NBER WORKING PAPER SERIES

DO SELL-SIDE ANALYSTS SAY “BUY” WHILE WHISPERING “SELL”?

David Hirshleifer
Yushui Shi
Weili Wu

Working Paper 30032
http://www.nber.org/papers/w30032

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2022, Revised February 2024

We thank Jeffrey Busse (discussant), Chong Huang, Paul Irvine, Frank Weikai Li, Xi Li, Brandon Lock (discussant), Ben Lourie, Haoyi Luo (discussant), Lin Peng, Christopher Schwarz, Jinfei Sheng, Nan Xu, Yuhai Xuan, David Yang, Zheng Sun, Russ Wermers, Lu Zheng, and participants of the Northern Financial Association Annual Meeting, the Financial Management Association Annual Meeting, the Australasian Finance and Banking Conference, and seminars at University of California, Irvine, Peking University, and Monash University for valuable comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Do Sell-Side Analysts Say “Buy” While Whispering “Sell”?
David Hirshleifer, Yushui Shi, and Weili Wu
NBER Working Paper No. 30032
May 2022, Revised February 2024
JEL No. G12,G14,G2,G23,G24,G3,M41

ABSTRACT

We study here say-buy/whisper-sell behavior wherein analysts issue optimistic recommendations to attract retail investors while providing more accurate information to fund managers in private, sometimes resulting in fund managers selling the recommended stocks. We test whether fund managers return the favor using their votes for analysts in a Chinese “star analyst” competition. Managers are more likely to vote for analysts who exhibit greater “say-buy/whisper-sell” behavior toward these managers. This suggests that analysts reduce the accuracy of their public recommendations, thereby maintaining the value of their private advice to funds. Our findings help explain several empirical puzzles about analyst public recommendations.

David Hirshleifer
Marshall School of Business
University of Southern California
3670 Trousdale Pkwy
Los Angeles, CA 90089
and NBER
hirshlei@marshall.usc.edu

Weili Wu
Central University of Finance
and Economics,
School of Finance
Beijing
China
wlwu@cufe.edu.cn

Yushui Shi
Monash University
6 Oxford
Irvine, CA 92617
yushuis@uci.edu

1. Introduction

Past research highlights a tension between analysts' jobs delivering public information to the market versus delivering private information to their clients. On the one hand, analysts often issue overly optimistic stock recommendations to generate trades from a large audience of retail investors, because naïve small investors take analysts' public recommendations at their face value (e.g., Malmendier and Shanthikumar 2007; Kong et al. 2021). On the other hand, the literature has found that sell-side analysts provide useful information to a relatively small audience of fund managers via social networks (e.g., Gu et al. 2019; Li, Mukherjee, and Sen 2021).

The dual roles of analysts suggest that to preserve the value of analysts' private information to institutional investors, analysts may choose to provide less-accurate information to the public.[1] This idea is consistent with the model of García and Sangiorgi (2011), who find that it is optimal for a provider to sell either relatively precise information to a small group of investors or relatively imprecise information to a large group of investors. In this paper, we provide tests of this idea in the context of analyst recommendations.

We propose the following analyst recommendation strategy as a function of the analyst's private information. The analyst pools by issuing a favorable public recommendation about both high and relatively low-value firm types and privately tells the fund client these separate values. (We allow for the possibility of even lower value-types that are not recommended.) So, the information received by the fund is strictly more accurate than the recommendation. Such a pooling strategy (between these two value types) conceals from retail investors some of the analyst's private information about firm value. In consequence, the connected fund manager who receives information from the analyst profits by buying when the value of the stock is high,

[1] More accurate public recommendations make stock prices more efficient, which tends to reduce the expected profit to investors with private information. So accurate public disclosure can come at the expense of profits to analysts' private clients.

and by selling when the value of the stock is low. This is profitable as the market price has not fully incorporated the analyst's private information. In sum, there is *say-buy/whisper-sell behavior* (or more briefly, *whisper-sell behavior*).[2] A famous example of say-buy/whisper-sell behavior from the U.S. occurred during the millennial Dot-com bubble, when Merrill Lynch's tech analyst Henry Blodget touted tech stocks publicly to investors while disparaging the same stocks privately, calling them "dogs" and worse in private e-mails (Tharp 2002).[3]

A challenge to testing for whisper-sell behavior is that private communications between analysts and fund managers are unobservable. A starting point for our empirical strategy is to identify cases in which analysts' public positive recommendations are accompanied by selling by connected fund managers. However, this is a very noisy proxy for whisper-sell behavior as it is possible that even without any communication, fund managers for their own reasons sell even stocks that are positively recommended by analysts.

To refine our testing strategy, we exploit unique proprietary data on managers' voting to analysts in a "star analyst" competition in China. In this analyst competition, fund managers privately vote for analysts, and their votes determine star analysts.[4] Being a star analyst increases an analyst's reputation and leads to higher bonuses and greater chances of promotion (Stickel 1992). We argue that if the analyst provides useful information to a fund manager, the fund manager will reciprocate by giving a vote to the analyst. Therefore, we hypothesize that whisper-sell behavior by the analyst makes fund trading more profitable, making a fund manager more likely to vote for the analyst who exhibits more whisper-sell behavior with that manager. To the extent that our whisper-sell measure captures whisper-sell behavior, we would

[2] In principle, say-sell/whisper-buy behavior would also be plausible (recommending negatively while privately conveying favorable information to fund managers). However, Chinese analysts rarely issue negative public recommendations. So, in this paper, we focus on analyst's positive recommendations and say-buy/whisper-sell behaviors.

[3] A similar insight can apply in other contexts in which information providers produce both public recommendations and private signals, as in the model of Malenko, Malenko, and Spatt (2021) on the proxy voting recommendations made by advisory firms.

[4] This ranking procedure is very similar to the U.S. counterpart of *Institutional Investor* analyst ranking in which the ranking institution sends ballots to money management institutions. Moreover, the votes are not released publicly, which spares the quid pro quo and the underlying social connections from public scrutiny.

observe a positive relationship between whisper-sell measure and manager voting.

We focus on the prediction of a positive relationship between the whisper-sell measure and manager voting because it helps distinguish the scenario we hypothesize of private communication between fund managers and analysts from alternative scenarios. In one such alternative scenario, a fund manager obtains stock information only from analysts' public recommendations, not from private communications. In another, the manager and the analyst make independent decisions and the manager evaluates the analyst based on to what extent they have the same judgment on stock values. Under both scenarios, whisper-sell measure would be *negatively* associated with the manager voting for the analyst, because manager selling of the stock would indicate that the manager disagrees with the analyst's opinion as inferred from the public recommendation. This prediction is the opposite of our hypothesis and is not consistent with our evidence.

The empirical analysis starts by verifying the informativeness of fund managers' votes by linking their votes with their decisions to allocate trades between brokerages. Previous research has found that institutional clients use trade commissions as a metering device to solicit and pay for brokers' research services and that analysts' bonuses are also linked with institutional trade commissions (Irvine 2004; Goldstein et al. 2009). In light of this, we hypothesize that if the fund manager's voting for an analyst implies that the manager returns the favor for the analyst's information, the fund manager will also be more likely to allocate trades to the analyst's brokerage firm, as an alternative form of reward. Accordingly, we find that an increase in a broker's average ranking by a fund manager is associated with the fund manager's allocating more of the fund's future trades to that broker. This result suggests that the data on manager votes reflect useful information about managers' evaluations of analysts. Because the trade commission data is at the fund-brokerage level, we test our main hypothesis using more granular voting data at the fund manager-analyst level.

Next, we turn to the hypothesis that analysts use say-buy/whisper-sell behavior to preserve more-accurate information for fund managers that is not disclosed in analysts' public recommendations. Empirically, we measure whisper-sell (whisper-buy) behavior for any manager and analyst pairs as the percentage of the manager's sold (bought) stocks that are positively recommended by the analyst.[5,6] We find that an analyst's whisper-sell behavior is positively associated with the manager's vote for that analyst. An increase in whisper-sell behavior from the 25th percentile to the 75th percentile among the analyst industry peers is associated with a 10% increase, relative to the sample mean, in the probability of the manager voting for that analyst as his or her first choice. In regressions, we include controls that characterize analysts' public activities in that year, so we can differentiate managers who vote based on analysts' private communications from managers who vote based on analysts' public activities. The results suggest that analysts use say-buy/whisper-sell behavior to provide fund managers with more-accurate information about stock values than analysts include in their public recommendations.

We provide further tests of the hypothesis based on variables that are predicted to modulate the size of the effects. These tests draw on the fact that our whisper-sell measure is noisy. It follows that in circumstances in which the whisper-sell measure is more likely to capture private communications between analysts and managers, we predict a stronger effect of whisper-sell measure on the voting rank.

Conditions under which we expect private communications to be especially important are (1) when the manager has less investment skill in the industry and therefore relies more on outside information from analysts,[7] (2) when the manager has a preexisting business tie with

---

[5] Positive recommendations are defined as Buy, and Strong Buy recommendations without a subsequent downgrade in the same semi-year.

[6] The manager' selling decisions are inferred from the holdings changes in the two latest holdings disclosures. We use managers' implied trading to proxy for their general beliefs on firms' long-term prospects as compared to beliefs revealed from analysts' public recommendations. In that sense, although we do not observe managers' exact trades around analysts' recommendations, our argument does not critically hinge on whether managers trade around the public recommendation days.

[7] This result is also inconsistent with the hypothesis that fund managers profit solely by selling based on debiasing analysts'

the analyst's broker and therefore is more likely to have contact with the analyst, (3) when the reputation costs of whisper-sell behavior are relatively low, and (4) when the benefit from misleading retail investors is greater.

As hypothesized, we find that the sensitivity of whisper-sell measure on voting rank is greater when fund managers' portfolio weight in the analyst's industry (an inverse proxy for fund managers' industry-wide investment skills) is lower, when funds allocate significant trades to the analyst's brokerage, when the information asymmetry of the analyst's industry is high, and when the analyst's industry is of lottery stocks that are favored by retail investors.

In addition, we find that fund managers are more likely to vote for the analysts after managers find that the post-recommendation performance of the stocks that managers sold is poor. This supports the hypothesis that there is private communication between analysts and fund managers. If fund managers only learned from analysts' public recommendations, bad performance after positive recommendations would lead to a lower vote ranking of the analysts.

Furthermore, we explore what kinds of analysts are likely to engage in say-buy/whisper-sell behavior. There are two findings. First, analysts who issue more reports but cover fewer firms than their peers, indicative of greater effort per firm, are more likely to engage in whisper-sell behavior. As such analysts are likely to produce more private information per covered firm, this finding is consistent with our explanation for say-buy/whisper-sell. Second, we find that whisper-sell behavior is more common among analysts affiliated with larger brokerages. Intuitively, such analysts are more likely to engage in favor trading with fund managers by virtue of having more connections with buy-side institutions.

To test the robustness of the main results, we use several alternative measures of whisper-sell behavior. The results are robust. Specifically, we address the possibilities that whisper-sell measure could be mechanically higher if the analyst recommends many stocks or herds on

---

biased public recommendations. If this hypothesis were true, we would expect the results to be stronger among the industries that fund managers overweight in their portfolios.

recommendations made by the analyst's peers.

An alternative hypothesis is that the fund manager votes for the analyst because the analyst only provides the fund manager with industry knowledge and the fund manager trades more stocks when the manager is more informed about the analyst's industry. We address this alternative hypothesis by relating the analyst's stock-specific knowledge with the fund manager's trading decisions. If the analyst informs the manager of stock-specific information and the analyst's stock-level knowledge varies within an industry, we expect that the informed fund manager would trade stocks of which the analyst has better and more accurate knowledge. So, we predict that the analyst has more accurate knowledge of stocks traded by the managers who vote for the analyst than of other stocks not traded by these managers. This would be consistent with our hypothesis that the analyst provides stock-specific private information to the fund manager.

