Call Your Clients First:
An Examination of How Analysts Add Value to Their Fund Clients

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Abstract

This paper examines whether the sell-side research industry adds value to its mutual fund clients. I use a novel data set to identify the network of broker-client relationships. I find that, within a mutual fund's portfolio, the stocks covered by the fund's brokers outperform the uncovered stocks by 6.3% per year, on average. This supports the view that sell-side analysts add value to their clients by helping them make better investment decisions. I further test whether the value added can be attributed to private communications between analysts and their clients. First, I find that, before an analyst releases a negative (positive) recommendation on a stock, her clients sell (buy) significantly more of the stock than do non-clients. Second, among stocks with a strong buy recommendation, those bought by clients before the recommendation announcements earn a 120-day post-recommendation abnormal return that is 1.78% higher, on average, than those sold by clients before the recommendations. These results suggest that brokers help their clients gain an information advantage over non-clients by providing private services and information. Overall, the paper helps to make sense of the existence and size of the sell-side research industry.

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I. Introduction

Sell-side research, the research services provided by investment banks and broker dealers, is one of the most important and active information sources for investors in the capital markets. While there is a large literature on sell-side analysts,[1] a basic question remains unanswered: Does the sell-side research industry create value for its clients? Institutional investors spend billions of dollars on sell-side research each year.[2] Do they benefit from the research services provided by sell-side analysts? If so, what is the source of the value they derive from these services?

Much of the literature on sell-side research focuses on the return predictability of analyst recommendations and forecasts; see, for example, Womack (1996), Barber et al. (2001), and Jegadeesh et al. (2004). However, even if recommendations and forecasts can predict future stock returns, this does not mean that analysts add value to institutional clients. First, since institutional investors usually have their own research teams, the information revealed in analyst reports, while potentially new to retail investors, may be stale to institutional investors. Second, earnings forecasts and recommendations, the main focus of previous research, are public signals and are spread far beyond brokers' paying clients. The information contained in analyst forecasts or recommendations, on its own, is not sufficient to justify the money paid to the sell-side research industry. These payments must therefore represent compensation for some other services provided to institutional investors. This paper attempts to infer what these services are.

A key step in this attempt involves identifying the connections between brokers and their institutional clients. I collect a unique dataset to do so. Traditionally, institutional investors use commissions to pay for both transaction processing and research services.[3] Therefore, we can use their commission allocations to infer which brokers they bought research services from. I collect commission expense data for all mutual funds from N-

[1] See Bradshaw (2011) for a comprehensive survey of the literature.
[2] 2011 Greenwich Share Leaders: U.S. Equity Analysts Research, Greenwich Associates.
[3] Anecdotal evidence indicates that over half of total commissions paid by clients are allocated to research. See 2011 Greenwich Share Leaders: U.S. Equity Analysts Research, Greenwich Associates.

SAR reports filed with the SEC from 1995 to 2009.[4] I then match this dataset to mutual fund holdings data and to analyst recommendations data. I am then able to link each sell-side analyst to her mutual fund clients. In this network, the signals released by analysts, analysts' connections to fund clients, and the transactions conducted by these clients are directly observable. This gives me a unique opportunity to track the information flow between analysts and their clients.

With this dataset, I first examine whether analysts create value for their clients. To do this, I compare the performance of stocks owned by funds and covered by funds' brokers with that of stocks owned by funds but not covered by funds' brokers, because, for covered stocks, mutual fund managers can receive advice from sell-side analysts, but for uncovered stocks, they have to make independent decisions. I find that covered stocks outperform uncovered stocks by 6.3% per year after controlling for the Fama-French and momentum factors. There is no evidence that unobservable stock characteristics or analyst coverage decisions drive these results. The evidence suggests that analysts do help their clients make better investment decisions.

Next, I investigate the mechanism of value creation. Since the services and private information provided by sell-side analysts are unobservable, I adopt a "revealed information" approach, which assumes that fund managers are profit-maximizing and therefore that the trades they make will reveal the information they have. Specifically, I focus on fund trades prior to stock recommendation announcements. For each recommendation, I divide mutual funds into two groups: client funds, which are those that pay commissions to the broker issuing this recommendation, and non-client funds. I then compare client funds' trades with non-client funds' trades prior to the recommendation. The results show that client funds have a relative information advantage: Compared to non-clients, client funds buy more before a positive recommendation and sell more before a negative recommendation. Thus, clients appear to be aware of the information contained in recommendations before it is publicly released.

[4] N-SAR (Semi-annual report of registered investment companies) is an SEC filing that is specific to registered investment management companies, requiring them to disclose certain financial information.

I then explore whether clients obtain more accurate information than what is disclosed in recommendations. Empirically, conditioning on the same strong buy recommendation, I test whether clients' pre-recommendation trades can predict post-recommendation stock returns. I sort all stocks with a strong buy recommendation by clients' pre-recommendation trading direction and divide them into two groups: stocks *bought* by clients before the recommendation and stocks *sold* by clients before the recommendation. An event study analysis shows that the two groups have a very similar abnormal return on recommendation announcement days, but that stocks bought by clients before recommendations earn 1.78% higher 120-day post-recommendation abnormal returns than those sold by clients. As a placebo test, I check for a performance difference between stocks bought and sold by non-clients, and find that there is none. This implies that clients are able not only to infer the information contained in a recommendation and to trade ahead of it, but also to seize better signals than those contained in recommendations. If one thinks of a strong buy recommendation as a "noisy" public signal, clients are able to distinguish a "real" strong buy from a "noisy" strong buy.

Finally, funds' broker choices may reflect their specialty, i.e., a fund may tend to choose brokers who cover the industries that it focuses on; and the fund may have special knowledge on these industries. Therefore, it is possible that, even if brokers do not provide any information or services to their clients, we may still observe that client funds are more informed than non-client funds and that high coverage stocks outperform low coverage stocks. I conduct two robustness tests to address this endogeneity issue and find that the main results cannot be explained by funds' broker choices.

There are two possible interpretations of these results. The first interpretation is "private information transmission." Besides formal analyst reports, analysts may communicate with their clients in many informal ways: they may pass messages to clients through sales people, talk to clients on the phone, and even meet with some clients face to face. During the course of these informal communications, analysts may, however subtly, give clients hints about their upcoming recommendation changes. Such leaks are strictly prohibited by brokerage firms and may even violate certain laws. Nevertheless, they may still occur.

I emphasize, however, that there is a second, more benign interpretation of my findings. I label this interpretation “skill transmission”. Under this view, analysts may simply be “teaching” their clients. Anecdotal evidence indicates that sell-side analysts advise their clients on how to analyze certain industries or firms. In some cases, they share their earnings estimation methods and valuation models with their clients. Brokers also regularly arrange conferences that bring together firms and fund managers, thereby allowing fund managers to understand these firms better. In summary, analysts may help fund managers to improve the way they collect and analyze information. This, in turn, may help fund managers forecast an analyst’s future recommendation change even without receiving any direct hint of it.

Most of the evidence in this paper is consistent with both of the above explanations, but some indirect evidence that I will discuss later is more consistent with the “private information transmission” explanation. Without details of the communications between analysts and fund managers, it is hard to know whether analysts are instructing clients or transmitting information. Hence, I do not rule out either of the two explanations. Of course, they are not mutually exclusive. Both of them may be true to varying extents.

In summary, my results demonstrate that brokers provide some services and information only to their clients, which helps clients gain an information advantage over non-clients. In short, whether through private information transmission or skill transmission, sell-side analysts do create value for their clients, value that these clients are happy to pay for. These results help us better understand the existence of the sell-side research industry.

This paper can be linked to three strands of the literature. The first strand is the large literature on the market for information, following the seminal work of Grossman and Stiglitz (1980) (e.g., Admati and Pfleiderer (1986, 1990), Allen (1990)). This paper takes the sell-side research industry as an example of a market for information services. The richness of my dataset allows me to identify information flows between information sellers and buyers. I show that information sellers simultaneously provide noisy public signals and more accurate private signals to different market participants, which partly solves the free-rider problem in markets for information.

The second strand is the recent research on information exchange between connected institutions or individuals. For example, geographic distance (e.g., Coval and Moskowitz (2001), Malloy (2005), Hong et al. (2005)) and a common educational background (e.g., Cohen et al. (2008), Cohen, Frazzini, et al. (2010), Shue (2011)) have been shown to be important determining factors for information transmission. This paper shows that the broker-client relationship is another important factor for information transmission.

The third strand is the large literature on analyst incentives. To attract investment banking deals or to generate extra trading, analysts are predisposed to be optimistic (Michaely and Womack (1999), Cowen et al. (2006)). Brokers' institutional clients could alleviate analysts' overoptimistic tendency (Ljungqvist et al. (2007)), but may induce other biases (Gu et al. (2009), Firth et al. (2012), Chung and Teo (2012)). This paper shows that sell-side analysts have incentives to maintain good relationships with clients, although this paper focuses more on information transmission rather than on the recommendation and forecast biases.

This paper is also related to several others. Irvine et al. (2006) and Anderson and Martinez (2012) find abnormal trading activities prior to recommendation announcements. These results suggest the existence of information leakages and are consistent with the findings in this paper. Green (2006) shows that institutional investors can make abnormal profits by trading stocks just after recommendations. My paper, by contrast, focuses on pre- rather than post-recommendation trades of clients. Edelen et al. (2012) discuss the relationship between commissions and fund performance, focusing on the information motive and agency cost behind commissions; my paper discusses whether, and how, sell-side analysts create value. Busse et al. (2012) compare the performance of buy-side institutional investor trades and sell-side analyst stock recommendations. Consistent with my finding for non-clients, they find that mutual fund trades generally are not incrementally informative relative to analyst recommendations. However, my paper also shows that analysts' mutual fund clients are able to discern the quality of recommendations. Griffin et al. (2012) examine the trades of brokers and their clients before takeover announcements, IPOs and SEOs. They find little evidence that brokers use the information obtained from investment banking business to make profits.

My paper examines the interaction between analysts and funds, but does not discuss the information source of brokers.

The rest of the paper is organized as follows: Section II presents some institutional background about sell-side research. Section III discusses the data sources, the matching method, and reports summary statistics. Section IV presents evidence on the performance difference between covered and uncovered stocks. Sections V and VI discuss the two channels of value creation. Section VII discusses the decomposition of clients' superior performance and an endogeneity issue. Section VIII concludes.

II. **Institutional background**

Brokerage firms do not directly receive any payment for their research services. Instead, research services are paid for in a bundled way. When an institutional investor trades via a brokerage firm, the commission it pays is not only compensation for transaction costs, but also for the research services provided by the brokerage firm. This payment form is a legacy of commission regulation. Before 1975, all brokerage firms used a fixed price commission schedule published by the NYSE. Since they could not compete with each other by lowering commissions, they soon began to provide premium services, like equity research, to their institutional clients. This became known as "bundling". The part of commissions allocated for services beyond order execution has also been called "soft dollars".

In 1975, fixed commission pricing was terminated by the government. Since then mutual fund managers are not allowed to use commissions to pay for other services. The only exception is the "safe harbor" provision,[5] which permits institutions to pay for qualifying sell-side research services out of brokerage commissions. After 36 years, even with the competition from discount brokers, most brokers still bundle transaction and research services together (Goldstein et al. (2009)). To maintain a premium status in a brokerage house and hence access to private research services, an institutional investor has to trade through this brokerage house and pay commissions above a minimum amount.

[5] See Section 28(e), Securities Exchange Act of 1934.

Sell-side research is one of the largest markets that involve the sale of information. Commission income is a major revenue source for most brokerage houses, even the largest ones. For example, in 2010, commission income accounted for about 20% of Merrill Lynch's total revenue, more than investment banking and asset management. The quality of research services is the most important factor when institutional investors choose brokers. In addition, it is estimated that about half of commissions are allocated to research related services.[6] Mutual funds alone pay billions of dollars for sell-side research each year.[7]

Brokers provide a variety of research services to their clients, including traditional analyst services, organizing research conferences, and arranging direct meetings with company' management. Among these, analyst services are considered the most important.[8] A research report is a summary of an analyst's work. Analysts' formal conclusions in the reports, like earnings forecasts and stock recommendations, are recorded and archived by data providers such as I/B/E/S and First Call; these are accessible to a wide range of market participants.

However, analyst reports are not the only way for sell-side analysts to communicate with investors. In practice, urgent and important information is delivered to clients in a more efficient and private way.[9] For example, when an analyst receives breaking news about a specific firm or industry, she contacts the sales department. The salespeople then directly call their buy-side clients with the analyst's investment advice. Less urgent news is discussed during morning research conference calls, which are usually held before the stock market opens. The results are summarized by salespeople and are then transmitted to the most important clients. In addition, fund managers often directly call sell-side analysts to seek their opinions.

