Information flows are a two-way street: the effect of fund-analyst relationships on analyst outputs*

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September 6, 2023

Preliminary draft - Please do not cite or circulate without authors' permission

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Abstract

Prior literature examines the flow of information from analysts to investors, but information is a two-way street and little is known about the flows of information from investors to analysts. We use an SEC rule requiring the disclosure of commission payments from funds to brokerages to identify analyst-fund pairs likely to be interacting and examine how variation in client portfolio holdings of funds influences the research outputs of analysts. Consistent with funds influencing research outputs, we find that ownership by an analyst's clients predicts recommendation optimism, price target optimism, revision frequency, and earnings forecast accuracy in subsequent periods. Cross-sectional tests are more consistent with these forecast changes arising because of superior information (particularly about positive firm news), rather than incentives to cater to client preferences by issuing biased forecasts. Tests examining changes in future commission payments from fund investors suggest analysts have financial incentives to issue accurate forecasts in stocks widely held by clients. While we find optimism increases with these accuracy incentives, univariate tests do not show a significant association between optimism and commissions. Collectively, our evidence suggests that investor clients' supply and demand for information affect the development of quantitative analyst forecasts.

1 Introduction

Analysts' quantitative research outputs, such as earnings forecasts, price target forecasts, and recommendations, are widely disseminated. These information flows, which have been studied extensively in the prior literature, are a one-way street with the analyst pushing information to investors. However, valued clients have personalized interactions with analysts through phone calls and e-mails, which consume the majority of the analysts' time (e.g., Bradshaw et al., 2017). Through these interactions, information flows between these valued fund clients and analysts are often a two-way street. The clients explain their investment theses to the analyst, seeking feedback, while also attempting to integrate the analysts' information into their valuation. Presumably, analysts can enrich their research outputs after these interactions, by receiving information from funds and grasping funds' information demand. Yet, little is known about whether and how information from funds influences analyst information production, due to the challenges in observing these interactions empirically.

We utilize a novel dataset, which exploits an SEC disclosure rule requiring funds to report the top ten brokerages to which they paid commissions in the prior year, to identify brokerage-fund relationships in which soft information is more likely to be transmitted from the fund to the brokerage and vice-versa. Leveraging this data, we examine whether and how mutual fund clients' demand and supply of information interplay to affect analyst outputs. From the demand perspective, mutual fund clients could pressure analysts to issue optimistically biased research to inflate the value of their holdings (catering hypothesis). This catering hypothesis suggests the optimistic bias should come at the expense of accuracy (e.g., Gu et al., 2013; Firth et al., 2013; Zhang, 2021). An alternative view is that personalized communications inform analysts about the clients' specific information demands. This, in turn, motivates analysts to produce insights that enable funds to profitably trade in and out of their positions (effort hypothesis). Under this hypothesis, we would predict more accurate forecasts, but not necessarily more optimistic forecasts. Finally, funds also supply information to analysts, which can take the form of a detailed investment thesis, as seen in fund activism, or it could be questions and thoughts that inform analysts of investors' perspectives. Given the prevalence of 'long-only' investment strategies among funds, we predict this supply of information would predominantly be positive, but would tend to improve accuracy rather than decrease it (information supply). These latter two hypotheses can interplay; for example, when an analyst adopts certain aspects of a fund's investment thesis, significant effort is still required for the analyst to integrate the information and explain the view to the client.

To identify the effect of client information demand and supply on analyst investment research products, we first compute the number of clients that own each stock in the analysts' coverage universe. We define an analyst as having a relationship with a fund if the fund ranks among the top ten based on annual commissions paid to the brokerage. Then we regress research outcomes, such as optimism, accuracy, and revision frequency, on our measure of client investment interest and brokerage x quarter and firm x quarter fixed effects. For a given quarter, our fixed effect structure orthogonalizes our measure of fund investment relative to the average for the brokerage and the firm, allowing our coefficients to capture the effect of abnormal client-fund ownership on analyst research outputs. Moreover, the inclusion of brokerage x quarter fixed effects differentiates fund information from time-varying brokerage characteristics.

Our main finding is that client investor holdings predict analysts' research outputs, inducing more optimistic but also more accurate forecasts, which are accompanied by more frequent revisions. More specifically, while we find client fund holdings lead to a significant increase in share price target optimism, there is no significant increase in share price forecast errors, which the catering hypothesis would predict. Furthermore, we find more frequent earnings forecast revisions, translating into improved earnings forecast accuracy. The increased frequency and greater accuracy of earnings forecast revisions provide strong evidence that the presence of clients induces more effort from analysts. In addition, the greater accuracy of earnings forecasts, combined with more optimistic price target forecasts that are not less accurate, is more consistent with funds supplying positive information to analysts, rather than analyst catering, which would predict a decrease in accuracy. Thus, although the SEC disclosure data does not allow us to fully disentangle supply and demand, we argue our main results are consistent with the notion that, through personalized communications, the client information demand and supply interplay to induce more positive and accurate quantitative forecasts. While our main results examine the *level* of prior holdings on subsequent analyst forecasts, our results also hold when we regress the *change* in investor holdings over the year leading up to the issuance of analyst forecasts on the subsequently issued forecasts.

To further corroborate our main findings, we conduct a series of cross-sectional tests, focusing on the following five dimensions: commission fees, investor position size, client funds' performance, the size of the brokerage, and analyst busyness.[1] The first two cross-sectional variables, commission fees and investor position size, measure the importance of the client-analyst relationship to the analyst and the investor, respectively. Specifically, we predict that personalized communications are more likely to occur between clients and analysts: (1) when a client pays a higher dollar amount of commission fees; and (2) when a stock holds greater value to the client, leading to greater information flows. While these variables might also increase analysts' incentives for catering (e.g., Gu et al., 2013; Firth et al., 2013), we find they both amplify the increase in price target optimism without sacrificing price target forecast accuracy and even improve earnings forecast accuracy, which is more consistent with the production of positive information by analysts than merely a catering story. The next three cross-sectional tests provide further support. We see more optimism when the funds with the best performance own the stock, consistent with analysts being more influenced by the information from client funds with stronger skills (e.g., Berk and Green, 2004). We also find the main results on forecast optimism are mainly driven by those analysts who

[1] We note that this analysis uses commission fees paid by investors who rank within the top-ten, rather than from all investors with a brokerage relationship.

work for the largest brokers. This further argues against a catering explanation for our main results because analysts at the largest brokers face the greatest scrutiny from compliance officers and are arguably least beholden to their clients. Finally, we find that when analysts have a greater number of firms to cover, their outputs become more responsive to fund ownership. This suggests analysts substitute toward investor information and away from their own information production when they face greater time constraints.

Next, we provide further support for client-analyst personalized communications inducing the production of positive information by examining whether the change in commissions paid by investors to brokerages is a function of the research outputs issued by the brokerages. If client funds incentivize analysts to issue catering revisions, we should see commissions increase when analysts issue positive recommendations for stocks held by client funds. In contrast to this prediction, we find commissions increase with share price target and earnings forecast accuracy. While we find an insignificant association between price target optimism and commissions in the full sample, we observe that commissions increase significantly more with accuracy for optimistic price targets. These results collectively indicate that analysts are rewarded for accuracy, with stronger incentives to issue accurate optimistic forecasts.

Our final test examines investor portfolio holdings and whether clients of a brokerage respond significantly more to recommendations from that brokerage than others. Presumably, client funds obtain a benefit from interactions with brokerage analysts that is equal to or larger than the monetary cost of access, but it is unclear whether that access complements or substitutes for the utilization of the public recommendation signal. The substitute view argues that clients will obtain information directly from the brokerage and thus rely less on the public signal. The complement view suggests that the interactions with the analyst complement the processing of the public signal or indicate that the analyst places greater weight on the brokerage's beliefs in portfolio allocation. We have three main findings. First, after controlling for returns, which have been shown to be determinants of changes in portfolio holdings, we find portfolio allocations change in response to buy recommendations. Second, these associations vary with brokerage. For example, our evidence suggests Morgan Stanley's recommendation has a significant influence on portfolio allocations, while Nomura's does not. Third, we do not find evidence of an association between changes in recommendations and client portfolio allocations, after including controls for the fifty brokerages that receive the most commissions. For example, J.P. Morgan in our sample is the brokerage receiving the most commissions. We find that fund portfolios respond to J.P. Morgan recommendation changes but that there is no incremental effect for client funds. Our results hold after controlling for portfolio x reporting date fixed effects, which absorbs the average change in portfolio holdings as well as firm x year fixed effects. Taken together with our earlier analysis, the lack of association between recommendations and client portfolios suggests that if analysts generate value for clients it is not through the published recommendation, which is widely available to clients and non-clients alike.

Our results make several contributions to the literature. First, we make a methodological contribution by introducing commission disclosures as a way of identifying flows of information between clients and analysts. The prior literature investigates the effect of analyst following on the information environment and finds broadly they have an ameliorative effect, improving liquidity and facilitating price discovery (e.g., Kelly and Ljungqvist, 2012; Lang et al., 2023). However, the business of financial analysts involves providing superior services to clients than non-clients. We develop a method to identify these relationships and thus facilitate research into how this asymmetric provision of information, which potentially induces information asymmetry (e.g., Berger et al., 2019), affects forecast quality.

Second, we show that analyst forecasts are responsive to changes in client holdings. Survey evidence suggests that information flows are a two-way street (e.g., Brown et al., 2015), so our study provides empirical confirmation for the existence of these flows. Cross-sectional evidence is most consistent with an information story, because of either increased information gathering incentives or the supply of information from funds.

Third, we make a contribution in showing that client portfolio holdings are not significantly responsive to changes in quantitative forecasts of analysts, suggesting that much of the value clients derive from analyst services must lie elsewhere. This suggests these forecasts largely serve a marketing role, alerting non-clients to material changes in the brokerage's investment thesis, rather than providing new information to existing clients.

