentrated returns.

Next, I examine whether managers' trades can predict the earnings surprises of their covered firms. Earnings surprise is defined herein as the deviation of actual earnings from analysts' consensus forecasts.[20] Analysts' consensus forecasts represent the expectation of a firm's earnings using all publically available information. If fund managers have more information about the firm, their trades should be able to predict earnings surprises. Using managers' trades instead of their holdings might increase the researcher's ability to detect their information advantage. Because trading incurs transition costs and the possible realizations of capital gains, it represents a better signal of fund managers' information to outside observers than continuing to hold, which might be due to inertia or other difficult to observe factors.[21]

To calculate earnings surprises, this study uses the consensus forecasts and actual forecasts from I/B/E/S summary file. Stocks that managers bought or sold in a quarter are inferred from comparing the consecutive snapshots of their quarterly holdings. The earnings surprises in the subsequent quarter for stocks that managers bought or sold are averaged using the same calendar-time portfolio approach, both for covered holdings and non-covered holdings. Panel B presents the results. One can observe that for non-covered holdings, both buys and sells predict positive earnings surprises around 2.8%. This is consistent with previous research findings that analysts

[20] Consensus is measured in the month before actual earnings announcements and the difference is scaled by the actual earnings to make earnings surprise comparable across firms. This study also winsorizes it to be within -100% and 100% so as to alleviate the effect when dividing by actual earnings near 0.

[21] This methodology was first explored in Chen, Jegadeesh and Wermers (2000).

provide beatable earnings forecasts before the announcements.[22] To adjust for the positive earnings surprise caused by such analysts' forecast biases, I examine the earnings surprise difference between the stocks that managers bought and the stocks they sold. Such differencing cancels out biased positive surprise. In this case, managers' buys-minus-sells do not predict earnings surprise for non-covered stocks (-0.15% and insignificant). On the contrary, their buys-minus-sells predict a positive earnings surprise of 4.86% subsequently for covered holdings. This is due to the large earnings surprise of 6.41% predicted by buys and non-significant surprise of 1.55% predicted by sells. Consistently, the buys-minus-sells predict a surprise of 5% for the long-short portfolio. Overall, the results indicate that managers possess information beyond what is publically available on covered stocks, and this information potentially helps them better predict the firms' earnings.

4. Alternative Explanations for Fund Managers' Information Advantage

While business connections may be the most naturally considered source of fund managers' information advantage on their covered stocks, there are several other possible interpretations of the results. For example, fund managers that worked as analysts before may possess special ability in analyzing stocks for investment. This interpretation is easy to rule out because if fund managers have such ability, the ability should help them invest in other stocks as well. Yet we do not observe any superior performance from their holdings except for the stocks they covered before. Another alternative story is that the superior performance of investments in covered stocks might be due to the fact that analysts accumulate knowledge about the covered firms or develop better skill in interpreting the firm's public information, such as better understanding of the firm's financial reports. To differentiate business connections from the explanations based on knowledge or skill, I perform three tests.

[22] For example, see Skinner and Sloan (2002), Richardson, Teoh and Wysocki (2004) and Cotter, Tuna and Wysocki (2006).

4.1. Regulation FD

First, a regulation change during the sample period, Regulation FD, which the SEC enacted in October of 2000, is explored. The regulation prohibits the selective disclosure of corporate information by firms to a subset of market participants instead of the general public. This type of disclosure gives a few selected people an informational advantage. In this paper, the fund managers are exactly the people who could benefit from selective disclosure through their prior work-related connections. If the connection-based information advantage exists, one would expect such an advantage to decrease after Regulation FD.

Table 8 reports the calendar portfolio returns before and after Regulation FD. First, focusing on the DGTW risk-adjusted returns, one observes that the return for covered holdings decreased from 24.7% to 10.96% after the implementation of Regulation FD. As a control, the returns for non-covered holdings are not significantly different from 0 during either the pre- or post-regulation implementation periods. The long-short portfolio return also fell from 23.7% to 12.18%. The 4-factor alphas of the returns depict similar results: relationships made during their previous employment as analysts are an important mechanism that fund managers use to obtain their information advantage on covered stocks. Such an advantage decreased when selective disclosure was banned with the implementation of Regulation FD.

4.2. Covered Industries

Next, I test whether fund managers have information advantage over their covered industries. Prior employment as analysts might provide managers with extensive knowledge and analyzing skills of their specialized industries, in addition to their expertise on covered stocks (Clement (1999); Jacob, Lys and Neale (1999)). While knowledge and skills might more easily be generalized to industries, connections are more company-specific and therefore not easily replicable to other companies in the industry. If fund managers' information advantage on their covered stocks comes from their superior knowledge or skills, they would also be more likely to have information advantage on the industries they specialized in.

Table 9 replicates the previous portfolio weights and return tests, replacing the comparisons between covered and non-covered stocks with comparisons between covered and non-covered industries. This study uses the 2-digit Global Industry Classification Standard code (GICS) to identify industries.[23] Panel A shows the pooled regression of stock portfolio weights on an additional covered-industry dummy. The industry dummy equals 1 if the stock belongs to the industry that managers have covered previously. The results show that managers put more weights on stocks in their covered industries, with 35 basis points more weight than the 78 basis points for non-covered industries. If the stock was covered previously by them, the weight increases an additional 77 basis points. The results are similar and significant after adding in controls and possible fixed effects.

Panel B details the returns of calendar-time portfolios on covered industries, non-covered industries, and the differences between them. The first three columns indicate that fund managers' holdings in their covered industries do not produce higher returns than their holdings in non-covered industries. This is the case for both raw returns and risk-adjusted returns. For example, the long-short portfolio of buying covered industries and selling non-covered industries only earns a DGTW-adjusted return of 0.42%, which is not significant. Occasionally, fund managers may have to hold stocks in their covered industries not because they expect them to perform better, but for such reasons as their investment goals, or the characteristics of their funds, or to diversify their funds. In such case, we cannot detect the fund manager's information advantage in these covered industries by comparing the returns of these covered industries with returns of other industries. To address this issue, this study tests the managers' abilities to pick stocks within their covered industry. In other words, if a fund manager possesses superior

[23] I also conduct tests using 4-digit and 6-digit GICS, which are finer classification of the industries, and Fama French 48 industry classification. The results are similar.

information about an industry he or she covered as an analyst, his or her selection of stocks from within that industry should still outperform other stocks in the industry[24]. I calculate stock returns adjusted for mean return of the industry to measure managers' selections of stocks within industries and report the industry-adjusted returns in the last column. The results show that stocks picked from fund managers' covered industries do not outperform other stocks in the same industry.

Reviewing these findings, neither the managers' performance in their covered industry nor their stock picks within the covered industry reveal evidence that fund managers possess information advantages in their covered industries. Their information advantages for covered stocks most likely come from their connections with the management rather than their knowledge. Another interesting finding is that managers do prefer stocks from their covered industries, possibly because of familiarity, although such preferences do not seem to earn superior returns.

4.3. Corporate Executive Changes

As an additional way to discern whether fund managers' information advantages depend on their connections with company management, this subsection explores how changes in corporate executives affect such advantages. If fund managers obtain information advantage through their connections with company management, changes in company executives will cause an exogenous breakup of the managers' information channel. This creates a natural experiment through which to examine the effects of business connections on fund managers' information advantage.

Company executive data are obtained from Compustat Executive Compensation database. The database provides executive names filed in company proxy statements each year, from which the executive's employment start and end dates can be obtained. I consider only the instance when an

[24] Boni and Womack (2006) show that analyst recommendation changes lead to more profitable trading strategies within industries than across industries, suggesting that analysts are able to distinguish performance within industry, but are not good predictors of sector/industry performance.

executive left the company, rather than the time she left the position, because as long as she remains in the company, a feed of information may continue. Executives should also have been in their positions when fund managers followed the firms as an analyst, thus ensuring that fund managers had opportunities to build relationships with the executives. For companies with multiple executive changes during a fund manager’s tenure, the first executive change is considered.

To determine the effect of company executive changes on fund managers’ information advantages, I compare both the portfolio weights and the abnormal returns of covered stocks before and after executive changes. The average portfolio weight is computed for each stock both before and after company executive changes. To reflect fund managers’ choice to not hold the stocks, the weight is set to zero if the stock is not held before or after executive change. I then average the weights across stocks for covered and non-covered stocks, computing t-statistics assuming weight independence across stocks. To calculate returns I form calendar time portfolios by assigning stocks into one of the four portfolios based on whether the fund manager covered the stock before and whether there is an executive change. The portfolios are rebalanced every calendar quarter, and the value-weighted risk-adjusted returns are calculated.

Panel A of Table 10 presents portfolio weights before and after executive changes. After company executive changes, fund managers decrease the average weight they put on covered stocks from 1.3% to 0.6%. This decrease in weights is 0.7% and significantly different from 0. The significant decrease of covered stock weights indicates that fund managers receive less information about the companies after the loss of their connection. In contrast to the weight change in covered stocks, the average weight of non-covered stocks does not decrease, but rather, increases a little after executive change—0.08%. Because executive changes may lead to other changes in the company, such as policy shifts, the weight change in non-covered stocks serves as a necessary control. For non-covered stocks, the weight increase after executive change may reflect fund managers' optimism about the company when entrenched or less competent executives are substituted with new ones.

Panel B reports the risk-adjusted calendar time portfolio returns of stocks before and after executive changes. The results confirm that fund managers lose their information advantages on their covered stocks after company executive changes. For example, fund managers earn 21.6% DGTW characteristic-adjusted return on their covered stocks before executive change, yet no significant abnormal return after executive changes. As a control, fund managers' performance on non-covered stocks slightly improves after executive changes, from 0% to 2.38%, although neither is significantly different from zero. The long-short portfolio of buying covered holdings and selling non-covered holdings earns 21.6% before executive changes and no abnormal return after executive changes.

5. Determinants of the Information Advantages

This subsection explores potential factors that might influence fund managers' information advantage obtained from their business connections. To determine when the managers' comparative advantages are stronger—and, therefore, more valuable to them—one might examine two variables: the lapse of time and the number of analysts providing coverage of the stocks. The lapse of time is defined as the length of time between when a fund manager last covered the stock as an analyst and when that person begins to manage the fund. Intuitively, fund managers should lose their information advantages as their connections naturally loosen over time. Therefore, one may surmise that the longer the period of time since managers stop covering the stock as an analyst, the less information advantages they possess. As their information advantage decreases, they should earn lower abnormal returns from their covered stocks.

The second factor that may affect a fund manager's information advantage is the number of analysts who provided coverage of the manager's previously covered stocks. If fund managers' information advantage comes from their connections with the management, this advantage could depend on how close those relationships were. A closer relationship would predictably be relatively easier to build when the manager was the only one—or one of a few—analysts covering the firm. In other words, the analyst faces less competition while forming the connections. For example, the analyst could get more chances to ask questions or more time to interact with the management. On the other hand, for firms covered by many analysts concurrently, a more personal relationship with the management may be harder to build.

To test these effects, this study replicates the calendar portfolio tests with the added determinants of the information advantage. In the case of covered holdings versus non-covered holdings, the covered stock portfolio is divided equally into two portfolios based on the lapse of time or the number of analysts providing coverage. Then I construct the long-short portfolio for each group[25]. The examination of the covered stocks held versus covered stocks not held, and also of the earnings announcement returns for covered versus non-covered stocks employ this same methodology.

Panel A of table 11 reports the DGTW-adjusted returns of the long-short portfolios. For the group with a shorter lapse of time, covered holdings outperform non-covered holdings by 25.45% which is not only statistically significant, but it is also higher than the 18.07% for the whole sample from Table 4. In contrast, the long-short portfolio return is only 2.71% (not significant) for the longer lapse-of-time group. The return difference of the long-short portfolios between shorter and longer lapse of time is 22.20%, 2.58 standard errors from 0. Similarly, for the shorter lapse-of-time group, the held covered stocks outperform the not-held covered stocks by 21.20%; this greatly contrasts to 1.80% for the longer lapse-of-time group. Likewise, the long-short portfolio returns around earnings announcements show a difference of 5.95% between shorter and longer lapse-of-time portfolios, although the difference is not significant. In general, fund

[25] For the analyst coverage test, the non-covered portfolio is also divided into two based on the number of analysts providing coverage. This serves a necessary control, because stocks with less analyst coverage may be more subjected to limits of arbitrage and be more likely to be mispriced, giving fund managers more opportunities to earn higher returns on them.

managers have less information advantage and earn lower abnormal returns from their covered stocks the longer the length of time that has passed since they stopped covering the stocks as analysts**.** The results from portfolios sorted by analyst coverage also support this study's hypothesis. For the lower analyst coverage group, the long-short portfolio strategy of buying covered holdings and shorting non-covered holdings earns a DGTW-adjusted return of 25.49%, which is statistically significant[26] and remarkable when compared to the statistically insignificant 3.57% return for the higher analyst coverage group. The return difference between the two analyst coverage groups is 21.24%, and it also is significant. Returns from covered stocks held versus covered stocks not held and earnings announcements show similar results. These findings are consistent with the idea that fund managers gain more of an information advantage on firms with less analyst coverage, a situation which allows the analyst to build relationships with the management team more easily.

Figure 1 presents a more detailed view of how managers' information advantages decrease over the period of time after they have left their analyst positions. The covered stocks are assigned to quintiles based on the lapse of time since managers last covered them. The average lapse of time is plotted on the x-axis, and the DGTW returns of the long-short portfolios of covered versus non-covered stocks are plotted on the y-axis. This figure clearly shows how the managers' information advantages decrease with time, as the long-short portfolio return decreases from 20% at 7 months after the coverage, to 5% at 143 months after the coverage. The average lapses of time for the first two quintiles are less than 20 months and the average for the third quintile is less than 40 months, while the average is 75 months for the fourth quintile and more than 140 months for the fifth quintile. This shows that more covered stocks are held within a short period after fund managers stopped covering them, consistent with the finding that shorter lapse of time provides managers more information advantage and therefore higher returns.

[26] Although the analyst coverage can also proxy for size, the size effect in return is controlled by DGTW adjustments.

One may wonder how the regulation-FD effect interacts with the lapse of time effect. Compared to pre-Reg-FD period, fund managers may have been away from their analyst job longer in the post-Reg-FD period. Therefore they may lose their informational advantage not because of the regulation, but the loosening of their connections over time. To check whether this is the case, I run a multivariate regression with both Reg-FD dummy and lapse of time as independent variables. The monthly DGTW returns of individual funds' covered and non-covered holdings are regressed on covered dummy, Reg-FD dummy, the interaction term of the two, number of analyst covering and lapse of time. I standardize both number of analyst covering and lapse of time for easy comparison of the coefficients.