Besides giving direct advice, analysts also help their clients to improve their analysis skills. For example, institutional investors sometimes discuss analytical frameworks with

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[6] See 2011 Greenwich Share Leaders: U.S. Equity Analysts Research, Greenwich Associates.
[7] See the summary statistics in Section III.
[8] "As Analyst Workload Gets Heavier, Institutions Lean on Sell-Side Research and Services," Greenwich Associates report, June 2011.
[9] A detailed and very helpful discussion about the communications between analysts and investors can be found in Michaely and Womack (2005). This paragraph is largely based on their discussion.

sell-side analysts, or ask analysts to share their earnings forecast models. Some funds may compare models from different banks and then create their own models. All of these informal discussions are restricted to clients of brokerage firms.

In summary, sell-side research services are provided by brokerage firms to attract institutional investors' commissions. The services consist of different parts. Besides writing analyst reports, which are available to a broad range of investors, analysts maintain frequent communications with their institutional clients, including transmission of urgent market news and discussion of analysis techniques.

III. **Data**

A. Data Sources

The commission allocation data I use come from the SEC's N-SAR filing. In this semi-annual filing, every mutual fund is required to disclose the identities of the ten brokerage firms it paid the most commissions to. I collect N-SAR filings from SEC EDGAR for all mutual funds from 1994 to 2009, a total of 339,174 filings. For the purpose of this paper, I mainly focus on domestic equity mutual funds. N-SAR filings are reported at the registered investment company level, which may include one or several funds. In my sample, most registered investment companies include one or two equity funds. This commission data has also been used in a few previous papers to address topics other than those I focus on here (e.g., Edelen et al. (2012), Reuter (2006)).

My other data sources are standard. Mutual fund holdings data is obtained from Thomson Reuter. Analyst forecast and recommendation data is from I/B/E/S. Stock related data is from CRSP. The Fama-French four factor data is from Kenneth French's website. DGTW benchmark returns and stock assignments are from Russ Wermers's website.

I use the same screening procedure as in previous research to select domestic equity funds (e.g., Cremers and Petajisto (2009), Lou (2012)). First, I require the investment objective code of the mutual funds reported by CDA/Spectrum to be aggressive growth, growth, growth and income, unclassified, or missing. Moreover, since some mutual funds misreport their investment objective codes, I only keep funds whose ratio of equity holdings to total net assets is larger than 70%. Finally, I exclude index funds by checking fund names.

Since there is no common fund identifier between N-SAR and other mutual fund databases, I match funds by their names. Specifically, I first merge the Thomson Reuter database with the CRSP mutual fund database to obtain mutual funds' full names. Then I match fund names reported by CRSP with fund names reported in N-SAR. The matching process is first done by algorithm and all results are double checked by hand. To further ensure there is no mismatching, I compare total net assets (TNA) reported in Thomson Reuter and in N-SAR, and then delete observations with significantly different reported TNAs.[10] In the end, I am able to match about 90% of the funds identified as domestic equity funds in the Thomson Reuter database.

The second step is to match brokers reported in N-SAR to contributors in I/B/E/S. This is also done by matching names. I adjust for mergers and acquisitions among brokerage firms. In the final sample, I am able to match about 80% of the brokers reported in N-SAR. The remaining 20% are mainly brokers who do not contribute to I/B/E/S, discount brokerage firms who do not provide research services, and foreign brokerage firms.

B. Summary Statistics

As mentioned in Section II, commission income is a major revenue source for brokerage firms. As the largest institutional investor category, mutual funds manage about 12 trillion in assets and account for a significant part of brokers' total commission income. Figure I shows the total commission expenses reported by all mutual funds. From 1995 to 2009, the total amount of commissions increases from 2 billion to 7 billion. About half are paid by the equity funds identified in my sample. Assuming half of the commissions are compensation for research services, equity mutual funds pay about 1.5 billion per year for sell-side research.

Panel A of Table I provides summary statistics for the brokerage firms examined in this paper. The number of brokers that have at least one equity fund client decreases from 194 to 143 between 1995 and 2009; this reflects a trend of consolidation in the brokerage industry. The average number of clients for a broker increases from 43 in 1995 to 106 in 2005. The brokerage industry is highly concentrated. The median broker has less than 10

[10] In most cases, I delete the observations where the average difference in TNA is larger than 15%.

clients in most years. In contrast, the top 10 brokers have 500 to 1000 clients. The largest three brokers typically have a business connection with 70% of all equity funds. Panel C of Table I presents the total incomes and numbers of clients for the top 10 brokers in 2007.

Panel B of Table I reports summary statistics for the equity funds examined in this paper. From 1995 to 2007, the number of equity funds increases from 606 to 1578. The average TNA of equity funds is about 1.3 billion in the last 10 years. The total assets under management of all equity funds peaked in 2007 at 2.4 trillion.

IV. The Performance Comparison between Covered and Uncovered Stocks

A. Benchmark Test

In this section, I try to answer one very basic question: Do sell-side analysts create value for their clients? One way to answer this question is to compare the performance of two groups of stocks held by funds. For the first group of stocks, fund managers have access to sell-side analysts' advice. For the second group of stocks, fund managers have to make independent trading decisions. If the first group outperforms the second one, sell-side analysts indeed benefit their clients.

Empirically, I first calculate "broker coverage" for each stock within every mutual fund's holdings. A stock's broker coverage is defined as the number of analysts covering this stock *and* working in one of the brokerage firms commissioned by this fund. This variable differs from analyst coverage, which is the total number of all analysts covering this stock. The broker coverage of any given stock varies across different funds. In N-SAR filings, mutual funds report the brokers that they have paid commissions to in the past six months. For each fund, I match the list of brokers commissioned by this fund with lists of the stocks that these brokers cover during the same period.[11] I am then able to count the number of brokers covering each stock held by this fund.

Next, I sort all stocks within a given mutual fund by their broker coverage. The top 10% of stocks are classified as "high coverage stocks" since most of them are covered by

[11] If a broker publishes any one-year or one-quarter EPS forecast for this stock, the stock is considered to be covered by this broker.

multiple sell-side analysts. The bottom 40% of stocks are classified as "low coverage stocks". The remaining 50% of stocks are classified as "medium coverage stocks".[12] I use bottom 40% rather than 10% as the threshold for low coverage stocks because many stocks are not covered or are only covered by one broker and it is hard to clearly identify the bottom 10% low coverage stocks.

Stocks in the high coverage group of each mutual fund are then aggregated together to form a portfolio, weighted by the total amount of money that all funds invest in these stocks ("holding-weighted"). This portfolio is rebalanced at the end of every quarter based on the latest fund holdings and is held for the next quarter. For example, suppose there are 100 mutual funds, and that each of them holds 200 stocks. At the end of every quarter, I sort the stocks of each fund by their recent broker coverage. The 20 most covered stocks of each fund are picked out to form a high coverage portfolio. Since funds' holdings may overlap, the number of stocks in the aggregated high coverage portfolio will be less than 2000. For instance, IBM may appear among the top 20 most covered stocks for multiple funds. I then sum up the total amounts that these funds invested in IBM as the weight for IBM in the high coverage portfolio. The low coverage and medium coverage portfolios are formed in a similar way. Using this methodology, I effectively mimic the aggregated mutual fund holdings with different broker coverage. Because I compare the stocks within each fund's holdings, I control for the stock picking skill of fund managers.

Panel A of Table II presents the characteristics of the stocks in the three coverage portfolios. In the low coverage portfolio, the average broker coverage is 0.7, while in the high coverage portfolio, it is 4.7. Because large stocks usually receive more attention, it is not surprising that stocks in the high coverage portfolio are about three times larger than the ones in the low coverage group. The average portfolio weight for stocks in the low coverage portfolio is 0.7%, lower than the 0.9% average portfolio weight for stocks in the medium and high coverage portfolios. Using the market portfolio as a benchmark, I compute the Active Share measure proposed by Cremers and Petajisto (2009) for the

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[12] In unreported tests, I try different portfolio thresholds: for example, labeling the top 20% of stocks with the highest broker coverage as the "high coverage stocks" and the bottom 30% or 50% of stocks as the "low coverage stocks". The results are quantitatively similar.

three portfolios; this measures the extent to which stocks' weights in these portfolios differ from their weights in a benchmark index. The average Active Shares for low and high broker coverage groups are 0.512 and 0.560 respectively, higher than the 0.297 for the medium broker coverage group. This suggests that both the low and high broker coverage portfolios are actively managed, but that the medium broker coverage portfolio is closer to the market portfolio.

Panel B of Table II, which examines the performance of the three portfolios, presents my first major finding. The first column reports excess returns over the risk-free rate. The average monthly return for the low coverage portfolio is 0.39% per month, as compared to 0.75% for the high coverage portfolio. The difference is 0.36% per month and is significant at the 5% level. The next four columns show the coefficients from a Fama-French four-factor regression. In general, there is no difference in the loadings on the market and momentum factors for the high and low coverage portfolios. Stocks in the high coverage portfolio are more likely to be growth stocks and large stocks, consistent with the summary statistics shown in Panel A. After controlling for risk, the pattern is clearer. The four-factor alpha for the high coverage portfolio is 0.31% and highly significant (t=2.97). The alpha for the low coverage portfolio is -0.20% (t=-3.07). The difference between these two portfolios is statistically significant (t=4.43) and economically large (0.51% per month or 6.3% per year). [13] The alphas estimated from the Fama-French three-factor model and the CAPM model and the DGTW adjusted returns are reported in the last three columns of Panel B, Table II. The pattern is quite similar. The high coverage portfolio significantly outperforms the low coverage portfolio. Overall, these results suggest that sell-side analysts do add value to fund managers; they help them choose better stocks.

Does the value added by analysts exceed the money they charge? Here is an approximate calculation. If we assume that half of the commissions are compensation for research services, then, from 1995 to 2009 equity mutual funds paid about 0.1% of their total assets under management (AUM) for sell-side research each year, on average. Meanwhile,

[13] Although it is not the focus of this paper, I also calculate the alpha for a tradable strategy, for which I require all information to be publicly accessible when the portfolios are formed. The alpha is 3.9% per year.

the top 10% high coverage stocks earn a 3.8% annualized alpha. Therefore, net of commissions they paid, mutual funds make an economic profit equal to 0.28% of their AUM.[14] In dollar terms, this is about 4.2 billion, based on the total AUM of mutual funds in 2009.

B. Mutual Holdings and Broker Coverage

The benchmark test results above show that high coverage stocks held by funds outperform the market. My interpretation of this is that analysts provide their clients with valuable services or information about these stocks; clients are therefore able to pick stocks that will outperform the market from this high coverage group. However, an alternative interpretation is that the information or services provided by analysts are irrelevant and that all high coverage stocks have superior performance relative to the market. First, broker coverage may coincide with stock characteristics that I have not controlled for and that could lead to better performance. Second, analysts are more likely to cover stocks they believe to have good prospects (McNichols et al. (1997)). If, on average, they are right, high coverage could predict higher stock returns.

Therefore, I need to show that only those high coverage stocks selected by fund managers, rather than all of them, have superior performance. To test this, I form portfolios in the same way as I do in the benchmark test, but weight stocks by their market capitalizations ("value-weighted") rather than by the aggregated mutual fund holdings ("holding-weighted"). If *all* high coverage stocks have superior performance, not just those selected by fund managers, the value-weighted high coverage portfolio should outperform the value-weighted low coverage portfolio. The four-factor alphas for the value-weighed portfolios are reported in the first column of Table III. As a comparison, I present the benchmark test results in the second column of Table III.

The table shows that, the alpha for the value-weighted high coverage portfolio is only 0.05% per month (t=1.37), much smaller than the 0.31% figure in the benchmark test. The alpha for the value-weighted long-short portfolio is only 0.06% per month (t=2.78). Although the coefficient is statistically significant, the magnitude is economically

[14] Here I assume the portfolio weight for the top 10% high coverage stocks is 10%.

negligible. The results suggest that fund managers' dynamic stock selection is the key here. Simply buying *all* high coverage stocks does not generate abnormal returns. By contrast, the high coverage portfolio in the benchmark test earns abnormal returns because fund managers, with the help of analysts, put more money on the right stocks at the right time. Broker coverage is a proxy for the amount of information and services that client funds can obtain from analysts, rather than a predictor of future stock performance.

To further explore this point, I divide stocks in the three coverage portfolios into two groups: stocks overweighted by funds and stocks underweighted by funds. If a stock's weight in the holding-weighted portfolios is larger than its weight in the market portfolio, this stock is considered to be "overweighted" by funds, and vice versa. For overweighted stocks, I adopt a "sophisticated" strategy: I weight them by their weights in the holding-weighted portfolios in excess of their weights in the market portfolio, i.e., by how much funds overweight in these stocks. For underweighted stocks, I adopt a "naïve" strategy: I weight them by their market capitalizations and do not employ any fund holdings information. Then, within each coverage portfolio, I compare the performance of stocks overweighted by funds with that of stocks underweighted by funds.