2 Literature review

Our study examines whether the stock holdings of institutional investors who have a relationship with a brokerage can predict the research outputs produced by that brokerage. We refer to these institutional investors as "client funds," and refer to analysts who cover stocks held by client funds as "client analysts." We have three main findings. First, the changes in client funds' holdings predict subsequent forecasts issued by client analysts, who issue more positive recommendations and price targets and more accurate earnings forecasts than other analysts. Second, commissions paid by client funds increase with the accuracy of analyst research outputs. Although we find commission payments are more sensitive to accuracy for optimistic forecasts, we find an insignificant association between optimism and commissions. Third, client funds do not react to the public issuance of their client analysts' buy recommendations. In this section, we put these findings in the context of the prior literature on the impact of and determinants of analyst forecasts.

2.1 The literature on analyst tipping and catering

Analysts are prominent information intermediaries in capital markets. They both interpret recent information events and engage in information search activities to attempt to anticipate future information releases. Regulators and other market participants view analysts' information production role as enhancing the informational efficiency of security prices (e.g., Kothari et al., 2016). However, analysts are employed by brokerages who seek to maximize profits rather than the informational efficiency of security prices. This profit incentive has been alleged to influence analyst forecasts through a number of channels.

First, prior literature investigates whether analysts tip institutional clients about impending recommendation changes. Using a database on institutional order flow, Irvine et al. (2007) demonstrate abnormal buy orders immediately (five days) before analysts' initial reports (initiations) with positive recommendations, which they interpret as evidence of 'tipping' institutions as to future recommendations. They also supplement this empirical evidence with anecdotal evidence of a broker who tipped off clients and was subsequently fired for doing so. Our study is related to tipping in that we show changes in institutional investor holdings predict future recommendation changes. However, the longer time frame makes the exchanged information more likely related to firm fundamentals and directly affected by clients either through their supply of information or their demand for it. In addition, our study comes after Regulation Analyst Certification ("Regulation AC"), which became effective on April 14, 2003, and regulates the interaction of broker-dealers and their ability to leak information.[2]

There is also substantial evidence from China that analysts provide optimistic opinions on stocks held by their mutual fund clients, which has been interpreted in the prior literature as 'catering' to the demands of these investors for optimistic recommendations (e.g., Gu et al., 2013; Firth et al., 2013). However, the Chinese market differs from the U.S. market on a number of dimensions that makes it unclear whether the catering results from the Chinese setting generalize. First, the Chinese capital market is young and still developing, and the incentive structures that have been developed lead to a relatively short-term focus. Commission fees account for approximately half of the revenue of Chinese brokers (Gu et al., 2013), as compared with 24% in a comparable time period reported for the U.S. brokers in Agrawal and Chen (2008). Unlike China, in the well-developed U.S. market, institutional investors generally demand high-quality research and play a monitoring role in reducing bias (e.g., Cowen et al., 2006; Ljungqvist et al., 2007). Consistent with this thesis, our evidence shows fund-brokerage information flow results in more accurate, rather than more biased

[2] https://www.sec.gov/rules/final/33-8193.htm

forecasts.

Second, in Chinese markets, analysts have stronger incentives to cater to institutional investors, whereas, in U.S. capital markets, this type of collusive behavior would constitute fraud. New Fortune Magazine organizes the most influential annual "star analyst" ranking in China. Analysts who rank high enjoy immediate increase (300%-1500%) in compensation and celebrity status (Lobo et al., 2020). Unlike in the U.S., active campaigning for brokerage votes is tolerated.[3]

Our measure of commission volume, which captures both soft- and hard-dollar commissions, adds to prior evidence on how financial incentives affect the production of quantitative forecasts using trading volume (e.g., Lehmer et al., 2022). In particular, Lehmer et al. (2022) leverage brokerage-level trading volume data, which captures aggregated trading directed through a brokerage from all investors. There are several advantages to our empirical approach. First, our more granular data enables us to measure relationships at the brokerage x fund level and thus examine the influence of this relationship in the cross-section. As commissions are driven largely by broker-votes (e.g. Groysberg and Healy 2013) there is substantial ex-post settling up in this market so that funds allocate commissions using their perceived value over relatively long windows. Second, we directly measure commissions rather than brokerage volume, which is a noisy proxy for soft-dollar commissions and excludes hard-dollar commissions. There are also some disadvantages of our measurement approach, such as the measure only being available by year, which limits our ability to examine the market reaction to specific forecasts.[4]

[3]For example, it was prevalent in recent years that during the "election season" for the fortune magazine star analyst competition, the research teams at the brokerages sent out staffers to campaign for "votes" with bribes spanning from small gifts, vacation packages, to "red envelope" in exchange for a favorable vote. In 2018, a video of analysts partying raucously with a client leaked to social media and went viral, raising serious questions about how analysts behave to win votes. As a result, the Securities Association of China suspended the star analyst contest for a year (Bloomberg, 2018).

[4]In 2018, MiFID II forbade soft dollar commission payments to brokerages. As European investment funds, who are affected by the regulation, are not required to fill out the SEC forms we use to extract brokerage commissions, we argue our results should be largely unaffected by the implementation of MiFID II.

2.2 The literature on investor's demand for analyst research

Our study is also related to prior literature that investigates the demand of clients for analysts' research products. In contrast to the large literature on the associations between quantitative forecasts and returns, this literature finds investors predominantly demand qualitative information from analysts (e.g., Brown et al., 2015; Bagnoli et al., 2009). "Industry knowledge" and "accessibility" rank near the top of the attributes investors value while "stock selection" and "earnings forecast accuracy" rank near the bottom. Groysberg et al. (2011) similarly finds that brokerages provide analysts incentives to cater to the demands of institutional investors, as their compensation and the commissions we measure are largely a function of votes of institutional investors conducted by the brokerage. Additionally, in describing analysts' day-to-day responsibilities, Bradshaw et al. (2017) note that "In contrast to the prevailing view that equity analysts spent most of their day buried in spreadsheets and numbers, the majority is actually spent on communicating with clients, management teams, and other professionals. Indeed, much of analysts' compensation depends on qualitative rather than quantitative measures." Although investors state a preference for qualitative information over quantitative information, it is not clear whether the quantitative forecasts are largely explained by qualitative information.

3 Sample and key variables

3.1 Data and sample construction

Our research design merges analyst forecasts with active fund portfolio holdings, using commissions flowing from funds to brokerages as a partitioning variable, to identify broker-fund pairs most likely to have information flows. We focus on the top ten mutual fund clients for each brokerage in a given year. Due to the nature of the disclosure requirements, clients of larger brokers are more likely to be observed in the SEC filings, as larger brokers are more likely to be included in an investment company's top ten list. This leads us to observe a much greater number of clients for larger brokers, compared with their smaller counterparts. However, for a significant number of these brokers, as shown in Table 1, most of the commissions each broker receives come from the largest clients. Therefore, to capture the major client-brokerage relationships, we focus on the top ten clients per brokerage annually. The top ten clients are identified based on the annual commissions paid to the brokerage.

To measure analyst research outputs, we obtain data on analyst recommendations, target price forecasts, and quarterly EPS forecasts from I/B/E/S. One empirical challenge in identifying all recommendation ratings is that I/B/E/S does not consistently generate a recommendation record for each analyst report. In particular, I/B/E/S is much more likely to generate a record for a change in opinion— like upgrades, downgrades, and initiations— and less likely to include reiterations (e.g., Chan et al., 2018; Hirshleifer et al., 2019). To overcome this challenge, we follow Zhang (2021) and supplement the I/B/E/S data with reiterations that were originally not recorded in it. We identify reiterations using the revision dates of other research outputs recorded by I/B/E/S (i.e., target price and EPS forecasts). The underlying assumption is that if the analyst revises other forecasts but does not adjust the recommendation, they essentially choose to maintain their prior recommendation. Note that for the more frequent revised forecast outputs (i.e., price targets and EPS forecasts), we base our analysis on the existing I/B/E/S records and do not impute missing values. To construct a sample that combines the three types of analyst research outputs, we compute the mean values of stock recommendations, target price forecasts, and quarterly EPS forecasts at the analyst-firm-quarter level, respectively.

Next, we obtain data on trading commissions from the SEC filings— Form N-SAR and Form N-CEN. Enforced by the Investment Company Act of 1940, registered investment companies are mandated to file N-SAR reports bi-annually with the SEC. However, starting from June 1, 2018, Form N-SAR has been replaced by Form N-CEN, and registered investment companies are required to submit Form N-CEN annually to the SEC. In both N-SAR and N-NCEN filings, the investment companies report a list of the top ten brokerages as measured by the dollar value of commissions paid to each, as well as the specific commission amounts. We follow Chernenko and Sunderam (2020) to parse N-SAR and N-CEN filings and obtain the commission data. For our empirical analysis, we aggregate the commission data to the year level for each investment company-brokerage pair.[5] As discussed above, we concentrate on the top ten clients for a brokeage in a given year, to capture the major brokerage-client relationships.

We then merge the portfolio holdings data with the year-level data on broker-clients-trading commissions. We obtain portfolio holdings data from CRSP Mutual Fund Holdings Database, retaining all non-index funds. In linking trading commission data with CRSP, we leverage the CRSP_CIK_MAP file provided by WRDS.

Lastly, we link the trading commissions data with the analyst research outputs data. We manually match these two databases based on the names of brokerage houses. We focus on the commissions reported by domestic equity funds only, as our data on analyst research only cover the publicly traded companies in the U.S. As the disclosure of broker names in N-SAR and N-CEN filings is not standardized, we take a cautious approach in the name-matching process. If the name of the brokerage house reported in N-SAR and N-CEN filings does not clearly indicate it is a branch in the U.S., we exclude the particular observation. We note that our approach could potentially underestimate the commissions received by each brokerage house.

Our final sample is constructed at the analyst-stock-quarter level. The sample period starts in 2008, as the CRSP mutual fund holdings database became reliable in 2008 (Schwarz and Potter, 2016), and ends in 2020. The number of observations varies depending on data availability for each test.

[5]Given the different reporting frequencies of N-SAR and N-CEN filings, we measure commission fees at the year level so that we can combine the data from these two filings.