Panel B of table 11 presents the results. In pre-FD period, non-covered holdings do not have any significant return (constant=0), while covered holdings generate 3% per month more return (Covered=3%). Covered holdings generate 1.7% less return in the post-FD period (Covered * Post-FD= -1.7%), while non-covered holdings generate 0.3% less return in the post-FD period (Post-FD= -0.3%). The reduction of return is much large in magnitude for covered holdings than non-covered holdings. The lapse of time effect is still significantly negative at -1.2% (t= -1.78). The results show that Reg-FD effect and lapse of time effect are independently significant.

6. Optimal Weight of Covered Stocks

Given that covered stocks generate higher returns than non-covered stocks, one might ask: why do fund managers not hold even more of the stocks they once covered as analysts? One possible reason is that, on non-covered stocks, managers' expected returns are higher than the realized returns. However, if fund managers had known the covered stocks would perform better in comparison, would the chosen weights in covered stocks be optimal? To answer these questions, this study conducts three tests using Sharpe Ratio and Information Ratio as the criteria for portfolio optimization. Information Ratio is also considered because a single mutual fund may not truly represent the final portfolios held by investors.

Table 12 presents the results. Panel A lists the average Sharpe Ratios and Information Ratios of individual funds' covered holdings and overall holdings. Although both ratios are higher for the covered holdings than for the overall holdings, the differences between them are very small and not statistically significant, which is unlike the statistics computed on aggregate fund holding portfolios. For example, the Sharpe Ratio for the covered holdings is 0.16, higher than 0.15 for the overall holdings, with a t-statistic of only 0.34 on the difference[27]. This suggests that because of the need for diversification it may not be optimal for an individual fund to invest more in covered stocks. Panel B describes the findings of the test to identify funds that had the potential to benefit from investing more in covered stocks. This test runs a time-series regression of a fund's returns in covered holdings on its returns in total holdings. A significant alpha from the regression means that, to improve its Sharpe Ratio, the fund could choose a combination of its covered holdings with all its holdings. The result shows that I am able to reject the null that the alpha is equal to 0 for only 5% of the funds, indicating that only a small percentage of funds would have improved their Sharpe Ratio by holding more covered stocks. The result in Panel B may be subject to the power of the test. So I resort to simulations for further testing. Finally, Panel C reports the simulation results that assume managers shift their allocation of funds from non-covered stocks into covered stocks (holding total asset constant) by increasing the dollar weights in covered stocks by 2, 5, 10, 20 or 30 times, respectively. The improvements in both the Sharpe Ratio and Information Ratio are small and not significant. For example, the change in Sharpe Ratio is 0.01 for an increase of 2 times and 0.00 thereafter, and none of them are significant. Overall, the results show that only a small number of managers would have been better off by investing more in covered stocks. Because, for each manager, the number of covered stocks is so small, putting more weight on the covered stocks means taking more idiosyncratic risks; this may not improve either their Sharpe Ratios or Information Ratios.

[27] The Sharpe Ratio differences between a fund's covered holdings and its overall holdings may not be independent across funds. This means the estimate of the t-statistic may be biased upwards.

IV. Conclusions

This study identifies an important source from which some informed investors obtain their information advantage: business connections garnered from their prior employment. In particular, the findings indicate that mutual fund managers, specifically, place more weight and earn substantial abnormal returns on stocks for which they had provided research coverage when previously employed as financial analysts. Additional tests show that fund managers' holding of their covered stocks is driven by their information advantage, rather than simple familiarity. The majority of the abnormal returns on covered stocks are realized around earnings announcements, and funds' trades predict subsequent earnings surprises—thus indicating that fund managers possess superior information about the covered firms and the information helps them better predict firm future earnings. Further tests indicate that the connections made through fund managers' previous employment as an analyst—rather than skills or knowledge—play a major role in their information advantage.

By focusing on mutual fund managers who were previously employed as financial analysts, the results of this paper's research illustrate that investors' connections formed during prior employment can significantly impact their information set. Other interesting possibilities to explore related to this research include looking at other types of employment histories of fund managers to see what effect, if any, the connections built might have on those managers' investing decisions. This paper also links sell-side information generation with buy-side decisions. By comparing managers' research performance as analysts with their trading decisions as fund managers, future research could study the effects of skills versus biases in analyst research. In addition to fund managers, financial analysts move on to different positions in the financial industry. It is also worth studying the potential impact their experience as analysts has on their future decisions.

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Table 1: Summary Statistics

This table reports the summary statistics of the sample mutual fund managers who once worked as financial analysts. Mutual fund and their manager information are from the CRSP mutual fund database and Morningstar. Fund holdings are from CDA/Spectrum. Analyst names and their research coverage information are from Nelson's Directory of Investment Research and I/B/E/S. The sample period of mutual fund managers is from 1993 to 2006. Panel A shows the number of managers and the number of funds they manage. Panel B shows the summary of the funds, their holdings, the managers and their work as analysts. "% of active equity fund universe" is the time series statistics of the sample funds' total assets as a percentage of the active equity fund universe. Statistics for the remaining variables are cross sectional average.

Panel A: Fund Manager Sample

Fund Managers	Funds
152	199

Panel B: Characteristics of Funds, Managers and Stocks.

	Average	Std	Min	Median	Max
% of active equity fund universe (assets)	5.88	1.84	2.65	5.57	13.71
Fund assets (million)	589.5	1,743.3	0.7	129.6	15,967.2
Number of stocks in funds	84	90	4	58	587
Number of stocks analysts covered	25	24	1	18	116
Number of covered stock held at one time	2.59	2.32	1.00	1.91	10.50
Number of total covered stock held	4.47	3.77	1.00	3.00	17.00
Average holding time (month), non-covered stocks	8.25	4.93	3.00	6.95	33.42
Average holding time (month), covered stocks	6.34	4.70	3.00	4.39	21.33
Number of analyst covering the stock held	19	13	1	16	61
Time between last coverage and start to manage a fund (month)	57	53	1	40	223

Table 2: Portfolio Weights: Covered vs. Non-covered Stocks

This table examines fund managers' portfolio weights in covered and non-covered stocks using pooled OLS regression. Mutual funds' quarterly portfolio weights in stocks are regressed on the covered-stock dummy (COVERED) and the control variables. The units of observation are fund-stock-quarter. The dependent variable is the dollar weight (in percentage) of a given stock in its fund portfolio. The COVERED dummy is equal to 1 if the fund manager has provided analyst coverage on the stock before, and 0 otherwise. The control variables included are: ME, BM, and R12, which are percentiles of market value of equity, book to market, and past 12-month return; %STYLE, the percentage of the fund's total net assets invested in the style corresponding to the stock in question, where style is defined in Daniel, Grinblatt, Titman and Wermers (1997) as one of the 125 portfolios formed by sorting CRSP stocks into size, book-to-market, and past 12-month return quintiles. Quarter, firm, industry (Fama French 48), IOC (funds' investment objective code) and fund fixed effects are included where indicated. Standard errors are adjusted for clustering at the fund-stock level and are reported in parenthesis below the coefficient estimates. * p<0.1. ** p<0.05. *** p<0.01.

	1	2	3	4	5	6	7	8
Constant	0.888***	-0.340***	-0.317***	-0.122***	2.106***	1.631***	1.788***	1.354***
	(0.009)	(0.049)	(0.048)	(0.046)	(0.241)	(0.157)	(0.162)	(0.177)
COVERED	1.010***	0.988***	0.967***	0.781***	0.721***	0.769***	0.703***	0.414***
	(0.115)	(0.113)	(0.110)	(0.118)	(0.116)	(0.116)	(0.113)	(0.093)
ME		0.015***	0.014***	0.012***	0.005***	0.013***	0.018***	0.015***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BM		-0.002***	-0.002***	-0.002***	-0.001**	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R12		0.001***	0.001***	-0.000	0.001**	-0.000	-0.000	0.000*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
%STYLE			0.020***	0.020***	0.019***	0.020***	0.020***	0.019***
			(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Fixed effects				Quarter	Quarter	Quarter	Quarter	Quarter
Fixed effects					Firm	Industry	IOC	Fund
Adjusted R^2	0.005	0.041	0.185	0.261	0.332	0.266	0.299	0.434

Table 3: Returns on Covered Holdings

This table shows calendar time portfolio returns of covered holdings and non-covered holdings. At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned to one of the two portfolios: covered and non-covered, based on whether the fund manager has provided research coverage for the stock as analysts. Value-weighted monthly returns are computed, weighting stocks by their actual dollar weights in the fund. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report. Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. Excess returns are computed as portfolio raw returns minus Treasury bill returns. Returns are in annual percentage. Long/Short is a zero-cost portfolio which holds the portfolio of covered stocks and sells short the portfolio of non-covered stocks. T-statistics are shown below the coefficient estimates; 5% statistical significance is indicated in bold.

Annual value-weighted excess returns	All Holdings	Covered Holdings	Non-covered Holdings	Long/Short
Mean	8.59	**29.28**	8.45	**19.35**
t	(1.87)	(3.98)	(1.84)	(3.08)
Std	18.51	27.34	18.53	24.25
Skewness	-0.58	0.10	-0.58	0.03
Kurtosis	1.46	1.51	1.46	1.33
Sharpe ratio	0.46	1.07	0.46	0.80

Table 4: Abnormal Returns on Covered Holdings

This table shows risk-adjusted calendar time portfolio returns of covered holdings and non-covered holdings. At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned to one of the two portfolios: covered and non-covered, based on whether the fund manager has provided research coverage for the stock as analysts. Value-weighted monthly returns are computed, weighting stocks by their actual dollar weights in the fund. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report. Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. DGTW characteristic-adjusted returns are defined as raw returns minus the return on a value-weighted portfolio of CRSP stocks in the same size, book-to-market, and 12-month past return quintile. 4-factor regression alpha is the intercept on the regression of monthly excess returns on the Fama and French (1993) three factors and the Carhart (1997) momentum factor. Returns and alphas are in annual percentage. Long/Short is a zero-cost portfolio which holds the portfolio of covered stocks and sells short the portfolio of non-covered stocks. T-statistics are shown below the coefficient estimates; 5% statistical significance is indicated in bold.

	Raw	DGTW	4-factor
All holdings	**13.20**	0.45	0.03
	(2.82)	(0.34)	(0.02)
Covered	**34.68**	**18.29**	**18.49**
	(4.62)	(3.20)	(2.73)
Non-covered	**13.05**	0.19	-0.08
	(2.79)	(0.14)	(-0.05)
Long/Short	**19.35**	**18.07**	**18.58**
	(3.08)	(3.18)	(2.84)

Table 5: Returns: Covered Stocks Held vs. Covered Stocks Not held

This table shows calendar time portfolio returns of covered stocks being held and covered stocks not being held by funds. At the beginning of each calendar quarter, stocks that each mutual fund manager has covered previously are assigned to one of the two portfolios: Held and Not-held, based on whether the fund manager hold the covered stock in their fund portfolio. Value-weighted monthly returns are computed, weighting stocks held by their actual dollar weights in the fund and stocks not held by their market value. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report. Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. Panel A lists the average number of covered stocks per manager, the equally weighted (EW), and the value weighted (VW) fraction of covered stocks held by the manager. Panel B reports average returns, DGTW-adjusted returns and 4-factor regression alphas. DGTW characteristic-adjusted returns are defined as raw returns minus the return on a value-weighted portfolio of CRSP stocks in the same size, book-to-market, and 12-month past return quintile. 4-factor regression alpha is the intercept on the regression of monthly excess returns on the Fama and French (1993) three factors and the Carhart (1997) momentum factor. Returns and alphas are in annual percentage. Long/Short is a zero-cost portfolio which holds the portfolio of covered stocks held by the funds and sells short the portfolio of covered stocks not held by the funds. T-statistics are shown below the coefficient estimates; 5% statistical significance is indicated in bold.

Panel A: Covered Stock Universe

Number of Covered Stocks	% Held (EW)	% Held (VW)
25.05	9.85	22.30

Panel B: Returns

	Raw	DGTW	4-factor
All covered	**20.73**	5.06	5.96
	(3.90)	(1.59)	(1.54)
Covered held	**34.68**	**18.29**	**18.49**
	(4.62)	(3.20)	(2.73)
Covered not held	**15.27**	1.04	1.99
	(2.92)	(0.34)	(0.55)
L/S	**17.21**	**16.57**	**15.88**
	(2.51)	(2.51)	(2.16)

Table 6: Reporting Lags and Risk Adjusted Returns

This table reports how long the risk-adjusted return of covered holdings can persist by introducing various lags between the reported fund holdings and the measured returns. At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned to one of the two portfolios: covered and non-covered, based on whether the fund manager has provided research coverage for the stock as analysts. Value-weighted monthly returns are computed, weighting stocks by their actual dollar weights in the fund. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report. Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. DGTW characteristic-adjusted returns are defined as raw returns minus the return on a value-weighted portfolio of CRSP stocks in the same size, book-to-market, and 12-month past return quintile. The table reports a long-short portfolio which holds the portfolio of covered stocks and sells short the portfolio of non-covered stocks. The long-short portfolio of buying covered stocks held and selling covered stocks not held by the mutual fund managers are computed similarly. Reported returns are expressed as annual percentage rates. T-statistics are shown below the coefficient estimates; 5% statistical significance is indicated in bold.

	Lags between reported holdings and risk-adjusted returns			
	1 month	2 month	3 month	4 month
Covered - Non-covered	**15.60**	**10.63**	**8.88**	5.76
	(2.89)	(1.96)	(1.68)	(1.12)
Covered held - Covered not-held	**15.57**	8.86	8.17	4.84
	(2.50)	(1.44)	(1.37)	(0.84)

Table 7: Returns around Earnings Announcements and Earnings Surprise Prediction

Panel A shows calendar time portfolio returns around earnings announcements. At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned to one of the two portfolios: covered and non-covered, based on whether the fund manager has provided research coverage for the stock as analysts. Monthly stock returns are separated into two parts: first, the compounded returns of a three trading-day window (-1, 0, 1) around earnings announcements, and, second, the returns of the remaining days in the month. Value-weighted returns are then computed for each portfolio, weighting stocks by their actual dollar weights in the fund. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report. Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. The first row reports the proportion of trading days in the earnings announcement window to the total trading days in a month (assuming 252 trading days per year). Long/Short is a zero-cost portfolio which holds the portfolio of covered stocks and sells short the portfolio of non-covered stocks. Returns are in annual percent. T-statistics are shown below the estimates; 5% statistical significance is indicated in bold. Panel B shows the subsequent earnings surprise following fund managers' trades. The earnings surprise is the difference between the actual and consensus forecast of earnings per share (EPS), scaled by the actual EPS. Consensus and actual EPSs come from the I/B/E/S summary file. The subsequent earnings surprises within the quarter are averaged equal-weighted across managers' buys, sells, and buys-minus-sells, on covered holdings, non-covered holdings, and the long-short portfolio buying covered stocks and shorting non-covered stocks. Earnings surprises are in percentage.