We measure an analyst's stock-specific knowledge by the accuracy of earnings forecasts he/she gives to these stocks. Among stocks that are positively recommended by an analyst, we define those that the analyst's voting fund managers sell as "fund-sell" stocks and the stocks that the analyst's voting fund managers buy as "fund-buy" stocks. We find that among the stocks that an analyst recommends positively in a given semi-year, on average, the analyst issues more accurate earnings forecasts on both fund-sell and fund-buy stocks than on other stocks that are not traded by the analyst's voting managers. Similarly, the analyst issues more reports and has more coverage experience on fund-sell and fund-buy stocks, which indicates that the analyst spends more effort in studying these stocks and thus is more likely to produce private information.

Lastly, we test whether fund-buy stocks outperform fund-sell stocks after the recommendations. Such an outcome would be consistent with our hypothesis that fund managers receive more accurate information from analysts than that included in analysts' public recommendations. We examine stock performance around public recommendation dates using a standard event-study approach. We find that cross-sectionally, fund-buy recommendations outperform fund-sell recommendations after the recommendation dates.

Furthermore, the market still reacts positively to the fund-sell recommendations around the announcement dates: the event-day abnormal returns from −1 to 1 trading days, on average, equal 1.24%, most of which are reversed in the following 40 trading days. This result suggests that at least some investors, likely retail investors, buy stocks upon positive recommendations and cannot distinguish between fund-buy and fund-sell stocks. The uninformed investors who buy unconditionally upon positive public recommendations would, on average, earn 1.49% fewer DGTW-adjusted returns from 2 to 40 trading days after the recommendation dates than the informed managers who only follow fund-buy recommendations. We attribute such differences in investment returns among market participants in part to the information asymmetry caused by analysts' different information disclosure strategies.

This paper contributes to the broader literature that documents that analysts issue strategic recommendations because of conflicts of interest.[8] One strand of this literature examines how analysts balance delivering valuable private information to clients versus making accurate public recommendations. Past work has documented that analysts create information asymmetry through tipping behavior—sharing their information with their clients before making it public (e.g., Irvine, Lipson, and Puckett 2006; Juergens and Lindsey 2009; Kadan, Michaely, and Moulton 2018; Even-Tov and Ozel 2021) or providing insider information to their clients without any public disclosure (Li, Mukherjee, and Sen 2021). Drawing on the insights of the information sales theory of Admati and Pfleiderer (1988) and Cespa (2008), we

[8] Previous literature has attributed this phenomenon to analysts' misaligned incentives originating from investment banking underwriting (Lin and McNichols 1998; Michaely and Womack 1999; O'Brien, McNichols, and Lin 2005; Ljungqvist, Marston, and Wilhelm 2006), institutional investor relationships (Ljungqvist et al. 2007; Mola and Guidolin 2009; Firth et al. 2013; Gu, Li, and Yang 2013), management relations (Das, Levine, and Sivaramakrishnan 1998; Lourie 2019; Bradley, Jame, and Williams 2022), and trade generation (Irvine 2000, 2004; Cowen, Groysberg, and Healy 2006; Agrawal and Chen 2008). In contrast with papers that document that analysts introduce directional biases in their recommendations, this paper shows that analysts introduce noise in their public recommendations.

test here for another form of opportunistic analyst behavior: analysts use a pooling strategy in their public recommendations to avoid distinguishing different value types in order to preserve the trading value of their private information to fund managers.

Specifically, this paper provides a test of the predictions of the model of García and Sangiorgi (2011) about optimal information sales. In that model, a private information provider's optimal selling strategy calls for selling: (1) imprecise information to a large group of investors, or (2) precise information to a small set of investors. Consistent with their approach, we find that analysts use say-buy/whisper-sell behavior to provide noisy information to the public and accurate information to a small group of institutional investors.

Our paper shares an insight similar to that of Malmendier and Shanthikumar (2014), who document "two-tongue" behavior of analysts who issue overly positive recommendations but less optimistic forecasts to target different audiences. Complementing their paper, we find that analysts disclose signals with different levels of accuracy to different audiences, and we find a linkage between such behavior and tacit rewards (in the form of voting behavior) conferred upon analysts by private clients.

This paper also contributes to the literature that examines private communication among financial professionals (e.g., Hochberg, Ljungqvist, and Lu 2007; Cohen, Frazzini, and Malloy 2008, 2010; Cao et al. 2014). We focus on potential information flows from sell-side analysts to buy-side mutual fund managers. At the stock level, some literature has found evidence that institutional aggregate trades correlate with analyst recommendations (Busse, Green, and Jegadeesh 2012; Brown, Wei, and Wermers 2014; Kong et al. 2021). Gu et al. (2019) find that mutual fund managers tend to hold and benefit from stocks covered by their connected analysts as identified by social ties.

In contrast with these papers, we use managers' votes to measure managers' evaluation of analysts. Moreover, we infer private communication through cases in which managers diverge from analysts' public recommendations rather than cases in which managers follow analysts' recommendations, which helps us distinguish from alternative hypotheses. As a result, our paper reconciles the fact that analysts pass valuable information to fund managers with the puzzle that analysts' public recommendations have relatively low information content.

Using the same voting data as our study, Cheng et al. (2021) examine how the incentive to win votes in star analyst competition affects the quality of analyst research outputs across firms. They find that for firms held by the voting funds, analysts issue more accurate earnings forecasts but more optimistic stock recommendations. Our focus is on a different research question: how analysts provide different information to the general public (via recommendations) than to fund managers.

The remainder of this paper is organized as follows. Section 2 develops hypotheses. Section 3 presents the data and the construction of the main variables. Section 4 presents a preliminary analysis of managers' voting to show its informativeness. Section 5 tests the main hypotheses by looking into the relationship between analysts' whisper-sell behavior and managers' voting decisions. Section 6 provides further tests, Section 7 discusses news insights on analyst recommendations, and Section 8 concludes.

2. Say-buy/whisper-sell behavior and main hypotheses

In this section, we first introduce the regulatory background of Chinese analysts in Section 2.1 and then explain analysts' different disclosure strategies toward different audiences in Section 2.2. In Section 2.3, we develop a series of hypotheses to test whether analysts use whisper-sell behavior to provide private and more-accurate information to fund managers than the information disclosed in public recommendations.

2.1 Regulation of Chinese analysts

A Chinese regulatory entity, the China Securities Regulatory Commission, issues codes to regulate analysts' behaviors.[9] These standards, like Reg FD, proscribe analysts from disseminating insider information or any information that is not disclosed in their published reports. However, as we now discuss, we provide evidence that shows that it is hard to enforce the standards and, thus, to discipline the analyst misbehavior.

We manually check the regulatory enforcement towards analysts by the Securities Regulatory Bureau in Shanghai and Shenzhen.[10] From 2013 to 2022, the regulators issued a total of 15 warnings to analysts for the violation of standard codes. Among these warnings, there is only one case in which the analyst reportedly disseminated undisclosed information via his/her private network. This suggests that it is uncommon for analysts to be disciplined directly for their say-buy/whisper-sell behavior because it is hard for regulators to find physical evidence on private communication. In most cases, the grounds for citation are that analysts made excessively positive or unsubstantiated statements in their reports that misled investors. Such cases can be the consequence of say-buy/whisper-sell behavior. We further find that none of these warnings resulted in legal lawsuits. Moreover, all analysts continue to work in the industry after receiving the warnings.

In sum, it is not common for analysts to be punished for whisper-sell behavior. There are, nonetheless, some potential reputational costs of whisper-sell behavior; if the whisper-sell stocks perform badly ex-post, there is a chance that analysts will be scrutinized by the regulators on the grounds of misleading investors.

2.2 Say-buy/whisper-sell behavior

Here, we discuss informally a setting in which say-buy/whisper-sell behavior occurs. The analyst can privately learn the value of a single firm and issues a public recommendation about the firm type. The analyst also privately sells the analyst's private signal to a fund manager.[11]

---

[9] These regulatory standards can be found at https://neris.csrc.gov.cn/falvfagui/.

[10] The detailed cases in Chinese can be found in http://www.csrc.gov.cn/shanghai/and http://www.csrc.gov.cn/shenzhen/.

[11] The fund manager can gain even if the manager only gets the private information after the public recommendation. The potential gain is even higher if the manager gets the private information before the public recommendation. Thus, the results

The analyst derives utility from the trades generated by retail investors who follow public recommendations, and from indirect side-payments from the mutual fund, which may be able to trade profitably based upon the analyst's private message. We also make an auxiliary assumption reflecting a feature of the Chinese market, which is that the analyst only issues positive recommendations. Specifically, the analyst makes a positive recommendation for firm values above certain thresholds and does not issue any public recommendations if the firm value is too low or if the analyst has not yet learned the firm value.[12]

For simplicity, the firm is publicly recommended by the analyst for the two highest possible value types. (There are lower possible types that are not recommended by the analyst.) As our focus is only on these two types, we call the second-highest type the "low" type. The high type has $\nu_H = 2$ and the low type has $\nu_L = -1$, though ν_L could alternatively be positive. The probabilities of these two types conditional on positive recommendation are the same, $1/2$.

The analyst chooses a public recommendation based on the firm value. The analyst can follow either: 1) a pooling strategy of issuing the same positive recommendation for both high and low firm values, or 2) a separating strategy of making a strong positive recommendation when $\nu_H = 2$ and a weak positive recommendation when $\nu_L = -1$, which fully distinguishes these two types.

If the mutual fund's profits are important enough to the analyst (owing to indirect side payments), it is optimal for the analyst to use the pooling strategy to issue the same positive recommendation for both the high and low types. A pooling strategy does not reveal whether the firm value is high or low. In consequence, the fund manager who receives the information of firm value from the analyst can benefit from informed trading.

Before the firm value is revealed, the stock price of the firm is normalized to 0, which reflects the fact that the firm has possible values below the low type, which reduces

are robust to the timing of the private communication.

[12] The general intuition still holds if the analyst issues a negative recommendation on a very-low firm value.

unconditional expected cash flows.

Upon the occurrence of a positive recommendation by the analyst, and assuming that the fund manager has not yet traded, the stock price, which is set by a risk-neutral market maker, is set at

$$E[\nu|\text{Positive Recommendation}] = 0.5\nu_H + 0.5\nu_L = 0.5 > 0. \tag{1}$$

So the stock market rationally reacts positively to the analyst's positive recommendation. This is true even though there is a possibility that the firm's type is low. The remaining uncertainty about firm value conditional upon the recommendation is what preserves the value of the analyst's private message to the fund manager.

To sum up, in this setting the analyst makes a pooling recommendation that partly conceals the analyst's private information and sells a private message to the fund manager which fully conveys the analyst's private signal. In practice, there are costs to following such a pooling strategy. Ex post, there is a chance that the analyst gets scrutinized and criticized for making an excessively optimistic recommendation about a low-type firm. So, whether the outcome we describe occurs is an empirical question.

Also, for the scenario described here to be consistent, the analyst also needs to make sure that the public positive recommendation is, in an appropriate sense, informative for retail investors. Otherwise, retail investors would gradually learn to ignore the analyst's public recommendations. Our example above illustrates how public information can be meaningful, yet trading profits can still be available to fund managers who receive the analyst's private signal.

In our empirical tests, we classify a stock with a positive recommendation that is bought by the connected fund manager as a whisper-buy stock. In our conceptual framework, this sequence of events occurs for a high-value firm.[13] We classify a stock that is sold by the connected fund manager as a whisper-sell stock. In our conceptual framework, this sequence of events occurs for a low-value firm. We use the occurrence of whisper-sell (and whisper-buy) behavior to proxy for the extent of private communication between any manager-analyst pair.

2.3 Main hypotheses

Following the insight of our conceptual framework, we can measure analysts' whisper-buy and whisper-sell behaviors based on the overlap between analysts' public recommendations and fund managers' portfolio holdings. For identification, we focus on whisper-sell measure since the opposing private and public behaviors help distinguish alternative hypotheses. Because we observe simultaneous actions between analysts and managers, there are three potential scenarios regarding how the manager interacts with the analyst: (1) the manager learns private information from the analyst (the private-communication scenario), (2) the manager learns public information from the analyst's public recommendations (the public-recommendation scenario), and (3) the analyst and the manager behave independently based on common external signals (the common source scenario).