3.2 Key variable definitions

We measure optimism in analysts' opinions based on the stock recommendations, target price forecasts, and quarterly EPS forecasts issued by an analyst for a stock quarter. Specifically, *RECCD* represents stock recommendation ratings. In I/B/E/S, recommendations range from 1 to 5, representing strong buy, buy, hold, underperform, and sell. We reverse the number value of the recommendation ratings so that a higher value indicates a more optimistic recommendation. *Opt_TGT* is an indicator variable that equals one if the price target is greater than the actual stock price, measured as the closing price 12 months subsequent to the target issuance date. *Opt_QtrlyEPS* is the signed difference between the analyst forecast and the actual EPS.

We measure information in analysts' outputs using three variables: absolute forecast errors in target price forecasts (*AbsErr_TGT*) and in quarterly EPS forecasts (*AbsErr_QtrlyEPS*), as well as the frequency of EPS forecast revisions (*FreqRev_QtrlyEPS*) for the stock quarter. Specifically, *AbsErr_TGT* is calculated as the absolute difference between the price target and the actual stock price, measured as the closing price 12 months after the target issuance date, and scaled by the same actual stock price. *AbsErr_QtrlyEPS* is defined as the absolute differences between the analyst forecast and the actual EPS.

For each of the above six variables, we first take the average at the broker-quarter-firm level (except *FreqRev_QtrlyEPS*), then convert them (except *Opt_TGT* and *RECCD*) to a percentile rank within each firm-quarter. The second step helps mitigate the influence of outliers and facilitates cross-sectional comparisons.

We measure the amount of information flow between the brokerage houses (financial analysts) and the buy-side clients at the analyst-stock-quarter level as well, using the number of client funds that hold the stock covered by the analyst in the quarter q-1. As discussed in Section 3.1, we restrict to the top ten mutual fund clients ranked by the trading commissions for each broker.

Appendix A.1 provides more detailed definitions of all variables used in the empirical tests. Continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme observations. We cluster standard errors two ways by firm and quarter-year.

3.3 Descriptive Statistics

Panels A and B of Table 1 compare the characteristics of the top ten clients with all mutual fund clients observable in the SEC filings. Panel A provides summary statistics at the brokerage-year-mutual fund client level. The left-hand side of the panel provides the statistics focusing on the top ten mutual fund clients for a given brokerage house. In terms of the size of the investment company, the average (median) asset under management is $30.7 billion ($4.4 billion). These numbers are $3.6 billion (mean) and $0.53 billion (median) at the fund level. Turning to the right-hand side of the panel, which also includes less economically significant relationships we see these values decrease as smaller clients are included.

Panel B reports the characteristics of the top ten brokers in terms of annual commission revenue received from the top ten mutual fund clients. J.P. Morgan tops the list with total commissions from the top ten clients of $0.12 billion, followed by Merrill, Credit Suisse, Morgan, Goldman Sachs, and Deutsche Bank. Turning to the characteristics of the clients of the top ten brokers, we do find larger brokers typically have more observable client data. When focusing on the top ten mutual fund clients for each broker, we find larger funds tend to match with larger brokerage houses. We see the commissions paid to brokers are heavily concentrated in their top ten clients, as for example, JP Morgan receives 119.9 million dollars from their top ten clients in the average year and 110.0 million from the other 307 disclosed relationships. As a result, limiting each brokerage to ten client funds ensures each relationship has a similar economic meaning to the brokerage, enabling us to compare the effect of client ownership on analyst outputs in the cross-section.

Panel C of Table 1 provides summary statistics on the number of client funds holding stocks in an analyst's portfolio at the analyst-stock-quarter level, and the changes in three time windows: q-5 to q-1, q-1 to q+1, and q+1 to q+5. On average, 1.87 client funds hold a given stock covered by an analyst. Notice that the median is zero, suggesting that more than half of the stocks in the average analyst's portfolio are not held by a client. Looking down the column, the average lagged holding change is 0.218, suggesting clients' holding can predict increases in analyst coverage.

Table 2 provides descriptive statistics for the aforementioned list of dependent and independent variables. An average analyst recommendation level is 3.68, between a "hold" and "buy." We show 53.2% of the target price forecasts tend to be optimistic, consistent with the prior evidence in the literature that overall sell-side analysts' outputs tend to be optimistic (e.g., Bradshaw et al., 2013). The remaining four dependent variables, which have highly skewed distributions, are percentile ranked and the number of observations depends on the availability of the forecast item. The empirical fact that analysts are less likely to update target price forecasts than EPS forecasts, results in a smaller sample size for that variable. The bottom of Table 2 reports summary statistics for the logged number of client funds that hold a specific stock covered by a given analyst. For the change variables, we first take the absolute value of the change in the number of funds holding the stock, then apply the natural logarithm, and finally multiply by the sign of the change. This procedure has the effect of reducing the influence of outliers and increasing the power of our tests.

4 Do client holdings predict analyst research outputs?

4.1 Client fund holdings and analyst research outputs

To test whether client holdings predict quantitative analyst research outputs, we estimate the following regression model:

$$\begin{aligned} Analyst\,Research\,Outputs_{i,j,k,q} = \gamma_0 + \gamma_1 Ln(\#Client\_Funds)_{i,j,k,q-1} + Stock_j * Year\text{-}qtr_q\,FE \\ + Broker_k * Year\text{-}qtr_q\,FE + \epsilon_{i,j,k,q}, \qquad (1) \end{aligned}$$

where the outcome variable $Analyst\,Research\,Outputs_{i,j,k,q}$ represent the research outputs produced by analyst i from brokerage house k for firm j in quarter q. Because we define the brokerage k as the last brokerage an analyst i reported an estimate for firm j in quarter q, each analyst-firm-quarter has a unique brokerage. As discussed in Section 3.2, we examine six dimensions of analyst research outputs, including recommendation ratings, the forecast optimism and accuracy of price targets and quarterly EPS, as well as the frequency of EPS forecast revisions. The main independent variable of interest is $Ln(\#Client\_Funds)_{i,j,k,q-1}$, representing the number of investors that the broker k's clients and hold stock j in quarter q-1. And, the stock j is covered by analyst i in quarter q. We include brokerage-quarter and firm-quarter two-way fixed effects. This fixed effect structure controls for all time-varying firm and brokerage house characteristics, and orthogonalizes our measure of fund investment relative to the average for the brokerage and the firm. Therefore, our coefficient captures the effect of abnormal client fund ownership on analyst research outputs. We cluster our standard errors two ways by firm and year-quarter.

Table 3 presents the results. First, we find a positive and statistically significant association between analyst research outcomes for stock j in quarter q and the number of client investors holding the same stock in quarter q-1. Specifically, we find that the client fund holdings in q-1 lead to more positive recommendation ratings and more optimistic price target forecasts. In economic terms, a single unit increase in our variable of interest—i.e., increasing the number of client funds by 1.72—boosts the recommendation rating and price target optimism by 1.5% and 1.7% of their unconditional means (3.682 and 53.2% respectively). In column (3), we find an insignificantly negative association between holdings and price target errors. Even though price targets are abnormally positive and this is associated with errors in forecasts (e.g., Bradshaw et al., 2013), the incremental positive news incorporated as a result of holdings is not associated with forecast errors. This suggests it reflects information about future performance.

Turning to the quarterly EPS forecasts, column (4) shows a negative and statistically significant association between *Opt_QtrlyEPS* and institutional holdings. As *Opt_QtrlyEPS* is measured as the difference between an EPS forecast and the actual EPS, the negative association suggests that increased client fund holdings correspond to a heightened average likelihood of meeting or beating the analyst forecasts. In column (5), we find a negative and statistically significant association between *AbsErr_QtrlyEPS* and institutional holdings variable, suggesting that increased client fund holdings lead to more accurate quarterly EPS forecasts. Finally, the positive and statistically significant coefficient in column (6) suggests that higher client fund holdings correlate with more frequent forecast revisions. This is consistent with the incremental accuracy in column (5) arising, at least in part, because of increased information gathering and effort.

Collectively, the results in Table 3 suggest that more commission-paying clients holding a firm leads to more optimistic forecasts, but not less accurate analyst research outputs. This is consistent with the information from client funds directly contributing to the information set of an analyst, or indirectly encouraging the production of information, particularly positive information.

4.2 Changes in the number of client funds and analyst research outputs

Although we measure our institutional holdings data before the forecast issuance, one concern with the interpretation of our results is that the forecasts issued are endogenously related to the institutional holdings, so the holdings do not cause the forecasts. To better understand the impact of institutional holdings on forecast outputs, in this section we modify our research design in Table 3 by investigating how changes in the number of client funds are associated with the analyst research outputs. The regression model is as follows:

$$
\begin{aligned}
Analyst\,Research\,Outputs_{i,j,k,q} = {} & \gamma_0 + \gamma_1 \mathit{Ln(Chg\_\#Client\_Funds)}_{i,j,k,q-5\,to\,q-1} \\
& + \gamma_2 \mathit{Ln(Chg\_\#Client\_Funds)}_{i,j,k,q-1\,to\,q+1} \\
& + \gamma_3 \mathit{Ln(Chg\_\#Client\_Funds)}_{i,j,k,q+1\,to\,q+5} \\
& + Stock_j * Year\text{-}qtr_q\, FE + Broker_k * Year\text{-}qtr_q\, FE + \epsilon_{i,j,k,q},
\end{aligned} \tag{2}
$$

where the outcome variables are defined in the same way as those in Table 3. To measure the changes in client fund holdings, we examine three time windows: changes from q-5 to q-1, from q-1 to q+1, and from q+5 to q+1. Within each time window, we take the logarithm of the absolute value in the change in the number of funds and multiply that value by the sign of the change. Logging the change in the number of funds reduces the influence of outliers on our regression coefficients.

Table 4 presents the results. We find that the results on changes in client funds before the issuance of the forecast $\mathit{Ln(Chg\_\#Client\_Funds)}_{i,j,k,q-1\,to\,q+1}$ is similar to those in Table 3. Specifically, changes in client fund holdings can predict subsequent analyst research outputs, including more positive stock recommendation ratings, more optimistic price targets, more accurate quarterly EPS forecasts, and more frequent forecast revisions.