Panel A: Returns around Earnings Announcements

	Others	Earnings Announcements
% of trading days in a month	85.71%	14.29%
Covered	8.80	**19.17**
	(1.07)	(3.71)
Non-covered	**10.95**	**4.79**
	(2.89)	(3.83)
Long/Short	-1.95	**13.78**
	(-0.27)	(2.69)

Panel B: Earnings Surprise

	Buys	Sells	Buys - Sells
All holdings	**2.78**	**2.94**	-0.16
	(7.34)	(4.30)	(-0.23)
Covered	**6.41**	1.55	**4.86**
	(4.93)	(1.17)	(2.64)
Non covered	**2.74**	**2.89**	-0.15
	(7.28)	(4.16)	(-0.20)
Long/Short	**3.67**	-1.33	**5.00**
	(2.81)	(-0.91)	(2.58)

Table 8: Returns on Covered Holdings: Regulation FD

This table shows risk-adjusted calendar time portfolio returns before and after the Regulation FD (before 2001 and from 2001 onwards). At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned to one of the two portfolios: covered and non-covered, based on whether the fund manager has provided research coverage for the stock as analysts. Value-weighted monthly returns are computed, weighting stocks by their actual dollar weights in the fund. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report. Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. DGTW characteristic-adjusted returns are defined as raw returns minus the return on a value-weighted portfolio of CRSP stocks in the same size, book-to-market, and 12-month past return quintile. 4-factor regression alpha is the intercept on the regression of monthly excess returns on the Fama and French (1993) three factors and the Carhart (1997) momentum factor. Returns and alphas are in annual percentage. Long/Short is a zero-cost portfolio which holds the portfolio of covered stocks and sells short the portfolio of non-covered stocks. T-statistics are shown below the coefficient estimates; 5% statistical significance is indicated in bold.

	Before Regulation FD			After Regulation FD		
	Raw	DGTW	4-factor	Raw	DGTW	4-factor
All holdings	**16.58**	0.91	0.89	4.62	-0.89	-2.38
	(3.90)	(0.72)	(0.45)	(0.56)	(-0.40)	(-0.93)
Covered	**43.90**	**24.70**	**21.13**	**19.34**	10.96	12.63
	(4.27)	(2.97)	(2.16)	(1.97)	(1.72)	(1.70)
Non covered	**16.47**	0.77	0.79	4.56	-1.10	-2.44
	(3.87)	(0.61)	(0.40)	(0.56)	(-0.50)	(-0.94)
Long/Short	**22.67**	**23.70**	**20.20**	**14.19**	**12.18**	**15.41**
	(2.56)	(2.89)	(2.12)	(1.97)	(1.90)	(2.19)

Table 9: Portfolio Weights and Returns in Covered vs. Non-covered Industries

Panel A examines fund managers' portfolio weights in covered and non-covered industries using pooled OLS regression. Mutual funds' quarterly portfolio weights in stocks are regressed on the covered-stock dummy, covered industry dummy and the control variables. The units of observation are fund-stock-quarter. The dependent variable is the dollar weight (in percentage) of a given stock in its fund portfolio. Covered stock/Covered industry dummy is equal to 1 when the fund manager used to cover the stock or the industry as an analyst, and 0 otherwise. The control variables included are: ME, BM, and R12, which are percentiles of market value of equity, book to market, and past 12-month return; %STYLE, the percentage of the fund's total net assets invested in the style corresponding to the stock in question, where style is defined in Daniel, Grinblatt, Titman and Wermers (1997) as one of the 125 portfolios formed by sorting CRSP stocks into size, book-to-market, and past 12-month return quintiles. Quarter, firm, industry (Fama French 48), IOC (funds' investment objective code) and fund fixed effects are included where indicated. Standard errors are adjusted for clustering at the fund-stock level and are reported in parenthesis below the coefficient estimates. * $p<0.1$. ** $p<0.05$. *** $p<0.01$. Panel B shows calendar time portfolio returns on covered industries and non-covered industries. The first three columns list the results using normal stock returns. The last column list the results using stock returns adjusted for industry average, which emphasize managers' abilities to pick stocks within certain industries. At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned to one of the two portfolios: covered and non-covered, based on whether the fund manager has provided research coverage for the industry as analysts. Value-weighted monthly returns are computed, weighting stocks by their actual dollar weights in the fund. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report. Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. DGTW characteristic-adjusted returns are defined as raw returns minus the return on a value-weighted portfolio of CRSP stocks in the same size, book-to-market, and 12-month past return quintile. 4-factor regression alpha is the intercept on the regression of monthly excess returns on the Fama and French (1993) three factors and the Carhart (1997) momentum factor. Returns and alphas are in annual percentage. Long/Short is a zero-cost portfolio which holds the portfolio of covered stocks and sells short the portfolio of non-covered stocks. T-statistics are shown below the coefficient estimates; 5% statistical significance is indicated in bold.

Panel A: Portfolio weights in covered vs. non-covered industries

	1	2	3	4	5	6	7	8
Constant	0.779***	-0.569***	-0.544***	-0.283***	2.014***	1.478***	1.728***	1.331***
	(0.011)	(0.047)	(0.046)	(0.047)	(0.245)	(0.165)	(0.164)	(0.176)
Covered stock	0.766***	0.723***	0.704***	0.639***	0.559***	0.630***	0.651***	0.411***
	(0.115)	(0.114)	(0.111)	(0.116)	(0.114)	(0.115)	(0.113)	(0.093)
Covered industry	0.353***	0.387***	0.384***	0.243***	0.250***	0.243***	0.097***	0.009
	(0.019)	(0.018)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.016)
ME		0.016***	0.015***	0.013***	0.004***	0.013***	0.018***	0.015***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BM		-0.002***	-0.001***	-0.001***	-0.001**	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R12		0.001**	0.000	-0.000	0.000**	-0.000	-0.000	0.000*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
%STYLE			0.020***	0.020***	0.019***	0.020***	0.020***	0.019***
			(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Fixed effects				Quarter	Quarter	Quarter	Quarter	Quarter
Fixed effects					Firm	Industry	IOC	Fund
Adjusted R^2	0.019	0.057	0.201	0.266	0.336	0.271	0.300	0.434

Panel B: Returns on covered industries vs. non-covered industries

	Raw	DGTW	4-factor	Stock Selection
All holdings	**13.78**	0.61	0.65	-0.13
	(3.63)	(0.54)	(0.47)	(-0.11)
Covered	**13.82**	-0.27	0.14	0.76
	(3.22)	(-0.15)	(0.06)	(0.46)
Non covered	**13.29**	0.02	-0.28	-0.83
	(3.62)	(0.01)	(-0.15)	(-0.69)
Long/Short	0.47	-0.29	0.42	1.60
	(0.18)	(-0.14)	(0.15)	(0.96)

Table 10: Portfolio Weights and Abnormal Returns Before and After Corporate Executive Changes

This table shows the portfolio weights and the abnormal returns of covered and non-covered stocks before and after corporate executive changes. For companies with multiple executive changes, the first executive change is considered. Panel A presents portfolio weights before and after company executive changes. Portfolio weight is the fund's dollar investment in a stock as a percentage of total net assets of the fund. The average weight before and after the executive change is computed for each stock, then averaged across stocks for covered and non-covered stocks. T-statistics are computed assuming weight independence across stocks and are shown below the estimates. Panel B shows the risk-adjusted calendar time portfolio returns of stocks before and after executive changes. At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned into one of the four portfolios based on whether the fund manager covered the stock before and whether there is an executive change. Value weighted monthly returns are computed, weighting stocks by the fund's dollar holdings, and across fund weighting by the fund's total net asset value. Portfolios are rebalanced every calendar quarter based on the most recent SEC filing. DGTW characteristic adjusted returns are computed as raw returns minus the returns on a value weighted portfolio of all CRSP firms in the same size, book-to-market, and one year momentum quintile. 4-factor alpha is the intercept of regression of monthly returns on Carhart (1997) four factors. Returns are annual percentages. T-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

Panel A: Portfolio Weights

	Before	After	Difference
Non-covered	**0.569**	**0.646**	**0.077**
	(48.81)	(40.68)	(4.24)
Covered	**1.301**	**0.603**	**-0.698**
	(11.85)	(5.17)	(-4.63)

Panel B: Abnormal Returns

	DGTW			4-factor alpha		
	Covered	Non-covered	Long/Short	Covered	Non-covered	Long/Short
No CEO/CFO Change	**21.60**	0.00	**21.60**	**25.68**	-1.16	**27.13**
	(3.62)	(0.00)	(3.67)	(2.55)	(-0.54)	(2.77)
CEO/CFO Change	5.67	2.38	3.23	-0.49	2.50	-2.92
	(0.42)	(0.94)	(0.23)	(-0.04)	(0.86)	(-0.21)

Table 11: Determinants on Managers' Information Advantage

This table shows the effects on fund managers' information advantage of both the lapse of time and the number of analysts providing coverage of the firm once covered by that fund manager. Lapse of time is the length of time between when the fund manager last covered the stock as an analyst and when she began to manage the fund. The number of analysts providing coverage is the number of analysts covering the stock during the year when the fund manager last covered the stock as an analyst. Panel A shows the returns of covered stocks and non-covered stocks sorted on lapse of time and analyst coverage. I first divide the covered stock portfolio equally into two portfolios, based on the lapse of time or the number of analysts providing coverage, and then construct the long-short portfolio for each of them. The first two rows detail calendar time portfolio returns of longing covered stocks and shorting non-covered stocks. The next two rows detail the calendar time portfolio returns of longing covered stocks being held by funds and shorting covered stocks not being held by funds. The last two rows show calendar time long-short portfolio returns of longing covered stocks and shorting non-covered stocks over the three-day window periods around earnings announcement days. At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned to one of the two portfolios: covered and non-covered, based on whether the fund manager has provided research coverage for the stock as analysts. Value-weighted monthly returns are computed, weighting stocks by their actual dollar weights in the fund. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report. Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. DGTW characteristic-adjusted returns are defined as raw returns minus the return on a value-weighted portfolio of CRSP stocks in the same size, book-to-market, and 12-month past return quintile. Returns are in annual percentage. T-statistics are shown below the coefficient estimates; 5% statistical significance is indicated in bold. Panel B shows the regression of fund covered holding returns on variables that determine manager's informational advantage.

Panel A: Returns sorted on determinants

	Lapse of time			Number of Analyst Covering		
	Shorter	Longer	Shorter-Longer	Fewer	More	Fewer-More
L/S portfolio return in covered vs. non-covered (DGTW)	**25.45**	2.71	**22.2**	**25.49**	3.57	**21.24**
	-3.49	-0.56	-2.58	-3.6	-0.72	-2.51
L/S portfolio return in covered held vs. covered not-held (DGTW)	**21.2**	1.8	**19.08**	**17.53**	7.82	9.06
	-2.63	-0.33	-2.25	-1.8	-1.08	-0.83
L/S portfolio return around EAD in covered vs. non-covered	**13.18**	7.23	5.95	**18.85**	2.46	16.04
	-2.54	-1.08	-0.68	-2.43	-0.52	-1.8

Panel B: Regression results

	Coefficient	T-stats
Constant	0.000	0.98
Covered	0.030	4.92
Post-FD	-0.003	-3.74
Covered * Post-FD	-0.017	-2.53
Number of analyst covering	-0.017	-2.19
Lapse of time	-0.012	-1.78
N	29925	
Adjusted R2	0.002	

Table 12: Optimal Weight in Covered Stocks

This table reports the results of several tests to determine how optimal the funds' actual weights on the covered stocks are. Panel A shows the average Sharpe ratios and information ratios of individual funds. For each fund manager, I compute the ratios for covered stocks and all holdings, and then average them across funds. The third column shows the t-statistics of the difference between covered stocks and all holdings. Panel B reports the percentage of funds that could have increased their Sharpe Ratio in-sample by investing more in covered stocks. This percentage is computed for each fund manager using a time-series regression of the fund's monthly returns in covered stocks in excess of Treasury bills on the fund's total excess returns: the fraction of funds for which the null hypothesis alpha=0 is rejected at 5% significance are reported. Panel C shows the resulting Sharpe ratios and information ratios if fund managers increase the dollar weights in covered stocks by 2, 5, 10, 20 or 30 times (holding total assets constant). T-statistics are shown below the changes in ratios.