The prediction for the whisper-buy measure for voting is the same under all scenarios; a higher whisper-buy measure implies that the manager gives a higher ranking to the analyst. The manager may vote for the analyst who provides either private or public information that usefully leads to the manager buying stocks. Furthermore, the manager may also vote for the analyst with whom the manager shares similar value judgments even if the manager's trading decision is unaffected.

In contrast, the prediction for the whisper-sell for voting differs across the scenarios. Under the public-recommendation or the common source scenario, whisper-sell behavior suggests

[13] It might seem that in this sequence of events, the fund manager is just following the public recommendation. However, in our setting, if the analyst instead were to whisper sell, that would indicate low value to the fund manager, who would still sell despite the public buy recommendation.

that the manager disagrees with the analyst's public opinions inferred from their public recommendations, leading to a *lower* ranking of the analyst by the manager. On the other hand, under the private-communication scenario, whisper-sell behavior suggests that the manager sells more stocks based on the analyst's private information, leading to a *higher* voting rank. Therefore, we focus on whisper-sell measure but also include whisper-buy measure in regressions to control for the public-recommendation and common source effects.

H1a: *Public-recommendation or common source scenarios: whisper-sell behavior* negatively *correlates with the manager's voting rank for the analyst.*
H1b: *Private-communication scenario: whisper-sell behavior* positively *correlates with the manager's voting rank for the analyst.*

We develop further hypotheses about analyst private communication with fund managers to test our main hypothesis. We explore contexts in which analysts' private information communication with fund managers is likely to be more important, so our whisper-sell measure is predicted to have a higher signal-to-noise ratio.

Managers who have weak skills in a specific industry have more need for analyst information. Also, managers who have strong business ties with a broker are more likely to communicate privately with analysts working in that brokerage house. We expect a stronger statistical relationship between whisper-sell behavior and voting rank among these manager-analyst pairs.

H2: *The positive relationship between whisper-sell behavior and voting ranks will be* stronger *for managers who have weak investment skills in the analysts' industries.*

H3: *The positive relationship between whisper-sell behavior and voting ranks will be* stronger *for managers who have important business ties with the analysts' brokers.*

We also expect information asymmetry to influence analyst behavior. If the information environment is very transparent, there is little room for opportunistic whisper-sell behavior. It is because that such behavior is likely to hurt the analyst's reputation when the quality of the analyst's public recommendations is more verifiable. Also, in such a transparent environment, a given analyst can generate little private information, which reduces the benefit to whispering sell. Therefore, analysts will be more likely to engage in whisper-sell behavior when the information environment is less transparent and firm information asymmetry is high.

H4: *The positive relationship between whisper-sell behavior and voting ranks will be* stronger *when analysts work in an industry in which stock information asymmetry is high.*

If the analyst issues less-accurate public recommendations to promote trades of retail investors, the analyst will benefit most when the analyst targets categories of stocks that are favored by retail investors.

H5: *The positive relationship between whisper-sell behavior and voting ranks will be* stronger *when analysts work in an industry that is favored by retail investors.*

Unconnected managers may evaluate the analyst more favorably if the analyst's positive recommendation performance is higher. However, if managers sell the stock based on the analyst's private information, managers are more likely to vote if managers observe bad performance of the stock even though the analyst publicly recommends this stock.

H6: *The positive relationship between whisper-sell behavior and voting ranks will be* stronger *after the post-recommendation performance of the whisper-sell stocks is poor.*

Since managers trade stocks based on the analyst's more-accurate private information, their informed trading should generate higher returns than unconditionally following the analyst's public recommendations. In other words, among the analyst's positive recommendations, the stocks bought by the managers who vote for the analyst should outperform the stocks sold by these managers after the recommendation dates.

H7: *Whisper-buy recommendations outperform whisper-sell recommendations after the recommendation dates.*

3. Data

We describe the voting data in Section 3.1, the matching of fund managers and analysts in Section 3.2, analysts' public recommendations in Section 3.3, the measure for analysts' whisper-sell behavior in Section 3.4, and analyst characteristics in Section 3.5.

3.1 Voting data

The primary data we use come from the voting data of the "Crystal Ball Awards for Sell-Side Analysts" from 2010 to 2016 in China. This analyst competition is hosted by *Capital Week* magazine, which is the only media outlet authorized to publish listed firms' disclosures in China. Analysts (single or multiple analysts as a team) take part in the competition each year across industry sectors; within each industry sector, each brokerage house has only one analyst team. Fund managers are invited to vote for the best-performing sell-side analysts in each industry sector. The voting takes place at the end of October. Based on managers' votes, the best three or five (depending on the industry) analyst teams are announced at the end of the year. Managers vote privately, meaning their votes will not be publicly disclosed. This voting feature allows managers to reveal their genuine preferences without being concerned about the revelation of their private social connections or trading strategies.

The main dependent variable is managers' voting decisions on analysts. Each fund manager can vote for at most five teams of analysts with preferences among candidates in each industry. We assign a numerical measure (*VoteRank*) for their votes (the first choice = 5; the second choice = 4; the third choice = 3; the fourth choice = 2; the fifth choice = 1; no vote = 0).

3.2 Fund managers and analysts

We match fund managers with their names and fund companies as listed in the China Stock Market & Accounting Research (CSMAR) database. Managers come from mutual funds, private funds, insurance funds, national pension funds, and other wealth management companies. We only use mutual fund managers because of the availability of their stockholding data. Table 1 reports the number of mutual fund managers used in this paper each year from 2010 to 2016. The number of fund managers participating in the voting has increased over the years, approximately tripling from 2010 to 2016, which reflects the booming development of financial institutions in the Chinese capital markets. Among the mutual fund managers listed in the CSMAR database, we can identify across years approximately two-thirds of mutual fund managers who voted in these yearly competitions.

[Insert Table 1]

Among identified mutual fund managers, we use active fund managers and remove index fund and bond fund managers because active fund managers mostly invest based on stock information. In total, we use 2,391 fund manager-year observations with nonmissing holding information; 2010 has the lowest number of managers at 213, and 2016 has the highest number of managers at 535. Our sample accounts for, on average, 34% of total active funds existing in that year; the percentages remain stable across years.[14]

We infer the fund trades based on fund disclosures of total portfolio holdings. In China, mutual funds must disclose their total asset holdings information semi-yearly, in the second and fourth quarters. All funds' fiscal years correspond to the calendar year. Funds also disclose their top-ten holdings quarterly. In our main results, we use fund trades implied from the semi-yearly holdings because we can access the total asset holdings of the funds. We also use quarterly holdings to produce robust results. Panel A of Table 2 shows the characteristics of active funds' holdings and implied trades in our sample. Active funds, on average, invest in 58.75 stocks across 16.90 industries. The relatively broad coverage of industries by fund managers suggests that they may not specialize in all the industries they invest in and therefore may seek advice and information from analysts who specialize in certain industries. Between two semi-yearly holding disclosures, fund managers implement significant portfolio changes, which results in, on average, 45.39 stocks with shares being increased and 49.49 stocks with shares being decreased, and a high semi-year turnover ratio of 57.58%.

[Insert Table 2]

On the other hand, we match the analysts in the voting data with their names and brokerage house names in the CSMAR database and adopt the analyst teams when we can successfully identify at least one of their team members. In China, a brokerage house typically assigns multiple analysts to form teamwork to cover one industry; on average, 34 brokerage houses take part in the competition each year across 27 industries.[15] Even though some analysts issue reports as sole authors, they often incorporate their coworkers' opinions. Naturally, a team of

[14] In Internet Appendix Table IA.1, we compare the fund-year observations used in this study with the whole sample from the CSMAR database. There is no strong difference between the two samples in terms of fund characteristics. If anything, the funds included manage larger amounts of assets and have higher raw returns than the average fund during our sample period.

[15] The industry classification uses the CITIC Securities (China International Trust and Investment Corporation) industry classification system. Detailed information can be found in Wind database. CITIC Securities is the leading domestic investment bank in China.

analysts specializing in one industry sign up for the competition, representing their brokerage house. For brevity, we call a team of analysts the "analyst" regardless of the number of analysts in that team.

Table 1 also reports the numbers of analysts recorded in the voting data that we successfully match in the CSMAR database and that we use in the analysis (removing analysts with missing information on characteristics variables) across years. In total, our analysis uses 3,146 analyst-year observations, which is more than three-quarters of the analysts in the original voting data. When we count analysts individually, our sample accounts for roughly 40% of analysts who issued at least one report in the corresponding year.

The recommendation and earnings forecast data are also from the CSMAR database. We assign a recommendation or an earnings forecast to the analyst if at least one group member is listed as the issuer of that recommendation (or earnings forecast) in the CSMAR database.[16] Analyst recommendations in CSMAR are recorded using the standardized five-digit rating system similar to I/B/E/S, which goes from 1 (Strong Buy) to 5 (Strong Sell). Other data on stock returns and related variables are also from the CSMAR database.

3.3 Analyst public recommendations

Public recommendations made by analysts are one of the major focuses of this paper. In this paper, we examine 123,097 public recommendations issued by analysts who engage in analyst ranking competition in our sample from 2010 to 2016. Of those recommendations, 45.48% are Strong Buy; 49.44% are Buy; 4.97% are Hold; 0.03% are Sell; and 0.08% are Strong Sell.[17] In terms of the rating changes, 7.55% are first-ever recommendations, 3.35% are

[16] Note that within each industry, only one analyst (or analyst group) represents their brokerage house. Therefore, it is extremely unlikely that one recommendation would be counted twice for two analyst groups from two brokerage houses.

[17] If we calculate the probability of a stock within the industry being recommended, an analyst on average issues "Strong Buy" with a likelihood of 6.4%, "Buy" with a likelihood of 8.8%, "Hold" with a likelihood of 1.2%, "Sell" with a likelihood of less than 0.001%, and "Strong Sell" with a likelihood of less than 0.001%. This suggests that Chinese analysts are not simply recommending that investors buy all stocks. On the contrary, analysts selectively choose stocks to recommend but they disproportionately issue positive recommendations compared to negative recommendations.

upgrades, 82.91% are recommendations whose ratings are the same as the previous one, 1.94% are downgrades, and the rest are undefined.

The distribution of recommendations indicates that Chinese analysts tend to issue positive recommendations only and tend to be reluctant to issue recommendation changes. This is consistent with our premise that analysts limit the informativeness of their public recommendations but use optimistic recommendations to generate retail trades. On the other hand, even though_most recommendations are Buy and Strong Buy, Chinese analysts' recommendations are not pure noise. In our sample, Strong Buy (Buy) recommendations produce DGTW-abnormal returns of 1.55% (0.98%) over the −1 to +1 event window. This indicates that the announcement of a Strong Buy or Buy recommendation has a positive impact on stock prices.[18]

3.4 The Say-buy/whisper-sell measure

To measure whisper-sell (whisper-buy) behavior, we calculate the overlap between the fund's selling (buying) stocks and the analyst's positive recommendations. We formally define *FundSell* and *FundBuy* for analyst *l* and fund *j* in semi-year *s*, as follows.

$$\text{FundSell}_{l,j,s} = \frac{\sum_{i\in \mathrm{A}_{l,s}\cap \mathrm{B}_{j,s}} |\min(v_{i,j,s} - v_{i,j,s-1}, 0)\, p_{i,s}|}{\sum_{i\in \mathrm{B}_{j,s}} |\min(v_{i,j,s} - v_{i,j,s-1}, 0)\, p_{i,s}|}, \tag{2}$$

$$\text{FundBuy}_{l,j,s} = \frac{\sum_{i\in \mathrm{A}_{l,s}\cap \mathrm{B}_{j,s}} |\max(v_{i,j,s} - v_{i,j,s-1}, 0)\, p_{i,s}|}{\sum_{i\in \mathrm{B}_{j,s}} |\max(v_{i,j,s} - v_{i,j,s-1}, 0)\, p_{i,s}|}, \tag{3}$$

where $v_{i,j,s}$ is the number of shares of stock *i* held by fund *j* in semi-year *s*; $p_{i,s}$ is the price of stock *i* at the end of semi-year *s*; $A_{l,s}$ is the set of stocks that analyst *l* recommended as Buy, Strong Buy in semi-year *s*; $B_{j,s}$ is the set of stocks that fund *j* traded during semi-year *s*. Because,

[18] Several effects can contribute to the positive abnormal returns on the analyst recommendations announcement. The market could positively react to analysts' positive recommendations even if investors ex ante know that analysts mix low-value value types in their positive recommendations. On the other hand, it is possible that retail investors naively believe that analysts only recommendation good firms (Malmendier and Shanthikumar 2007), resulting in overpricing of recommended firms.

for each analyst, we only focus on the industry of which the analyst signs up in the competition, the industry subscript is not included in the above equations. In short, *FundSell*, defined at the fund-semi-year level and in relation to an analyst, is the percentage of the sales during a semi-year conducted by a fund, that occur despite the analyst's positive public recommendation.