Our changes specification also allows us to examine the association between contemporaneous changes in institutional holdings and forecast outputs. Interestingly, we find that there is no statistically significant association between the contemporaneous analyst research outputs and changes in client fund holdings. In addition, there is no significant association between the changes in client fund holdings in q+1 and positive recommendations and optimistic price targets issued in q. These findings imply that analyst forecasts may not predict client fund positions in the contemporaneous and future periods.

Overall, the results in Table 4 reinforce our main findings, and further support the idea that the information flows from clients to analysts by either directly influencing an analyst's information set or indirectly stimulating the production of information in line with funds' preferences.

5 Cross-Sectional Analysis

Our next set of tests exploits cross-sectional variation in fund, broker and analyst characteristics, to better understand the underlying mechanisms that drive the associations between prior holdings and subsequent analyst research outputs. These tests are predominantly designed to differentiate between two non-mutually exclusive alternative explanations for our results, catering and information. Under the catering story, analysts cater to funds' preferences with forecasts that drive the stock price upwards but constitute bias, which is inconsistent with our main results. Alternatively, under the information story, the positive correlations could exist because investors pass information along to analysts through their interactions, which then leads to more positive recommendations and price targets without bias.

5.1 Commission dollars

First, we investigate whether the dollar amount of commissions amplifies the association between analyst research outputs and the number of client funds. Prior studies suggest that when analysts cater to buy-side clients, the forecast accuracy tends to decrease simultaneously (e.g., Zhang, 2021). Therefore, if our main results are primarily driven by analysts catering to fund preferences, we expect that higher commissions will lead to more positively biased and thus less accurate forecasts. However, if it is positive information flow that drives our main results, we expect to observe more positive and informative analyst research outputs. To test this conjecture, we interact the cross-sectional cut-off *DollarComm* with $Ln(\#Client\_Funds)_{i,j,k,q-1}$ in Equation (1), and re-estimate the regression model. Here, *DollarComm* is measured as the average dollar amount of commissions paid by client funds to the broker k. We transform this variable into its corresponding percentile ranks within a given stock-quarter, and scale it to range from zero to one.

Panel A of Table 5 presents the results. We find that the interaction term, *Ln(#Client_Funds)* * *DollarComm*, loads with positive and statistically significant coefficients for stock recommendations and optimism of price targets and quarterly EPS forecasts, suggesting more positive research outputs. We find a negative and insignificant coefficient on the interaction term of interest when the forecast error of a price target is the dependent variable. Meanwhile, the interaction term predicts lower absolute errors in quarterly EPS forecasts and more frequent forecast revisions. Collectively, our evidence of more accurate forecasts for stocks held by more influential clients is consistent with the notion that the analysts receive more positive information from clients, and/or analysts are more motivated to gather information, particularly positive information.

5.2 Magnitude of the client fund holdings

Second, we investigate how our main results vary with the magnitude of the client fund holdings. If the information flow explanation drives our main results, we expect that larger holdings lead to more optimistic and informative analyst research outputs. To test this conjecture, we interact the variable *MoreImpt_Stock* with $Ln(\#Client\_Funds)_{i,j,k,q-1}$ in Equation (1), and re-estimate the regression model. Here, *MoreImpt_Stock* represents the importance of stock j in the client funds' portfolios, which is determined by the market value of holdings, as a fraction of the total market value of all stocks within a client funds' portfolio. We compute the mean value of this variable at the analyst-stock-quarter level, transform it into percentile ranks within each stock-quarter, and scale it to range from zero to one.

Panel B of Table 5 presents the results. We find that the interaction term, *Ln(#Client_Funds)* * *MoreImpt_Stock* , loads with positive and statistically significant coefficients for stock recommendations, optimism of price targets and quarterly EPS forecasts, and forecast revisions. In the meantime, we find the interaction term loads with a negative and statistically significant coefficient for absolute errors of quarterly EPS forecasts. These results suggest that when client fund holdings increase in magnitude, the number of these funds correlates with more positive and, importantly, more accurate analyst research, consistent with the information flow explanation.

5.3 Fund portfolio-level performance

Third, we investigate how our main results vary with fund skill. Under the information explanation, we would expect that analysts are more likely to be influenced by the information from funds with higher portfolio performance. Alternatively, we would not expect any associations under the catering explanation. To test this conjecture, we interact the variable *Fund_Perform* with $\textit{Ln(\#Client\_Funds)}_{i,j,k,q-1}$ in Equation (1), and re-estimate the regression model. Here, *Fund_Perform* is measured as average monthly abnormal portfolio-level returns within q-1. We compute the mean value of this variable at the analyst-stock-quarter level, transform it into corresponding percentile ranks within each stock-quarter, and scale it to range from zero to one.

Panel C of Table 5 presents the results. We find that the interaction term, *Ln(#Client_Funds) * Fund_Perform* , loads with positive and statistically significant coefficients for stock recommendations and optimism of price targets. These results are consistent with the notion that when the client funds have a greater skill, the analysts are more inclined to consider the information from or the preferences of these funds.

5.4 Broker size

Next, we explore how the broker size affects the associations between the number of client funds and the analyst research outputs. Given the greater regulatory scrutiny faced by larger brokers, under the catering story, we anticipate less catering to buy-side clients. Alternatively, the information flow explanation would suggest more pronounced results for larger brokers, because they actively communicate with the buy-side clients with better resources. To test this conjecture, we interact the variable *Broker_Size* with $Ln(\#Client\_Funds)_{i,j,k,q-1}$ in Equation (1), and re-estimate the regression model. Here, *Broker_Size* is measured as the number of sell-side analysts in the brokerage house k. This variable is also transformed into percentile ranks within each stock-quarter, and then scaled to range from zero to one.

Panel D of Table 5 presents the results. We find that the interaction term, *Ln(#Client_Funds)* * *Broker_Size* , loads with positive and statistically significant coefficients for stock recommendations, optimism of price targets and quarterly EPS forecasts, and forecast revisions. In addition, we find the interaction term predicts lower EPS forecast errors. These results suggest that the main associations we find in Equation (1) are amplified for larger brokers. As large brokers are less likely to cater to buy-side clients, these results further support our main results being driven by the information flow explanation, rather than by the catering story.

5.5 Analyst coverage

Lastly, we explore the influence of analyst coverage on our main results. We expect that analysts are more receptive to clients' feedback, when they have more stocks to cover, because the larger coverage universe increases workload, leading analysts to substitute toward client information and away from their own information gathering. To test this conjecture, we interact the variable *Analy_Cov* with $Ln(\#Client\_Funds)_{i,j,k,q-1}$ in Equation (1), and re-estimate the regression model. Here, *Analy_Cov* is measured as the number of stocks covered by analyst i in quarter q. We transform it into percentile ranks within each stock-quarter, and then scale it to range from zero to one.

Panel E of Table 5 presents the results. We find that the interaction term, *Ln(#Client_Funds)* * *Analy_Cov* , loads with positive and statistically significant coefficients for stock recommendations and optimism of price targets. These results are consistent with the notion that when burdened with a larger coverage portfolio, analysts are more receptive to client information. Consequently, their forecasts tend to be more optimistic. The insignificant coefficients on our accuracy variables suggest this does not necessitate compromising accuracy.

6 How is analyst performance associated with commissions?

Having explored how changes in client holdings are associated with changes in analyst research outputs, we now investigate whether and how analyst performance is associated with the commissions paid by buy-side clients. Our main findings suggest that personalized communications between a valued client and an analyst can enhance the analyst's information set by supplementing their information with positive buy-side information and/or encouraging the analyst to acquire more information, particularly positive information. Given the potential value of the improved analyst research to buy-side clients, analysts are expected to be rewarded for their increased efforts in information collection, so we would expect commissions to correlate with accuracy. To empirically test this, we investigate the associations between the commissions and different types of analyst research outputs. The regression model is as follows:

$$\begin{aligned} \mathit{Ln\_Commissions}_{k,j,t} = \gamma_0 + \gamma_1 \mathit{AnalystPerformance}_{k,j,t-1} \\ + \mathit{Broker\ FE} + \mathit{Investment\ Company{*}Year\ FE} + \epsilon_{i,j,p}, \end{aligned} \tag{3}$$

where the outcome variable $\mathit{Ln\_Commissions}_{k,j,t}$ represents the natural logarithm of one plus the dollar amount of commissions paid by the buy-side client j to the brokerage house k in a given year t. Regarding analyst performance, we examine the optimism and accuracy of analyst research outputs issued within 12 months prior to the commission reporting date.[6] To gauge the performance, we calculate the value-weighted average of the optimism of recommendations (*Avg(Opt_RECCD)*), price targets (*Avg(Opt_TGT)*), and EPS forecasts

[6]Reporting dates represent the end date of the period for which the fund is disclosing commission fees.

(*Avg(Opt_QtrlyEPS)*), as well as the absolute errors of price targets (*Avg(AbsErr_TGT)*) and EPS forecasts (*Avg(AbsErr_QtrlyEPS)*), for all stocks owned by the broker k's buy-side client j, using the client j's holdings as weights. The optimism of a recommendation for a particular stock is measured by comparing the broker k's recommendation to those issued by other analysts for that stock. The optimism and absolute errors of an individual price target, as well as an individual EPS forecast, is measured in the same way as those in our main analysis (discussed in Section 4.1). The unit of observation for this analysis is at the broker*investment company*year level. Investment company*year fixed effects are included to control for time-varying buy-side characteristics, such as increases or decreases in total commission payments. We include broker fixed effects to control for variation in resources that affect the properties of forecasts. We choose not to include broker*year fixed effects, as doing so would remove inter-temporal variation in forecast properties that we expect will influence commission payments. We cluster the standard errors at the broker level.