Panel A: Average Ratio of Individual Funds

	Covered	Overall	T-statistic of difference
Sharpe Ratio	0.16	0.15	0.34
Information Ratio	0.13	0.10	0.61

Panel B: Funds with potential increase in Sharpe ratio (Regression)

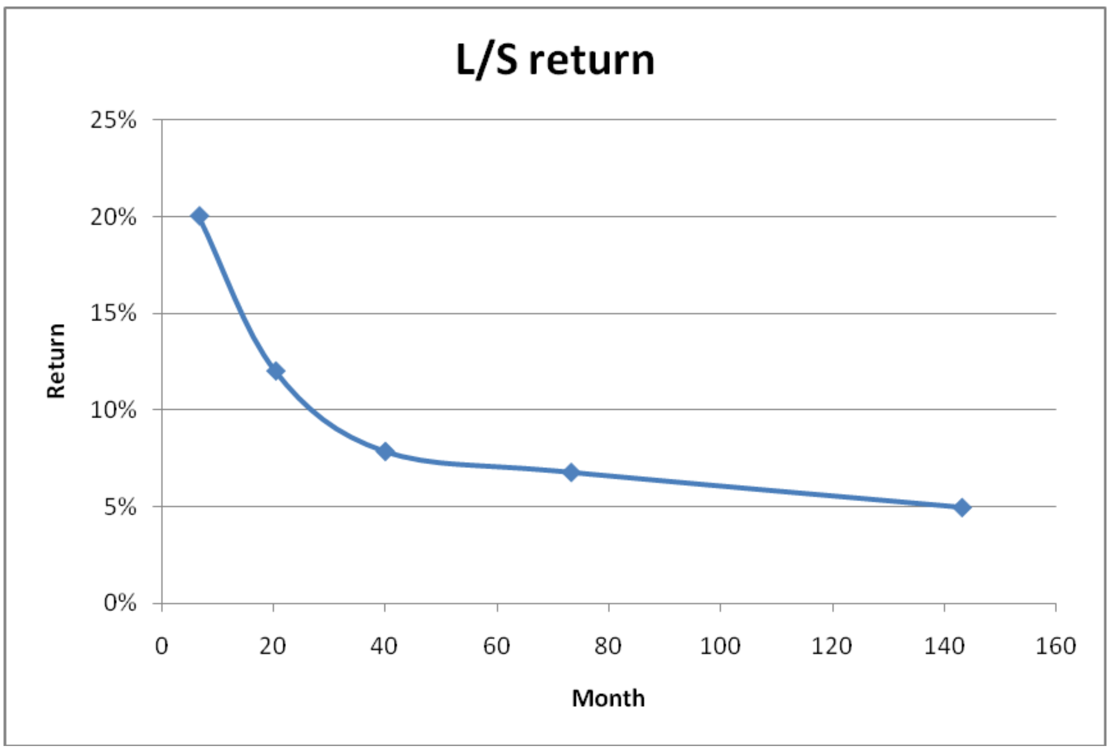
Funds with Potential Increase in SR	5%

Panel C: Funds with potential increase in Sharpe ratio (Simulation)

	Original	2 times	5 times	10 times	20 times	30 times
Change in Sharpe Ratio	0.15	0.01	0.00	0.00	0.00	0.00
		(1.07)	(0.14)	(-0.07)	(-0.15)	(-0.13)
Change in Information Ratio	0.10	0.01	0.02	0.03	0.02	0.01
		(1.54)	(0.93)	(1.05)	(0.36)	(0.19)

Figure 1: Abnormal Return of Covered Holdings and the Lapse of Time Since Coverage

This graph shows DGTW risk-adjusted returns of long-short portfolios that long covered holdings (for different lapse of time since the manager last covered the stock) and short non-covered holdings. Lapse of time is the length of time between when the fund manager last covered the stock as an analyst and when she began to manage the fund. At the beginning of each calendar quarter, stocks in each mutual fund portfolio are assigned to one of the two portfolios: covered and non-covered, based on whether the fund manager has provided research coverage for the stock as analysts. The covered stocks are further assigned to quintiles based on the lapse of time since managers last covered them. Value-weighted monthly returns are computed, weighting stocks by their actual dollar weights in the fund. The portfolios are rebalanced each quarter based on the most recent SEC filings. This calculation assumes that a fund does not change its holdings until the next report. Then the value-weighted returns of the portfolios across funds are calculated, weighting each individual fund portfolio by the fund's net asset value. DGTW characteristic-adjusted returns are defined as raw returns minus the return on a value-weighted portfolio of CRSP stocks in the same size, book-to-market, and 12-month past return quintile. Returns are in annual percentage. The average lapse of time is plotted on the x-axis and the returns are plotted on the y-axis.



Second Essay: Institutional Trades around Takeover Announcements: Skill Vs. Inside Information

I. Introduction

Institutional investors own about 73% of publicly traded stocks in the US.[28] Several studies find that larger institutional ownership results in more efficient stock prices. For example, Badrinath, Kale and Noe (1995) find that returns of stocks with large institutional ownership lead returns of stocks with small institutional ownership by up to two months. They conclude that this evidence is consistent with the hypothesis that institutional investors are informed investors, and therefore stocks with large institutional ownership incorporate information faster into their prices than other stocks. Related papers by Sias and Starks (1997) and Boehmer and Kelley (2009) also find that stocks with large institutional ownership are more efficiently priced. These findings contribute to the view in the literature that institutions in general are better informed than other investors. A natural question that arises is, how do institutional investors gain such informational advantage?

Several possible factors may contribute to institutions' superior investment skills relative to small investors. Since large institutions hire professional fund managers and analysts, they may be able to analyze public information better than the general market. It is also possible that institutions are better able to interpret the value relevance of publicly available information such as accounting statements and corporate announcements. For instance, the top-performing mutual fund manager in 2008 attributed his success to "his focus on companies with strong competitive positions, strong balance sheets and strong cash flows,"[29] suggesting that his ability to process public information gives him an edge.

Institutional investors are also able to spend resources to privately gather information because of their scale, while small investors generally rely on publicly reported information. For instance,

[28] Source: Securities Industry Association Fact Book (2007).
[29] "U.S. equity income funds show tortoises can win," Reuters News, July 22, 2009.

fund managers and buy-side analysts routinely contact firms they follow and they have better access to sell-side analysts than small investors. The assertion in a New York Times article 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"[30] illustrates the general perception of such advantages for large investors. In addition, some buy-side funds also conduct their own surveys to gather information. Such ability to privately gather and process information may also contribute to the investment skills of large investors.

Finally, institutional investors may have access to inside information because of their special contacts with brokerages and other business associates. While statutory regulations prohibit trading based on inside information, regulators and the media have expressed concerns that favored clients may nevertheless benefit from information leakage. For instance, a recent New York Times article reports that the "Securities and Exchange Commission begins inquiry into whether Wall Street bank employees are leaking information" and that "concerns about insider trading have escalated as mergers and buyouts have boomed."[31]

This paper examines whether these three potential sources of informational advantage contribute to the performance of institutional investors. We examine institutional trading patterns and profitability of institutional trades around merger and acquisition announcements to investigate this issue. Mergers and acquisitions provide a unique setting for our analysis. It has been well documented that takeover announcements result in significant abnormal returns to target shareholders (e.g. Jensen and Ruback (1983), Betton, Eckbo and Thorburn (2008)). Institutions that are able to privately obtain information about likelihoods of takeover would be able to buy target shares before the announcement and, hence, profit from their ability to privately

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[30] New York Times, December 23, 2002, "Can settlements actually level the playing field for investors?"
[31] New York Times, February 6, 2007, "SEC is looking at stock trading."

collect information. The pattern and profitability of institutional trades before takeover announcements would shed light on institutions' ability to privately obtain such information.

Keown and Pinkerton (1981) find that prices run up significantly before takeover announcements and conclude that "leakage of inside information is a pervasive problem" prior to takeovers, although they do not provide direct evidence that indicates leakage of private information. Information regarding prospective takeovers could potentially leak through investment advisors hired by bidders and targets prior to public announcements. If institutional investors have access to inside information prior to takeovers from investment banking advisors, then funds that mainly use their brokerage arms are more likely to buy target shares before the announcement than other institutions. Additionally, if there were leakages, we expect trades by these funds to be more profitable than other trades.

Funds may also benefit from any special skills by trading target shares after takeover announcements since post-announcement target prices are on average below bidders' offer prices. For instance, Hsieh and Walkling (2005) find that on the last day of the announcement quarter, target prices are about 10.49% below bidders' offer prices on average. The discount to the offer price is due to the fact that some offers fail. While targets of failed takeover attempts face eventual losses, targets of successful takeover offers enjoy positive returns from the takeover date to the completion date. Targets that attract multiple bidders typically experience even larger returns.

If institutions have the skill to process public information after a takeover is announced, they should be in a better position to assess the likelihood of takeover success and of the likelihood of multiple bidders competing for the target than the market in general. If they have such skill, then institutional trades would be useful in predicting outcomes of takeover offers. Additionally, institutions' post-offer trades would earn positive abnormal returns.

Our analyses of trading patterns and profitability of institutional trades around takeover announcements use institutional trade data from Abel-Noser over the 1998 to 2008 period. We find that funds, on average, are marginally net sellers of the targets in the month prior to takeover announcements. A strategy that mimics both fund purchases and sales in the period before a takeover announcement and holds both the long and short positions through the announcement does not yield significant abnormal returns. These findings indicate that funds as a group are not skilled at privately obtaining information about takeovers prior to public announcements.

After takeover announcements, funds intensely sell target shares. For example, the net sales of funds in our sample is about 2.9% of the shares outstanding in the month following takeover announcements, compared with net sales of 0.006% during the six months prior to the announcements. Fund trades after the announcements result in negative returns. For example, a strategy that mimics both fund purchases and sales over a 10-day window after takeover announcements and holds both the long and short positions through 90 days after announcements loses about 0.57%. Therefore, funds do not exhibit skills in analyzing the value implications of public information after takeover announcements.

In contrast with the evidence for the full sample, funds whose main brokers[32] are also the brokerage arms of investment banks that advise the targets are significant net buyers of target shares prior to announcements. These funds also sell significantly more shares in the month after takeover announcements. The pre-takeover trades of these funds are significantly profitable, but the trades of other funds are not. Therefore, the primary source of private information that allows funds to make profits comes from the brokerages that advise targets.

While funds as a group may not be more skilled than the rest of the market, it is possible that a subset of funds possesses superior skills in privately obtaining information than other funds. To examine this hypothesis, we classify funds as "smart" and "non-smart" based on their net purchases of target shares during a 30-day window prior to announcements in a given year and track their performance the following year. We find that the smart funds are more likely to buy

[32] Institutional funds typically trade through multiple brokers. We identify main brokers by ranking brokers according to the share volume executed for the fund during the one-year period before the deal announcement. The top decile brokers are identified as main brokers.

target shares before takeover announcements the following year than non-smart funds. Moreover, the pre-takeover trades of smart funds are significantly profitable, but those of the other funds are not. Both smart and non-smart funds are equally likely to use target advisors as their main brokers, and smart fund trades are profitable after controlling for funds whose main brokers are target advisors. Therefore, the ability of smart funds to privately gather information is not due to information leakage from advisors.

The rest of this paper is organized as follows. The next section presents a literature review and places our study in perspective. Section 3 discusses the data. Section 4 presents an analysis of institutional trades and takeover outcome. Section 5 discusses the profitability of institutional trades. Section 6 examines trades by funds whose main brokers are advisors in the deal. Section 7 investigates the persistence of smart funds and Section 8 concludes.

II. Related Literature

Several studies in the literature examine trading patterns of large investors around selected events to assess whether they reveal superior information. For example, Irvine, Lipson and Puckett (2007) and Busse, Green and Jegadeesh (2010) examine institutional trading around recommendation revisions. Ali, Durtschi, Lev and Trombley (2004) and Battalio and Mendenhall (2005) examine large trades before and after earnings announcements.

Ashraf and Jayaraman (2007) examine changes in institutional ownership around takeover announcements. They primarily focus on investigating whether institutions herd around takeovers and whether they vote with the management. In contrast, we investigate the pattern and profitability of institutional trades around takeover announcements. Also, since Ashraf and Jayaraman use holdings data from CDA-Spectrum 13f filings database, they analyze quarterly changes in institutional holdings. Our dataset, however, contains the date of fund trades and trade prices and allows us to investigate trades and profitability at daily intervals.

A recent paper by Griffin, Shu and Topaloglu (2008) examines institutional trades before takeover announcements and earnings announcements. Their database contains transaction data that record the identity of the broker executing the trades, but not the identity of the investor on whose behalf they trade. Griffin et al. (2008) classify each brokerage as ones that predominantly execute trades by institutions, individuals or mixed. They find that pre-announcement trades through institutional brokers are not profitable and that they do not predict takeover outcomes. Therefore, they conclude that trades through institutional investors as a group do not use private information about takeovers.

Our paper differs from Griffin et al. (2008) in many respects. Unlike Griffin et al., we use actual institutional trades in our empirical analysis, which has several advantages. Griffin et al. classify all trades through a particular brokerage as individual or institutional trades according to their broker classifications and not based on the identity of the end investor. Therefore, as they note, their classification may result in some trades being misclassified. Furthermore, the aggregate trade data they use will be heavily weighted toward large institutions since they trade more than small institutions.

In contrast to the data that Griffin et al. (2008) use, we have fund-level trading data that has several advantages. For instance, our dataset also allows us to identify the brokers through which funds trade and funds' level of relations with each broker, which are important for identifying potential avenues of leakage. Also, we are able to track trades of individual funds through all brokers, and not just the main broker through whom they may have had access to any particular piece of information. For instance, a fund may receive information about a potential takeover from the target advisor, but it may trade on that information through many different brokers. Therefore, if one were to focus only on trades through the target advisor, as Griffin et al. do, then one would not get an complete picture. Our data set also allows us to examine performance differences across funds, and the pattern of funds' post-announcement trades.

We also focus on a number of additional issues. Since institutional trades represent an overwhelming majority of the total trading volume, it is unlikely that the performance of aggregate trades will be very different from market performance. For example, Jones and Lipson (2004) report that non-retail trading accounted for 96% of New York Stock Exchange (NYSE) trading volume in 2002, which represents virtually the entire market. Our study examines whether at least some funds possess skills in acquiring private information. We also examine the performance of institutional trades after takeover announcements to investigate whether they are able to process public information better than the market.

Additionally, we examine whether funds obtain information through their main brokers when the brokerages are also the advisors for the bidder or the target. Therefore, our analysis provides insights into the source of pre-announcement information that funds obtain. Our results also have important public policy implications since we find that in spite of statutory restrictions on trading based on inside information, funds do benefit from information leakages through their brokers.

Our paper also adds to the literature that documents information leaks through advisory banks. Massa and Rehman (2008) find that mutual funds use information available to affiliated lending banks around the time of granting loans to trade equity. Acharya and Johnson (2007) and Ivashina and Sun (2009) report that lending banks use their private information to profitably trade credit default swaps and equity of their clients. Bodnaruk, Massa and Simonov (2009) find that the investment banking advisors for bidders in mergers and acquisitions significantly increase their holdings of target shares, either directly or through affiliated financial entities, prior to mergers.

While tthese papers examine flow of inside information from bankers or investment bankers to other divisions within the conglomerates, we investigate whether inside information leaks from investment banks to their clients. While Bodnaruk et al. (2009) examine direct and indirect holdings of bidders' advisors we examine trades of outside funds that trade through brokerage arms of advisors of both bidders and targets. Also, since Bodnaruk et al. (2009) use quarterly holdings data in their analysis they focus on quarterly changes in institutional holdings, but we examine daily trading patterns around takeover announcements.

III. Data

We obtain the sample of mergers and acquisitions from the Securities Data Corporation (SDC) database. Our sample comprises all takeover offers in the 1998 to 2008 period, regardless of the final outcome, that satisfy the following criteria:

1. Both the acquirer and the target must be publicly traded companies, with stock prices available from CRSP database;
2. The transaction value is at least $10 million; and
3. The acquirer seeks more than 50% of the target stock and control of the target.