The third and fourth columns of Table III present results for underweighted and overweighted stocks. The alpha for the underweighted high coverage portfolio is -0.09% per month (t=-1.33). The alpha for the overweighted high coverage portfolios is 0.39% per month (t=2.53), which is even larger than the 0.31% figure in the benchmark test. Within high coverage stocks, the stocks overweighted by funds significantly outperform the stocks underweighted by funds. The difference in alpha is 0.48% per month (t=2.39). These results further confirm that analysts help clients pick better stocks; not all high coverage stocks have superior performance.

C. Robustness Checks

One alternative explanation for the benchmark test results is that analysts provide information to all mutual funds rather than only to their clients. Then, for stocks covered by multiple analysts— analysts who do not necessarily work for funds' own brokers— should outperform uncovered stocks. To test this hypothesis, I sort all stocks by analyst coverage, rather than by broker coverage, where analyst coverage is the total number of analysts who cover this stock. I form the three coverage portfolios in the same way as in the benchmark test. The results are shown in Panel A of Table IV. There is no significant performance difference between stocks with high and low analyst coverage. Analysts without a business connection to funds do not appear to be able to provide useful information.

As shown in Panel A of Table II, stocks in the high coverage portfolio are larger than stocks in the low coverage portfolio. It is possible that mutual fund managers spend more time collecting information for large stocks and are therefore able to pick better stocks in this group. Moreover, the average weights in funds' portfolios for high coverage stocks are higher than for low coverage stocks. It is possible that mutual fund managers spend more time collecting information for their most important holdings (e.g., Cohen, Polk, et al. (2010)). Fund managers therefore show better stock picking ability for high coverage stocks, even without any help from analysts. To test these two alternative explanations for the benchmark test results, I construct portfolios after controlling for size and portfolio weight. Every quarter, I first regress broker coverage on size in a cross-sectional regression. Then I use the residuals from the regression to sort stocks and form the portfolios. This procedure alleviates the potential bias created by stock size. The results are shown in Panel B of Table IV. The performance of the long-short portfolio is unchanged. The alpha is 0.47% per month (t=3.10) and is very close to the 0.51% figure in the benchmark test. Next I repeat this procedure using portfolio weights as the independent variable in the first-stage cross-sectional regression. The alpha of the long-short portfolio is 0.53% (t=4.50), which is again very similar to the benchmark results.

In Aug 2000, the SEC passed Regulation Fair Disclosure (Regulation FD), which requires that all publicly traded companies disclose material information to all investors at the same time. Before this regulation, firm managers often disclosed non-public materials to particular stock analysts. Regulation FD eliminates such selective disclosure. Analysts' ability to generate valuable information has been markedly reduced after Regulation FD (e.g., Gintschel and Markov (2004)). Correspondingly, the value added by sell-side research may also have decreased after Regulation FD. Hence it will be interesting to compare the results of conducting the main test above both before and after Regulation FD. This regulation change should not affect the alpha of the long-short portfolio if the performance difference between the high and low coverage portfolios comes from sources other than the information transmitted by analysts.

I therefore divide the sample into two subperiods: 1995-2000, the pre Regulation FD period and 2001-2009, the post Regulation FD period. The regression results are presented in Panel C of Table IV. There is no notable difference in factor loadings for the long-short portfolio before and after 2001. However, the four-factor alpha decreases after the regulation takes effect: before 2001, the alpha is 0.71% (8.9% annualized, t=3.73); after 2001, the alpha is reduced by half to 0.36% (4.4% annualized, t=3.86). The value created by analysts decreases with their ability to collect information. Nonetheless, even after Regulation FD, high broker coverage stocks still significantly outperform low broker coverage stocks. Sell-side analysts may be still able to justify the dollars paid to them. The results also shed some light on the source of value creation. If the value-added were due to an improvement in fund managers' skill, the performance difference would be unlikely to change dramatically after Regulation FD. The findings are therefore more consistent with the "private information transmission" explanation.

In summary, within mutual funds' holdings, stocks covered by funds' brokers significantly outperform uncovered stocks. The difference is statistically and economically significant. Only high coverage stocks picked by funds, rather than all high coverage stocks, outperform. The results are not driven by differences in stock size, portfolio weight, or analyst coverage. The evidence suggests that the information and services provided by sell-side analysts help fund managers make better investment decisions.

V. Value Creation Channel I: Early Awareness of Recommendation Changes

A. Benchmark Results

The results in Section IV suggest that sell-side analysts create value for their clients. But the value creation mechanism is still unclear. Here I adopt a "revealed information" approach. I compare client and non-client funds' trades before important informational events in order to infer the information that they have. Specifically, I test whether brokers' clients are more informed than non-clients before stock recommendation announcements.

A stock recommendation is a strong signal that an analyst releases to the market. In most analyst reports, stock recommendations appear as the conclusion of the analysis. Previous research shows that stock recommendations have price effects: favorable (unfavorable) changes in recommendations are accompanied by positive (negative) stocks returns at the time of their announcement. (e.g., Womack (1996). Hence fund managers can potentially make profits (or avoid losses) by trading ahead of recommendation announcements.

At the same time, stock recommendations are largely public information. They are frequently cited by public media and are systematically collected by large data providers, such as I/B/E/S and First Call. For example, of the recommendations recorded by I/B/E/S, 70% were announced and recorded by I/B/E/S on the same day. Even if recommendations contain valuable information, a fund manager can see a broker's recommendation even without paying that broker; indeed he can trade via other cheaper discount brokers. Hence, the information conveyed by recommendations is, by itself, insufficient to justify the money paid to analysts. As discussed in Section II, private communications between fund managers and analysts could instead be very important. Valuable information may be transmitted during their talks, or fund managers' skills may be improved through their discussions with analysts. Unlike recommendations, these interactions are restricted to brokers' clients. The purpose of the following test is to examine whether the private communications have information value, especially before recommendations are announced.

I face the disadvantage that mutual funds' trades are not directly observable; I have to infer them from funds' quarterly holdings data. The intra-quarter trades are therefore not captured by the data. But the time period between the moment when an analyst communicates with a client and the moment when she makes a public recommendation could be less than one quarter. Therefore, the results presented here may underestimate the true value of private communications. To alleviate this problem, I only examine recommendations that convey the strongest signals. By the definition of I/B/E/S, there are five categories of recommendations: strong buy, buy, hold, underperform, and sell. On the positive side, I only look at strong buy recommendations. On the negative side, I look at both underperform and sell.[15,16] In addition, since brokers often keep giving a stock the same recommendation, I only examine recommendation *changes*.[17,18]

For every strong buy, underperform, or sell recommendation, I divide mutual funds into two groups: client funds and non-client funds. Client funds are those that pay commissions to the broker issuing the recommendation. The remaining funds are classified as non-clients.[19] Trades are inferred from funds' position changes between two adjacent quarters. If a fund increases its holding in stock A,[20] it is considered to be buying. Similarly, a decrease in holdings corresponds to selling. For every stock recommendation, I check funds' trades in the recommended stock that occurred one to three months prior to the recommendation. For example, if Goldman Sachs issues a strong buy recommendation for IBM on July 7th, I examine trades on IBM stock that occurred between April and June. Most mutual funds report holdings at the end of the quarter, i.e., on June 30th, in this case. Hence I check their holding changes from March 31st to June 30th.

To measure the average trading direction of each of these two mutual fund groups, I construct the following two proxies:

$$Trade_{i,t} = \frac{(num\ of\ funds\ buy\ i - num\ of\ funds\ sell\ i)}{(num\ of\ funds\ buy\ i + num\ of\ funds\ sell\ i)}$$

[15] The number of negative recommendations is much lower than positive recommendations (Barber et al. (2007)), so I examine both underperform and sell.
[16] The results for buy and hold recommendations are qualitatively similar.
[17] A recommendation change could be the initial recommendation given by a broker to a stock for the first time, a recommendation that is different from the last one, or a recommendation that is issued at least 180 days after the last recommendation.
[18] Hereafter, I use "recommendation" and "recommendation change" interchangeably.
[19] Sometimes the same broker publishes two identical recommendations in the same quarter. In this case I only keep the first one. In some other cases, more than one broker publishes the same recommendation for the same stock in the same quarter. I combine the clients of these brokers together. In other words, if a fund is a client of any of these brokers, it will be identified as a "client". I use the issue date of the earliest of these recommendations as the event date.
[20] I have adjusted for stock splits and dividend payments.

$$POSCH_{i,t} = \sum_{j=1}^{n} \left(\frac{V_{i,j,t}}{TV_{j,t}} - \frac{V_{i,j,t-1}}{TV_{j,t-1}}\right) \times \frac{TV_{j,t}}{\sum_{1}^{n} TV_{k,t}},$$

where $V_{i,j,t}$ is the money that fund *j* invested in stock *i* at time *t*, and $TV_{j,t}$ is the total value of all equity positions of fund *j* at time t. $Trade_{i,t}$ is the number of funds buying stock *i* minus the number of funds selling stock *i*, divided by the total number of funds that trade stock *i* in quarter *t*. It ranges from -1 to 1 and measures the average trading direction of a mutual fund group. A high value of *Trade* implies more buying. The second measure, $POSCH_{i,t}$ (Position Change), is the value-weighted average change in portfolio weight in stock *i*. It measures not only the direction of trade, but also the quantity of trade. For each recommendation change, I calculate these two measures for the two fund groups and present the results in Table V.

Panel A of Table V presents the benchmark results of this section. The first column shows the number of stock recommendations. Consistent with previous research, the number of strong buy recommendations is much larger than the number of sell/underperform recommendations. The next two columns, Client and Non-client, show the means of the two measures, *Trade* and *POSCH*, for the two fund groups. The fourth column reports the difference between client and non-client groups. The fifth column presents the t-statistics for the difference. Before strong buy recommendations, the mean *Trade* measure is 0.106 for clients and 0.109 for non-clients. For underperform/sell recommendations, the mean is 0.028 for clients and 0.051 for non-clients. Both clients and non-clients buy more before a strong buy than before a sell/underperform. There is no significant difference between the trading direction of clients and non-clients before a strong buy. However, clients significantly sell more than non-clients (t=-2.81) before a sell/underperform recommendation. For the *POSCH* measure, clients again outperform non-clients. Before a strong buy recommendation, on average clients increase their portfolio weight in the stock by 0.025%, but non-clients only increase it by 0.013% (difference=0.012% and t=2.66). Before a sell or underperform recommendation, non-clients sell -0.013%, but clients sell more, namely -0.023% (difference=0.01% and t=2.01).

The results reveal several interesting patterns. First, all mutual funds are more likely to buy before a strong buy than before a sell/underperform, which means that clients and non-clients funds are both partially aware of the information to be released in future recommendations. Recommendation announcements usually accompany important firm or industry news. Funds may therefore infer the information from other sources. The second, and more interesting finding is that clients appear to be *more* informed than non-clients, i.e., they sell more than non-clients before underperform/sell recommendations and buy more before strong buy recommendations. Given that the stock price will strongly react to the recommendation change, selling (buying) in advance helps clients avoid losses (make profits).

Another interesting finding is that for the *Trade* measure, the difference between clients' trades and non-clients' trades is only significant before negative recommendations. This could be because negative recommendations are more informative than positive recommendations. The average price reaction to a negative recommendation is twice as large as to a positive recommendation.[21] Hence clients have more incentive to trade prior to negative recommendations.

B. Robustness Checks

If the differences in fund trades are motivated by the information that will be released in future recommendations, the effect should be more significant when the future signals are stronger. To test this implication, I do two tests. First, I examine the cross-sectional difference between large and small brokers. Large brokers' recommendations are considered more informative than small brokers'.[22] Hence client funds should trade more aggressively before large brokers' recommendations. Every quarter, I sort all brokers by the number of clients, and label the top 10% of brokers with highest number of clients as "large brokers" and the rest as "small brokers". The results for the two groups are shown in Panels B and C of Table V. In three of four tests, the results for large brokers are stronger than for small brokers.

[21] This result will be presented in the next section.
[22] I will show in the next section that the market reacts more to recommendations issued by large brokers.