For the consideration of positive recommendations, we are aware that analysts' other actions may implicitly tell their pessimistic beliefs while they are issuing Strong Buy and Buy recommendations; so, we exclude the stocks if a subsequent downgrade (either in recommendations or earnings forecast) happens during the same period.

In the analyst voting, each fund manager can vote for analysts in all industry sectors. To limit the analysis to the most relevant manager-analyst pairs regarding information transmission, we restrict the sample to the fund-analyst–semi-year observations in which the fund has at least 5% of its total equity holdings in the analyst's industry.[19] We also restrict the sample to the observations in which the fund has both bought and sold at least one stock, respectively, in that industry. This filter ensures that the fund manager sells stocks for informational reasons; that is, they tilt the portfolio from some stocks to others for better future performance, rather than for liquidity reasons, such as fire sales or investment policy changes.

In our main analysis, we use the *FundSell* and *FundBuy* measures at the manager-analyst-year level by averaging the values across manager m's fund j and across semi-year s of year t.

$$\begin{aligned} \text{FundSell}_{l,m,t} &= \text{Average}\left(\text{FundSell}_{l,j,s}\right), \\ \text{FundBuy}_{l,m,t} &= \text{Average}\left(\text{FundBuy}_{l,j,s}\right). \end{aligned} \tag{4}$$

Table 2, Panel B reports the *FundSell* and *FundBuy* measures at the manager-analyst-year level. *FundSell* has a mean of 0.30 and a standard deviation of 0.34. This means there is significant variation across manager-analyst pairs as the 25th percentile is zero, whereas the

[19] The holding percentage is calculated as the average of the total percentage holding across stocks that belong to the analyst's industry from the half-year report and the year-end report in that year. Setting the holding percentage criterion at 10% generates similar empirical results.

75th percentile is 0.50.

If analysts' public recommendations are highly informative, so that managers either follow analysts' public recommendations or make the same decisions independently, we would expect *FundBuy*, on average, to be much higher than *FundSell*. However, the mean of *FundBuy*, is approximately equal to the mean of *FundSell* (0.30 versus 0.30). This result suggests that fund managers, in general, trade differently than the public recommendations of analysts would indicate, which is consistent with analysts' public recommendations having low information content.

3.5 Analyst characteristics

To examine how fund managers vote for analysts in the star competition, we construct control variables that characterize analysts' recommendations and other activities. Emery and Li (2009) research U.S. analyst rankings, and we borrow many control variables from them. Appendix Table A.1 shows the detailed construction of these variables. These analyst characteristics include the number of reports (recommendations or earnings forecasts) issued (*Nrec*), the number of stocks recommended (*Nstock*), the return performance (*InfoRatio*) and the riskiness (*Risk*) of analyst positive recommendations, the optimism of analyst recommendations (*Optism_recom*) and of earnings forecasts (*Optism_feps*), the tendency of analysts to issue upgrade recommendations (*Upgrade*), and recommendation propensities for large-cap stocks (*Firmsize*) and attention-grabbing stocks (*Attention*).[20] To measure the popularity or name recognition of an analyst, we also include measures for the analyst's work experience (*Experience*), the size of the analyst's brokerage house (*Brokersize*), whether the analyst's brokerage house has a significant business relationship with the fund (*TradeBroker*), and whether the analyst was a winner in the previous year's competition (*PreAward*).

[20] We do not include the measure for earnings forecast accuracy because the actual earnings numbers are not available when votes occur.

Panel C of Table 2 shows the summary statistics on these analyst characteristics. The analysts in our sample, on average, cover 13.83 stocks and publish 38.68 reports in a year. Like the general analysts in the Chinese market, most of their recommendations are Strong Buy and Buy, and few of them are upgrade ratings (an average of 4%). The portfolios mimicking their public recommendations for a holding period of 3 months, on average, do not generate significant positive returns against the industry benchmark; the average portfolio alpha is −0.35% per month.

Panel D of Table 2 reports the correlations between *FundSell* and the analyst characteristics variables. Overall, *FundSell* has low correlations with these analyst characteristics; among the highest estimates is its correlation with the number of stocks recommended (*Nstock*) and the size of recommended stocks (*Firmsize*) at 0.19 and 0.31, respectively. Analysts who cover more stocks and who cover common large-cap stocks on average may have higher values of *FundSell* than other analysts. Later, in Section 5.4, we will construct alternative measures to further neutralize such mechanical effects. The correlation between *FundSell* and *FundBuy* in our sample is not very high (estimate = 0.43), suggesting that *FundSell* contains different information from *FundBuy*.

4. Votes as manager evaluations of analysts

In this section, we examine whether managers' voting decisions reveal useful information about their evaluations of analysts. Previous literature shows that institutions use trade commissions to incentivize brokers to provide premium services including giving valuable information (Conrad, Johnson, and Wahal 2001; Goldstein et al. 2009; Juergens and Lindsey 2009; Firth et al. 2013; Gu, Li, and Yang 2013) and that analysts' bonuses are often linked to trade commissions generated by their recommendations (Irvine 2000, 2004). Therefore, if managers' votes contain information about managers' evaluations of analysts, we would expect a positive relationship between voting decisions and subsequent trade allocations.

To test this hypothesis, we collect information about the fund trade allocations in dollar value among brokers for each mutual fund and each year from the Wind Financial Database (WindDB).[21] We aggregate the voting rank at the fund-broker level by taking the average of the fund manager's voting ranks across all analysts of the same broker each year. Then, we estimate the ordinary least-squares (OLS) regressions as follows.

$$Ln\left(\text{TradeShare}_{g,j,t+1}\right) = \beta\Delta\overline{\text{VoteRank}}_{g,j,t} + \gamma Ln\left(\text{TradeShare}_{g,j,t}\right) + \varepsilon_{g,j,t+1}. \quad (5)$$

The dependent variable is the natural logarithm of the percentage share (from zero to 100) of trades allocated from fund j to brokerage house g in year t+1.[22] The independent variable of interest, $\Delta\overline{VoteRank}_{g,j,t}$, is the change in the average vote ranking from the previous year. We also control for the trade allocation this year. We expect the coefficient β to be positive, suggesting that higher voting leads to higher future trade allocations. The analysis is based on each fund-broker-year unit in the sample and conditioned on existing fund-broker partnerships (with nonzero trading allocations) in the current year. The standard errors are adjusted for the two-way clustering of broker and fund.

[Insert Table 3]

Table 3 reports the regression estimates. The univariate regression in column (1) shows that the change in the average voting rank positively correlates with future trade allocation shares for the same broker. We also include in column (2) the trade allocation shares in the current year and obtain similar results. Further, in columns (3) to (5), we add broker, broker-year, and broker-fund/broker-year fixed effects, respectively, and find robust results. Regarding the

[21] We use the dollar volume of trades rather than the exact commissions on trades because the commission fee per trade may vary across brokers. WindDB collected these data from the yearly regulatory filings of each mutual fund in China as mandated by Chinese regulators.

[22] We add one to the original *TradeShare* in percentages before the log transformation to avoid zeros. Furthermore, evidence in Internet Appendix Table IA.2 indicates that the results are robust to using a ranking value of *TradeShare* as the dependent variable.

economic magnitude, we find that a one-unit increase in the average voting rank (e.g., from 4 to 5) is associated with a 2.91% to 5.18% increase in the future trade allocation share, depending on the specification.

By linking managers' votes with their real-world actions in allocating trade commissions between brokers, we provide consistent evidence that managers' votes are informative of their evaluations of analysts' services.[23] However, the results so far do not provide causal evidence as there may be unobserved variables that affect funds' trading, voting, and trade allocation decisions. Because the commission data is at the broker-fund level, in the next section, we use more granular voting data at the analyst-fund-manager level to test our main hypothesis.

5. Do managers vote for whisper-sell behavior?

Next, we test the main hypothesis that analysts use say-buy/whisper-sell behavior to provide more-accurate information to fund managers than analysts do in their public recommendations. We test this hypothesis in Section 5.1 by examining whether managers vote for analysts with more whisper-sell behavior as a reward for the analysts' more-accurate information. Then, we provide further evidence by exploiting the conditional effect of whisper-sell behavior in Section 5.2. We explore the relationship between analyst characteristics and whisper-sell behavior in Section 5.3. We provide robustness checks in Section 5.4.

5.1 Whisper-sell behavior and voting decisions

We analyze the relationship between managers' voting decisions and analysts' whisper-sell measure. The main OLS regression we estimate is shown as follows.

---

[23] Similarly, we also find that managers' votes are positively associated with the say-buy/whisper-sell measure for the same fund-manager-analyst pair in the subsequent year. This suggests that managers who rank analysts highly in the star analyst competition engage in more private communications with the same analysts in the future. The results are reported in Internet Appendix Table IA.9.

$$\begin{aligned}\text{VoteRank}_{l,m,t} = \beta_0 + \beta_1\text{FundSell}_{l,m,t} + \beta_2\text{FundBuy}_{l,m,t} \\ +\gamma\text{Analyst Characteristics}_{l,t} + \delta_{g,k} + \varepsilon_{l,m,t}.\end{aligned} \tag{6}$$

The dependent variable (*VoteRank*) is fund manager *m*'s vote choice for analyst *l* in year *t*. The independent variables of interest, *FundSell* and *FundBuy*, and analyst characteristics variables are defined in detail in Section 3. For each continuous independent variable, we also use the percentage ranking of the original value within the industry-analyst group in that year, with the highest value being assigned the value of one and the lowest value being assigned the value of zero. The variables with such conversion are indicated with an "s" suffix. We make this conversion because the manager would make decisions based more on analysts' relative performance among their peers than on their performance alone. It also helps alleviate any concerns about extreme outlier values. $\delta_{g,k}$ is the fixed effect for the time-invariant business relationship between analyst *l*'s brokerage house *g* and manager *m*'s fund company *k*. Standard errors are adjusted for analyst-year clustering.

[Insert Table 4]

If the analyst's private information drives the fund manager's selling decisions and the manager rewards the analyst with his/her vote, we expect a positive relationship between *VoteRank* and *FundSell*. In column (1) of Table 4, we find that the coefficient on *FundSell* is 0.084, which is statistically significant at the 1% level.[24] This result implies that analysts use say-buy/whisper-sell behavior to provide fund managers with private information that is incrementally informative relative to analysts' public recommendations.

We also include *FundBuy* in the regression and find that the coefficient is positive and statistically significant (estimate = 0.132).[25] As stated in Section 2, this is also consistent with

[24] The voting occurs at the end of October, so most of the activities documented in the *FundSell* measure happen before the voting occurs. We perform a robustness check by using the *FundSell* measure only for the first half-year and find similar results.

[25] The fact that the coefficient of *FundBuy* is greater than the coefficient of *FundSell* is consistent with our prediction. *FundSell* captures the cases where the manager sells the stock based on the analyst's private information and the cases where a fund manager disagrees with the analyst's public recommendations. The former case implies a positive impact on the manager's

fund managers learning information from analysts' public recommendations and with fund managers recognizing the analysts who are similar to them. The inclusion of *FundBuy* helps control for these two effects.