In addition, we exclude takeovers identified as mergers of equals since SDC does not identify a target in these transactions. In case of multiple offers for the same target, we include only the first offer in the sample.

Table 1 describes the sample of takeovers that satisfy the above criteria. Our sample comprises 2,316 takeover offers out of which 658 are stock offers, 865 are cash offers, 600 are mixed stock and cash offers, and 193 are offers where SDC does not identify offer type. Overall, about 96% of the offers are friendly offers, as classified by SDC. The average time between announcement and the final outcome, either a completed takeover or a withdrawn offer, is 133 days.

In Table 1, price run-up is the cumulative target stock return during the four weeks prior to the takeover announcement and premium is the percentage difference between the initial offer price and the target closing price one day before the announcement. The average price run-up is 8.18%, which indicates pre-announcement information leakage. The average premium is 32.30%.

Target share prices are on average below the offer price on the day after takeover announcement. The average spread, which is the percentage difference between the initial offer price and the closing price on the day after the announcement, is 8.63%. The average spread for stock deals is 14.13%, which is significantly greater than the spread of 4.56% for cash deals.[33] The average two-day announcement returns, which is the compounded returns over the announcement day and the following day (days 0 and 1) is 21.45% for the target, and -2.09% for the bidder. The average target return is 28.59% for cash deals compared with 16.13% for stock deals. For bidders, announcement returns are close to zero for cash offers, and -4.34% for stock offers, which is significantly negative. Overall, these results are consistent with the results documented in the literature.

We obtain institutional trading data from Abel-Noser Corporation, a consulting firm that assists institutional investors monitor and manage their transaction costs. Abel-Noser's clients include pension plan sponsors and money managers. The Abel-Noser database has been previously used in a number of studies to examine institutional trades, e.g. Puckett and Yan (2008), Goldstein, Irvine, Kandel and Wiener (Forthcoming).

The Abel-Noser data provide institutional trades over the 1998 to 2008 period. The database does not provide the name of the institution or fund manager, but trades are identified by client codes and manager codes. The data set also includes the date of trade execution, the identity of the stock, number of shares bought or sold, and execution price for each trade.

Table 2 presents a summary of the Abel-Noser data. During the 12-month window (-6 to 6) around takeover bid announcements, 898 institutions and 4,443 portfolio managers traded 24.4 billion shares of the target, totaling $721.9 billion. The trade distribution is skewed towards larger trades. The average value of target shares that institutions traded within this window is $312 million, and the median value is $10.5 million. At the level of a fund manager, the average trade size is $7.2 million and the median is $244,549.

[33] We compute spread for stock deals and mixed deals based on the closing price of bidder shares one day before takeover announcements.

IV. Institutional Trades around Takeover Announcements

This section examines the pattern of institutional trades around takeover announcements and the determinants of such trades. We also examine whether institutional trades, both before and after announcements, predict the likelihood of success of takeover bids.

1. Institutional Trades

Table 3 presents monthly institutional trades within a six-month window around takeover announcements. Month -1 in this table is the 30-day period prior to the takeover announcement, month -2 is the 30-day period prior to that and so on. Month +1 is the 30-day period starting from the day of takeover announcement, month +2 is the subsequent 30-day period and so on. For each target, we separately compute the number of shares that institutions buy and sell, and their net trade (total number of shares bought minus total number of shares sold) within each event window. We divide buys, sells and net trade by shares outstanding to compute the fraction of a target that institutions trade. We winsorize trades at 99% and 1% to avoid the effect of outliers.[34] Panel A of Table 3 reports the averages net trades across all deals for target shares and panel B reports for bidder shares.[35] We compute standard errors assuming that the trades are uncorrelated across deals.

Aggregate institutional trades of target shares do not reveal any systematic pattern until month -1. For instance, the results in Panel A indicate that both buying and selling of the target stocks remain at about 0.08% per month during months -6 through -2, and the net trades during this period are not significantly different from zero. However, funds significantly sell shares in month

[34] We found that one fund was recorded as having traded 53% of target shares through a target advisor in the month before the takeover. This outlier has a significant effect on some results, particularly on results related to profitability of trades through target advisors. To avoid the influence of such outliers, we winsorize trades at individual fund level across deals.

[35]Net trade is on average positive in our sample period, reflecting the fact that institutional ownership generally increased over this period. Therefore, we also examined the pattern of net trades after subtracting the average trades across all stocks by the institutions in our sample. The results after making this adjustment were similar to the results without this adjustment. Therefore, we report only the results without subtracting the average trades.

-1. Perhaps, following the pre-takeover run-up, target shares on average reached the prices that triggered sale of target shares by funds in this month. These results do not reveal any abnormal institutional trading patterns prior to takeover announcements.

We next examine institutional trades after merger announcements. Institutional sales of target shares increase significantly after takeover announcements. Institutions sell about 3.6% of shares outstanding in the month following the takeover announcement, more than four times their average sells over the previous six months. They buy 0.69% in month 1, which is less than the buys in any of the previous six months. Institutional net trades are significantly negative in each of six months following the announcement although net trades decline in magnitude over time.[36]

Figure 1 presents daily institutional buys and sells from days -30 to +30 around announcements. Hollow bars in the figure above 0 represent buys while solid bars below 0 represent sells. Institutional selling sharply increases on the day of the announcement and intense selling continues in the following days. Interestingly, buys also increase after takeover announcements, but not as sharply as sells. Buys remain abnormally large for about a week after announcements, but then drop below pre-announcement levels.

Figure 2 plots daily net trades and it superimposes 95% confidence intervals on the net trade bars. The pattern of net trades is similar to the pattern of sells since sells are much larger than buys in the period after announcement. Although net selling continues to decline during the 30-day period after announcement, it remains significant over this entire period.

Institutional trading patterns here provide preliminary evidence about their own perception of their informational advantage around takeovers. The fact that institutions are not net buyers of target shares in the pre-takeover period indicates that as a group, they are not skilled at privately acquiring information before takeover announcements. The evidence that institutions are heavy sellers of target shares after the announcement indicates that they do not believe that they have

[36] Some targets leave the sample before month +6 because their takeovers are consummated. We compute average net trades for each month based on the targets that remain in the sample.

superior skills in assessing the likelihood of takeover success or the likelihood of better offers emerging in the future relative to the market.

One possible explanation for institutional sales of target shares after announcement is that they may seek to avoid overweighting target shares in their portfolio. Since target prices increase significantly on takeover announcements, the post-announcement value of their target holdings may exceed funds' desired positions. If funds sell to revert to their pre-announcement portfolio weights of target shares, then we would expect that they sell only a part of their pre-announcement holdings. To investigate this hypothesis, we examined future target share sales by funds that sell their holdings the month after announcement. We found that over 62% of the funds that sell target shares in the first month after announcement do not sell any more target shares in the following five months. Therefore, it appears that most of the funds that sell target shares in the month after announcement sell their entire holdings rather than just a part of their holdings to reduce the value of target shares to pre-announcement levels. A majority of funds seem to sell their entire holdings of target shares right after the announcement because they prefer not to be exposed to any takeover related uncertainty.

Table 3, Panel B presents institutional trades of bidder shares. Institutions are net buyers of bidder shares in the months before the takeover announcement, although the net trades are not reliably different from zero in month -1. After the announcement, however, institutions increase both the buying and selling of acquirer stocks. For instance, institutional buying increases from 0.89% in the month prior to the announcements to 1.33% in the month following the announcements and their selling also increases from 0.90% to 1.10%. In marked contrast with the trading pattern for target shares, institutions are significant net buyers of bidder shares in the month after takeover announcements. Net trades generally declines over event time after the first month, but they remain statistically significant until month 5.

Mitchell and Pulvino (2001) and Baker and Savasoglu (2002) find that a merger arbitrage strategy that takes a long position in target shares and a short position in bidder is profitable post announcement. Therefore, the evidence that institutions buy bidders and sell targets in the post-announcement period is somewhat surprising. Perhaps, the pattern of institutional trades could explain why post-announcement spreads allow for profitable merger arbitrage opportunities. These funds may want to avoid taking on merger-related uncertainty and quickly cash in the profits on their target shares after the announcements. They are probably willing to sell shares at a discount in return for immediate execution of their trades. Funds that specialize in merger arbitrage likely take the opposite positions and earn abnormal returns as compensation for providing liquidity.

2. Determinants on Institutional Trading

Although funds do not buy target shares prior to takeover announcements when we consider the entire sample, it is possible that they may buy shares in certain types of takeovers. This subsection examines whether institutional net trades of target shares are related to any of the deal characteristics. To do so, we fit the following cross-sectional regressions:

$$\begin{aligned}\text{Net Trades}_i &= a_0 + a_1 \times \text{Cash}_i + a_2 \times \text{Stock}_i + a_3 \times \text{Deal Value}_i + a_4 \times \text{Attitude}_i \\ &\quad + a_5 \times \text{Toehold}_i + a_6 \times \text{Spread}_i + \varepsilon_i\end{aligned} \tag{1}$$

where Net Trades is the net number of shares bought by funds in each deal divided by the number of shares outstanding. Cash and Stock are dummy variables equal to 1 for cash and stock deals, respectively, and 0 otherwise. Deal Value is natural logarithm of the offer value of the offer. Attitude is a dummy variable that equals 1 if the offer is a friendly offer and 0 otherwise, and Toehold is the percentage of target shares outstanding held by the bidder at the time of the offer. Spread is the percentage difference between the offer price and the target price one day after the takeover announcement. We fit this regression separately during the pre-announcement and post-announcement windows. The pre-announcement window is event day -10 to -1 and the post-announcement window is event day 0 to +10.

Table 4 presents the regression results. Institutional trading in pre-announcement period is not associated with any salient deal characteristics. Therefore, funds do not seem to have the ability to privately gather information for any type of takeovers.

In the post-announcement period, however, net trades are related to a number of takeover characteristics. The positive coefficient on Spread indicates that funds sell significantly fewer shares when the spread is large. Therefore, funds seem to anticipate that spreads would eventually narrow, and hold on to more of their target shares. Funds also sell 0.92% fewer target shares in stock deals. Stock deals are typically associated with larger spreads (see Table 1), but the Stock coefficient is significantly positive even after controlling for spreads. Quite likely, some of the funds may consider bidders to be attractive investments, and, hence, they may hold on to target shares after takeover announcements, resulting in the positive coefficient for Stock deals.

3. Institutional Trading and Merger Outcomes

This subsection examines whether fund trades around merger announcements predict eventual outcome of the mergers. Target share prices are on average 8.63% below the offer price after takeover announcements, which reflect the uncertainty about the success of the takeover bids. Target prices increase to the offer price if the takeover is eventually successful but they drop significantly if the offer fails (Mitchell and Pulvino (2001)). If funds are skilled in predicting the success of takeovers based on public information, then their post-announcement trades will be related to the final outcome.

To examine this hypothesis, we fit a logit regression where the dependent variable equals 1 if the takeover is successful and equals 0 otherwise. The primary independent variables are funds' net trades of target shares in the pre- and post-announcement periods. In addition, we include all the control variables that we used in Regression (1) plus target return, which is market adjusted return of target stock from four weeks before the announcement to day 1 after the announcement.

Table 5 presents the logit regression estimates. We find that the coefficients on target return and attitude are significantly positive, indicating that bids with larger premiums and friendly bids are more likely to succeed. Spread is negatively related to takeover success. Spreads reflect the market's assessment of success, and the market assessment is, on average, correct.

Fund trades in the pre-announcement period are not related to takeover success. This result should not be surprising since the pattern of funds' pre-announcement trades do not indicate that they anticipate takeover bids and, hence, it is unlikely they anticipate the eventual outcome of takeover bids. Funds' post-announcement trades are not related to the probability of success either. Therefore, funds are not skilled at predicting the outcome of takeover bids based on publicly available information.

V. Profitability of Institutional Trades

To further examine whether institutions have special skills in privately collecting or interpreting information around mergers and acquisitions, this section examines returns generated by institutional trading on target stocks around announcements. Any abnormal returns that their pre-announcement trades generate will shed light on their ability to privately gather information, while abnormal returns that their post-announcement trades generate will shed light on their ability to interpret public information.

We compute market-adjusted abnormal returns within different event windows and liquidation dates, as follows. Suppose a fund makes a trade of target *i* at time t_0 within the trade window under consideration. Let *E* be the end of holding period. If the fund does not reverse its trade before *E*, we compute market-adjusted abnormal return for this as follows:

$$AR_{t_o,E}^{i} = \prod_{t=t_0}^{E}\left(1+r_{i,t}\right) - \prod_{t=t_0}^{E}\left(1+r_{m,t}\right), \qquad (2)$$

Where $r_{i,t}$ and $r_{m,t}$ are date *t* returns on stock *i* and the market respectively. We compute stock *i* returns on date t_0 based on the actual price at which the fund executes the trade and the closing price on that date.

If a fund reverses the position it opened on date t_0 before *E* (either a buy on date t_0 followed by a sell of the same number of shares or a sell followed by a buy) then we compute abnormal returns based on actual trades. Specifically, if the fund closes the position on date *T* and *T*<*E*, then we compute abnormal returns as:

$$AR^{i}_{t_o,E} = \prod_{t=t_0}^{T}\left(1+r_{i,t}\right) - \prod_{t=t_0}^{T}\left(1+r_{m,t}\right) \quad \text{if} \quad T < E. \qquad (3)$$

In this case, we compute stock returns on date *T* based on the closing price of the previous day and the actual trade price. We then take the negative of the abnormal returns for sells or sell-buy round trips. The abnormal returns measure the profits from date t_0 to the end of the holding period for buys and the opportunity costs for any sells. If funds' trades on t_0 are unrelated to potential takeovers, then abnormal returns would on average be zero.

For each takeover announcement, we first compute abnormal returns for each fund trade within the event window. We then compute average abnormal returns for each deal and then average across all takeovers. Table 6 presents the results. The first two columns of this table present the start and end date of the event windows we consider. The headers in the subsequent column present the end of the holding period. For example, the first row of panel A presents abnormal returns for trades during the -90 to -61 day window prior and holding periods ending on dates -1, 2, and 30 relative to the announcement dates. We allow for different holding period ending dates to capture abnormal returns on funds' trades at different periods during a merger process. We compute standard errors for statistical tests assuming that abnormal returns are uncorrelated across deals.

Panel A and Panel B of Table 6 present abnormal returns from trades before and after takeover announcements, respectively. Abnormal returns from fund trades in the pre-announcement period are typically close to zero. For example, fund trades in the -30 to -1-day window earn abnormal returns of .68% when held for 30 days after the announcements, and fund trades in the -60 to -30-day window generate abnormal returns of .85%, which are not significantly different from zero.