Table 6 presents the results. Specifically, columns (1) to (5) presents the results estimated from regressing *Ln_Commissions* on each individual dimension of analyst performance, respectively. For optimism, none of the three variables *Avg(Opt_RECCD)* , *Avg(Opt_TGT)* , and *Avg(Opt_QtrlyEPS)* loads with statistically significant positive coefficients, indicating that more optimistic sell-side research outputs are not associated with more commission fees. Turning to accuracy, we find statistically significant negative coefficients on both *Avg(AbsErr_TGT)* and *Avg(AbsErr_QtrlyEPS)* , suggesting that analysts are rewarded for more accurate forecasts. While we do not find evidence of a univariate association between optimism and commission payments, one possibility is that accuracy matters more for optimistic forecasts, those which could potentially induce a long-only investor to take or increase a position. To test for this possibility, we include both accuracy and optimism in the same model and also include the interaction of these two variables. In column (6), we find the interaction term, *Opt_TGT *Avg(AbsErr_TGT)* , loads with a statistically significant negative coefficient, while *Opt_TGT* loads with a statistically significant positive coefficient.

These two findings together suggest that commissions are more sensitive to accuracy for optimistic price target forecasts. Turning to the EPS forecasts, column (7) shows that the interaction term, *Avg(Opt_QtrlyEPS) *Avg(AbsErr_QtrlyEPS)* , loads with a statistically significant negative coefficient, which is again consistent with commissions decreasing more with inaccuracy for optimistic forecasts.

Collectively, these results provide evidence that indicates analysts are rewarded for accuracy over mere optimism, which is more consistent with the notion that the personalized client-analyst communications induce the production of positive information, rather than the the catering story.

7 Differential client fund reactions: client vs. non-client analyst research outputs

Prior research explores whether analyst recommendations generate market reactions and affect fund portfolio holdings. For non-client funds, the information from analysts flows one way, as they generally do not have an ability to interact with the analyst they only see the quantitative and qualitative content. For client funds, who have access to the analyst and thus have an ability to offer their own views and ask questions of the analyst, this supplemental information can either substitute or complement the weight the fund places on the public signal in portfolio allocation. The substitute view argues that clients will obtain directly from the brokerage and thus rely less on the public signal. The complement view suggests that the interactions with the analyst complement the processing of the public signal or indicate that the analyst places greater weight on the brokerages beliefs in portfolio allocation.

In Section 4.2, we do not find a significant association between contemporaneous changes in analyst forecasts and client fund positions. We also do not find any evidence that clients respond to quantitative forecast outputs of client analysts with a lag, so client analyst outputs do not predict changes in investor positions in future periods. In this section, we flip our regression model and examine whether client fund change portfolio positions in response to the public issuance of recommendations by client analysts. The regression model is as follows:

$$
\begin{aligned}
Chg\_Holdings_{i,j,p} = \gamma_0 &+ \gamma_1 \%BuyReccd\_Client_{\ i,j,p} + \gamma_2 \%BuyReccd_{\ j,p} \\
&+ \gamma_3 MKT\_3_{\ i,p} + \gamma_4 MKT\_6_{\ i,p} + \gamma_5 MKT\_12_{\ i,p} \\
&+ \gamma_6 INIT\_Per_{i,j,p} + \gamma_7 INIT\_Val_{i,j,p} \\
&+ A\ set\ of\ fixed\ effects + \epsilon_{i,j,p},
\end{aligned} \tag{4}
$$

where the outcome variable $Chg\_Holdings_{i,j,p}$ represents the change in the fund i's position in firm j over the reporting period p, measured as a percent of average fund holdings at the portfolio disclosure dates at the beginning and end of the reporting period p.[7] Specifically, we define the change in holding as the split-adjusted change in the number of shares, converted to dollar values using the average share price at the beginning and end dates of the reporting period, scaled by the average assets under management at the beginning and end dates of the reporting period.[8] The independent variable of interest *%BuyReccd_Client* is measured as the percentage of buy recommendations issued by client analysts for a stock. The variable *%BuyReccd* is measured as the percentage of buy recommendations issued by both client and non-client analysts and thus controls for the association between average recommendations and changes in holdings. Its inclusion allows us to separate analyst optimism from client-analyst optimism. We require at least one client and one non-client analyst issues a recommendation within the reporting period, so we can measure our variable of interest. We include a fund x quarter fixed effect, which controls for any fund-specific variable such as change in assets under management. We also include the percentage of the portfolio allocated to the stock at the beginning of the period (*INIT_Per*), and the value of the position

[7]Mutual funds are required to report holdings quarterly, but a minority report monthly, so for these firms we calculate the change in holdings over a month.

[8]Valuing changes in shares for the position and the assets under management for the fund at the average price ensures our results are not affected by market movements.

(*INIT_Value*). We also include either a firm or a firm x year fixed effect to control for firm-level factors that can affect the decision to issue a recommendation for different brokerages. Collectively, these variables control for how we would expect positions to change because of mean reversion and growth in AUM, in the absence of new information, to better estimate the association between recommendation changes and client positions. We two-way cluster the standard errors by firm and reporting period end date.

Columns (1) and (2) of Table 7 present the results estimated from Equation (4). In both columns, we find the variable *%BuyReccd* loads with a positive coefficient statistically significant at the 1% level, suggesting recommendation changes are positively associated with portfolio changes. We also find our variable of interest *%BuyReccd_Client* loads with a positive coefficient statistically significant at the 1% level, suggesting funds respond significantly more to brokerages to whom they pay commissions.

There are two potential explanations for the increased responsiveness to recommendations from client analysts. First, brokerages that receive the most commissions also drive portfolio allocations, but do so similarly for both client and non-client funds. Under this explanation, the funds choose to allocate commissions to brokerages whose investment advice they rely on, but the commissions do not drive the differential allocation. Second, access to analysts complements the processing of recommendations so that funds change portfolio allocations more in response to recommendations from client analysts. To differentiate between these explanations in columns (3) and (4), we estimate identical regressions except we include a separate indicator variable for whether the brokerage issues a buy recommendation for a firm-quarter and an indicator for a recommendation announcement. We include these indicator variables for the fifty brokerages that receive the highest commission payments, regardless of whether the brokerage has a relationship with the fund. After including these variables, we no longer find a significant association between *%BuyReccd_Client* and portfolio changes in either specification. We conclude the evidence is most consistent with funds selecting to pay brokerages whose investment advice they value driving the significant coefficients in columns (1) and (2).

In Figure 1, we report the buy coefficient indicators for the ten largest brokerages by commission dollars. We find all have positive coefficients and nine of the ten have significantly positive buy coefficients. These coefficients suggest actively managed funds increase portfolio allocations in response to recommendations from high-status brokers and we leave further explanation for these associations to future research.

8 Robustness Analysis

In this section, we conduct a robustness analysis by re-estimating our main regression model Equation (1) using a sample that includes all mutual fund clients observed in the SEC filings. Table 8 presents the results. We find our main results are robust to this sample selection. Consistent with our main results in Table 3, we find that client fund holdings lead to more positive recommendations, more optimistic price targets, as well as more frequent forecast revisions. Moreover, the EPS forecast accuracy improves while the price target forecast accuracy remains unaffected. Again, these findings are most consistent with our information flow explanation, rather than the catering story.

9 Conclusion

Prior literature primarily focuses on how analyst research affects investor decisions, implicitly assuming information flows from brokerages to investors. However, information flows between fund clients and analysts are a two-way street. Particularly, personalized interactions with analysts through phone calls and e-mails are reserved for the most valued clients, or those with the highest potential value. Through these interactions, funds can convey their investment theses and their specific information demands to the analyst. This study examines how client information demand and supply affect analyst research outputs.

We use novel data on commission payments from funds to brokerages to identify broker-fund relationships that are most likely to have personalized interactions. Consistent with funds influencing brokerage research outputs, we find that changes in client fund ownership predict recommendations, share price target optimism and revision frequency in subsequent periods. Cross-sectional tests suggest these predictable forecasts arise largely because of both direct flows of information from investors and stronger incentives for analysts to gather information, but not consistent with analysts catering to investors' demand to issue optimistically biased reports, as we do not observe a decline in forecast accuracy. In addition, tests on the association between commissions and analyst performance suggest that analysts are rewarded for accuracy, and especially accurate optimistic forecasts, but not for mere optimism. Lastly, we do not find client fund holdings react to the public issuance of buy recommendations from client analysts, suggesting that if analysts generate value for clients, it is not through the published recommendations that are widely available to both clients and non-client investors. Collectively, our evidence suggests that personalized client-analyst communications induce the production of positive information by analysts.

Our methodology to identify fund-brokerage relationships can potentially be used in future research to better understand the economics of information intermediation and we conclude by offering some thoughts on potential questions that can broaden our findings to studying dynamics in the relationship between brokers and funds. First, what type of research in prior periods leads funds to sever relationships with brokers, or alternatively to strengthen the relationship by paying higher commissions? Do commissions increase in future periods from a fund to a brokerage when the fund portfolio responds contemporaneously to recommendations or when the fund is able to anticipate recommendations? Do analysts whose research generates larger market reactions in the current period, see growth in their client portfolio in future periods? Presumably, these non-clients are listening to them and find their investment thesis interesting, so they could be converted into clients in future periods.

Second, our findings condition on analyst following and examine the effect of funds on analyst research and vice-versa. In a dynamic model, the decision of an analyst to follow the firm will also be a function of client holdings. So research could investigate whether coverage initiations respond to fund holdings. If analysts initiate because many clients hold the stock, does this generate weaker market reactions than when they initiate and many clients do not hold the stock (i.e., when they initiate because they have something to say). We leave the exploration of these questions to future research.