Second, I use the time gap between the fund holding report date and the recommendation announcement date as an instrument for the informativeness of recommendations. Mutual fund trades are inferred from their holding changes and most funds report their holdings at the end of every quarter. Therefore the recommendations released in the first half of every quarter, compared to the ones released in the second half, are chronologically closer to the trades that can be observed by econometricians. Correspondingly, the information contained in these recommendations is more valuable to fund managers when they execute the trades. Therefore, I divide all recommendations into two groups depending on which half of the quarter the recommendations are released. The results are presented in Panels D and E of Table V. Consistent with the conjecture, the difference in trade between clients and non-clients is much stronger for first-half recommendations. In both this and the above tests, the difference between client and non-client trades is larger when recommendations are more informative. It is hard to explain this based on other non-informational reasons.

Finally, I look at differences among clients. Based on commissions paid by funds, I classify the top 10% of funds for each broker as "large clients" and the rest as "small clients".[23] The results are presented in Panel F of Table V. Before a strong buy, the mean of *Trade* is 0.099 for large clients, 0.088 for small clients and 0.082 for non-clients. Before a sell/underperform, the mean of *Trade* is -0.034 for large clients, 0.026 for small clients and 0.037 for non-clients. In both cases, large clients have an edge over small clients and non-clients. Since large funds on average underperform small funds (Chen et al. (2004)), these results are unlikely to be explained by large clients' information-collection ability. In contrast, they imply that analysts may treat their more important clients differently.

VI. **Value Creation Channel II: The Information beyond Recommendations**

A. Benchmark Test

The results of Section V suggest that brokers' clients may be aware of the information contained in recommendations before it is released to the public. In this section, I

[23] To ensure there is enough cross-sectional variation in commissions, I only examine brokers with at least 50 clients.

examine whether clients have incremental information beyond that contained in recommendations. Empirically, I test whether clients' trades before a recommendation announcement are able to predict post-recommendation stock performance, conditioning on the recommendation.

Traditionally, we assume that analysts' forecasts and recommendations represent their best estimates of future stock performance. However, recent research shows that conflicts of interest may result in analysts publishing biased recommendations. For example, they may issue inflated recommendations for their investment banking clients (e.g., Michaely and Womack (1999)). Also analysts could be overoptimistic because of career concerns (Hong and Kubik (2003)). The market understands this well: the average price reaction to a positive recommendation is much weaker than to a negative recommendation (Womack (1996)). If positive recommendations are noisy public signals, is it possible that analysts reveal more accurate private signals to their clients? Or, after their analytical skills have been improved through interactions with analysts, are clients able to distinguish biased recommendations?

Similar to the methodology adopted in Section V, I rely on mutual funds' trades to infer the information they have. For every strong buy recommendation, based on client funds' trades before the announcement, I calculate the *Trade* measure defined in the previous section. It is the proxy for the information client funds have. A higher *Trade* measure suggests that, on average, client funds have a more positive signal.[24] Next, I sort all stocks with a strong buy recommendation by the *Trade* measure. I put the top 50% of stocks with the highest *Trade* measures into a "high trade group" and the bottom 50% into a "low trade group". Stocks in the high trade group are generally stocks bought by clients before the recommendations, while stocks in the low trade group are generally stocks sold by clients before the recommendations. For the two groups, I do an event study analysis to examine their performance over the 120 days starting on the announcement day. Performance is measured in the way proposed by Daniel et al. (1997)

[24] To reduce noise, I exclude observations with less than three fund transactions. The results are similar if I vary this threshold.

(DGTW).[25] I calculate the value-weighted average returns for the high and low trade groups for different periods: the announcement day (day 0), day 1 to day 30, day 1 to day 60, day 1 to day 90, and day 1 to day 120.[26] I also calculate the differences between the two groups and the corresponding t-statistics.

The main results of this test are presented in Panel A of Table VI and are plotted in Figure IV. Consistent with previous research (e.g., Womack (1996)), both the high and low trade groups have high positive abnormal returns on the announcement day. There is almost no difference between the returns of the two groups on the announcement day. But surprisingly, from day 1 to 60, the high trade group begins to outperform the low trade group. 90 days after the announcement, the cumulative return difference between the high trade group and the low trade group is 1.39% (t=2.30, 5.67% annualized). After 120 days, the cumulative difference grows to 1.78% (t=2.42, 5.44% annualized), which is both statistically and economically significant. Comparing the total performance of the two groups from day 0 to day 120, the high trade group on average earns a 2.23% abnormal return (t=4.59), but the low trade group only earns an insignificant abnormal return of 0.41% (t=0.94). This suggests that the high and low groups are two different kinds of strong buy: one kind is "real" strong buy, which predicts a high abnormal return, and the other kind is "noisy" strong buy, which predicts an insignificant abnormal return. The difference is not a temporary effect. From day 1 to day 210, there is still a 1.5% cumulative return difference between the high and low trade groups. The results do not reverse in the long term.

Panel A of Table VI also reports results for underperform and sell recommendations. The average abnormal return on the announcement day is -2.18% for the high trade group and -1.63% for the low trade group. The market reaction to a negative recommendation is about twice as large as to a positive recommendation. The average cumulative abnormal return from day 0 to day 120 is -1.74% (t=2.30) for the high trade group and -1.42% (t=2.00) for the low trade group. Both groups earn negative abnormal returns after the

[25] Specifically, all stocks are sorted into 125 portfolios based on B/M, size and past one year return. The abnormal return for stock i is defined as the difference between the return of stock i and stock i's benchmark portfolio return.
[26] More precisely, the weight is each stock's market capitalization before the announcement day.

announcement, and there is no significant difference between the performance of the two groups (difference=0.31% and t=0.31).

The results in Panel A reveal two interesting patterns. First, stocks bought by clients before strong buy recommendations significantly outperform stocks sold by clients. In other words, clients' trades predict stocks' post-recommendation performance. This implies that clients may have extra information beyond what is revealed by the recommendation. Second, on the announcement day, there is no performance difference between two groups. The market is unable to distinguish the two types of strong buy when recommendations are released: price appreciation on the announcement day only reflects the market's unconditional expectation. It takes as long as three months for market prices to reflect all the information.

Why is there no performance difference between the high and low trade groups after a negative recommendation? It may be that, since analysts are reluctant to give a negative recommendation, most sell recommendations are "real". As shown in Section V, before a negative recommendation, clients significantly sell more than non-clients, but the difference is weaker before a strong buy recommendation. Clients may react differently to positive and negative recommendations. Since not every strong buy is truly good news, clients only buy before "real" strong buy recommendations. On the other hand, sell recommendations are consistently bad news. Clients are more likely to indiscriminately sell all of those stocks before the announcements.

B. Robustness Checks

First, as a placebo test, I examine whether the trades of non-clients have the same predictive power that clients' trades do. I repeat all of the above analysis using non-clients' *Trade* measure. The results are shown in Panel B of Table VI and plotted in Figure IV. For strong buy recommendations, the abnormal returns for the high and low trade groups are very similar: there is no significant performance difference in any of the time periods. I do not detect any performance difference between the two groups for sell/underperform recommendations either. Overall, there is no evidence that trades of non-client mutual funds can predict the performance of a stock after a recommendation announcement. Therefore, the above results for clients' trades cannot be explained by mutual funds' general information collection ability. The broker-client relationships are central to these results.

Panel C of Table VI repeats the benchmark test in the previous subsection for large brokers and small brokers. There are three results worth noting. First, as mentioned before, the market reacts more to recommendations issued by large brokers than to those issued by small brokers on the announcement day. Second, for both large and small brokers, the high trade group outperforms the low trade group. Third, similar to the results in Section V, the effect is stronger for large brokers.

Finally, in the benchmark test, I use market capitalization as the weight when I calculate average returns. But since the events I am studying happen at different times, these capitalizations may not be directly comparable. Hence, I replace market capitalization with market capitalization share, which is defined as a stock's market capitalization divided by the total market capitalization, and repeat the benchmark test. The results are reported in Panel D of Table VI. The main results do not change using this new weighting scheme. The high trade group still outperforms the low trade group by 1.63% (t=2.44) over the 120 days after an announcement. The low trade group's day 0 to day 120 abnormal return is 0.48% and is insignificant (t=1.17).

C. Calendar-time portfolios

In this section, I examine the performance of calendar-time portfolios. Because the cutoff point for the *Trade* measure is not known *ex ante*, I use a simple rule of thumb to determine the threshold. For every strong buy recommendation, if clients' *Trade* measure is larger than 0, I add this stock to the high trade portfolio and if the *Trade* measure is below 0, I add it to the low trade portfolio. The stocks are held from 30 days to 90 days after the announcement and are weighted by their market capitalizations before the recommendation.[27] I rebalance the two portfolios whenever a new stock is added or deleted. The four-factor time-series regression coefficients and the intercepts from the

[27] I exclude the first 30 days to avoid the influence of delayed reactions to the announcement and the influence of short-term reversals.

Fama-French three-factor and CAPM models are presented in Panel A of Table VII. In Panel B of Table VII, I repeat all tests using non-clients' *Trade* measure and report the results.

The high trade portfolio constructed based on clients' *Trade* measure earns an annualized 5.13% alpha (t=2.21). The low trade portfolio earns an annualized alpha of -1.77% (t=-0.64). The annualized alpha of the long-short portfolio is 6.99% (t=1.93). The annualized alpha of the long-short portfolio based on non-clients' *Trade* is -1.98% and insignificant (t=-0.66). All of these results are consistent with the findings of the benchmark test.

VII. Further Tests

A. Industry or Firm Level Information

Sell-side analysts usually provide two kinds of information to their clients: industry-level information and firm-level information. It is therefore worth checking which kind of information, industry or firm level, is more valuable for fund managers. To decompose the information into two parts, I repeat the performance comparison test for covered and uncovered stocks in Section IV but replace stock returns with industry-adjusted returns. If analysts only provide industry-level information to their clients, there should be no performance difference between the high and low coverage portfolios when I use industry-adjusted returns. The industry-level information will be captured by the industry return adjustment.

Industries are defined as in Fama and French (1997). For each of the 48 industries, I calculate its value-weighted return as a benchmark. The industry-adjusted return is the individual stock return in excess of its industry benchmark return. All portfolios are formed in the same way as in Section IV. The regression results are shown in Table VIII. The industry-adjusted alpha of the long-short portfolio is 0.32% (t=3.80). This is still significant but is smaller than the 0.51% figure in the benchmark test. It suggests that about 60% of the value added by analysts can be attributed to firm-level information and the remaining 40% to industry-level information.

B. Endogenous Broker Choices

Brokers are chosen by funds. Funds' endogenous broker choices may reflect their specialty, i.e., a fund may tend to choose brokers who cover the industries that it focuses on. Meanwhile, this fund may spend more time than other funds researching these industries. Within this fund, the manager may also allocate more energy to these industries as compared to other industries. Therefore, it is possible that, even if brokers do not provide any information or services to their clients, we may still observe that client funds are more informed than non-client funds and that high coverage stocks outperform low coverage stocks.

To examine this possibility, I conduct the following experiment. First, I identify industries in which funds have a specialty. For each fund, I calculate its average relative industry portfolio weights for all industries over the previous three years. The relative weight is a fund's portfolio weight in an industry in excess of this industry's market weight. The top 20% of industries with the highest average relative portfolio weight are labeled "overweighted" industries. I then repeat the performance comparison test from Section IV.A, but exclude any fund position if the stock belongs to this fund's overweighted industries. This procedure removes about one-third of fund positions from the sample. Simply put, I have excluded stock positions for which funds could be considered to have special knowledge. The results are presented in Panel A of Table IX. The high coverage portfolio still significantly outperforms the low coverage portfolio. The magnitude and significance of the alpha are similar to those in the benchmark test.

Next, for every stock recommendation, I exclude any fund from the calculation of the *Trade* measure if the stock is in one of this fund's "overweighted" industries.[28] Using the new *Trade* measure, I repeat the main tests from Section V in Panel B of Table IX. As with the results in Panel A of Table V, clients sell significantly more than non-clients before negative recommendations. Panel C of Table IX repeats the tests of Panel A of Table VI. Stocks bought by clients before strong buy recommendations still significantly outperform stocks sold by clients. In other words, my results are robust to controlling for funds' particular expertise.

[28] I do not examine the *POSCH* measure here because only stocks with low relative portfolio weight are kept in the test. Since the *POSCH* measure is based on portfolio weight changes, this test may bias the estimation of *POSCH*.

Another way to address the endogeneity problem is to compare client funds with non-client funds for which at least one of their brokers covers the stock that receives a recommendation. Note that funds in both groups have chosen to hire brokers who cover this stock. The only difference is whether their brokers release a new recommendation in the next quarter, in other words, whether their brokers bring new information to the market. The results are presented in Table X. Consistent with the benchmark results, clients sell more before a negative recommendation as compared to non-clients. And trades of these covered non-clients still cannot predict future stock performance. Combined with the findings of Tables IX and X, these results suggest that funds' endogenous broker choices are unlikely to explain the value added by analysts and information advantage of clients that I document in the previous tests.