In column (2), we find a similar result when we use the percentage ranking value of *FundSell*; the coefficient estimate on *FundSell_s* is 0.096 and is statistically significant. In column (3), we use analyst-year fixed effects that absorb all analyst-year-specific variables and find similar results. Additionally, we control for the institutional relationships between analysts and fund managers. In column (4) for *FundSell* and column (5) for *FundSell_s*, we adopt the company-broker fixed effects that control for any time-invariant relationship between the manager's fund company and the analyst's brokerage house.

In column (6), we use manager-broker fixed effects to control for each manager's time-invariant preference for analysts from one specific broker; we find robust results. In column (7), we incorporate the average voting rank across other managers of the same fund company who do not invest in the analyst's industry to control for a potential connection between the analyst and the fund company in that specific year. The coefficient on *FundSell_s* remains significant but drops to two-thirds of previous estimates along with other control variables, which raises the possibility that there may be social influences among managers in the same fund company in terms of which analysts to vote for.

From columns (8) to (12), we relate *FundSell_s* to the managers' binary voting decisions, that is, whether the manager votes as the first choice, votes as the second choice or higher, votes as the third choice or higher, votes as the fourth choice or higher, or votes as the fifth choice or higher.[26] Results are consistent across all binary indicators. We find that whisper-sell

voting, but the latter case implies a negative impact. On the other hand, as for *FundBuy*, both cases imply a positive impact on the manager's voting. Since the regression coefficient captures a mixture of these possibilities, it is plausible that the coefficient on *FundBuy* would be higher than the coefficient on *FundSell*.

[26] We report the results from the OLS regressions because we can read economic magnitudes directly from coefficient estimates. We also run multiple logistic regressions (in unreported tables) and find similar results.

measure has a relatively strong effect on the first-choice vote. According to column (9), an increase in *FundSell_s* from 0.25 (approximately the 25th percentile) to 0.75 (approximately the 75th percentile) leads to an increase of 50 basis points in the probability of an analyst being voted as the first choice; this translates into an approximately 10% increase relative to the unconditional probability of being voted as the first choice (5.03%).

5.2 Conditional effects of whisper-sell behavior

We explore the heterogenous effect of whisper-sell behavior on voting decisions and have five key findings. First, such whisper-sell-voting relationship should be more pronounced when the manager has relatively low investment skills in the analyst's industry such that the manager relies on outside knowledge from the analyst (*Hypothesis* 2). Second, the relationship between whisper-sell measure and voting is strengthened when the manager has an important business tie with the analyst's broker and is more likely to communicate privately with the analyst (*Hypothesis* 3).

[Insert Table 5]

Table 5 tests the hypotheses mentioned above. Following the work by Kacperczyk, Sialm, and Zheng (2005), we use the portfolio weight for the respective industry in the previous year to proxy for the manager's investment skill in that industry. Columns (1) and (2) show that having a lower industry-wide ability (low portfolio weight) enhances the relationship between whisper-sell measure and vote.

We define the manager's important partner brokers as those whose trade allocation percentages from the manager's fund in the previous year are above the sample median.[27] Columns (3) and (4) show that having an important business tie with the manager has a positive

[27] The sample median is calculated among fund-broker observations that are positive (existing zero observations). In untabulated tables, we use alternative indicators for the funds' top five (or ten) brokers based on the allocated trades and find similar results.

effect on the relationship between whisper-sell measure and vote.

Third, a less transparent information environment may lead to more whisper-sell behavior because of less reputational concerns and of more benefits to finding private information (*Hypothesis* 4). To test this prediction, we first calculate stock-level information asymmetry using an average of the Z-score of four measures: (1) (inversely) number of analyst reports, (2) (inversely) number of covered analysts, (3) earnings forecast dispersion, and (4) stock idiosyncratic volatility. Then, we average the stock-level measure by industry, as the voting regression is estimated at the industry dimension and define *InfoAsymmetry* as equal to one if the industry-level information asymmetry is above the median in the previous year. In columns (5) and (6), we find that the coefficient estimate on the interaction term between *FundSell_s* and *InfoAsymmetry* is positive and statistically significant, which suggests that whisper-sell behavior is more likely to occur when the information asymmetry is high.

Fourth, the analyst is likely to engage in whisper-sell behavior for stocks that are preferred by retail investors (*Hypothesis* 5). The reason for this is that for such stocks, optimistic analyst recommendations should induce more buy orders from retail investors. Based on the finding that retail investors are attracted to investing in lottery stocks (e.g., Kumar 2009; Bali et al. 2021), we use lottery stocks as a proxy for retail investor habitats. We define *Lottery* as equal to one if the proportion of lottery stock in that industry is above the median in the previous year. In column (7), we find that the coefficient on the interaction term between *FundSell_s* and *Lottery* is 0.156 and statistically significant. The coefficient is about twice as large as the unconditional estimate of the coefficient on *FundSell_s* (0.82 in column (5) of Table 4). The result suggests that say-buy/whisper-sell behavior is more likely to occur among stocks that are attractive to retail investors.

Fifth, if the fund manager sells the stocks based on the analyst's private information, the manager will give a higher vote to the analyst when the manager sees poor returns from such stocks (*Hypothesis* 6). Accordingly, we calculate the analyst's whisper-sell stocks' performance as the industry-adjusted abnormal return from the recommendation dates to the current semi-year-end. We include whisper-sell stocks' performance and its interaction with *FundSell_s* in our main regressions.

In column (9), we find that the coefficient on the interaction term between *FundSell_s* and fund-sell stocks' performance is negative (−0.305) and statistically significant.[28] This suggests that when the average returns of fund-sell stocks are one percent lower than zero, the sensitivity of votes on *FundSell_s* increases by 6.8% (0.305 * 0.01 / 0.045). This result indicates that fund managers are more likely to vote if they see poor returns from the fund-sell stocks, even though these stocks are positively recommended in public.

Overall, the conditional tests in this subsection provide further support for the hypothesis that analysts use say-buy/whisper-sell behavior to provide stock-specific private information to fund managers that is more accurate to the information in analysts' public recommendations.

5.3 Which analysts would likely pursue whisper-sell behavior?

What kinds of analysts are more likely engage in whisper-sell behavior? To answer this question, we relate an indicator for whisper-sell behavior to a variety of analyst characteristics. We first identify analysts who are likely to engage in whisper-sell behavior. For each analyst-year observation, we run a univariate regression of *FundSell* on *VoteRank* and use the coefficient to measure the likelihood of the analyst engaging in whisper-sell behavior. Formally, we define those analysts whose coefficient estimates of *FundSell* fall in the top three (or five) among their industry peers as whisper-sell-prone analysts. Then, we run OLS regressions of being whisper-sell-prone analysts on analyst characteristics variables constructed in that year. For ease of comparison, we standardize analyst characteristics variables except for indicator

[28] For this test, we limit the manager-analyst observations to those with at least one whisper-sell stock in that year. Because of this, the total observations are reduced from 271,551 to 159,790.

variables.

Table 6 reports the results and highlights two interesting results. First, we find that issuing more reports (*Nrec*) but covering fewer stocks (*Nstock*) is positively associated with being a whisper-sell analyst. Because analysts have limited time and resources, the analysts who allocate their time to fewer stocks could gain more private information on covered stocks.

[Insert Table 6]

Second, broker size (*Brokersize*) and previous awards (*PreAward*) are positively associated with being whisper-sell analysts. These findings suggest that analysts who come from large brokerage houses and are well-recognized in the industry are more likely to engage in whisper-sell behavior. Such analysts have more business ties to private clients, which would enable whisper-sell behavior to maximize the trading value of their private information.

5.4 Robustness checks

We run several robust checks. First, we construct whisper-sell and whisper-buy measures using the quarterly disclosures of top-ten holdings. Though the measures are constructed with incomplete information of fund holdings,[29] in Internet Appendix Table IA.3, we still find robust results for the same specifications as Table 4.

Second, we use several alternative whisper-sell measures. We calculate a parsimonious version of *FundSell* that is insensitive to trade turnover.

$$\mathrm{FundSell}_{l,j,s}^{\mathrm{count}} = \frac{\sum_{i\in \mathrm{A}_{l,h,s}\cap \mathrm{B}_{j,h,s}} I\left(v_{i,j,s} - v_{i,j,s-1} < 0\right)}{\sum_{i\in \mathrm{B}_{j,h,s}} I\left(v_{i,j,s} - v_{i,j,s-1} < 0\right)}, \tag{7}$$

Compared to Eq. (2), *FundSell*^{count} of Eq. (7), using the indicator function *I* (.), counts the number of stocks actively sold by fund managers and the number of fund-sell stocks and does

[29] Because the quarterly disclosure only includes top-ten holdings, we regard buying stocks as those whose numbers of held shares increase or whose rankings enter the top ten and selling stocks as those whose numbers of held shares decrease or whose rankings drop out of the top ten.

not weight stocks by the trading volume.

$$\text{FundSell}^{\text{adjusted}}_{l,j,s} = \text{FundSell}_{l,j,s} - \frac{\sum_{i \in \text{B}_{j,h,s}} \omega^{l}_{i,s} \left|\min\left(v_{i,j,s} - v_{i,j,s-1}, 0\right) p_{i,s}\right|}{\sum_{i \in \text{B}_{j,h,s}} \left|\min\left(v_{i,j,s} - v_{i,j,s-1}, 0\right) p_{i,s}\right|}. \tag{8}$$

The second alternative measures control for the mechanical effect that recommending more stocks or herding with other analysts will lead to higher values of *FundSell*. In Eq. (8), we subtract the expectation of *FundSell* of Eq. (2) under the assumption that analysts randomly recommend stocks. The variable $\omega^{l}_{i,s}$ refers to the probability of analyst l positively recommending stock i in semi-year s, given the number of positive recommendations issued. We consider two possible assumptions on the probability of picking a stock from the industry pool. One is that there is an equal chance across stocks.[30] Alternatively, we assume that the chance of picking one stock is proportional to how many analysts of other brokers issued positive recommendations on the same stock.[31] By doing so, we further control for analysts' herding tendency, such as recommending popular large-cap stocks.

[Insert Table 7]

Table 7 replicates the main regressions of Table 4 using the alternative whisper-buy and whisper-sell measures defined above. Columns (1) and (2) use the whisper-sell measure based on the number of the analyst's whisper-sell stocks and the manager's selling stocks; the coefficient estimates are positive and statistically significant, in keeping with our main results. Furthermore, columns (3) to (6) use the measures in Eq. (8) that adjust for the expectations.

[30] In particular, the probability of picking stock i from industry h by analyst l, $\omega^{l}_{i,s}$, equals $1 - \left(1 - \frac{1}{\#(i \in \mathit{industry}\ h)}\right)^{\#(A_{l,h,s})}$, where $\#(i \in \mathit{industry}\ h)$ counts the number of stocks in industry h and $\#(A_{l,h,s})$ counts the number of stocks in industry h that analyst l recommends as positive in semi-year s. Put differently, we calculate $\omega^{l}_{i,s}$ as 1 minus the probability of never picking stock i over the number of trials that is equal to the number of stocks the analyst recommended as positive. Here, for ease of calculation, we assume that stocks are picked with replacement. However, because the number of stocks in an industry is often much higher than the number of stocks analysts recommend, such approximation does not produce significant measurement errors.

[31] We count multiple analyst recommendations from the same broker only once and give zero probability to stocks that no other analysts ever recommended.

We find positive and statistically significant estimates on whisper-sell and whisper-buy measures across these specifications. This suggests that our main results are robust to the potential biases arising from analysts covering many stocks and/or herding.

Third, for the identified fund-sell stocks, fund managers may buy and sell the same stocks at different dates within a semi-year. We show that our results are robust when considering the possibilities of these within-semi-year turnovers by funds. Our results still hold when we include only the fund-sell stocks that analysts publicly recommended in the second half of the semi-year (see Internet Appendix Table IA.4). Under this definition, *FundSell* excludes cases in which fund managers first buy a stock because the managers are unconditionally following positive public recommendations issued by analysts in the first half of the semi-year (rather than buying only when fund managers also receive positive whispers from analysts). In addition, we find the results are robust when we include only the fund-sell stocks of which fund managers sold all the holding shares (see Internet Appendix Table IA.5).