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Table 1 Characteristics of client funds

Panel A: All brokers

	Top Ten Clients				*All Clients Observed in SEC Filings*			
	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3
Avg_Num_Funds	8.56	2.00	4.00	10.00	6.63	1.00	3.00	8.00
Avg_AUM_InvestCompLevel (in billions)	30.73	0.80	4.41	23.88	13.74	0.75	3.00	11.09
Avg_AUM_FundLevel (in billions)	3.63	0.12	0.53	1.68	2.46	0.11	0.40	1.36

Panel B: Top ten brokers

	Top Ten Clients					*All Clients Observed in SEC Filings*				
	rank	*#Clients*	*Commissions paid by the top ten clients (in millions)*	*Avg_Num_Funds InvestComp Level*	*Avg_AUM InvestComp Level (in billions)*	*rank*	*#Clients*	*Commissions paid by all clients (in millions)*	*Avg_Num_Funds InvestComp Level*	*Avg_AUM InvestComp Level (in billions)*
JPMORGAN	1	10.00	119.87	17.40	114.36	1	317.23	229.93	7.12	15.18
MERRILL	2	10.00	101.76	11.91	126.62	5	215.77	168.68	5.44	14.21
CREDIT SUISSE (N.A.)	3	10.00	80.74	17.53	86.57	4	270.00	180.01	7.74	16.00
MORGAN STANLEY	4	10.00	76.36	17.14	102.66	2	287.46	183.04	7.21	16.66
GOLDMAN SACHS	5	10.00	70.05	16.48	101.46	3	278.77	182.12	7.14	16.29
DEUTSCHE BANK (N.A.)	6	10.00	59.13	15.39	62.20	6	174.31	108.61	8.33	19.06
BARCLAYS	7	10.00	37.22	17.03	89.41	7	174.85	75.67	7.81	15.42
SANFORD BERNSTEIN & CO.	8	10.00	22.99	9.15	46.77	8	118.38	34.58	5.64	10.70
JEFFERIES	9	10.08	14.06	12.78	49.05	9	118.54	27.75	5.98	12.90
NOMURA (U.S.)	10	10.00	12.92	15.21	30.30	11	28.10	15.18	9.99	19.19

Table 1 (cont.) Characteristics of client funds

Panel C: Number of client funds with portfolio holdings overlapped with analyst coverage						
	N	Mean	SD	Q1	Median	Q3
$\#Client\_Funds_{\ q-1}$	1,056,604	1.866	4.115	0.000	0.000	2.000
$Chg\_\#Client\_Funds_{\ q-5\,to\,q-1}$	1,056,604	0.218	1.632	0.000	0.000	0.000
$Chg\_\#Client\_Funds_{\ q-1\,to\,q+1}$	1,056,604	0.027	1.273	0.000	0.000	0.000
$Chg\_\#Client\_Funds_{\ q+1\,to\,q+5}$	1,056,604	-0.113	1.733	0.000	0.000	0.000

Notes. This table presents the characteristics of client funds for brokers that are identifiable in I/B/E/S. We focus on the top ten clients for each broker in the regression analysis for whether client holdings predict analyst research outputs. The top ten clients are identified based on the annual commissions they paid to a broker. Panel A provides descriptive statistics for all brokers in our sample, while panel B examines the top ten brokers in our sample, ranked by total commissions brokers receive from their top ten clients, averaged across years. In addition, we also provide the same set of statistics for all clients observed in the SEC filings, to facilitate a comprehensive comparison. $Avg\_AUM\_InvestCompLevel$ represents the market value of assets under management at the investment company-report date level. $Avg\_AUM\_FundLevel$ represents the market value of assets under management at the portfolio-report date level. Avg_Num_Funds represents the number of funds managed by an investment company. For the left-hand side of Panel B, *Commissions* are calculated by summing all commissions paid by the top ten clients for a broker in a given year, whereas the right-hand side represents all commissions paid by all clients observed in the SEC filings for a broker in a given year. Panel C shows the number of client funds that own a specific stock covered by a given analyst within a quarter. See the detailed definitions of all variables in Appendix A.1.

Table 2 Summary Statistics

	N	Mean	SD	Q1	Median	Q3
Outcome variables						
RECCD	705,398	3.682	0.880	3.000	4.000	4.000
Opt_TGT	448,737	0.532	0.487	0.000	1.000	1.000
AbsErr_TGT	448,737	49.697	23.324	33.000	50.000	66.000
Opt_QtrlyEPS	789,797	49.718	24.260	30.000	50.000	70.000
AbsErr_QtrlyEPS	789,797	49.117	24.265	29.000	50.000	69.000
FreqRev_QtrlyEPS	789,910	51.101	24.376	31.000	50.000	71.000
Independent variables						
Ln(#Client_Funds) $_{q-1}$	1,056,604	0.548	0.857	0.000	0.000	1.099
Ln(Chg_#Client_Funds) $_{q-5\,to\,q-1}$	1,056,604	0.080	0.628	0.000	0.000	0.000
Ln(Chg_#Client_Funds) $_{q-1\,to\,q+1}$	1,056,604	0.010	0.547	0.000	0.000	0.000
Ln(Chg_#Client_Funds) $_{q+1\,to\,q+5}$	1,056,604	-0.048	0.657	0.000	0.000	0.000

Notes. This table reports the summary statistics for variables used in the main regression analyses. The unit of observation is at the analyst-stock-quarter level. The outcome variables represent six dimensions of analyst research outputs. *RECCD* represents the average recommendation ratings provided by an analyst for a specific stock within q. *Opt_TGT* represents the percentage of price targets provided by an analyst for a specific stock with q that exceeds the actual stock price, measured as the closing price 12 months subsequent to the forecast issuance date. *AbsErr_TGT* represents the average absolute errors of price targets provided by an analyst for a specific stock within q. *Opt_QtrlyEPS* represent the average optimism of quarterly EPS forecasts issued by an analyst for a specific stock within q. *AbsErr_QtrlyEPS* represents the average absolute errors of quarterly EPS forecasts issued by an analyst for a specific stock within q. *FreqRev_QtrlyEPS* represents the number of forecast revisions made by an analyst for a specific stock within q. We convert the following dependent variables into percentile ranks within a firm-quarter to address outlier issues: *AbsErr_TGT* , *Opt_QtrlyEPS* , *AbsErr_QtrlyEPS* , and *FreqRev_QtrlyEPS* . The independent variables capture the overlaps between client fund holdings and analyst coverage. *#Client_Funds* represents the number of client funds that hold a specific stock covered by an analyst within a given quarter. *Chg_#Client_Funds* represents a change in *#Client_Funds*. We take natural logarithm transformations for *#Client_Funds* and *Chg_#Client_Funds*. The steps for the transformations are specified in Appendix A.1. More detailed definitions of all variables are also provided in Appendix A.1.

Table 3 Do client holdings predict analyst research outputs?

	RECCD $_q$	*Opt_TGT* $_q$	*AbsErr_TGT* $_q$	*Opt_QtrlyEPS* $_q$	*AbsErr_QtrlyEPS* $_q$	*FreqRev_QtrlyEPS* $_q$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(#Client_Funds) $_{q-1}$	0.0517***	0.0088***	-0.0496	-0.1869*	-0.1556**	1.1516***
	(10.82)	(6.83)	(-0.35)	(-1.97)	(-2.06)	(8.65)
Stock*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.426	0.793	0.037	0.066	0.056	0.146
N	705,398	448,737	448,737	789,797	789,797	789,910

Notes. This table presents the OLS regression results of whether client fund holdings in q-1 predict the analyst research outputs in q. We focus on the top ten mutual fund clients for each brokerage in a given year. The top clients are identified based on annual commissions paid to the brokerage. The unit of observation is at the analyst-stock-quarter level. Both dependent and independent variables are defined in the same way as Table 2. The independent variable of interest in this analysis is *Ln(#Client_Funds)* $_{q-1}$, measured as the natural logarithm of one plus the number of client funds that hold the stock covered by the analyst in q-1. For all tests reported in this table, we include stock*year-quarter fixed effects, and broker*year-quarter fixed effects. We cluster the standard errors two ways by stock and year-quarter. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See more detailed definitions of all variables in Appendix A.1.

Table 4 Changes in the number of client funds and analyst research outputs

	RECCD $_q$	*Opt_TGT* $_q$	*AbsErr_TGT* $_q$	*Opt_QtrlyEPS* $_q$	*AbsErr_QtrlyEPS* $_q$	*FreqRev_QtrlyEPS* $_q$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Chg_#Client_Funds) $_{q-5\,to\,q-1}$	0.0081***	0.0024**	0.1331	0.1036	-0.0937*	0.2623***
	(3.07)	(2.49)	(1.54)	(1.43)	(-1.79)	(3.48)
Ln(Chg_#Client_Funds) $_{q-1\,to\,q+1}$	0.0021	0.0004	0.2312**	0.1088	-0.0497	0.0195
	(0.75)	(0.50)	(2.55)	(1.54)	(-0.73)	(0.25)
Ln(Chg_#Client_Funds) $_{q+1\,to\,q+5}$	-0.0017	0.0008	0.5050***	0.0791	-0.1118*	0.0790
	(-0.60)	(1.03)	(5.42)	(1.22)	(-1.76)	(0.91)
Stock*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.426	0.793	0.037	0.066	0.056	0.145
N	705,398	448,737	448,737	789,797	789,797	789,910

Notes. This table presents the OLS regression results of how changes in client fund holdings in varying time windows are associated with analyst research outputs. The unit of observation is at the analyst-stock-quarter level. Both dependent and independent variables are defined in the same way as Table 2. The independent variables of interest in this analysis are the change variables. *Chg_#Client_Funds* represents a change in the number of client funds that own a specific stock covered by an analyst within a given quarter. We examine the changes in client fund holdings in three time windows: q-5 to q-1, q-1 to q+1, and q+1 to q+5. We take natural logarithm transformations for the change variables. The steps for the transformations are specified in Appendix A.1. For all tests reported in this table, we include stock*year-quarter fixed effects, and broker*year-quarter fixed effects. We cluster the standard errors two ways by stock and year-quarter. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See more detailed definitions of all variables in Appendix A.1.