C. The Sources of Value Creation

As I mentioned in the Introduction, there are two possible sources of the value created by analysts. The first is that analysts transmit valuable private information to their clients; the second is that analysts help their clients to improve their analytical skills. Most of the test results in this paper are consistent with both explanations. But two pieces of evidence are more in line with the "private information transmission" explanation.

First, as shown in Section IV.C, the performance difference between the high and low coverage portfolios decreases by half after the introduction of Regulation FD. Regulation FD reduces analysts' ability to obtain information from firm managers, and thereby reduces the information that analysts can transmit to their clients, but it does not prevent analysts from helping clients improve their analytical skills. Hence, the decrease in the performance difference after Regulation FD supports the "private information transmission" hypothesis.

Second, in the previous subsection, Section VII.B, I show that funds whose brokers issue a new stock recommendation in the next quarter are more informed than funds whose brokers do not issue a new recommendation, conditioned on both groups of funds having hired at least one broker covering this stock. The only difference between the two fund groups is whether funds' brokers issue a new recommendation in the next quarter. If client funds' information advantage comes from improved analytical skill, the skill should be persistent and is unlikely to be changed by one stock recommendation. However, if client funds' information advantage comes from the private information transmitted by their analyst, the advantage largely depends on whether the analyst has new information, which is in turn reflected by whether the analyst issues a new recommendation in the next quarter. Therefore, the results of Section VII.B are also more consistent with the "private information transmission" explanation.

VIII. **Conclusion**

This paper examines the sell-side research industry from the perspective of investors. I use a rich dataset which allows me to link the signals released by analysts to the transactions conducted by mutual funds. The results show that, conditioning on each fund manager's information set, analysts help fund managers to pick stocks that perform significantly better; in other words, analysts add significant value to their clients. There are at least two channels through which this may happen. First, with analysts' help, clients may become aware of the likely information contained in a recommendation before this is known by other market participants. Second, clients may be able to distinguish noisy from real recommendations. The information advantage of clients may be due to analysts transmitting private information to them or to analysts helping them improving their analytical skills. Some indirect evidence is more consistent with the private information transmission explanation. Overall, the paper provides a way of understanding the existence and size of the sell-side research industry.

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Figure I

This figure plots the total commission fees (in thousands of dollars) reported by all mutual funds filed an N-SAR, and by equity mutual funds, from 1995 to 2009. The definition of equity funds is discussed in Section III.A.

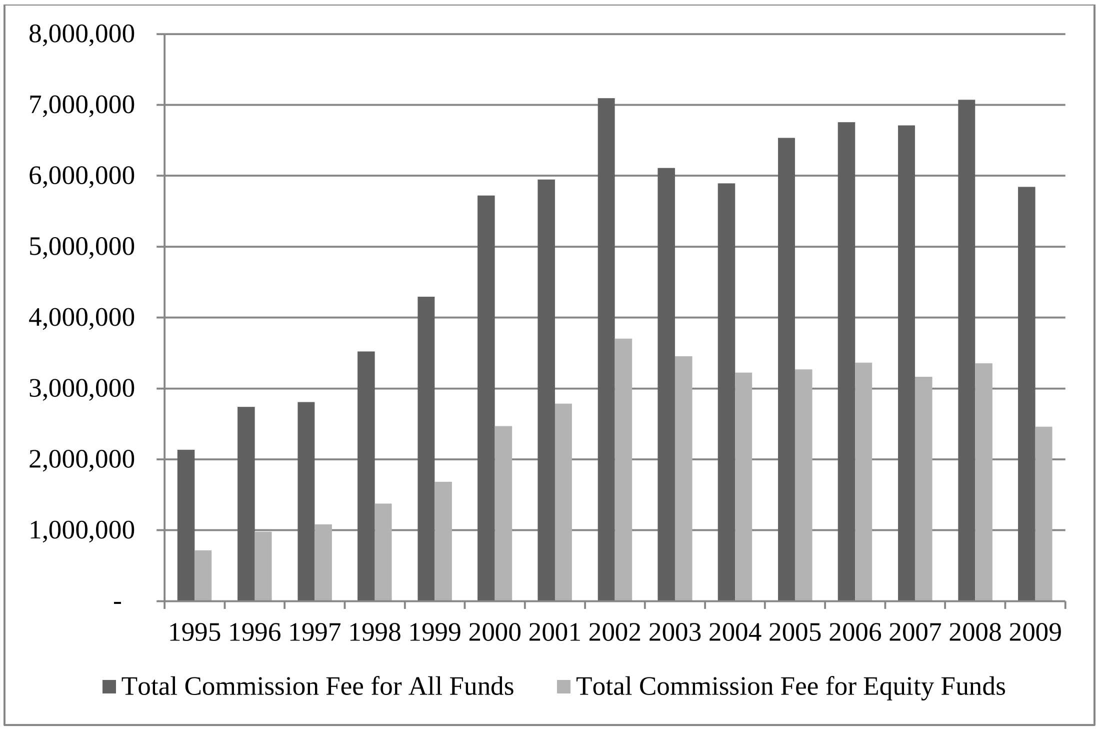
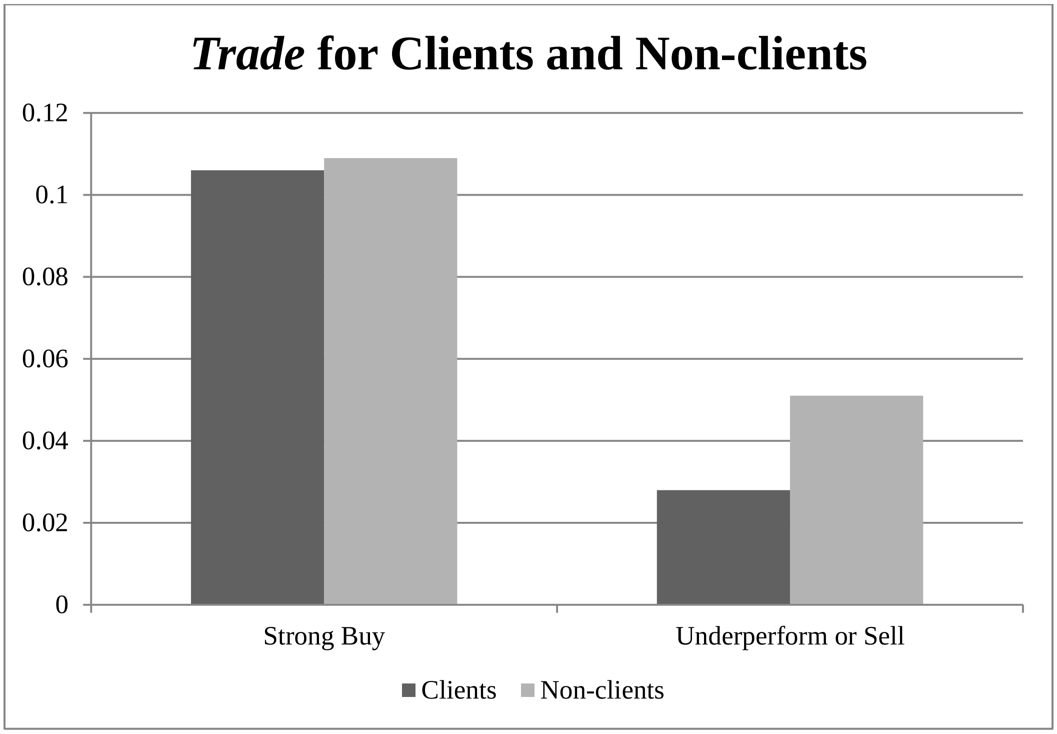


Figure II

This figure plots the *Trade* and *POSCH* measures for two different fund groups: clients and non-clients. The *Trade* and *POSCH* measures are defined in Section V. Client funds are those that pay commissions to the broker that makes the recommendation. The remaining funds are non-client funds.



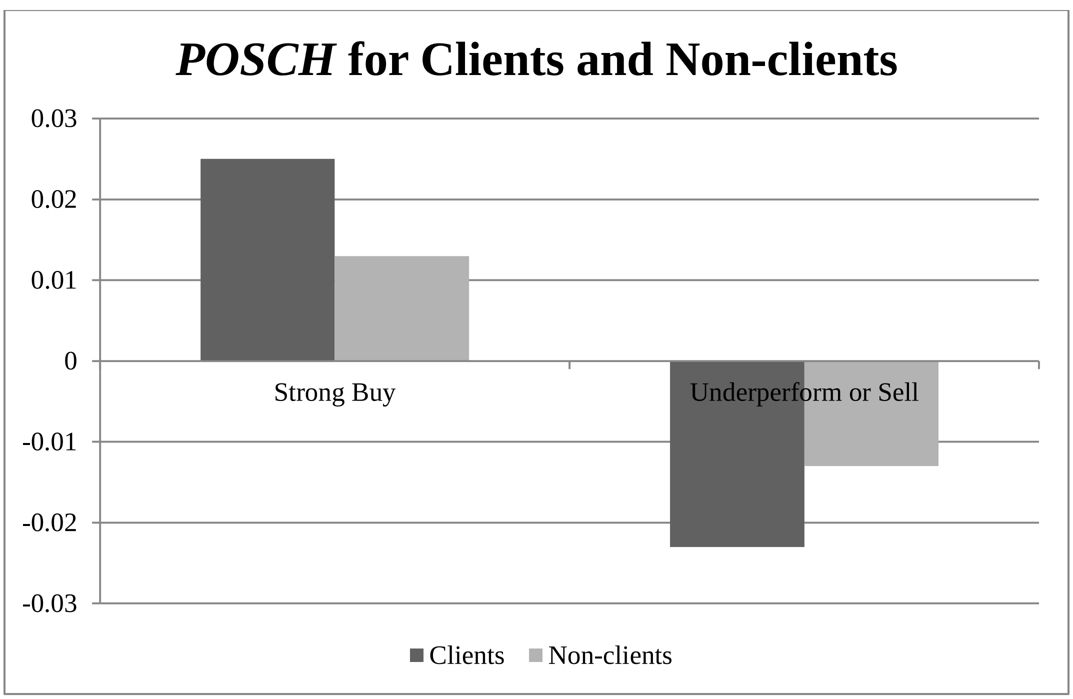


Figure III

This figure plots the *Trade* and *POSCH* measures for three different fund groups: Large clients, small clients and non-clients. The *Trade* and *POSCH* measures are defined in Section V. Client funds are those that pay commissions to the broker which makes the recommendation. The remaining funds are non-client funds. Among clients, for each broker, the top 10% of funds paying the highest commissions are defined as large clients and the remaining clients are defined as small clients.