Fourth, analysts may issue optimistic public recommendations but pessimistic earnings forecasts of the same stocks (Malmendier and Shanthikumar 2014). To verify whether our results are driven by this particular analyst behavior, we include only the fund-sell stocks of which the analyst's earnings forecasts are above the median forecast; the result remains robust (see Internet Appendix Table IA.6). Fifth, we show that the results are not confounded by the analysts' general coverage of stocks held by fund managers (see Online Appendix Table IA.7) and the analysts' site visits (see Internet Appendix Table IA.8).

6. Further evidence on private information transmission

In Section 6.1, we examine whether analysts indeed have accurate private information on fund-sell and fund-buy stocks. In Section 6.2, we examine whether fund-sell and fund-buy stocks differ in their recommendation performance to further evaluate whether informed trading of analysts' recommended stocks generates higher returns than unconditionally following analyst public recommendations.

6.1 Do analysts provide accurate private information to fund managers?

Our hypotheses are based on the premise that the fund manager votes for the analyst because the analyst gives accurate and valuable information about stocks to the fund manager for profitable trading. In this subsection, we perform further tests of that premise. If the analyst gives stock-level private information to the fund manager and the analyst's stock-level knowledge varies across the analyst's covered stocks, then the fund manager will trade stocks of which the analyst has more-accurate information. We measure the accuracy of the analyst's information by the earnings forecast accuracy. Therefore, we predict that analysts issue more-accurate earnings forecasts for fund-sell and fund-buy stocks than for other stocks—those that fund managers choose not to trade.

This test helps us distinguish from the alternative account that the analyst only provides the fund manager with valuable information at the industry level but not at the stock level. If the analyst only provides industry-level information, then the manager's decision of which specific stocks to trade would correlate only with the accuracy of the manager's own stock-specific information but not the accuracy of the analyst's stock-specific information.

We first identify the fund-sell and fund-buy stocks among the analyst's positive public recommendations by measuring in what direction the managers who vote for the analyst, on average, trade the stocks. We define the average trades on stock *i* in semi-year *s* across funds whose managers vote for analyst *l*, *Portfolio_Chg*, as follows.

$$\text{Portfolio\_Chg}_{i,l,s} = \frac{\sum_{j\in \text{Fund}_{l,i,s}} a_{i,j,s}}{\sum_{j\in \text{Fund}_{l,i,s}} 1},$$
$$\text{where } a_{i,j,s} = \frac{(v_{i,j,s} - v_{i,j,s-1})p_{i,s}}{(mv_{j,h,s-1} + mv_{j,h,s})/2}. \tag{9}$$

$Fund_{l,i,s}$ represents the set of funds whose managers vote for analyst l in that year and trade stock i in semi-year s. To control for the heterogeneity of fund investments in a specific industry, the normalized portfolio change of fund j on stock i in semi-year s, a_{ijs}, is defined as the dollar turnover on stock i scaled by the average of fund j's portfolio weight, that is, $mv_{j,h,s-1}$, in industry h in semi-year s-1 and s.[32] For each stock i that analyst l recommends positively in semi-year s, we take an equal average of the normalized portfolio changes on stock i across analyst-voting funds, $Fund_{l,i,s}$.

For each semi-year, we assign each positive stock recommendation into one of three groups based on the sign of *Portfolio_Chg*: a fund-buy group if *Portfolio_Chg* is positive, a not-trade group if *Portfolio_Chg* is zero, and a fund-sell group if *Portfolio_Chg* is negative. In other words, the fund-buy (fund-sell) group represents whisper-buy (whisper-sell) stocks. In the sample, 33.6% of positive recommendations are fund-buy recommendations, whereas 32.3% of them are fund-sell recommendations; the remaining are not-trade recommendations.

[Insert Table 8]

In Table 8, we examine the relationship between analyst earnings forecast accuracy and voting managers' trading decisions in the cross-section of the analyst's positive recommendations.[33] In the regressions, we include analyst-semi-year fixed effects such that we only draw comparisons between stocks in the same industry that are recommended by the same analyst. The result, in column (1), indicates that analyst earnings forecast accuracy is higher on stocks that are traded (bought or sold) by the analyst's voting managers than on stocks that are not traded by these managers, suggesting that the analyst has more-accurate information on these traded stocks than on other stocks covered by the same analyst. Likewise, analysts cover

[32] Using the average of the portfolio weights in semi-year s - 1 and s instead of using the value in semi-year s avoids the occurrence of extreme values when a fund sells most of the stocks in that industry during semi-year s, which makes the ratio unreasonably high as the denominator is close to zero.

[33] Cheng et al. (2021) run similar tests, but they look at managers' stock holdings rather than changes in holdings.

these manager-traded stocks for a longer time and issue more reports on these stocks compared to nontraded stocks, suggesting that analysts invest more time and effort in these traded stocks and thus are more likely to produce private information. These results are consistent with analysts providing more-accurate stock-specific information to fund managers, instead of providing only industry-wide knowledge to fund managers.

We also examine whether analysts reveal fund-buy and fund-sell stocks in their public recommendation decisions. In column (4), we find that both fund-buy and fund-sell stocks are equally 10% more likely to be recommended as Strong Buy, compared to stocks not traded by analyst-voting managers. Overall, the evidence suggests that analysts provide information to fund managers that is more accurate than the information reflected in their public recommendations.

6.2 Return performance of stock recommendations

In this subsection, we compare the recommendation performances of fund-sell and fund-buy stocks. We hypothesize that the positive recommendations of fund-buy stocks outperform the positive recommendations of fund-sell stocks under the premise that fund managers trade these stocks based on analysts' more-accurate private information (*Hypothesis* 7). In other words, we expect that fund managers' informed trading of analysts' recommended stocks generates higher returns than unconditionally following analysts' public recommendations. We analyze the return performance around recommendation dates from −120 to 220 trading days using an event-study approach.

Figure 1 presents DGTW (1997)-adjusted daily returns around the public recommendation dates by different groups of positive recommendations. Consistent with the previous studies, the market, on average, reacts positively to analysts' positive recommendations for all three groups of positive recommendations. For example, according to Panel A of Table 8, fund-buy recommendations over the −1 to +1 event window experience 1.70% of cumulative abnormal returns (CAR), whereas fund-sell recommendations experience 1.24%.[34] The fact that fund-sell recommendations have positive event-date abnormal returns and are followed by negative returns of −1.37% from 2 to 40 trading days suggests that at least some investors do not access analysts' private information and thereby unconditionally follow the analysts' positive recommendations.

[Insert Figure 1]

[Insert Table 9]

These recommendations differ consistently and significantly in CARs around the recommendation dates. According to Panel A of Table 8, the CAR for fund-buy recommendations minus that for fund-sell recommendations is 1.86% from −40 to −2 trading days, 2.44% from 2 to 40 trading days, and 3.16% from 41 to 220 trading days.[35] The minimal and statistically insignificant return difference during the −120 to −41 event window suggests that the underlying stock information starts to change around the recommendations.[36] The overall persistent pattern of fund-buy recommendation outperforming fund-sell recommendations suggests that fund-buy stocks are better investment than fund-sell stocks.

Next, we calculate the difference in investment performance between informed versus uninformed investors. Assume conservatively that analyst-voting fund managers buy the stocks one trading day after positive public recommendations. Because informed fund managers will invest only in fund-buy recommendations, their buying strategy generates an average CAR of

[34] To address the cross-sectional dependence issue that arises because of multiple recommendations on the same days, we follow the procedure in the previous literature (Jegadeesh 2000; Jegadeesh and Kim 2006) by first calculating the average CAR across all recommendations in each month and then the time-series average across all monthly averages. When calculating the standard deviation, we also control for serial dependence. See Internet Appendix H for the detailed procedure.

[35] Note that in Table 9, the value of "fund buy" minus the value of "fund sell" does not equal the value for "fund buy – fund sell," because we first calculate the difference in the monthly average between fund-buy and fund-sell and then the time-series average where the weight being used is the average of the numbers of fund-buy recommendations and fund-sell recommendations in each month.

[36] The existence of return differences one month leading up to the recommendation dates suggests that analysts may tip off their institutional clients before the release of public recommendations (Irvine, Lipson, and Puckett 2006; Juergens and Lindsey 2009; Kadan, Michaely, and Moulton 2018; Even-Tov and Ozel 2021).

1.04% over 2 to 40 trading days after the public recommendations. On the other hand, uninformed investors cannot distinguish fund-buy and fund-sell recommendations, and hence can only buy positive recommendations unconditionally. Accordingly, their average DGTW-adjusted returns would be 1.04% * 33.6% + (−1.04%) * 34.1% + (−1.37%) * 32.3% = −0.45%. In other words, analysts' differentiation of information disclosure toward different audiences generates differential investment returns of 1.49% over 2 to 40 trading days after the public recommendations. This estimate may even be underestimated because the outperformance of fund-buy recommendations over fund-sell recommendations also exists from −40 to −2 trading days leading up to the recommendation dates.[37]

A possible concern is that retail investors may learn to ignore analysts' positive recommendations if investors find that the expected returns are sufficiently poor. However, the negative average return of −0.45% is evaluated against the DGTW benchmark. Retail investors may not evaluate analysts' performance against such a sophisticated benchmark (Ben-David et al. 2022). If we use the value-weighted market returns as the benchmark, according to Panel B of Table 9, analysts' positive recommendations on average generate a positive performance of 1.36% (3.11% * 33.6% + 0.91% * 34.1% + 0.00% * 32.3%). Moreover, retail investors may be attracted to the lottery-like return distribution of analyst positive recommendations (e.g., Kumar 2009 and Bali et al. 2021). Indeed, we find that the skewness of the after-recommendation returns in excess of the market returns is 2.87%. Thus, we conclude that analysts' positive recommendations on average may not appeal to institutional investors but may appeal to retail investors.

We acknowledge that in this event study setting of public recommendations, we observe stock returns and fund managers' trading contemporarily, which leaves room for alternative interpretations. We run several robustness tests to address some most likely alternative

[37] On the other hand, fund managers' trades may not be fully attributable to analysts' information (fund managers may have their own information inputs). In this sense, our estimate of the return difference may be overstated.

hypotheses. First, we ensure that managers' buying and selling decisions are not based on managers' differentiation of Strong Buy and Buy recommendations (see Internet Appendix Figure IA.1). Second, we control for funds' momentum trading by partitioning our sample into quintiles based on CARs from −40 to −2 trading days. In Internet Appendix Table IA.10, we find consistent differences in post-recommendation CARs between fund-buy and fund-sell recommendations across all quintiles; that is, the return patterns cannot be fully explained by fund momentum trading based on price movement leading to analyst recommendations.

In sum, we find that among analysts' public positive recommendations, fund-buy stocks persistently outperform fund-sell stocks. We also run similar tests based on fund managers' portfolio performances in Internet Appendix Table IA.11. These results suggest that among the stock holdings linked to fund managers' voted-for analysts, the stocks that the managers choose to sell underperform the stocks that the managers choose to buy or keep. These results are consistent with our main hypothesis that analysts provide more-accurate information to fund managers than they do to the public.

7. Discussion

The evidence we have provided suggests that analysts use say-buy/whisper-sell behavior to reduce the accuracy of their public recommendations to maintain the value of the private information. This phenomenon has several novel implications.

The first set of implications concerns the ability of researchers to infer analyst ability from the performance of their public recommendations. If the analyst intentionally includes relatively low-value stocks in the positive recommendations, as epitomized by whisper-sell behavior, one could not measure the analyst's true ability by simply measuring the performance of the public recommendations. So, our findings can help explain the insignificant relationship between the performance of analyst recommendations and analyst career outcomes (Mikhail, Walther, and Willis 1999; Hong and Kubik 2003; Emery and Li 2009).