Table 5 Cross-sectional analysis

Panel A: Commission dollars

	RECCD $_q$	*Opt_TGT* $_q$	*AbsErr_TGT* $_q$	*Opt_QtrlyEPS* $_q$	*AbsErr_QtrlyEPS* $_q$	*FreqRev_QtrlyEPS* $_q$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(#Client_Funds) $_{q-1}$ **DollarComm*	0.1425***	0.0413***	-0.0319	1.1919**	-1.0933***	2.6754***
	(6.13)	(6.72)	(-0.04)	(2.35)	(-3.13)	(4.00)
Ln(#Client_Funds) $_{q-1}$	-0.0220	-0.0142***	-0.1593	-0.5378*	0.3836*	-0.3282
	(-1.62)	(-3.86)	(-0.37)	(-1.77)	(1.78)	(-0.85)
DollarComm	-0.2022***	-0.0537***	-1.5411	-1.4307	0.5536	-0.6072
	(-4.56)	(-4.28)	(-1.07)	(-1.49)	(0.62)	(-0.46)
Stock*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.474	0.807	0.139	0.152	0.147	0.216
N	339,396	238,651	238,651	375,440	375,440	375,460

Panel B: Magnitude of the client fund holdings

	RECCD $_q$	*Opt_TGT* $_q$	*AbsErr_TGT* $_q$	*Opt_QtrlyEPS* $_q$	*AbsErr_QtrlyEPS* $_q$	*FreqRev_QtrlyEPS* $_q$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(#Client_Funds) $_{q-1}$ **MoreImpt_Stock*	0.0527***	0.0173***	-0.9027	0.8526**	-0.6448*	3.0983***
	(3.03)	(3.48)	(-1.62)	(2.12)	(-1.82)	(5.67)
Ln(#Client_Funds) $_{q-1}$	0.0264**	-0.0008	0.2949	-0.3555	0.1158	-0.5510*
	(2.64)	(-0.28)	(0.92)	(-1.54)	(0.54)	(-1.71)
MoreImpt_Stock	-0.0347	-0.0167**	1.3134*	-0.9584*	1.0177**	-3.1578***
	(-1.55)	(-2.56)	(1.75)	(-1.84)	(2.33)	(-4.42)
Stock*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.474	0.807	0.139	0.152	0.147	0.216
N	339,396	238,651	238,651	375,440	375,440	375,460

Table 5 (cont.) Cross-sectional analysis

Panel C: Fund portfolio-level performance

	$RECCD_q$	Opt_TGT_q	$AbsErr\_TGT_q$	$Opt\_QtrlyEPS_q$	$AbsErr\_QtrlyEPS_q$	$FreqRev\_QtrlyEPS_q$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(#Client_Funds) $_{q-1}$ **Fund_Perform*	0.0240*	0.0079*	-0.5102	0.0223	0.5008	0.9098
	(1.91)	(1.85)	(-1.09)	(0.06)	(1.32)	(1.56)
Ln(#Client_Funds) $_{q-1}$	0.0455***	0.0051*	-0.0162	0.1292	-0.5494**	0.7263**
	(4.89)	(1.93)	(-0.05)	(0.54)	(-2.04)	(2.05)
Fund_Perform	-0.0195	-0.0122*	0.9172	-0.6427	-0.6686	-1.1649
	(-1.11)	(-1.96)	(1.19)	(-1.18)	(-1.16)	(-1.56)
Stock*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.475	0.808	0.142	0.155	0.150	0.217
N	324,146	228,785	228,785	358,581	358,581	358,600

Panel D: Broker size

	$RECCD_q$	Opt_TGT_q	$AbsErr\_TGT_q$	$Opt\_QtrlyEPS_q$	$AbsErr\_QtrlyEPS_q$	$FreqRev\_QtrlyEPS_q$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(#Client_Funds) $_{q-1}$ **Broker_Size*	0.1566***	0.0245***	0.0280	0.4089	-1.1023***	1.7676***
	(7.81)	(4.91)	(0.04)	(1.14)	(-3.26)	(3.72)
Ln(#Client_Funds) $_{q-1}$	-0.0518***	-0.0074**	-0.0649	-0.4566*	0.5709**	-0.0122
	(-3.82)	(-2.03)	(-0.15)	(-1.86)	(2.63)	(-0.04)
Broker_Size	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
Stock*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.427	0.793	0.037	0.066	0.056	0.146
N	705,511	448,813	448,813	789,932	789,932	790,045

Table 5 (cont.) Cross-sectional analysis

Panel E: Analyst coverage

	RECCD $_q$	*Opt_TGT* $_q$	*AbsErr_TGT* $_q$	*Opt_QtrlyEPS* $_q$	*AbsErr_QtrlyEPS* $_q$	*FreqRev_QtrlyEPS* $_q$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(#Client_Funds) $_{q-1}$ **Analy_Cov*	0.0273***	0.0061**	0.1421	-0.1696	-0.1389	-0.1304
	(3.22)	(2.33)	(0.56)	(-0.77)	(-0.71)	(-0.44)
Ln(#Client_Funds) $_{q-1}$	0.0377***	0.0056***	-0.0541	-0.1011	-0.0689	1.2326***
	(5.57)	(2.87)	(-0.26)	(-0.69)	(-0.57)	(6.08)
Analy_Cov	-0.0075	0.0021	0.3133	-0.9815***	1.3243***	6.0945***
	(-0.65)	(0.60)	(0.88)	(-3.32)	(5.99)	(14.53)
Stock*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.444	0.802	0.074	0.098	0.087	0.176
N	592,686	381,158	381,158	663,986	663,986	664,088

Notes. This table presents the results estimated from the cross-sectional analysis. The unit of observation is at the analyst-stock-quarter level. The dependent variables and the independent variable *Ln(#Client_Funds)* in all panels are defined in the same way as Table 2. Panel A reports the results on whether the dollar amount of commissions exacerbates the main results, i.e., the associations between the analyst research outputs and the number of client funds. Panel B reports the results on how the main associations vary with the magnitudes of client fund holdings. Panel C reports the results on how the fund portfolio-level performance can affect the main associations. Panel D reports the results on how the main associations vary with the sizes of the brokerage houses. Panel E reports the results on how the main associations change with the analyst coverage. For all tests reported in this table, we include stock*year-quarter fixed effects, and broker*year-quarter fixed effects. We cluster the standard errors two ways by stock and year-quarter. *T*-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See more detailed definitions of all variables in Appendix A.1.

Table 6 How are commissions associated with analyst performance?

	DV = *Ln_Commissions*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg(Opt_RECCD)	0.9637						
	(0.72)						
Avg(Opt_TGT)		-0.7561				5.6356***	
		(-0.76)				(3.60)	
Avg(AbsErr_TGT)			-0.0276**			-0.0409***	
			(-2.58)			(-2.95)	
Avg(Opt_QtrlyEPS)				-0.0266**			0.0277
				(-2.33)			(1.57)
Avg(AbsErr_QtrlyEPS)					-0.0349***		-0.0241
					(-3.13)		(-1.34)
*Avg(Opt_TGT) *Avg(AbsErr_TGT)*						-0.3868***	
						(-3.69)	
*Avg(Opt_QtrlyEPS) *Avg(AbsErr_QtrlyEPS)*							-0.0031**
							(-2.57)
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Company*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.867	0.867	0.867	0.867	0.867	0.867	0.867
N	25,009	25,009	25,009	25,009	25,009	25,009	25,009

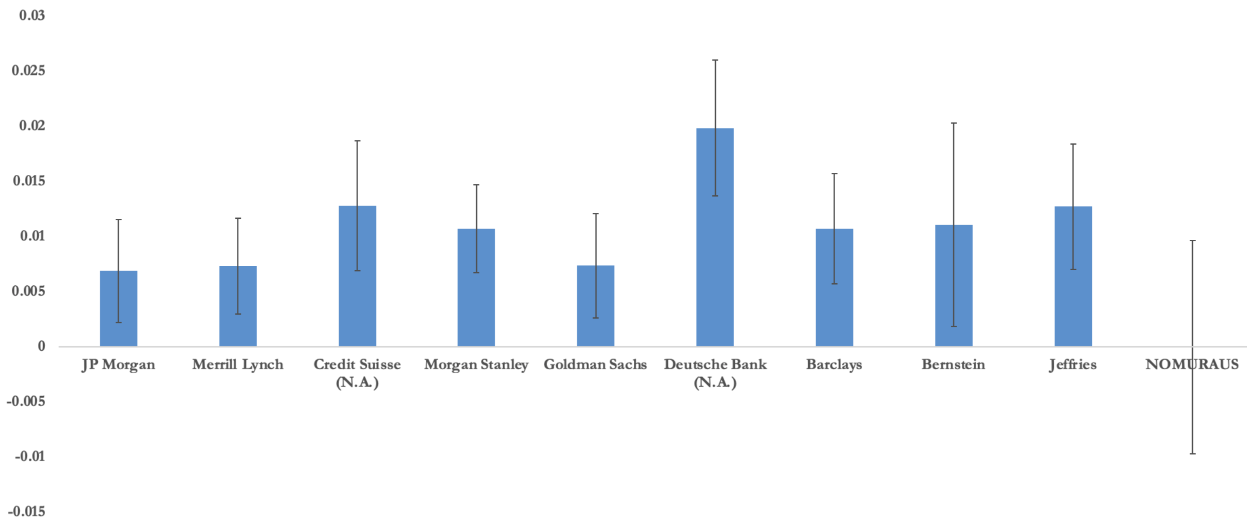
Notes. This table presents the results for how commissions are associated with analyst performance. The unit of observation is at the broker*investment company*year level. The dependent variable is *Ln_Commissions*, measured as the natural logarithm of one plus the annual commissions paid by a buy-side client to a broker. The independent variables capture the following dimensions of analyst performance: the optimism of recommendations (*Avg(Opt_RECCD)*), price targets (*Avg(Opt_TGT)*), and EPS forecasts (*Avg(Opt_QtrlyEPS)*), as well as the absolute errors of price targets (*Avg(AbsErr_TGT)*) and EPS forecasts (*Avg(AbsErr_QtrlyEPS)*). We measure each of these dimensions by calculating the value-weighted average at the broker*investment company*year level, using the client's holdings as weights. For all tests reported in this table, we include broker fixed effects, and investment company*year fixed effects. We cluster the standard errors at the broker level. *T*-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See more detailed definitions of all variables in Appendix A.1.