The abnormal returns to trades in the post-announcement periods are generally negative. For example, trades in the 0 to 10-day window and held until day 90 generate abnormal returns of -0.57%, which is significantly different from zero. As the results in Figure 1 indicate, funds intensely sell target shares in the 0 to 10-day window. Such intense selling, coupled with the fact that target share prices tend to increase after announcement (see Mitchell and Pulvino (2001) and Baker and Savasoglu (2002)), leads to negative abnormal returns for fund trades in this period. These results indicate that funds do not possess superior information in interpreting public information after takeover announcements.

VI. Pattern and Profitability of Trades by Funds whose Main Brokers are Advisors

Although there is little evidence that funds as a group possess the ability to privately gather information about takeovers, it is possible that some funds are able to privately gather such information. One potential source of such private information is the brokerage arms of the investment banks that are deal advisors. This section examines the profitability of trades by funds whose main brokers are also target advisors. We focus on main brokers because the reason that brokerages may leak information to their clients is to attract their order flow. Therefore, brokerages would have an incentive to leak information only to funds who direct their trades mainly through them and not to funds that trade mostly through other brokerages.

1. Main Brokers/Advisors

Institutional funds typically trade through multiple brokers, and funds likely have better relations with brokers through whom they execute more trades than with brokers who get a small share of their business. To identify their main brokers, we rank brokers according to the share volume executed for the fund during the one-year period before the deal announcement. The top decile brokers are identified as main brokers. Funds on average trade about 50% of their total trading volume through top decile brokers. For brevity, we refer to the main brokers who are target advisors as MB-TA.

We obtain acquirer and target advisor names from SDC merger and acquisition database. We classify both lead and non-lead advisors as investment banking advisors. We obtain the names of brokerages that execute institutional trades from the Abel-Noser database. We then identify funds whose main brokers are target advisors or bidder advisors.

Panel A of Table 7 compare net trades of MB-TA funds and others. Net trades of MB-TA funds are about the same as other funds in months -6 through -4. Net trades of MB-TA funds increase over months -3 and -2 and they are significantly larger than trades by other funds. However, net trade by MB-TA funds in month -1 is not significantly larger than the trades of other funds. The results in month -1 may at least in part be driven by selective selling by MB-TA funds in deals where prices reach close to the takeover price prior to public announcement. Therefore, to get a complete picture about potential information leakage, we should not only examine the trading pattern but also examine the profitability of the trades in month -1 and in other months.

In the month after the announcement, non-MB-TA funds sell 0.107% of target shares. Since the net purchases of these funds are on average not different from zero in the pre-announcement periods, the increased sales likely come from positions that they had built up well before announcements. MB-TA funds sell about 0.180% of target shares, which is significantly larger than the sales by non-MB-TA funds.

To provide another perspective on trades around takeovers, we also examine the average dollar value of net trades per fund each event month. For this analysis, we first aggregate the net trades of all funds in each category each event month for a particular deal. We then divided the aggregate net trade by the number of funds that traded the stock in a particular month to get the average net trade per fund for that deal. Finally, we compute the average of the net trades across all deals.

Panel B of Table 7 presents the dollar value of net trades per fund per deal. The average MB-TA fund trades range from -$34,679 to $68,801 in months -6 to -3, compared with trade sizes that range from $23,025 to $38,246 for non-MB-TA funds. In month -2 and -1, MB-TA funds trade sizes are $196,449 and $120,765 respectively, which are significantly greater than non-MB-TA fund trade sizes. Non-MB-TA funds in fact are significant net sellers of target shares in month -1. The MB-TA funds net sales in months 1 through 3 are significantly larger than that of other funds.

Figure 3 presents the daily net trades by MB-TA funds and others. Net trades by MB-TA funds are typically positive and higher than those by other funds in the pre-announcement period except in the last seven days before announcement. As we mentioned earlier, the net selling in this period may be driven by sales of shares in target where the pre-announcement prices ran up close to the offer price and we examine this possibility more closely when we later analyze the profitability of trades during this period. In the 30 days following announcements, net sales by MB-TA funds are generally larger than those by other funds.

Panel C of Table 7 presents the net trades of funds whose main brokers are bidder advisors (MB-BA funds) and those of other funds whose main brokers are neither target advisors nor bidder advisors. MB-BA funds do not buy target stocks in advance and their net trades are not significantly different from zero. The difference of net trades between MB-BA funds and other funds are not significant either. After takeover announcements, MB-BA funds are also net sellers of target stocks, but their net trades are significantly different from those of other funds only in month 1 and 3.

The stark difference between the pattern of trades by MB-TA funds and MB-BA funds seems somewhat surprising. Since bidders typically initiate takeovers, their advisors must have known about potential bids well before target advisors. Yet why does information leakage occur only through target advisors and not through bidder advisors?

The difference in information leakage is quite likely due to the fact that advisors to bidders and targets have different incentives. Information leakages result in target price run-up before the announcement. As target advisors have an incentive to extract higher price for the targets, price run-up will help them in their negotiations. In contrast, any target price run-up prior to a takeover potentially hurt the interest of acquirers. Due to such conflicting interests, bidders' advisors keep information about potential takeovers much more tightly guarded than target advisors.

Bodnaruk, Massa and Simonov (2009) find that the holdings of target shares by funds directly affiliated with bidder advisors increase prior to takeover announcements, indicating leakage of information within the conglomerates that advise bidders. Our evidence, however, indicates that there is no external leakage to their brokerage clients. There are at least two reasons why advisors to bidders may share information about impending takeovers within the firm but not with their brokerage clients. When leakage is restricted to only internal accounts, advisors can control the extent of leakage and the resulting volume of trades. However, if information is leaked to outsiders, the advisors have limited control over subsequent trades, and large amounts of purchases can follow, leading to substantial pre-announcement price run-ups. Moreover, when advisors use the information about impending takeovers to trade for their own accounts, they benefit fully from any profits from these trades. However, if they allow their clients to trade on such information, they gain only to the extent of trading commissions.

2. Returns of MB-TA Fund Trades

This subsection examines the profitability of MB-TA funds' trades and compares them with that of other funds' trades. We use the same procedure as in the last section to separately compute profitability of trades of these two categories of funds. For brevity, we only report returns of the strategies with holding periods ending on day +2 for pre-announcement trades and day +90 for post-announcement trades.

Panel A and Panel B of Table 8 report abnormal returns for pre-announcement and post-announcement trades. Trades of MB-TA funds are significantly more profitable than the trades of other funds in months -3 through -1. For example, MB-TA funds' trades in the month prior to the announcements generate 3.27% return, while trades by other funds generate -0.04% return.

This result may appear somewhat surprising since the net trades of MB-TA funds and others were not significantly different in month -1. However, as we mentioned earlier, part of the reason for the lack of significance in month -1 may be due to the fact that in some cases target prices ran up close to the offer price in the pre-announcement period and, hence, these funds exited their position before the announcement date. As Fig. 1 illustrates, most of the net selling in month -1 by MB-TA funds occurs in the seven days before the announcement. In untabulated analysis we found that MB-TA funds' net trades in this period held until day +2 was, in fact, positive, although they were net sellers.

Panel B presents returns from funds' trades after the announcements. MB-TA fund trades yield close to zero returns, but the Non-MB-TA funds' trades earn significantly negative returns. Although both MB-TA and Non-MB-TA are net sellers post announcement, it is somewhat surprising that the MB-TA funds on average do not sell at prices that are as unfavorable as Non-MB-TA funds.

VII. Are Some Funds Skilled?

This section examines whether some funds possess superior skills in obtaining private information before takeover announcements, although funds as a group do not exhibit superior skills relative to the market. If some funds possess such superior skills, then we would expect persistence of their abilities to identify potential targets before takeover announcements. In this section we identify funds that exhibit greater-than-average chance of trading in takeover targets in one period and examine their performance in subsequent periods to test whether their skills persist.

1. Identification of "Smart" Funds

We expect funds that possess any skill in identifying potential takeover targets to be more likely to purchase target shares before the announcement than other funds. Therefore, we first identify all funds that are net buyers of target shares during the 30-day window prior to any merger announcement in a particular calendar year.[37] Among these funds, some may have bought target shares purely by chance, rather than through skill. For instance, funds that trade more often are more likely to have hit the targets simply through luck, and we should not classify them as skilled funds.

Therefore, we partition the group of net buyers based on the probability that they hit the targets by chance. We use the following bootstrap procedure to determine the probability that a fund bought target shares during a particular period by chance conditional on the number of trades it executes during that period. First, for each calendar year, we identify all trades that are made by each fund. We then aggregate these stocks to get the universe of stocks traded by all funds in that year. For each fund, we replace each stock it trades with a random stock from the

[37] If funds buy some target shares in the month before a takeover announcement but sell at least as many shares, then they are not net buyers and they are not included in this group.

universe of traded stocks without replacements. We then compute the number of targets that each fund purchases in the month before the takeover announcement.

We repeat this experiment 10,000 times and generate a probability distribution of the number of targets that a fund purchases by chance, conditional on the number of stocks that the fund actually trades that year. We compare the number of targets that the fund actually bought in the 30-day period before the announcement with the empirical distribution to determine the probability of fund buying at least as many targets as it actually did by chance. We classify a fund as "smart" for the subsequent year if such probability is less than 50% and "non-smart" otherwise.[38] We redo the classification each calendar year. Since we classify funds based on prior year performance, funds are not classified during the first year that they enter the sample.

Panel A of Table 9 reports the sample size and the number of funds that are classified as smart and non-smart. There are more than 1,800 funds each year in our sample, except for 1998, when data are relatively sparse. Roughly 74% of the funds are not net buyers of any target shares in the 30-day period before takeover announcements each year, and we classify them as non-smart for the subsequent year. We classify about 20% of the total sample as smart funds.

We first examine whether funds that are classified as smart in one year are more likely to continue to be smart the following year. Panel B of Table 9 tabulates the transition probabilities between smart and non-smart categories from one year to the next. For example, the second row shows that 23.7% of the non-smart funds in 1999 turn out to be smart in 2000, while 36% of the smart funds continue to be smart in 2000. The table reports the chi-squared statistic under the hypothesis that a fund's classification as smart or non-smart in one year is uncorrelated with the classification in the previous year.

The chi-squared statistic is significant at the one percent level in nine out of the ten years in the sample. The test statistic is not significant in 1999. The lack of significance in 1999 is

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[38] We found similar results as those we report when we used a 40% or 30% probability cutoffs to classify smart and non-smart funds.

probably due to the lack of power since the sample size for that year is relatively small. To test the hypothesis that the classifications are uncorrelated across successive years over the entire sample, we compute the aggregate chi-squared statistic as the sum of the chi-squared statistic for individual years with degrees of freedom equal to the sum of the degrees of freedom each year. The aggregate chi-square is 600.8, which is significant at the 1% level, and we reject the null hypothesis. Therefore, funds that are classified as smart one year are more likely to be classified as smart the following year than others.

2. Returns of Smart Fund Trades

The ability to privately gather information would benefit funds only if they make profit from it. For smart funds to make higher profits than non-smart funds, they should not only be more likely to buy target shares the subsequent year prior to takeover announcements, but they should also buy them at prices that allow bigger profits. This subsection examines whether the persistence of fund categories that we found in the last subsection translates into higher profits for smart funds.

Table 10 presents the abnormal returns from target share trades by smart and non-smart funds. For brevity, we only report returns for trades with holding periods ending on day 2 for pre-announcement trades, and on day 90 for post-announcement trades. Smart funds' trades in the one- and two-month periods before takeover announcements are significantly profitable. Smart funds earn 2.03% and 1.18%, respectively, during this period. The point estimates of non-smart funds in the pre-announcement periods are negative. The differences between the abnormal returns on trades by smart and non-smart funds in the pre-announcement periods are significantly greater than zero.

Smart fund trades in the post-announcement period do not earn abnormal returns. However, non-smart fund trades during the 11 to 20 days after announcement earn an abnormal return of -0.97%, which is significantly negative. The difference between the abnormal returns on post-announcement trades by smart and non-smart funds is not significantly different from zero. Therefore, smart funds are skilled in identifying potential merger targets but not in identifying profitable trades after takeover announcements.

It is possible that smart fund trades are more profitable than non-smart fund trades because smart funds are more likely to have a main broker that also advises the target. To further examine whether smart fund profits are due to their relationship with target advisors, we examine their profits after controlling for their MB-TA and for other control variables. Specifically, we fit the following regressions:

$$AR_{i,j} = a_0 + a_1 \times \text{MB-TA}_{i,j} + a_2 \times \text{Smart}_{i,j} + a_3 \times \text{First\_year}_{i,j} + \varepsilon_{i,j}, \quad (4)$$

and

$$AR_{i,j} = a_0 + a_1 \times \text{MB-TA}_{i,j} + a_2 \times \text{Smart}_{i,j} + a_3 \times \text{First\_year}_{i,j} + a_4 \times Cash_{i,j} + a_5 \times \text{Stock}_{i,j} + a_6 \times \text{Deal Value}_{i,j} + a_7 \times \text{Attitude}_{i,j} + a_8 \times \text{Toehold}_{i,j} + \varepsilon_{i,j} \quad (5)$$

where $AR_{i,j}$ is the abnormal return on trades during the -30-day to -1-day event window and held through day 2 by fund i in deal j. MB-TA is a dummy variable that equals 1 if it is MB-TA fund and 0 otherwise. Smart is a dummy variable equal to 1 for funds classified as smart and 0 otherwise. Since we do not classify a fund as smart or non-smart during the first year that enter the sample, we set the First-_year dummy to 1 if the fund is unclassified and 0 otherwise. The second regression adds takeover characteristics in addition to the other variables. We fit a pooled cross-sectional regression and compute deal-clustered standard errors.

Table 11 reports the regression estimates. The estimates of the slope coefficient on MB-TA and Smart in regression (4) are .011 and .017 respectively and both these coefficients are significantly greater than zero. The intercept in this regression is an estimate of abnormal returns earned by non-smart funds and non-MB-TA funds. Interestingly, the intercept is significantly negative, indicating that these funds on average make a loss on their pre-takeover trades. It seems that these funds tend to sell before takeover announcements. One possible explanation for their actions is that the pre-announcement price run-ups of target shares may have pushed their prices above what these funds considered as fair values and hence triggered their liquidation.

The slope coefficients on MB-TA and Smart do not change significantly with the addition of control variables in regression (5). The results in this subsection provide further evidence that funds in general are not particularly skilled at predicting takeovers. However, trades of MB-TA funds and trades of smart funds are independently profitable.