The second concerns the information content of stock recommendations. Consistent with theoretical research, our evidence suggests that the analyst substitutes between the profitability of the private information that he/she provides to private clients, and the informativeness of the public recommendation that the analyst provides. Our argument is that it is in an analyst's interest to limit the informativeness of the analyst's public signals. Our findings help explain the fact that publicly disseminated stock recommendations have relatively low information content (Graham and Harvey 1996; Metrick 1999; Barber et al. 2001; Antweiler and Frank 2004; Jegadeesh et al. 2004; Engelberg, Sasseville, and Williams 2012).[38]

Third, our findings help explain why legal settlements that were intended to improve the informativeness of analyst recommendations have had limited effectiveness (Kadan et al. 2009). If an analyst has an interest in selling private information to his/her clients, the analyst is reluctant to make more informative public recommendations at the cost of compromising the profitability of the private information to be conveyed to fund managers. This suggests a possible value to investor education about the informativeness of analyst recommendation ratings.

8. Conclusion

Inspired by the theoretical models of information sales (Cespa 2008; García and Sangiorgi 2011), we test whether a financial analyst uses a pooling strategy in the analyst's public recommendation to mix different stock value types and tells the fund manager in private of the more-accurate stock information, resulting in analysts' say-buy/whisper-sell behavior. In

[38] Barber et al. (2001) find that a strategy of targeting the most favorable consensus recommendations can be profitable but requires substantial transaction costs. Jegadeesh et al. (2004) find that there is limited information in the level of consensus recommendations of analysts. For other public information vehicles, Graham and Harvey (1996) and Metrick (1999) find low information content in newsletter strategies. Antweiler and Frank (2004) find low information content in internet stock message boards, and Engelberg, Sasseville, and Williams (2012) find low information content in a popular television show for stocks. On the other hand, Womack (1996) finds that analysts' recommendations are informative and are followed by return drifts. Crane and Crotty (2020) find that U.S. analysts' recommendation revisions are informative.

particular, we argue that analysts sometimes issue optimistic recommendations even for mediocre stocks to incite retail investor purchases, while limiting the informativeness of their public recommendations. Doing so maintains the trading value of their private advice to mutual funds. It follows that informed fund managers will sell some of the analyst's publicly recommended stocks when the analyst's private information reveals a lower stock value than the market price. We test this hypothesis by examining the relationship between analysts' say-buy/whisper-sell behavior and voting by fund managers for analysts in star analyst competitions.

We find that managers are more likely to vote for the analysts who exhibit more say-buy/whisper-sell behavior with these managers, apparently as payback for the analysts' private information. This relationship is consistent with the hypothesis that analysts use say-buy/whisper-sell behavior to give fund managers private and more-accurate information than analysts give to the general public in their public recommendations. We further find that among the analysts' positive public recommendations, the stocks bought by the managers who vote for the analysts outperform the stocks sold by these managers, consistent with managers receiving more-accurate information.

Our empirical findings suggest that analysts balance the informativeness of their public recommendations against the trading value of their private information, resulting in say-buy/whisper-sell behavior. Analysts' whisper-sell behavior means that they limit the informativeness of public recommendations even under the pressure of government regulation. Furthermore, since analysts' public recommendations do not reveal analysts' true beliefs about stocks, the performance of analysts' public recommendations is an imperfect indicator of analysts' abilities and career prospects. The phenomenon that an information provider produces less-accurate public signals to create the value of his/her private signals may be present in other contexts such as voting recommendations of advisory firms.

References

Admati, Anat R., and Paul Pfleiderer, 1988. Selling and trading on information in financial markets. *American Economic Review* 78, 96–103.

Agrawal, Anup, and Mark. A. Chen, 2008. Do analyst conflicts matter? Evidence from stock recommendations. *Journal of Law and Economics* 51, 503–537.

Antweiler, Werner, and Murray Z. Frank, 2004. Is all that talk just noise? The information content of internet stock message boards. *Journal of Finance* 59, 1259–1294.

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

Bali, Turan G., David Hirshleifer, Lin Peng, and Yi Tang, 2021. Attention, social interaction, and investor attraction to lottery stocks. NBER working paper, No. 29543.

Ben-David, Itzhak, Jiacui Li, Andrea Rossi, and Yang Song, 2022. What do mutual fund investors really care about?. *Review of Financial Studies* 35, 1723–1774.

Bradley, Daniel, Russell Jame, and Jared Williams, 2022. Non-Deal Roadshows, Informed Trading, and Analyst Conflicts of Interest. *Journal of Finance* 77, 265–315.

Brown, Nerissa C., Kelsey D. Wei, and Russ Wermers, 2014. Analyst recommendations, mutual fund herding, and overreaction in stock prices. *Management Science* 60, 1–20.

Busse, Jeffrey A., T. Clifton Green, and Narasimhan Jegadeesh, 2012. Buy-side trades and sell-side recommendations: interactions and information content. *Journal of Financial Markets* 15, 207–232.

Cao, Ying, Dan Dhaliwal, Zengquan Li, and Yong George Yang, 2014. Are all independent directors equally informed? Evidence based on their trading returns and social networks. *Management Science* 61, 795–813.

Cespa, Giovanni, 2008. Information sales and insider trading with long-lived information. *Journal of Finance* 63, 639–672.

Cheng, Qiang, Xia Chen, An-Ping Lin, and Kun Wang, 2021. A Star is Born: Star Analyst Voting and Analyst Research. *Working paper*, Singapore Management University.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008. The small world of investing: board connections and mutual fund returns. *Journal of Political Economy* 116, 951–979.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2010. Sell-side school ties. *Journal of Finance* 65, 1409–1437.

Conrad, Jennifer S., Kevin M. Johnson, and Sunil Wahal, 2001. Institutional trading and soft dollars. *Journal of Finance* 56, 397–416.

Cowen, Amanda, Boris Groysberg, and Paul Healy, 2006. Which types of analyst firms are more optimistic? *Journal of Accounting and Economics* 41, 119–146.

Crane, Alan, and Kevin Crotty, 2020. How skilled are security analysts?. *Journal of Finance* 75, 1629–1675.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance* 52, 1035–1058.

Das, Somnath, Carolyn B. Levine, and Konduru Sivaramakrishnan, 1998. Earnings predictability and bias in analysts' earnings forecasts. *Accounting Review* 72, 277–294.

Emery, Douglas R., and Xi Li, 2009. Are the Wall Street analyst rankings popularity contests? *Journal of Financial and Quantitative Analysis* 44, 411–437.

Engelberg, Joseph, Caroline Sasseville, and Jared Williams, 2012. Market madness? The case of mad money. *Management Science* 58, 351–364.

Even-Tov, Omri, and Naim Bugra Ozel, 2021. What moves stock prices around credit rating changes? *Review of Accounting Studies* 26, 1390–1427.

Firth, Michael, Chen Lin, Ping Liu, and Yuhai Xuan, 2013. The client is king: do mutual fund relationships bias analyst recommendations? *Journal of Accounting Research* 51, 165–200.

García, Diego, and Francesco Sangiorgi, 2011. Information sales and strategic trading. *Review of Financial Studies* 24, 3069–3104.

Goldstein, Michael A., Paul Irvine, Eugene Kandel, and Zvi Wiener, 2009. Brokerage commissions and institutional trading patterns. *Review of Financial Studies* 22, 5175–5212.

Graham, John R., and Campbell R. Harvey, 1996. Market timing ability and volatility implied in investment newsletters' asset allocation recommendations. *Journal of Financial Economics* 42, 397–421.

Gu, Zhaoyang, Zengquan Li, and Yong George Yang, 2013. Monitors or predators: The influence of institutional investors on sell-side analysts. *Accounting Review* 88, 137–169.

Gu, Zhaoyang, Zengquan Li, Yong George Yang, and Guangqing Li, 2019. Friends in need are friends indeed: an analysis of social ties between financial analysts and mutual fund managers. *Accounting Review* 94, 153–181.

Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu, 2007. Whom you know matters: venture capital networks and investment performance. *Journal of Finance* 62, 251–301.

Hong, Harrison, and Jeffrey D. Kubik, 2003. Analyzing the analysts: career concerns and biased earnings forecasts. *Journal of Finance* 58, 313–351.

Irvine, Paul J., 2000. Do analysts generate trade for their firms? Evidence from the Toronto stock exchange. *Journal of Accounting and Economics* 30, 209–226.

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

Irvine, Paul J., Marc Lipson, and Andy Puckett, 2006. Tipping. *Review of Financial Studies* 20, 741–768.

Jacob, John, Thomas Z. Lys, and Margaret A. Neale, 1999. Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics* 28, 51–82.

Jegadeesh, Narasimhan, 2000. Long-term performance of seasoned equity offerings: benchmark errors and biases in expectations. *Financial Management*, 5–30.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles M. C. Lee, 2004. Analyzing the analysts: when do recommendations add value? *Journal of Finance* 59, 1083–1124.

Jegadeesh, Narasimhan, and Woojin Kim, 2006. Value of analyst recommendations: international evidence. *Journal of Financial Markets* 9, 274–309.

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

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005. On the industry concentration of actively managed equity mutual funds. *Journal of Finance* 60, 1983–2011.

Kadan, Ohad, Leonardo Madureira, Rong Wang, and Tzachi Zach, 2009. Conflicts of interest and stock recommendations: the effects of the global settlement and related regulations. *Review of Financial Studies* 22, 4189–4217.

Kadan, Ohad, Roni Michaely, and Pamela C. Moulton, 2018. Trading in the presence of short-lived private information: evidence from analyst recommendation changes. *Journal of Financial and Quantitative Analysis* 53, 1509–1546.

Kong, Dongmin, Chen Lin, Shasha Liu, and Weiqiang Tan, 2021. Whose money is smart? individual and institutional investors' trades based on analyst recommendations. *Journal of Empirical Finance* 62, 234–251.

Kumar, Alok, 2009. Who gambles in the stock market?. *Journal of Finance*, 64(4), 1889–1933.

Li, Frank Weikai, Abhiroop Mukherjee, and Rik Sen, 2021. Inside brokers. *Journal of Financial Economics* 141, 1096–1118.

Lin, Hsiou-wei, and Maureen F. McNichols, 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics* 25, 101–127.

Ljungqvist, Alexander, Felicia Marston, and William J. Wilhelm Jr., 2006. Competing for securities underwriting mandates: banking relationships and analyst recommendations. *Journal of Finance* 61, 301–340.

Ljungqvist, Alexander, Felicia Marston, Laura T. Starks, Kelsey D. Wei, and Hong Yan, 2007. Conflicts of interest in sell-side research and the moderating role of institutional investors. *Journal of Financial Economics* 85, 420–456.

Lourie, Ben, 2019. The revolving door of sell-side analysts. *Accounting Review* 94, 249–270.

Malenko, Andrey, Nadya Malenko, and Chester S. Spatt, 2021. Creating controversy in proxy voting advice. NBER working paper, No. 29036.

Malmendier, Ulrike, and Devin Shanthikumar, 2007. Are small investors naive about incentives? *Journal of Financial Economics* 85, 457–489.

Malmendier, Ulrike, and Devin Shanthikumar, 2014. Do security analysts speak in two tongues? *Review of Financial Studies* 27, 1287–1322.

Metrick, Andrew, 1999. Performance evaluation with transactions data: the stock selection of investment newsletters. *Journal of Finance* 54, 1743–1775.

Michaely, Roni, and Kent L. Womack, 1999. Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies* 12, 653–686.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1999. Does forecast accuracy matter to security analysts? *Accounting Review* 74, 185–200.

Mola, Simona, and Massimo Guidolin, 2009. Affiliated mutual funds and analyst optimism. *Journal of Financial Economics* 93, 108–137.

O'Brien, Patricia C., Maureen F. Mcnichols, and Lin Hsiou‐Wei, 2005. Analyst impartiality and investment banking relationships. *Journal of Accounting Research* 43, 623–650.

Stickel, Scott E., 1992. Reputation and performance among security analysts. *Journal of Finance* 47, 1811–1836.