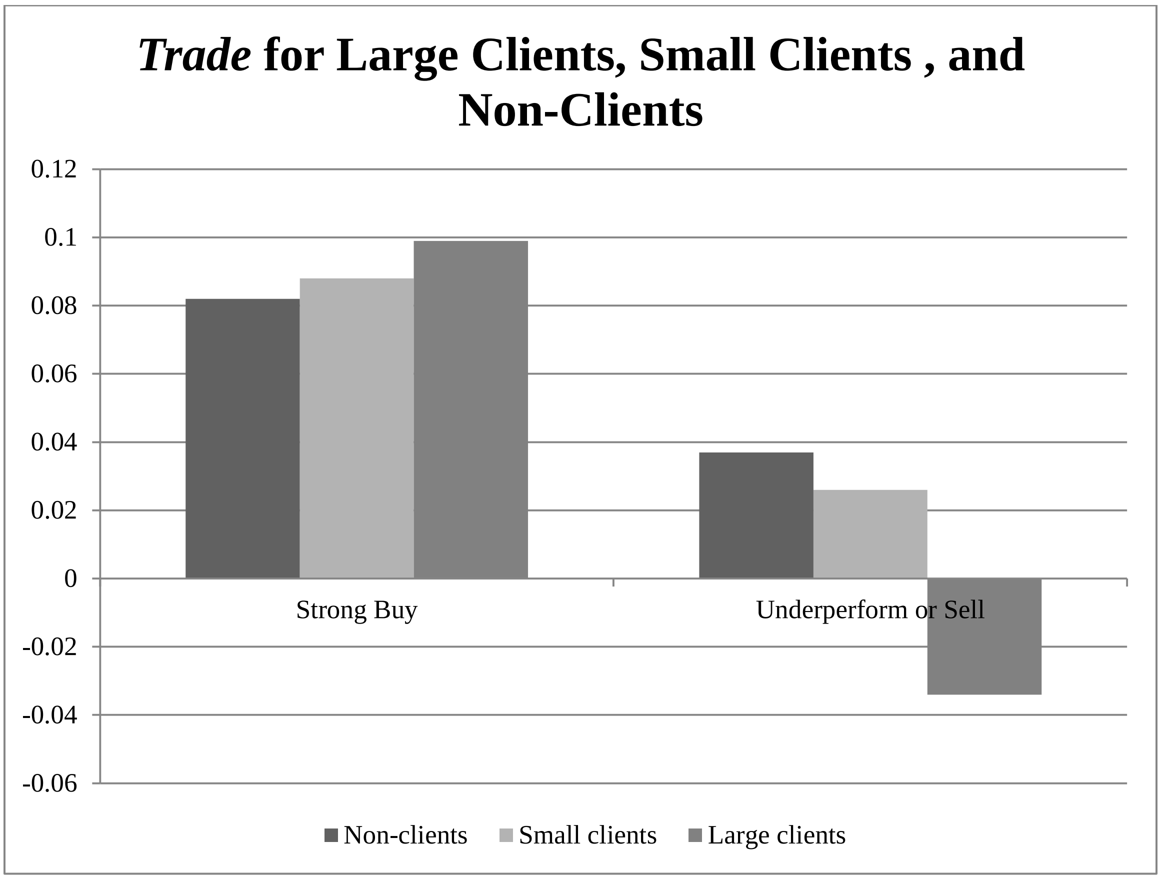


Figure IV

This figure presents abnormal returns on the recommendation announcement day and post-recommendation cumulative abnormal returns for four groups of stocks that receive a strong buy recommendation. Based on clients' *Trade* measure, all stocks with a strong buy recommendation are evenly divided into two groups. Stocks in the "Client Buy" group are generally these bought by clients before announcements. Stocks in the "Client Sell" group are generally these sold by clients before announcements. Similarly, I define the "Non-client Buy" and "Non-client Sell" groups based on non-clients' *Trade* measure. *Trade* measure is defined in Section V. The abnormal return for stock *i* is defined as the difference between the return of stock *i* and the return of the benchmark portfolio it belongs to. There are 125 benchmark portfolios and each stock is matched to one of them based on its size, BM and one year past return (Daniel et al. 1997). The average returns are weighted by stocks' capitalization before the recommendations.

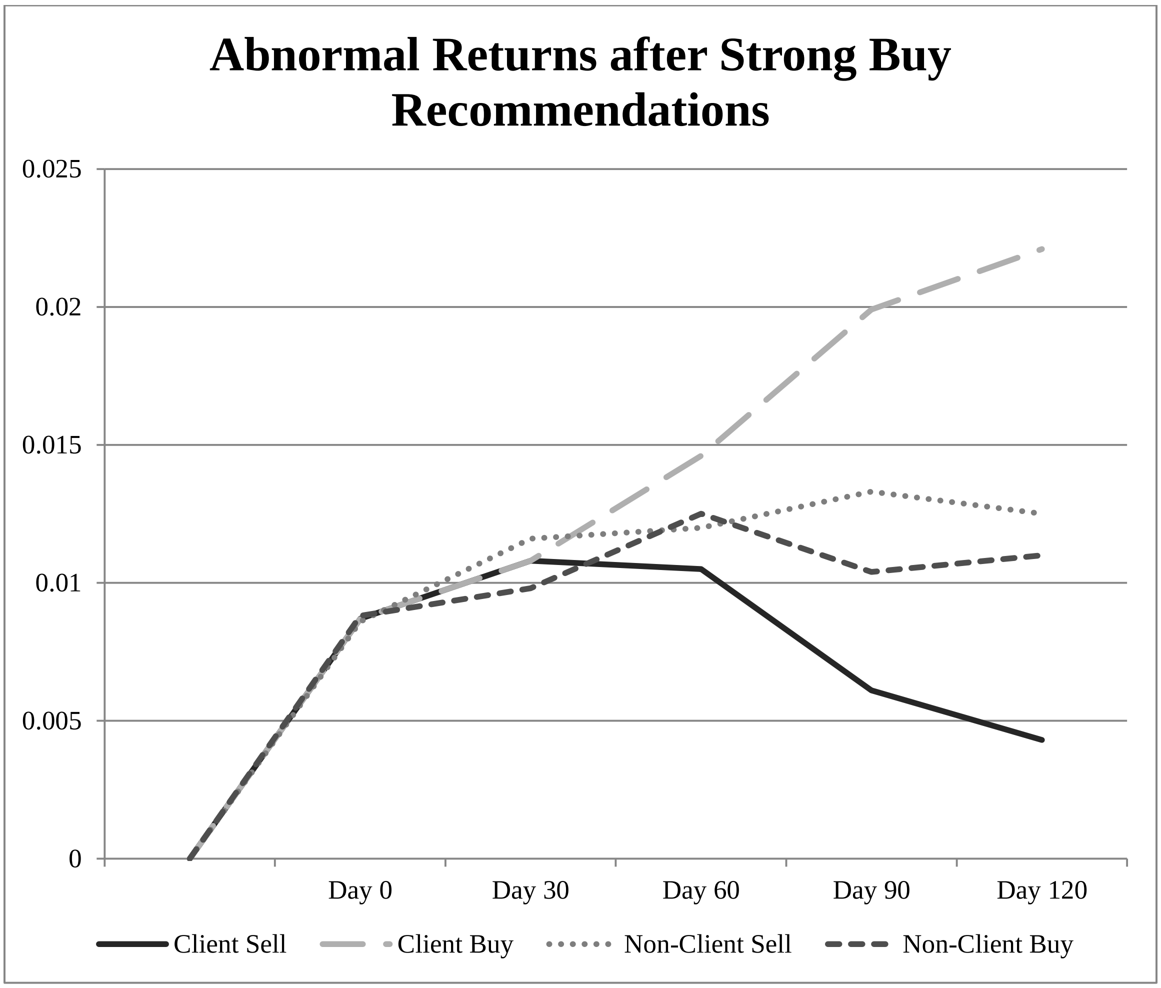


Table I

The table reports summary statistics for the brokerage firms and equity mutual funds examined in the paper. Panel A summarizes the annual commission incomes (in thousands of dollars) and the number of mutual fund clients for brokerage firms that have at least one equity fund client. Panel B presents the number, the average total net assets (TNA) (in millions of dollars), and the sum of TNA for all equity mutual funds. Panel C shows the top 10 largest brokerage firms in terms of commission income (in millions of dollars) in 2007.

Panel A: Summary Statistics for Brokerage Firms

		Num. Of Obs.	Mean	Std. Dev.	P25	P50	P75	P90
1995	Commission Income	194	3,695	11,819	34	199.5	1,195	7,235
	Num. of Clients		43	102	2	6	26	107
2000	Commission Income	187	13,205	48,863	54	239	1,732	12,109
	Num. of Clients		85	231	3	8	33	204
2005	Commission Income	174	18,795	66,646	55	244	1,646	15,691
	Num. of Clients		106	299	3	9	37	178
2009	Commission Income	143	17,192	58,600	74	417	3,078	12,938
	Num. of Clients		89	225	4	12	42	190

Panel B: Summary Statistics for Equity Mutual Funds (End-of-Year)

Year	Num.	TNA, Mean	TNA, Sum
1995	606	744	451,010
2000	1266	1,162	1,471,670
2005	1480	1,339	1,978,538
2007	1578	1,537	2,425,172
2009	1110	1,370	1,519,353

Panel C: Top 10 Brokerage Firms in 2007			
Broker Name	Total Commission Fee income	Num. of Clients	Clients as % of All Funds
MERRILL LYNCH	398	1427	79%
GOLDMAN SACHS	362	1210	67%
LEHMAN BROTHERS	337	1358	75%
CREDIT SUISSE	307	1206	67%
CITIGROUP	288	1356	75%
UBS	261	1162	64%
MORGAN STANLEY	254	1165	65%
J.P. MORGAN	192	1077	60%
BEAR STEARNS	164	1156	64%
DEUTSCHE BANK	116	737	41%

Table II

This table presents a performance comparison between stocks with high and low brokerage coverage. For each stock held by each fund, broker coverage is defined as the number of analysts covering this stock and working in one of the brokerage firms commissioned by the fund. All stocks held by the fund are sorted by broker coverage. The top 10% of stocks are put into a "high broker coverage" portfolio and are weighted by the total amount of money that all mutual funds invest in these stocks. Similarly, the bottom 40% are put into a "low broker coverage" portfolio while the remaining are put into a "medium broker coverage" portfolio. Panel A shows summary statistics for the three brokerage coverage portfolios. Panel B shows excess returns, Fama-French four-factor regression coefficients, and intercepts from Fama-French three-factor and CAPM models. Newey-West adjusted t-statistics are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary Statistics for Broker Coverage Sorted Groups

Broker Coverage Portfolio	Mean of Broker Coverage	Std. Dev. of Broker Coverage	Mean of Capitalization (in millions of dollars)	Std. Dev. of Capitalization (in millions of dollars)	Mean of Portfolio weight	Std. Dev. of Portfolio weight	Active Share	Std. Dev. of Active Share
Low	0.7	1.3	7,417	27,948	0.007	0.010	0.512	0.020
Medium	2.4	2.2	17,903	45,276	0.009	0.012	0.297	0.032
High	4.7	2.3	23,448	49,679	0.009	0.013	0.560	0.056

Panel B: Portfolio Performance for High and Low Broker Coverage Groups, Weighted by Aggregated Fund Holdings

Broker Coverage Portfolio	Excess Return	MKT	HML	SMB	UMD	Four-Factor Alpha	Three-Factor Alpha	CAPM Alpha	DGTW Adjusted
Low	0.0039	1.0424	0.085	0.1545	0.0109	-0.0020	-0.0019	-0.0013	-0.0008
	(0.9)	(57.19***)	(2.99***)	(4.38***)	(0.52)	(-3.07***)	(-2.83***)	(-1.57)	(-1.52)
Medium	0.0046	1.0731	-0.0439	-0.0177	0.0027	-0.0004	-0.0004	-0.0006	0.0001
	(1.08)	(74.75***)	(-2.93***)	(-0.74)	(0.23)	(-0.75)	(-0.74)	(-1.11)	(0.29)
High	0.0075	1.0683	-0.2067	-0.0795	-0.0005	0.0031	0.0031	0.002	0.0023
	(1.61)	(41.87***)	(-6.64***)	(-1.90*)	(-0.03)	(2.97***)	(2.91***)	(1.54)	(2.59**)
High-Low	0.0036	0.0258	-0.2917	-0.2341	-0.0115	0.0051	0.005	0.0033	0.0031
	(2.08**)	(1.03)	(-6.13***)	(-5.39***)	(-0.44)	(4.43***)	(4.13***)	(1.90*)	(3.01***)

Table III

This table reports the alphas of a Fama-French four-factor model for different broker coverage portfolios and the long-short portfolio. As in the method adopted in Panel B of Table II, for each fund, I sort stocks held by one fund by their broker coverage. The top 10% of stocks with the highest broker coverage of each fund are put into a “high broker coverage” portfolio; the bottom 40% are put into a “low broker coverage” portfolio and the remaining stocks are put into a “medium broker coverage” portfolio. Unlike Panel B of Table II, in the first column of this table, stocks are weighted by their market capitalization. The second column of this table replicates the results of Panel B of Table II, in which stocks are weighted by aggregated mutual fund holdings. In the third column, I keep only stocks whose weights in the aggregated mutual fund holding portfolios are smaller than their weights in the market portfolio. For these underweighted stocks, I weight them by their market capitalization. In the fourth column, I keep only stocks whose weights in the aggregated mutual fund holding portfolios are larger than their weights in the market portfolio. For these overweighted stocks, I weight them by their weights in the aggregated mutual fund holding portfolios in excess of their weights in the market portfolio. The fifth column shows the performance difference between over- and underweighted stocks. The Newey-West adjusted t-statistics are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Broker Coverage Group	Value-weighted	Holding-Weighted	Underweighted by Funds	Overweighted by Funds	Over minus Under
Low	-0.0001	-0.0020	0.0007	-0.0024	-0.0032
	(-0.65)	(-3.07***)	(1.59)	(-2.60**)	(-2.52**)
Medium	0.0000	-0.0004	0.0003	-0.0012	-0.0015
	(-0.06)	(-0.75)	(0.48)	(-0.91)	(-0.81)
High	0.0005	0.0031	-0.0009	0.0039	0.0048
	(1.37)	(2.97***)	(-1.33)	(2.53**)	(2.39**)
High-Low	0.0006	0.0051	-0.0016	0.0064	0.0080
	(2.78***)	(4.43***)	(-2.79***)	(4.19***)	(4.09***)