VIII. Conclusions

Academic studies and media accounts report that institutional investors exhibit superior skills when they invest in the stock market relative to small investors[39]. Several possible factors may contribute to institutions' superior investment skills. Since large institutions hire professional fund managers and analysts, they may be able to privately gather and analyze information better than the general market. It is also possible that institutions are better able to interpret the value relevance of publicly available information such as accounting statements and corporate announcements. Finally, institutions may have access to inside information typically not available to small investors and it may provide them with an unfair advantage.

This paper investigates the potential sources of institutional investors' informational advantages by examining the patterns and profitability of their trades around takeover announcements. We find that institutions as a group do not systematically buy target stocks prior to announcements. Also, their aggregate pre-announcement trades of target shares do not generate abnormal returns. Therefore, the average fund does not possess superior information relative to the market in the pre-announcement period.

Funds intensely sell target shares on the day of takeover announcement and they continue to be significant sellers over the following month. This trading pattern indicates that the funds do

[39] For example, see Badrinath, Kale and Noe (1995), Sias and Starks (1997) and Boehmer and Kelley (2009).

not perceive that they have any comparative advantage in interpreting public information after takeover bids. We also find that fund trades in the month after the takeover announcement lead to marginally negative abnormal returns. Therefore, institutional funds as a group do not exhibit superior skills in interpreting public information.

Two subsets of institutional funds, however, exhibit superior pre-announcement trading skills. The first one is the set of funds whose main brokers are also the brokerage arms of investment banks that advise the targets. These funds are significant net buyers of target shares in the months before takeover announcement. Moreover, their average trades earn about 5% abnormal returns. This finding provides strong evidence that the institutional clients of target advisors obtain private information prior to takeover offers.

We also find that a subset of funds is skilled at privately acquiring information prior to takeovers. Specifically, we find that funds that exhibit greater-than-average chance of buying target stocks prior to takeover announcements in one year are more likely than other funds to do so the following year. The pre-announcement target share trades of these funds ("smart" funds), are also significantly more profitable than the trades of other funds. Their trades are profitable after controlling for MB-TA funds. Therefore, the superior ability of smart funds is not attributable to any special access to inside information through their brokers.

The literature generally perceives institutions as sophisticated investors and finds that larger institutional ownership results in more efficient stock prices. Boehmer et al. (2009) argue that "one mechanism through which prices become more efficient is institutional trading activity." Our findings provide insights into how institutional investors obtain their informational advantage, which potentially leads to prices becoming more efficient through their trades. Some funds are skilled at privately gathering information prior to corporate announcements, such as takeovers, and their trades partly incorporate their information into market prices. However, some institutions obtain private information from their brokerages. Although their trades would also lead to incorporation of information into prices sooner than later, these trades are tantamount to insider trading and they potentially hurt market integrity.

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Table 1. Summary Characteristics of M&A Sample

The sample is comprised of all merger and acquisition offers in the 1998 to 2008 period in the SDC database that satisfy the following criteria: (1) Both bidder and target are public companies; (2) the bid is for more than 50% of the target; (3) the transaction value is at least $10 million; (4) SDC does not classify the offer as "merger of equals" and identifies a target firm; (5) for competing bids, only the first bid is considered; and (6) the target is traded by our institutional funds in the 12 month window surrounding the deal announcement. Others are offers where SDC does not identify offer type. "Acquirer size" is the market value of the acquirer four weeks prior to the announcement; "Run-up" is the target return from four weeks prior to the announcement to the day before the announcement; "Premium" is the percentage difference between the initial offer price and target closing price one day before the announcement; "Deal status" is the percentage of deals that were completed (For multiple bidder deals, the success status only reflects the outcome for the first bidder); "Duration" is the number of days between the announcement and final resolution of the deal; "Attitude" is the percentage of friendly deals as classified by SDC; "Spread" is the percentage difference between initial offer price and target closing price on the day after the announcement; and "Announcement day return" is the two day return starting from the announcement day (day 0 and 1).

Type of takeover	N	Transaction size (Mil)	Acquirer size (Mil)	Deal status	Duration	Attitude	Run-up	Premium	Spread	Announcement day return	
										Target	Acquirer
Stock	658	2,139	18,048	87.08%	134	97.56%	8.71%	33.05%	14.13%	16.13%	-4.34%
Cash	865	1,079	27,163	88.55%	106	94.08%	9.49%	34.77%	4.56%	28.59%	0.43%
Mixed	600	2,891	11,561	91.50%	164	97.17%	6.58%	28.63%	8.67%	18.05%	-3.30%
Others	193	1,521	14,336	81.35%	160	92.75%	5.44%	29.46%	8.38%	18.05%	-0.51%
Full sample	2,316	1,886	19,041	88.30%	133	95.76%	8.18%	32.30%	8.63%	21.45%	-2.09%

Table 2. Summary Statistics for Institutional Trades
This table reports summary statistics on the institutional trading sample from Abel Noser. The sample includes trades executed by Abel Noser clients on 2316 U.S. M&A targets from 1998 to 2008. The table presents the number of shares and dollar value traded during the [-6, +6] month window around the M&A announcements.

	Number of Institutions	Number of fund managers
Total Sample	898	4,443
	Shares traded	Dollars traded
Total Sample	24,350,979,866	721,893,923,691
Trading per target		
Mean	10,514,240	311,698,585
25th percentile	138,597	1,302,478
Median	1,317,058	16,644,280
75th percentile	7,341,700	166,641,265
Trading by fund per target		
Mean	244,549	7,249,751
25th percentile	3,800	100,374
Median	15,634	433,161
75th percentile	63,000	1,746,666

Table 3. Institutional Trading around Takeover Announcements

This table presents institutional trades of targets and acquirers from six months before the announcement dates to six months after takeover announcements. For each deal, we aggregate the shares bought, sold, and net trades (buy-sell) across funds, divide them by the total shares outstanding, and then average across all takeover announcements. The t-statistics are calculated assuming that trades are uncorrelated across announcements.

Panel A: Trading on targets

Month	-6	-5	-4	-3	-2	-1	1	2	3	4	5	6
Buy	0.856	0.856	0.814	0.857	0.796	0.746	0.686	0.351	0.302	0.321	0.332	0.304
Sell	-0.867	-0.830	-0.828	-0.800	-0.800	-0.838	-3.619	-1.112	-0.749	-0.614	-0.539	-0.557
Net	-0.011	0.026	-0.014	0.057	-0.004	-0.093	-2.933	-0.761	-0.447	-0.293	-0.207	-0.252
t-statistic (net)	(-0.30)	(0.80)	(-0.42)	(1.80)	(-0.13)	(-3.12)	(-25.30)	(-17.97)	(-13.24)	(-8.87)	(-6.18)	(-6.02)

Panel B: Trading on acquirers

Month	-6	-5	-4	-3	-2	-1	1	2	3	4	5	6
Buy	0.965	0.969	0.910	0.943	0.929	0.886	1.334	1.020	0.869	0.817	0.793	0.806
Sell	-0.884	-0.886	-0.853	-0.840	-0.872	-0.897	-1.100	-0.886	-0.762	-0.731	-0.675	-0.727
Net	0.081	0.083	0.057	0.103	0.057	-0.011	0.235	0.134	0.107	0.087	0.118	0.079
t-statistic (net)	(2.82)	(2.79)	(2.06)	(3.80)	(2.14)	(-0.44)	(6.55)	(4.56)	(3.68)	(2.70)	(3.32)	(1.66)

Table 4. Determinants of Trading

This table presents the regression results on the determinants of funds' trading. We regress funds' aggregate net trades of targets (as a percentage of total shares outstanding) on various deal characteristics. "Cash" and "Stock" are dummy variables denoting the type of the deal; "Deal value" is the log total market value of the offer in millions; "Attitude" is a binary variable that equals 1 for friendly deals and 0 otherwise; "Toehold" is the target shares, as a percentage of total shares outstanding, held by the acquirer before the announcement; "Spread" is the percentage difference between initial offer price and target closing price on the day after the announcement.

	Trades in (-10,-1)		Trades in (0,10)	
	Coefficient	T-statistic	Coefficient	T-statistic
Intercept	-0.077	-1.17	-1.651	-3.62
Cash	-0.037	-1.20	-0.852	-3.99
Stock	-0.025	-0.75	0.916	3.92
Deal Value	0.000	-0.76	0.000	-0.45
Attitude	0.031	0.49	-0.706	-1.61
Toehold	-0.174	-0.66	4.204	2.31
Spread	0.197	1.90	2.789	3.88
N	1,809		1,809	
Adjusted R^2	0.004		0.053	

Table 5. Prediction of Takeover Success

This table presents the estimates of a logit regression where the dependent variable equals 1 if a takeover offer is successful and 0 otherwise and the independent variables are deal characteristics and fund trades. "Cash" and "Stock" are dummy variables denoting the type of the deal; "Deal value" is the log total market value of the offer in millions; "Attitude" is a binary variable that equals 1 for friendly deals and 0 otherwise; "Toehold" is the target shares, as a percentage of total shares outstanding, held by the acquirer before the announcement; "Spread" is the percentage difference between initial offer price and target closing price on the day after the announcement.; "Target return" is market adjusted return of target stocks from four weeks before the announcement to day 1 after the announcement. Pre- and post-announcement trades are the aggregate net trades (as a percentage of shares outstanding) in event windows (-10,-1) and (0, 10).

	Coefficient	*p*-value
Intercept	-1.335	0.00
Cash	-0.137	0.54
Stock	-0.249	0.25
Deal Value	0.000	0.97
Attitude	3.879	0.00
Toehold	-0.072	0.97
Spread	-2.958	0.00
Target return	1.120	0.00
Pre-announcement trades (-10,-1)	0.189	0.21
Post-announcement trades (1,10)	-0.039	0.14
Number of observations	1,802	
Pseudo R^2	0.2762	

Table 6. Returns on Fund Trades of Targets

This table presents average market-adjusted returns on fund trades within various event windows. “Start Date” and “End Date” are the starting and ending dates of the event windows. “Hold until” date specifies the day on which the trades in the event windows are closed out. We first compute the principle weighted abnormal return for each fund trades within the event window. We average returns across all managers for each deal, and then average across deals. We compute t-statistics (reported in parentheses) assuming returns are uncorrelated across deals.

Panel A. Returns from trading before announcements

		Hold until		
Start Date	End Date	-1	2	30
-90	-61	0.83	0.55	0.47
		(2.17)	(0.88)	(0.71)
-60	-31	0.38	1.22	0.85
		(1.18)	(2.10)	(1.38)
-30	-1	0.07	0.69	0.68
		(0.37)	(1.39)	(1.24)

Panel B. Returns from trading after announcements

		Hold until		
Start Date	End Date	30	60	90
0	10	-0.19	-0.62	-0.57
		(-1.19)	(-2.65)	(-2.03)
11	20	-0.16	-0.43	-0.71
		(-1.44)	(-2.15)	(-2.76)

Table 7. Trades of funds whose main brokers are target advisors

Panel A presents the trades of funds whose main brokers are target advisors (MB-TA funds). We identify main brokers by ranking brokers according to the share volume executed for the fund during the one year period before the deal announcement. The top decile brokers are identified as main brokers. We do not differentiate between lead and other advisors. We compute the monthly net shares traded (buy minus sell and normalized by shares outstanding) for MB-TA funds and other funds, and then average across all takeover announcements. The t-statistics are calculated assuming that trades are uncorrelated across announcements. Panel B shows the net trades in dollar value. Panel C shows the trades of funds whose main brokers are bidder advisors (MB-BA funds).

Month	-6	-5	-4	-3	-2	-1	1	2	3	4	5	6
Panel A. Trades of funds whose main brokers are target advisors												
MB-TA funds	-0.0036	0.0029	-0.0014	0.0161	0.0131	0.0010	-0.1801	-0.0629	-0.0489	-0.0276	-0.0093	-0.0250
	(-0.38)	(0.45)	(-0.18)	(2.45)	(2.04)	(0.18)	(-11.89)	(-7.38)	(-6.14)	(-3.59)	(-0.99)	(-2.20)
Other funds	0.0016	0.0001	0.0048	0.0025	-0.0021	-0.0026	-0.1067	-0.0393	-0.0245	-0.0177	-0.0121	-0.0127
	(0.51)	(0.03)	(1.28)	(0.78)	(-0.53)	(-0.88)	(-15.16)	(-10.16)	(-7.25)	(-3.53)	(-2.55)	(-3.30)
MB-TA - Others	-0.0052	0.0028	-0.0062	0.0136	0.0152	0.0036	-0.0734	-0.0236	-0.0244	-0.0099	0.0028	-0.0123
	(-0.54)	(0.41)	(-0.75)	(2.06)	(2.06)	(0.58)	(-4.64)	(-2.64)	(-2.91)	(-1.10)	(0.27)	(-1.09)
Panel B. Trades (in dollar) of funds whose main brokers are target advisors												
MB-TA funds	66,376	47,462	-34,679	68,801	196,449	120,765	-2,570,960	-1,172,072	-975,886	-562,161	-220,292	-440,920
	(0.84)	(0.62)	(-0.40)	(1.02)	(3.10)	(1.24)	(-12.86)	(-7.99)	(-5.98)	(-3.32)	(-0.69)	(-2.58)
Other funds	38,246	25,810	23,025	25,134	14,223	-51,553	-1,261,257	-569,159	-383,077	-359,828	-247,514	-238,170
	(1.51)	(1.27)	(0.84)	(0.97)	(0.65)	(-1.94)	(-17.53)	(-12.43)	(-8.45)	(-5.36)	(-2.21)	(-3.14)
MB-TA - Others	28,130	21,652	-57,705	43,667	182,225	172,318	-1,309,703	-602,912	-592,809	-202,333	27,222	-202,750
	(0.34)	(0.28)	(-0.63)	(0.60)	(2.84)	(1.80)	(-6.63)	(-4.20)	(-3.60)	(-1.16)	(0.08)	(-1.16)

Panel C. Trades of funds whose main brokers are bidder advisors

MB-BA funds	0.0093	0.0217	0.0134	0.0110	0.0106	-0.0060	-0.2091	-0.0657	-0.0514	-0.0321	-0.0276	-0.0197
	(0.93)	(2.68)	(1.81)	(1.55)	(1.04)	(-0.69)	(-12.73)	(-6.65)	(-5.33)	(-3.76)	(-2.82)	(-1.93)
Other funds	0.0026	0.0022	0.0053	0.0025	-0.0006	-0.0052	-0.1248	-0.0516	-0.0400	-0.0195	-0.0163	-0.0106
	(0.70)	(0.55)	(1.28)	(0.55)	(-0.16)	(-1.54)	(-14.94)	(-10.68)	(-8.02)	(-3.69)	(-2.94)	(-2.40)
MB-BA - Others	0.0160	0.0180	0.0055	0.0018	0.0097	0.0034	-0.0939	-0.0119	-0.0271	-0.0143	-0.0103	-0.0089
	(1.59)	(2.00)	(0.66)	(0.25)	(0.91)	(0.36)	(-5.45)	(-1.00)	(-2.85)	(-1.51)	(-0.83)	(-0.90)

Table 8. Returns of Trades by MB-TA funds

The table presents the market-adjusted returns of trades by funds whose main brokers are target advisors (MB-TA funds). We identify main brokers by ranking brokers according to the share volume executed for the fund during the one year period before the deal announcement. The top decile brokers are identified as main brokers. We do not differentiate between lead and other advisors. "Start Date" and "End Date" are the starting and ending dates of the event windows. "Hold until" date specifies the day on which the trades in the event windows are closed out. We first compute the principle weighted abnormal return for trades of each fund within the event window. We average returns across all funds for each deal, and then average across deals. We compute t-statistics (reported in parentheses) assuming returns are uncorrelated across deals.