Table 7 Differential client fund reactions: client vs. non-client analyst research outputs

	DV = *Chg_Holdings*			
	(1)	(2)	(3)	(4)
%BuyReccd	0.03720***	0.02653***	0.00769**	0.00487*
	(14.95802)	(12.69944)	(2.57754)	(1.83422)
%BuyReccd_Client	0.00529***	0.00436***	0.00160	0.00193
	(4.29418)	(3.39801)	(0.99924)	(1.33189)
MKT_3	-0.02301***	-0.01155***	-0.02200***	-0.01211***
	(-5.22097)	(-2.95224)	(-5.58003)	(-3.15041)
MKT_6	-0.01212***	-0.01476***	-0.01360***	-0.01530***
	(-4.19341)	(-4.63508)	(-4.80346)	(-4.91380)
MKT_12	0.00257	-0.00242	0.00069	-0.00285
	(1.46052)	(-0.91197)	(0.37988)	(-1.08426)
INIT_Per	-0.26810**	-0.26519**	-0.26818**	-0.26510**
	(-2.37862)	(-2.35894)	(-2.37559)	(-2.35830)
INIT_Val	-0.03025***	-0.03135***	-0.03026***	-0.03129***
	(-28.66317)	(-30.77370)	(-28.64202)	(-30.80781)
Indicators for Buy Recommendation Issuance by Top 50 brokers	No	No	Yes	Yes
Indicators for Recommendation Issuance by Top 50 brokers	No	No	Yes	Yes
Fund*Report date FE	Yes	Yes	Yes	Yes
Stock FE	Yes	No	Yes	No
Stock*Year FE	No	Yes	No	Yes
R^2	0.232	0.244	0.234	0.244
Observations	1,738,852	1,738,852	1,738,852	1,738,852

Notes. This table presents the results for the analysis of whether client fund change portfolio positions in response to the public issuance of recommendations by client analysts. The unit of observation is at the fund*stock*reporting date level. The outcome variable *Chg_Holdings* represents the change in the fund position in a stock over a reporting period. The main independent variable *%BuyReccd_Client* is measured as the percentage of buy recommendations issued by client analysts for a stock. The variable *%BuyReccd* is measured as the percentage of buy recommendations issued by both client and non-client analysts. The fixed effects are specified in each column. For all tests reported in this table, we cluster the standard errors two ways by stock and fund reporting date. *T*-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See more detailed definitions of all variables in Appendix A.1.

Figure 1 Brokerage Buy Fixed Effects



Notes. This figure presents the coefficients of the buy recommendation indicators for the ten largest brokerages by commission dollars.

Table 8 Robustness analysis: Including all affiliated clients observable in the SEC filings

	RECCD $_q$	*Opt_TGT* $_q$	*AbsErr_TGT* $_q$	*Opt_QtrlyEPS* $_q$	*AbsErr_QtrlyEPS* $_q$	*FreqRev_QtrlyEPS* $_q$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(#Client_Funds) $_{q-1}$	0.0599***	0.0105***	0.1972	-0.1571	-0.2511***	1.5333***
	(11.13)	(8.13)	(1.38)	(-1.55)	(-2.82)	(11.31)
Stock*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker*Year-qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.426	0.793	0.037	0.066	0.056	0.146
N	705,398	448,737	448,737	789,797	789,797	789,910

Notes. This table reports the results re-estimated from Equation (1), using a sample that accounts for all affiliated clients observable in the SEC filings, rather than focusing on top ten. The unit of observation is at the analyst-stock-quarter level. Both dependent and independent variables are defined in the same way as Table 2. The independent variable of interest in this analysis is *Ln(#Client_Funds)* $_{q-1}$, measured as the natural logarithm of one plus the number of client funds that hold the stock covered by the analyst in q-1. For all tests reported in this table, we include stock*year-quarter fixed effects, and broker*year-quarter fixed effects. We cluster the standard errors two ways by stock and year-quarter. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See more detailed definitions of all variables in Appendix A.1.

A Appendix

A.1 Variable Definitions

Variable	Definition
Outcome Variables	
RECCD	Reversed IBES Recommendation Code (IRECCD). The reverse of the IBES recommendation code, so rankings range from one to five with the highest value indicating strong buy and the lowest strong sell. We impute the prior recommendation if an analyst continues to follow the stock.
Opt_TGT	An indicator variable that equals one if the price target is greater than the actual closing stock price 12 months subsequent to the target issuance date, and zero otherwise.
AbsErr_TGT	The absolute difference between the price target and the actual stock price 12 months after the target issuance date, scaled by the actual stock price. This variable is converted to a percentile rank within each firm-quarter to minimize the impact of outliers.
Opt_QtrlyEPS	The signed difference between the analyst forecast and the actual EPS. This variable is converted to a percentile rank within firm-quarter to minimize the influence of outliers.
AbsErr_QtrlyEPS	The absolute difference between the actual EPS and the analyst forecast. This variable converted to a percentile rank within each firm-quarter to minimize the influence of outliers.
FreqRev_QtrlyEPS	The frequency of the EPS forecast revisions. This variable converted to a percentile rank within each firm-quarter to minimize the influence of outliers.
Independent Variables	
#Client_Funds	The number of client funds that hold the stock covered by the analyst in a given quarter. We refer to funds among the top ten list for a brokage based on the annual commissions paid as client funds.
Chg_#Client_Funds $_{q-5\, to\, q-1}$	The change in *#Client_Funds* from the quarter q-5 to q-1.

Chg_#Client_Funds $_{q-1\,to\,q+1}$	The change in *#Client_Funds* from the quarter q-1 to q+1.
Chg_#Client_Funds $_{q+1\,to\,q+5}$	The change in *#Client_Funds* from the quarter q+1 to q+5.
Ln(#Client_Funds) $_{q-1}$	The natural logarithm of one plus *#Client_Funds* .
Ln(Chg_#Client_Funds) $_{q-5\,to\,q-1}$	One plus the logged absolute value of the change in the number of client funds holding the position from the quarter q-5 to q-1, multiplied by the sign of the change in the number of funds.
Ln(Chg_#Client_Funds) $_{q-1\,to\,q+1}$	One plus the logged absolute value of the change in the number of client funds holding the position from the quarter q-1 to q+1, multiplied by the sign of the change in the number of funds.
Ln(Chg_#Client_Funds) $_{q+1\,to\,q+5}$	One plus the logged absolute value of the change in the number of client funds holding the position from the quarter q+1 to q+5, multiplied by the sign of the change in the number of funds.

Cross-sectional Cutoffs

Moreimpt_Stock	The importance of a stock in a fund portfolio, determined by the market value of holdings, as a fraction of the total market value of all stocks within a client funds' portfolio. Market value is measured as of the fund reporting date. In the regression analysis, the variable is transformed into percentile ranks and scaled to range from zero to one.
DollarComm	The annual commission fees paid by investment companies, whose funds held the stocks covered by the analyst. In the regression analysis, the variable is transformed into percentile ranks and scaled to range from zero to one.
Fund_Perform	Fund Performance, measured as the average monthly abnormal fund returns within a given quarter. In the regression analysis, the variable is transformed into its corresponding percentile rank and scaled to range from zero to one.
Broker_Size	Broker Size. The number of analysts working for a broker in quarter q. In the regression analysis, the variable is transformed into percentile ranks and scaled to range from zero to one.

Analy_Cov	The number of stocks covered by an analyst. In the regression analysis, In the regression analysis, the variable is transformed into percentile ranks and scaled to range from zero to one.

Analysis on commissions and analyst performance

Avg(Opt_RECCD)	The value-weighted average optimism of recommendations issued by a broker for stocks owned by a specific buy-side client. We first measure the optimism level of the broker's average recommendations for a certain stock within a particular year, by comparing with those issued by other analysts for the same stock. We then compute a value-weighted average of the optimism for all stocks owned by the buy-side client, with the weight based on the client's holdings.
Avg(Opt_TGT)	The value-weighted average optimism of price targets issued by a broker for stocks owned by a specific buy-side client. The optimism of an individual price target is measured in the same way as *Opt_TGT* in the main analysis. We compute a value-weighted average of the optimism for all stocks owned by the buy-side client, with the weight based on the client's holdings.
Avg(AbsErr_TGT)	The value-weighted average absolute forecast errors of price targets issued by a broker for stocks owned by a specific buy-side client. The absolute forecast error of an individual price target is measured in the same way as *AbsErr_TGT* in the main analysis. We compute a value-weighted average of this measure for all stocks owned by the buy-side client, with the weight based on the client's holdings.
Avg(Opt_QtrlyEPS)	The value-weighted average optimism of quarterly EPS forecasts issued by a broker for stocks owned by a specific buy-side client. The optimism of an individual quarterly EPS forecast is measured in the same way as *Opt_QtrlyEPS* in the main analysis. We compute a value-weighted average of this measure for all stocks owned by the buy-side client, with the weight based on the client's holdings.

Avg(AbsErr_QtrlyEPS)	The value-weighted average absolute errors of quarterly EPS forecasts issued by a broker for stocks owned by a specific buy-side client. The absolute error of an individual quarterly EPS forecast is measured in the same way as *AbsErr_QtrlyEPS* in the main analysis. We compute a value-weighted average of this measure for all stocks owned by the buy-side client, with the weight based on the client's holdings.
Ln_Commissions	The natural logarithm of one plus the commissions paid by a given buy-side client to the broker.

Analysis on how funds change portfolio positions in response to analyst research outputs

Chg_Holdings	A percentage change in the fund position for a specific stock. It is calculated as the split-adjusted change in shares held from the beginning of the reporting period until the end, valued at the average price during the quarter, as a percentage of average assets under management.
%BuyReccd_Client	The percentage of buy recommendations issued by client analysts for a stock from the prior fund portfolio disclosures until the subsequent disclosure.
%BuyReccd	The percentage of buy recommendations issued by all analysts for a stock from the prior fund portfolio disclosure date until the subsequent disclosure date.
MKT_3	Abnormal market returns of a stock over a three-month window prior to the fund report date.
MKT_6	Abnormal market returns of a stock over a six-month window prior to the fund report date.
MKT_12	Abnormal market returns of a stock over a 12-month window prior to the fund report date.
INIT_Per	The percentage of the funds' assets under management allocated to a specific position. Defined as the shares held multiplied by the share price at the beginning of the period divided by the sum of all shares held by the fund multiplied by their corresponding share prices.
INIT_Val	The dollar value of the position at the beginning of the period, calculated as the product of the share price and shares held by the fund.