Table IV

This table reports robustness checks for the performance comparison between high and low broker coverage stocks. In Panel A, I sort all stocks by their analyst coverage. Analyst coverage is the total number of analysts covering the stock. I long the top 10% of stocks with the highest analyst coverage, short the bottom 40% of stocks with the lowest analyst coverage and weight them by the total amounts of money that all mutual funds invest in these stocks. Panel B presents two robustness checks. First, at the end of every quarter, I regress broker coverage on stock size in a cross-sectional regression. Then I sort stocks and form portfolios by the residuals from the regression. The results are reported in the first row of Panel B. Similarly, I regress broker coverage on stocks' portfolio weights in each fund, and use the residuals to form portfolios. The results are reported in the second row of Panel B. Panel C repeat the benchmark test in Panel B of Table II in two subsamples: 1995-2000 and 2001-2009. The Newey-West adjusted t-statistics are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Long-Short Portfolio Performance, Sorted by Analyst Coverage

	MKT	HML	SMB	UMD	Four-Factor Alpha	Three-Factor Alpha	CAPM Alpha
Analyst Coverage	0.0369	-0.28	-0.8968	-0.175	0.0008	-0.0011	-0.0035
	(0.93)	(-5.83***)	(-17.22***)	(-3.91***)	(0.60)	(-0.68)	(-1.16)

Panel B: Long-Short Portfolio Performance, Sorted by Residuals

	MKT	HML	SMB	UMD	Four-Factor Alpha	Three-Factor Alpha	CAPM Alpha
Size Residuals	0.0693	-0.0697	-0.0044	-0.0812	0.0047	0.004	0.0038
	(1.77*)	(-1.26)	(-0.08)	(-2.17**)	(3.10***)	(2.66***)	(2.64***)
Portfolio Weight Residuals	0.0224	-0.1195	-0.0909	-0.1013	0.0053	0.0044	0.0038
	(0.76)	(-2.98***)	(-2.30**)	(-4.35***)	(4.50***)	(3.59***)	(3.01***)

Panel C: Long-Short Portfolio Performance, Subsamples before and after Regulation FD

	MKT	HML	SMB	UMD	Four-Factor Alpha	Three-Factor Alpha	CAPM Alpha
1995-2000	-0.0810	-0.4836	-0.3699	0.0204	0.0071	0.0075	0.0052
	(-1.34)	(-3.45***)	(-5.44***)	(0.28)	(3.73***)	(3.45***)	(1.34)
2001-2009	0.0000	-0.224	-0.1535	-0.0341	0.0036	0.0036	0.0017
	(0.00)	(-5.99***)	(-4.13***)	(-1.67*)	(3.86***)	(3.71***)	(1.35)

Table V

This table compares client fund trades with non-client fund trades before recommendations announcements. For every strong buy, underperform, or sell recommendation, I divide all mutual funds into two groups. Client funds are those that pay commissions to the broker which makes the recommendation. The remaining funds are non-client funds. *Trade* and *POSCH* are defined in Section V. For both negative and positive recommendations, the number of observations, and the mean and standard error of the two measures for two fund groups are reported. Their difference and corresponding t-statistics are presented in the last two columns. Panel A shows the results for the whole sample. Panels B and C report the results for large and small brokers, respectively. Large brokers are the top 10% of brokers with the highest commission incomes. The rest are small brokers. Panels D and E show the results for recommendations issued in the first and second half of each quarter, respectively. Panel F reports results for large and small clients. Large clients are the top 10% of funds paying the highest commissions. The remaining are small clients. Standard errors are clustered by year-month and are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fund Trades Before Recommendations, Benchmark Test

	Recommendation	No. of Obs.	Clients	Non-clients	Difference	t Statistics
Trade	Strong Buy	17296	0.106	0.109	-0.002	-0.43
			(0.007)	(0.006)	(0.006)	
	Underperform or Sell	8349	0.028	0.051	-0.022	-2.81***
			(0.009)	(0.008)	(0.007)	
POSCH	Strong Buy	17115	0.025	0.013	0.012	2.66***
			(0.004)	(0.002)	(0.004)	
	Underperform or Sell	8319	-0.023	-0.013	-0.01	-2.01**
			(0.005)	(0.003)	(0.005)	

Panel B: Fund Trades Before Recommendations, Large Brokers

	Recommendation	No. of Obs.	Clients	Non-clients	Difference	t Statistics
Trade	Strong Buy	12059	0.116	0.114	0.001	0.27
			(0.008)	(0.007)	(0.006)	
	Underperform or Sell	6507	0.027	0.051	-0.023	-2.86***
			(0.008)	(0.008)	(0.008)	
POSCH	Strong Buy	11947	0.020	0.014	0.005	1.24
			(0.004)	(0.003)	(0.004)	
	Underperform or Sell	6481	-0.024	-0.013	-0.011	-2.77***
			(0.004)	(0.003)	(0.004)	

Panel C: Fund Trades Before Recommendations, Small Brokers						
	Recommendation	No. of Obs.	Clients	Non-clients	Difference	t Statistics
Trade	Strong Buy	5227	0.083	0.097	-0.014	-1.13
			(0.012)	(0.006)	(0.012)	
	Underperform or Sell	1842	0.033	0.051	-0.017	-0.82
			(0.024)	(0.01)	(0.021)	
POSCH	Strong Buy	5198	0.036	0.009	0.027	2.39**
			(0.011)	(0.002)	(0.011)	
	Underperform or Sell	1838	-0.020	-0.013	-0.007	-0.38
			(0.018)	(0.004)	(0.018)	

Panel D: Fund Trades Before Recommendations, First Half of Each Quarter						
	Recommendation	No. of Obs.	Clients	Non-clients	Difference	t Statistics
Trade	Strong Buy	11859	0.109	0.105	0.004	0.53
			(0.009)	(0.008)	(0.007)	
	Underperform or Sell	5131	0.016	0.048	-0.031	-3.25***
			(0.012)	(0.011)	(0.009)	
POSCH	Strong Buy	11789	0.026	0.012	0.014	2.66***
			(0.005)	(0.003)	(0.005)	
	Underperform or Sell	5119	-0.031	-0.013	-0.017	-2.56**
			(0.007)	(0.004)	(0.006)	

Panel E: Fund Trades Before Recommendations, Second Half of Each Quarter						
	Recommendation	No. of Obs.	Clients	Non-clients	Difference	t Statistics
Trade	Strong Buy	5437	0.099	0.117	-0.017	-1.62
			(0.01)	(0.007)	(0.01)	
	Underperform or Sell	5366	0.047	0.055	-0.007	-0.61
			(0.01)	(0.009)	(0.013)	
POSCH	Strong Buy	3218	0.023	0.015	0.007	0.85
			(0.008)	(0.004)	(0.009)	
	Underperform or Sell	3200	-0.011	-0.012	0.000	0.10
			(0.007)	(0.004)	(0.007)	

	Recommendation	No. of Obs.	Non-clients	Small clients	Large clients	Large-Non	t Statistics	Large-Small	t Statistics
Panel F: Fund Trades Before Recommendations, Large and Small Clients									
Trade	Strong Buy	7709	0.082	0.088	0.099	0.018	1.52	0.011	0.99
			(0.007)	(0.007)	(0.014)	(0.012)		(0.011)	
	Underperform or Sell	4912	0.037	0.026	-0.034	-0.073	-5.00***	-0.06	-3.69***
			(0.008)	(0.009)	(0.016)	(0.014)		(0.016)	
POSCH	Strong Buy	7666	0.012	0.023	0.024	0.01	1.65*	0.001	0.17
			(0.003)	(0.004)	(0.006)	(0.006)		(0.006)	
	Underperform or Sell	4812	-0.014	-0.027	-0.028	-0.014	-2.18**	0.000	-0.03
			(0.004)	(0.005)	(0.006)	(0.006)		(0.006)	

Table VI

This table reports the abnormal return on the recommendation announcement day and the post-recommendation cumulative abnormal returns for the high and low *Trade* stock groups. All stocks with a new recommendation are evenly divided into two groups based on clients' *Trade* measure defined in Section V. The high *Trade* group generally consists of stocks bought by clients before the recommendations and the low *Trade* group consists of stocks sold by clients before the recommendations. The abnormal return for stock i is the difference between the return of stock i and the return of the benchmark portfolio it belongs to. There are 125 benchmark portfolios and each stock is matched to one of them based on its size, BM and one year past return (Daniel et al. 1997). The average returns are weighted by stocks' capitalizations before the recommendations. The abnormal returns on the announcement day (day 0), day 1 to day 30, day 1 to day 60, day 1 to day 90, day 1 to day 120, day 0 to day 120, day 1 to day 150, day 1 to day 180 and day 1 to day 210 are reported. Panel A shows the benchmark results. Panel B shows the results based on non-clients' *Trade* measure. Panel C present the results for large and small brokers (Strong Buy only). Large brokers are the top 10% of brokers with the highest commission income. Panel D shows the results using market capitalization share rather than market capitalization as weight. Market capitalization share is defined as a stock's market capitalization over total market capitalization. Standard errors are clustered by year-month. All t-statistics are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post-recommendation Performance for Stocks with High and Low Client *Trade*

Days	0	1-30	1-60	1-90	1-120	0-120	1-150	1-180	1-210
Strong Buy									
Low Trade	0.0087	0.0021	0.0018	-0.0026	-0.0044	0.0041	-0.0012	-0.0015	0.0009
	(12.7***)	(1.04)	(0.58)	(-0.70)	(-0.97)	(0.94)	(-0.24)	(-0.33)	(0.19)
High Trade	0.0087	0.0021	0.0059	0.0112	0.0134	0.0223	0.0135	0.0106	0.016
	(10.16***)	(1.23)	(1.90*)	(2.87***)	(2.84***)	(4.59***)	(2.21**)	(1.62)	(2.36**)
High-Low	0.0000	0.0000	0.004	0.0139	0.0178	0.0181	0.0147	0.0121	0.015
	(0.06)	(0.01)	(0.82)	(2.30**)	(2.42**)	(2.44**)	(1.72*)	(1.38)	(1.64)
Underperform or Sell									
Days	0	1-30	1-60	1-90	1-120	0-120	1-150	1-180	1-210
Low Trade	-0.0163	-0.0061	-0.0065	0.0000	0.0025	-0.0142	0.0018	0.0001	0.0045
	(-11.49***)	(-1.60)	(-1.27)	(0.00)	(0.36)	(-2.00**)	(0.20)	(0.01)	(0.45)
High Trade	-0.0218	-0.0017	0.0022	0.0053	0.0049	-0.0174	0.0034	0.0051	0.0071
	(-6.69***)	(-0.43)	(0.50)	(1.00)	(0.72)	(-2.30**)	(0.47)	(0.63)	(0.79)
High-Low	-0.0055	0.0044	0.0088	0.0054	0.0023	-0.0031	0.0016	0.0049	0.0025
	(-1.60)	(0.82)	(1.33)	(0.70)	(0.25)	(-0.31)	(0.15)	(0.40)	(0.18)

Panel B: Post-recommendation Performance for Stocks with High and Low Non-client *Trade*									
Strong Buy									
Days	0	1-30	1-60	1-90	1-120	0-120	1-150	1-180	1-210
Low Trade	0.0086	0.0030	0.0034	0.0047	0.0039	0.0126	0.0055	0.0045	0.0101
	(11.57***)	(1.66*)	(1.14)	(1.35)	(1.06)	(3.33***)	(1.20)	(0.97)	(2.10**)
High Trade	0.0088	0.0010	0.0037	0.0016	0.0022	0.0111	0.0045	0.0026	0.0041
	(11.85***)	(0.57)	(1.21)	(0.36)	(0.42)	(2.07**)	(0.64)	(0.38)	(0.58)
High-Low	0.0001	-0.0020	0.0003	-0.003	-0.0016	-0.0014	-0.0009	-0.0018	-0.0059
	(0.21)	(-0.88)	(0.07)	(-0.48)	(-0.23)	(-0.2)	(-0.1)	(-0.2)	(-0.62)
Underperform or Sell									
Days	0	1-30	1-60	1-90	1-120	0-120	1-150	1-180	1-210
Low Trade	-0.0184	-0.0048	-0.0024	0.0023	0.0037	-0.0144	0.0037	0.0039	0.0098
	(-7.69***)	(-1.37)	(-0.42)	(0.36)	(0.54)	(-1.98**)	(0.43)	(0.43)	(1.14)
High Trade	-0.019	-0.0034	-0.0029	0.0023	0.0035	-0.0171	0.001	0.0001	0.0000
	(-11.57***)	(-0.9)	(-0.75)	(0.42)	(0.58)	(-2.91***)	(0.16)	(0.02)	(0.00)
High-Low	-0.0006	0.0014	-0.0004	0.0000	-0.0002	-0.0027	-0.0026	-0.0037	-0.0097
	(-0.24)	(0.31)	(-0.07)	(0.00)	(-0.02)	(-0.34)	(-0.29)	(-0.39)	(-1.01)