Panel A. Returns from trading before announcements

Start Date	End Date	Hold till day 2		
		MB-TA funds	Other funds	Difference
-90	-61	0.68	-1.56	2.24
		(0.85)	(-1.90)	(2.17)
-60	-31	1.57	-0.69	2.26
		(2.08)	(-0.89)	(2.31)
-30	-1	3.27	-0.04	3.30
		(4.73)	(-0.06)	(3.90)

Panel B. Returns from trading after announcements

Start Date	End Date	Hold till day 90		
		MB-TA funds	Other funds	Difference
0	10	-0.44	-0.93	0.49
		(-0.88)	(-2.06)	(1.01)
11	20	-0.27	-0.89	0.62
		(-0.63)	(-2.06)	(1.42)

Table 9: Persistence of Smart Funds

The table examines the persistence of smart funds. Funds are classified as “smart” and “non-smart” based on the likelihood that they bought target shares within 30 days before takeover announcements by chance. Panel A presents the number of funds in the sample each year and the percentage that are classified as smart. Panel tabulates the transition probabilities between smart and non-smart categories from one year to the next. The chi-squared statistics are computed under the hypothesis that the classification of a fund in one year is uncorrelated with its classification in the previous year.

Panel A. Smart fund

Year	N	Non-smart	Smart
1998	299	93.3	6.7
1999	2,076	77.4	22.6
2000	1,972	73.3	26.7
2001	2,082	84.0	16.0
2002	2,119	84.6	15.4
2003	2,038	85.6	14.4
2004	1,961	81.0	19.0
2005	1,854	78.2	21.8
2006	1,561	77.9	22.1
2007	1,440	75.1	24.9
2008	1,062	85.9	14.1

Panel B. Contingency table

	Non-smart		Smart			
Year	Non-smart	Smart	Non-smart	Smart	Chi	P-value
1999	69.1	30.9	50.0	50.0	3.1	0.08
2000	76.3	23.7	64.0	36.0	20.2	0.00
2001	85.6	14.4	75.6	24.4	21.2	0.00
2002	87.0	13.0	70.2	29.8	45.6	0.00
2003	87.5	12.5	70.0	30.0	49.4	0.00
2004	84.7	15.3	52.2	47.8	134.5	0.00
2005	83.1	16.9	56.8	43.2	85.0	0.00
2006	84.0	16.0	59.9	40.1	78.8	0.00
2007	81.1	18.9	51.3	48.7	97.1	0.00
2008	91.5	8.5	71.3	28.7	65.8	0.00
All					600.8	0.00

Table 10. Returns on Smart and Non-Smart Fund Trades

This table presents the market-adjusted returns of smart and non-smart funds' trades on the targets in the year following classification. "Start Date" and "End Date" are the starting and ending dates of the event windows. "Hold until" date specifies the day on which the trades in the event windows are closed out. We first compute the principle weighted abnormal return for trades of each fund within the event window. We average returns across all funds for each deal, and then average across deals. We compute *t*-statistics (reported in parentheses) assuming returns are uncorrelated across deals.

Panel A. Returns from trading before announcements

Start Date	End Date	Hold till day 2		
		Smart	Non-smart	Difference
-90	-61	0.27	-2.78	3.04
		(0.40)	(-3.43)	(2.92)
-60	-31	1.18	-1.71	2.89
		(1.83)	(-2.16)	(2.84)
-30	-1	2.03	-1.24	3.27
		(3.86)	(-1.91)	(3.90)

Panel B. Returns from trading after announcements

Start Date	End Date	Hold till day 90		
		Smart	Non-smart	Difference
0	10	0.05	-0.42	0.46
		(0.16)	(-1.13)	(0.98)
11	20	-0.25	-0.97	0.72
		(-0.87)	(-2.45)	(1.46)

Table 11. Fund Trades and Profits: Smart funds, MB-TA funds and other funds

This table presents the estimates of regressions where the dependent variable is the market-adjusted return on fund trades in event window (-30,-1) and that are close on day 2 after takeover announcements. The independent variables are: “MB-TA” equals 1 if the fund’s main brokers are target advisors; “Smart” equals 1 if the fund is classified as smart and 0 otherwise; “First_year” equals 1 if the fund appears in the sample for the first year and cannot be classified as smart or non-smart for that year; “Cash” and “Stock” are dummy variables denoting the type of the deal; “Deal value” is the log total market value of the offer in millions; “Attitude” is a binary variable that equals 1 for friendly deals and 0 otherwise; “Toehold” is the target shares, as a percentage of total shares outstanding, held by the acquirer before the announcement. We compute *t*-statistics using standard errors clustered by deals.

	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	-0.011	-2.16	-0.011	-0.88
MB-TA	0.011	1.96	0.012	2.12
Smart	0.017	3.05	0.017	3.03
First_year	0.025	3.64	0.024	3.57
Cash			-0.009	-1.21
Stock			0.005	0.68
Deal Value			0.000	-1.95
Attitude			0.005	0.43
Toehold			-0.148	-2.12
Number of observations	22,036		22,036	
Adjusted R^2	0.0015		0.0025	

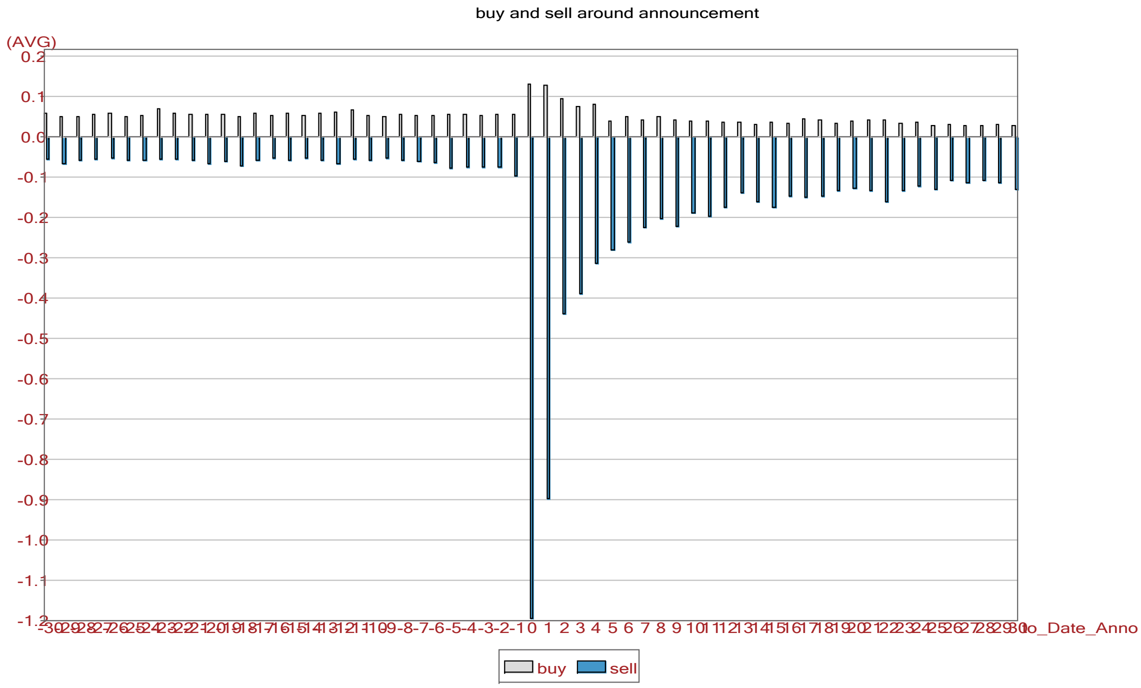

Figure 1. Institutional Trading around Takeover Announcements

The figure shows institutional buying and selling on U.S. M&A targets around the announcement dates. For each deal, we aggregate the shares bought and sold across funds and divide it by the total shares outstanding. The percentages of shares traded are then averaged across all M&A deals aligned by event dates.

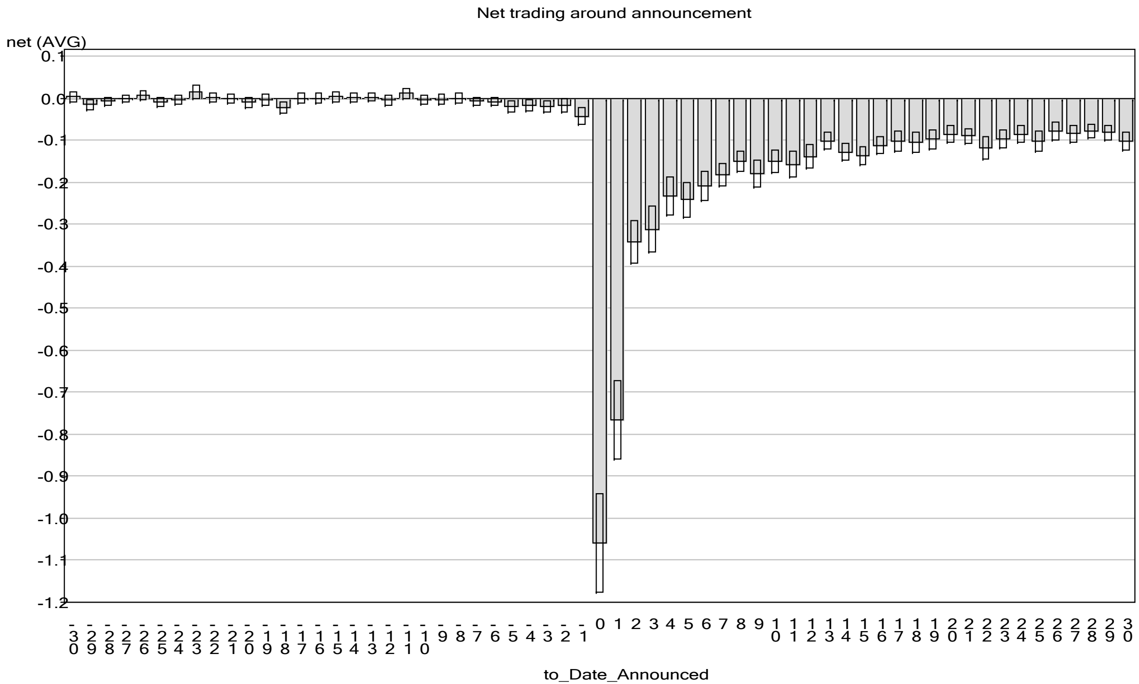

Figure 2. Trading Imbalance around Takeover Announcements
The figure shows the trading imbalance of institutional investors on U.S. M&A targets around the announcement dates. For each deal, we calculate the net trades by funds and divide it by the total shares outstanding. The percentages of shares traded are then averaged across all M&A deals aligned by event dates. The 95% confidence interval is calculated assuming M&As are independent.

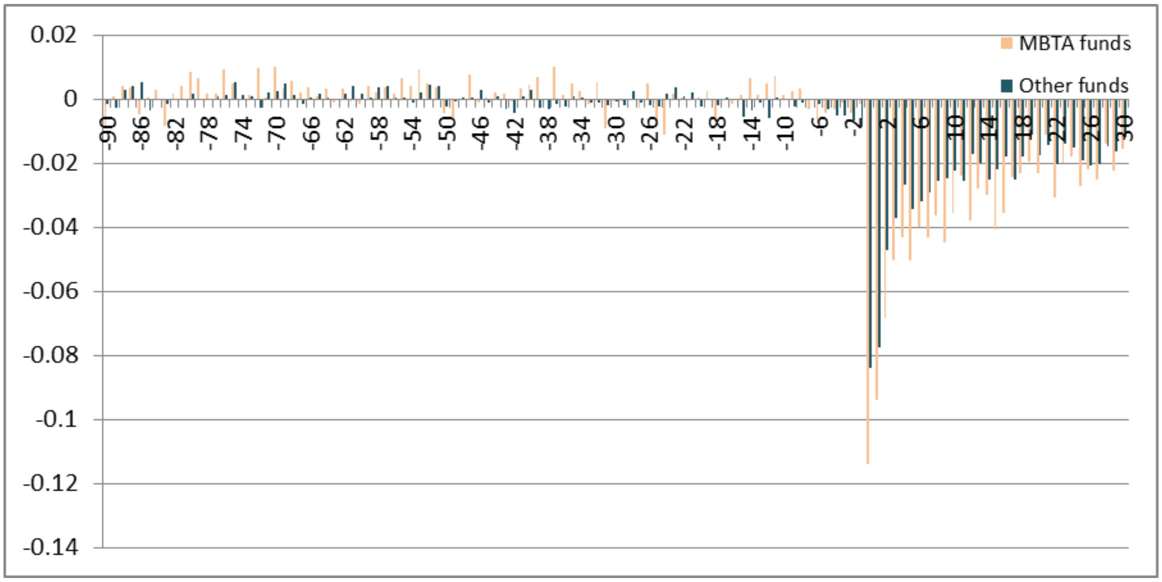

Figure 3. Trading on Targets by MB-TA and Other Funds
The figure presents the trades of MB-TA funds and other funds. We identify main brokers by ranking brokers according to the share volume executed for the fund during the one year period before the deal announcement. The top decile brokers are identified as main brokers. We do not differentiate between lead and other advisors. We compute the daily net shares traded (buy minus sell and normalized by shares outstanding) for MB-TA funds and other funds, and then averaged across all takeover announcements.