Panel C: Post-recommendation Performance for Stocks with High and Low Client *Trade*, Large and Small Brokers (Strong Buy)									
Large Brokers									
Days	0	1-30	1-60	1-90	1-120	0-120	1-150	1-180	1-210
Low Trade	0.0088	0.003	0.0037	0.0005	-0.0023	0.0064	0.0001	0.0003	0.0017
	(11.5***)	(1.31)	(1.07)	(0.14)	(-0.46)	(1.37)	(0.03)	(0.06)	(0.32)
High Trade	0.0088	0.0034	0.0082	0.0136	0.0158	0.0249	0.0155	0.0126	0.0185
	(8.87***)	(1.78*)	(2.46**)	(3.17***)	(2.84***)	(4.40***)	(2.20**)	(1.73*)	(2.42**)
High-Low	0.0000	0.0004	0.0045	0.013	0.0181	0.0184	0.0153	0.0122	0.0167
	(0.00)	(0.16)	(0.81)	(1.98**)	(2.15**)	(2.19**)	(1.58)	(1.26)	(1.60)
Small Brokers									
Days	0	1-30	1-60	1-90	1-120	0-120	1-150	1-180	1-210
Low Trade	0.0086	-0.0029	-0.0086	-0.0212	-0.0164	-0.0079	-0.0094	-0.0128	-0.0037
	(5.98***)	(-0.7)	(-1.16)	(-1.82*)	(-1.65*)	(-0.76)	(-0.72)	(-0.93)	(-0.26)
High Trade	0.0078	-0.0055	-0.0082	-0.0031	-0.0012	0.0066	0.0016	-0.0008	0.0019
	(4.13***)	(-0.88)	(-0.80)	(-0.29)	(-0.10)	(0.54)	(0.15)	(-0.06)	(0.15)
High-Low	-0.0007	-0.0025	0.0004	0.018	0.0151	0.0145	0.0111	0.012	0.0057
	(-0.35)	(-0.34)	(0.03)	(1.28)	(0.97)	(0.94)	(0.62)	(0.58)	(0.28)

Panel D: Post-recommendation Performance for Stocks with High and Low Client *Trade*, Market Capitalization Share Weighted (Strong Buy)									
Days	0	1-30	1-60	1-90	1-120	0-120	1-150	1-180	1-210
Low Trade	0.0083	0.002	0.0016	-0.0022	-0.0035	0.0048	-0.0005	-0.0005	0.0019
	(12.63***)	(1.03)	(0.56)	(-0.63)	(-0.84)	(1.17)	(-0.11)	(-0.12)	(0.42)
High Trade	0.0084	0.0019	0.0056	0.0103	0.0127	0.0214	0.0129	0.0109	0.015
	(10.15***)	(1.12)	(1.96*)	(2.78***)	(2.93***)	(4.78***)	(2.39**)	(1.91*)	(2.51**)
High-Low	0.00	0.00	0.004	0.0125	0.0163	0.0166	0.0134	0.0114	0.0131
	(0.08)	(-0.01)	(0.89)	(2.25**)	(2.44**)	(2.46**)	(1.78*)	(1.48)	(1.59)

Table VII

The table reports the calendar-time performance of portfolios sorted by clients' and non-clients' *Trade* measure. For each strong buy recommendation, if clients' *Trade* measure is larger than 0, the stock is added into the high *Trade* portfolio. If the *Trade* measure is below 0, it is added into the low *Trade* portfolio. The two portfolios are rebalanced whenever stock is added or deleted. Stocks are weighted by their market capitalizations before recommendations and are held from 30 days to 90 days after announcements. The four-factor time-series regression coefficients and the intercepts from the Fama-French three-factor and CAPM models are presented in Panel A. The results based on the non-clients' *Trade* measure are presented in Panel B. All returns are daily. Newey-West adjusted t-statistics are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Calendar-time Performance of Client *Trade* Sorted Portfolios

	MKT	HML	SMB	UMD	Four-Factor Alpha	Three-Factor Alpha	CAPM Alpha
Low Trade	1.0190	-0.1905	-0.1106	-0.0385	-0.00007	-0.00008	-0.00012
	(64.45***)	(-4.88***)	(-3.94***)	(-1.83*)	(-0.64)	(-0.78)	(-1.12)
High Trade	1.0792	-0.1165	-0.1490	-0.0300	0.0002	0.00018	0.00015
	(58.16***)	(-3.25***)	(-5.11***)	(-1.25)	(2.21**)	(2.12**)	(1.75*)
High-Low	0.0602	0.0740	-0.0383	0.0085	0.00027	0.00027	0.00028
	(2.76***)	(1.72*)	(-1.01)	(0.37)	(1.93*)	(1.96*)	(2.03**)

Panel B: Calendar-time Performance of Non-client *Trade* Sorted Portfolios

	MKT	HML	SMB	UMD	Four-Factor Alpha	Three-Factor Alpha	CAPM Alpha
Low Trade	1.0292	-0.1716	-0.1512	-0.0758	0.00017	0.00014	0.00011
	(70.55***)	(-4.99***)	(-6.87***)	(-3.68***)	(1.86*)	(1.56)	(1.16)
High Trade	1.0756	-0.0748	-0.1129	-0.0227	0.00009	0.00008	0.00006
	(67.96***)	(-1.91*)	(-4.04***)	(-0.85)	(1.09)	(1.00)	(0.74)
High-Low	0.0463	0.0967	0.0382	0.053	-0.00008	-0.00006	-0.00004
	(2.45**)	(2.23**)	(1.12)	(1.89*)	(-0.66)	(-0.50)	(-0.37)

Table VIII

This table reports the performance of broker coverage sorted portfolios after removing industry effects. The industries are defined as in Fama and French (1997). For each of the 48 industries, I calculated a value-weighted average return as the industry benchmark return. The industry-adjusted return is the difference between the individual stock return and the industry benchmark return. The four-factor time-series regression coefficients and intercepts from the Fama-French three-factor and CAPM models are presented. Newey-West adjusted t-statistics are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Broker Coverage Portfolios	MKT	HML	SMB	UMD	Four-Factor Alpha	Three-Factor Alpha	CAPM Alpha
Low	0.0433	0.0475	0.1347	0.0132	-0.0012	-0.0011	-0.0007
	(3.29***)	(2.74***)	(8.50***)	(1.30)	(-2.17**)	(-1.98**)	(-1.06)
Medium	0.0666	-0.015	-0.0182	0.0005	-0.0004	-0.0004	-0.0005
	(7.61***)	(-1.30)	(-1.73*)	(0.08)	(-1.24)	(-1.25)	(-1.53)
High	0.0649	-0.0421	-0.1105	-0.0035	0.002	0.002	0.0016
	(4.17***)	(-2.05**)	(-5.89***)	(-0.29)	(3.05***)	(3.05***)	(2.31**)
High-Low	0.0216	-0.0897	-0.2452	-0.0167	0.0032	0.0031	0.0023
	(1.08)	(-3.4***)	(-10.19***)	(-1.09)	(3.80***)	(3.68***)	(2.22**)

Table IX

This table repeats the benchmark tests after excluding fund positions that belong to funds' overweighted industries. Overweighted industries are the top 20% of industries with the highest average abnormal portfolio weights over the previous three years. Abnormal portfolio weight is an industry's portfolio weight in this fund in excess of its market weight. The industries are defined as in Fama and French (1997). Panel A of this table repeats the test of Panel B, Table II. Fund positions in funds' overweighted industries are removed from the three coverage portfolios. Panel B of this table repeats the test of Panel A, Table V. For every stock recommendation, I exclude any fund from the calculation of the *Trade* measure if the stock is in one of this fund's "overweighted" industries. Panel C of this table repeats the test of Panel A, Table VI. The high and low *Trade* groups are defined based on the new *Trade* measure calculated in Panel B of this table. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Performance Comparison, Removing Overweighted Industries

Broker Coverage Group	MKT	HML	SMB	UMD	Four-Factor Alpha	Three-Factor Alpha	CAPM Alpha
Low	1.0297	0.1334	0.1514	0.0074	-0.002	-0.0019	-0.0011
	(60.68***)	(4.34***)	(4.55***)	(0.36)	(-2.87***)	(-2.75***)	(-1.17)
Medium	1.0604	0.0128	-0.0211	0.0007	-0.0001	-0.0001	-0.0001
	(81.20***)	(0.65)	(-0.96)	(0.06)	(-0.26)	(-0.26)	(-0.22)
High	1.0611	-0.1116	-0.0846	0.0067	0.0035	0.0036	0.0029
	(49.58***)	(-3.24***)	(-2.08**)	(0.37)	(3.63***)	(3.61***)	(2.81***)
High-Low	0.0314	-0.2451	-0.2361	-0.0007	0.0055	0.0055	0.004
	(1.34)	(-5.82***)	(-5.76***)	(-0.03)	(4.84***)	(4.59***)	(2.60**)

Panel B: Fund Trades Before Recommendations, Removing Overweighted Industries

	Recommendation	No. of Obs.	Clients	Non-clients	Difference	t Statistics
Trade	Strong Buy	15509	0.124	0.131	-0.007	-1.09
			(0.008)	(0.006)	(0.006)	
	Underperform or Sell	7778	0.05	0.08	-0.03	-3.57***
			(0.009)	(0.008)	(0.008)	
POSCH	Strong Buy	15388	0.041	0.03	0.011	2.34**
			(0.004)	(0.003)	(0.005)	
	Underperform or Sell	7751	-0.016	-0.002	-0.014	-2.33**
			(0.006)	(0.003)	(0.006)	

Panel C: Post-recommendation Performance for Stocks with High and Low Client *Trade*, Removing Overweighted Industries									
				Strong Buy					
Days	0	1-30	1-60	1-90	1-120	0-120	1-150	1-180	1-210
Low Trade	0.0081	0.0004	0.0002	-0.0033	-0.005	0.003	-0.0001	-0.0012	0.001
	(11.58***)	(0.19)	(0.08)	(-0.84)	(-1.11)	(0.68)	(-0.02)	(-0.3)	(0.22)
High Trade	0.0092	0.0042	0.0067	0.0107	0.0127	0.0221	0.0105	0.0088	0.0141
	(9.54***)	(2.12**)	(2.19**)	(2.79***)	(2.77***)	(4.66***)	(1.69*)	(1.31)	(2.01**)
High-Low	0.001	0.0038	0.0065	0.0141	0.0177	0.0191	0.0106	0.0101	0.013
	(0.97)	(1.27)	(1.40)	(2.32**)	(2.51**)	(2.61***)	(1.34)	(1.21)	(1.45)

Table X

This table compares client funds' trades with covered non-client funds' trades. Client funds are those that pay commissions to the broker which makes the recommendation. Covered non-client funds are those that are not clients, but have at least one of their brokers covering the stock that receives a recommendation. Panel A reports statistics for the *Trade* and *POSCH* measures for the two groups. *Trade* and *POSCH* are defined in Section V. Panel B shows post-recommendation performance for the high and low trade stock groups based on covered non-clients' *Trade* measure. In Panel B, t-statistics are reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

Panel A: Fund Trades Before Recommendations for Clients and Covered Non-clients

	Recommendation	No. of Obs.	Clients	Covered Non-clients	Difference	t Statistics
Trade	Strong Buy	16413	0.099	0.103	-0.004	-0.70
			(0.007)	(0.007)	(0.006)	
	Underperform or Sell	7969	0.023	0.041	-0.017	-2.06**
			(0.009)	(0.008)	(0.008)	
POSCH	Strong Buy	16331	0.025	0.014	0.010	2.06**
			(0.004)	(0.003)	(0.005)	
	Underperform or Sell	7946	-0.024	-0.016	-0.008	-1.41
			(0.005)	(0.004)	(0.006)	

Panel B: Post-recommendation Performance for Stocks with High and Low Covered Non-client *Trade*

Strong Buy									
Days	0	1-30	1-60	1-90	1-120	0-120	1-150	1-180	1-210
Low Trade	0.0081	0.0035	0.0045	0.0031	0.0023	0.0105	0.0055	0.0057	0.0112
	(12.19***)	(1.65*)	(1.39)	(0.86)	(0.58)	(2.52**)	(1.17)	(1.27)	(2.24**)
High Trade	0.0092	0.0005	0.0024	0.0031	0.0038	0.0132	0.0044	0.0010	0.0027
	(10.61***)	(0.28)	(0.77)	(0.71)	(0.73)	(2.48**)	(0.65)	(0.15)	(0.37)
High-Low	0.0011	-0.0029	-0.0021	0.0000	0.0014	0.0027	-0.0011	-0.0047	-0.0084
	(1.19)	(-1.08)	(-0.42)	(0.00)	(0.20)	(0.35)	(-0.13)	(-0.52)	(-0.84)