Tharp, Paul, 2002, Tyco Bullhorn: Merrill analyst. 2002, September 14. *New York post.* https://nypost.com/2002/09/14/tyco-bullhorn-merrill-analyst/

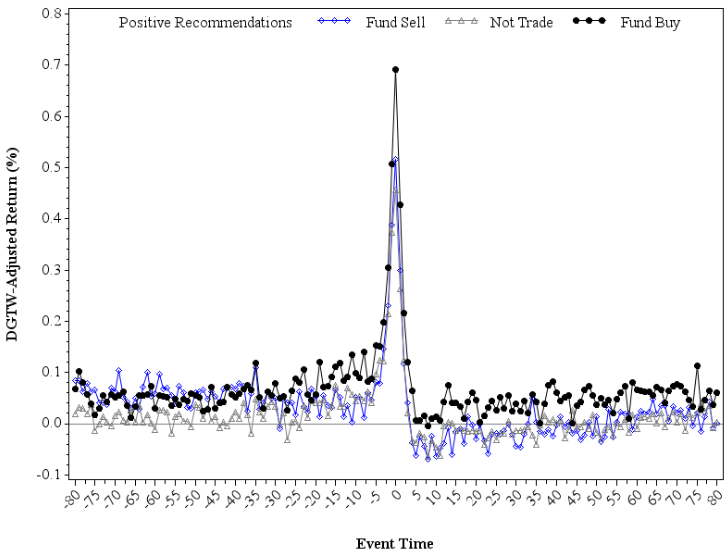
Womack, Kent L., 1996. Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51, 137–167.

Figures

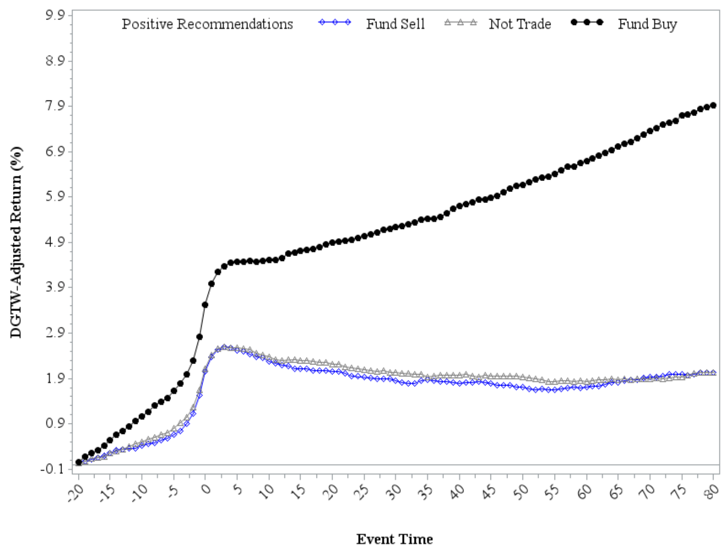
Figure 1 Abnormal daily returns around positive recommendations by fund trades

This figure presents the mean of abnormal daily returns around positive recommendations by the direction of the average trades by funds whose managers vote for the analyst. Positive recommendations are defined as Strong Buy and Buy. “Fund Buy” (“Fund Sell”) refers to the recommendations for which the average trades of the stock across the funds whose managers vote for the analyst are positive (negative). “Not Trade” recommendations are those for which the stocks are not traded by the analyst-voting fund managers. Abnormal return is measured by the difference between the raw return and the DGTW benchmark return. Panel A shows daily average returns from −80 to 80 trading days, whereas Panel B shows cumulative returns from -20 to 80 trading days.

Panel A: Daily average return



Panel B: Cumulative return



Tables

Table 1 Numbers of fund managers and analysts included

Table 1 reports the numbers of fund managers and analysts identified and used, respectively, in the analysis from 2010 to 2016. Column (1) reports the number of fund managers recorded in the voting data; column (2) reports the number of mutual fund managers successfully matched from the voting data to the CSMAR database; column (3) reports the number of active mutual fund managers used in the analysis; column (4) reports the percentage of active funds included in our sample, relative to the total active funds in the CSMAR database in that year; column (5) reports the number of analysts recorded in the voting data; column (6) reports the number of analysts successfully matched from the voting data to the CSMAR database; column (7) reports the number of analysts used in the analysis; column (8) reports the percentage of individual analysts included in our sample, relative to the total individual analysts who issued at least one report recorded in the CSMAR database in that year.

Year	Fund managers in the data	Mutual fund managers matched	Active fund managers used	% of funds in CSMAR	Analysts in the data	Analysts matched	Analysts used	% of analysts in CSMAR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2010	456	403	213	38.8%	529	495	445	27.0%
2011	585	523	240	34.3%	506	475	435	31.1%
2012	1,013	664	295	35.1%	608	580	549	45.0%
2013	1,015	630	296	30.2%	559	538	472	44.8%
2014	1,298	805	364	33.8%	540	517	475	47.5%
2015	1,421	923	438	34.5%	443	402	379	38.9%
2016	1,592	911	535	33.7%	455	421	391	43.3%
All	7,380	4,859	2,391	34.0%	3,640	3,428	3,146	39.3%

Table 2 Summary statistics

This table provides the summary statistics on the variables for funds' semi-yearly disclosed holdings (Panel A), the variables for analysts' whisper-sell and whisper-buy behavior (Panel B), the analyst-year specific characteristics variables (Panel C), and the correlations between these variables (Panel D). Panel A includes 5,076 fund-semi-year observations. *No_stock* is the number of stocks held by the fund. *No_industry* is the number of industries in which one fund invests. *No_buy* (*No_sell*) is the number of stocks of which one fund increases (decreases) the holding shares between two semi-yearly reports. *Turnover* is the ratio of total trading turnover in dollar between two semi-yearly reports to the total portfolio market value. In Panel B, *FundSell* (*FundBuy*) measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. Positive stock recommendations are Strong Buy and Buy without subsequent downgrade within the same semi-year. Variables presented in Panel C are analyst-year–specific measures. In total, there are 3,146 analyst-year observations. *InfoRatio* is the regression alpha of the excess daily returns of the analyst's positive-recommendations mimicking portfolio with at most 3-month holding period on the daily industry value-weighted returns. The monthly alphas are reported. *Risk* is the regression beta of the excess daily returns of the analyst's positive-recommendations mimicking portfolio on the daily industry value-weighted returns. *Nrec* is the number of reports issued by the analyst in that year. *Nstock* is the number of stocks recommended by the analyst in that year. *Optism_recom* (*Optism_feps*) is the average of the relative recommendation (earnings forecast) optimism across all recommendations (earnings forecasts) by the analyst in that year. *Upgrade* is the fraction of recommendations that upgrade the existing recommendation rating in that year. *Firmsize* is the average of the logged value of the market cap of stocks recommended by the analyst in that year. *Attention* is the fraction of recommended stocks that are past winners or losers based on the past 12 month's cumulative returns. *Experience* is the number of quarters since the analyst's first recommendation/earnings forecast in the CSMAR database. *Brokersize* is the number of active analysts in the analyst's brokerage house in that year. *PreAward* is an indicator variable for the analyst's winning a title in the previous year's competition. *TradeBroker* is an indicator variable for an important business relationship between the analyst's brokerage house and the fund. The detailed construction of these measures is in Appendix Table A.1. Panel D reports the correlations among variables for manager vote ranks (*VoteRank*), analyst whisper-sell and whisper-buy behavior, and analyst-year–specific characteristics. Manager-analyst-years are used as the unit of the correlation analysis.

Panel A: Summary statistics for fund semi-year holdings						
Variable	*N*	Mean	SD	P25	P50	P75
No_stock	5,076	58.75	61.10	31	44	65
No_industry	5,076	16.90	6.00	13	17	21
No_buy	5,076	45.39	44.04	25	36	51
No_sell	5,076	49.49	49.73	27	38	55
Turnover (%)	5,076	57.58	173.09	35.57	52.08	69.56
Panel B: Summary statistics for stock overlap measures						
Variable	*N*	Mean	SD	P25	P50	P75
FundSell	271, 551	0.30	0.34	0.00	0.18	0.50
FundBuy	271, 551	0.30	0.33	0.00	0.18	0.50
Panel C: Summary statistics for analyst characteristics						
Variable	*N*	Mean	SD	P25	P50	P75
InfoRatio (%)	3, 146	−0.35	2.07	−1.44	−0.36	0.70
Risk	3, 146	1.03	0.14	0.95	1.02	1.09
Nrec	3, 146	38.68	32.87	16	30	52

Nstock	3, 146	13.83	8.89	8	12	18
Optism_recom	3, 146	0.05	0.31	−0.22	0.09	0.29
Optism_feps	3, 146	0.03	0.13	−0.06	0.02	0.10
Upgrade	3, 146	0.04	0.06	0	0.02	0.05
Firmsize	3, 146	16.70	0.98	16.05	16.55	17.11
Attention	3, 146	0.35	0.17	0.25	0.33	0.44
Experience	3, 146	9.52	7.58	3.75	8.33	13.67
Brokersize	3, 146	72.82	42.77	44	64	89
PreAward	3, 146	0.21	0.41	0	0	0

Panel D: Correlations

	VoteRank	*FundSell*	*FundBuy*	*InfoRatio*	*Risk*	*Nrec*	*Nstock*	*Op._recom*	*Op._feps*	*Upgrade*	*Firmsize*	*Attention*	*Experience*	*Brokersize*	*TradeBroker*	*PreAward*
VoteRank	1															
FundSell	0.10	1														
FundBuy	0.10	0.43	1													
InfoRatio	0.01	0.04	0.07	1												
Risk	0.01	−0.04	−0.02	−0.05	1											
Nrec	0.13	0.25	0.25	−0.03	−0.01	1										
Nstock	0.10	0.19	0.20	−0.03	0.02	0.86	1									
Optism_recom	0.03	−0.02	−0.02	0.00	0.06	−0.07	−0.10	1								
Optism_feps	0.06	−0.02	−0.02	−0.02	0.04	0.01	−0.02	0.20	1							
Upgrade	−0.03	0.01	0.01	0.03	−0.02	−0.07	−0.02	−0.01	−0.05	1						
Firmsize	0.03	0.31	0.31	0.04	0.00	−0.06	−0.11	0.01	−0.04	−0.03	1					
Attention	−0.00	0.05	0.04	−0.03	0.03	−0.05	−0.06	0.03	0.06	0.01	0.01	1				
Experience	0.01	0.04	0.05	−0.03	−0.06	0.07	0.03	−0.06	−0.07	0.02	0.07	−0.05	1			
Brokersize	0.12	0.13	0.12	−0.02	0.01	0.28	0.27	−0.17	0.05	−0.03	0.02	−0.03	0.02	1		
TradeBroker	0.01	0.01	0.01	0.00	0.00	0.01	0.01	−0.01	0.00	0.00	0.00	0.00	0.00	0.02	1	
PreAward	0.24	0.13	0.14	−0.01	0.01	0.23	0.20	0.02	0.04	−0.03	0.05	−0.02	0.10	0.19	0.01	1

Table 3 Voting decisions and future trade allocations

This table reports the effect of fund managers' voting decisions on their trade allocations to the brokers in subsequent years. The dependent variable in columns (1)–(5) is the log value of the percentage share (from 0 to 100) of trades allocated from the fund to the broker in the subsequent year. $\Delta\overline{VoteRank}$ is the change in the average vote ranking to the broker's analysts from the fund's managers in the current year. The trade share measure in the current year is also included as a control. Standard errors, clustered by broker and fund, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	Ln(TradeShare) t+1				
	(1)	(2)	(3)	(4)	(5)
$\Delta\overline{VoteRank}\ t$	0.051**	0.036*	0.029*	0.043**	0.039***
	(0.020)	(0.018)	(0.016)	(0.016)	(0.014)
Ln(TradeShare) t		0.495***	0.468***	0.470***	−0.055***
		(0.017)	(0.017)	(0.017)	(0.017)
Fixed effects	-	-	Broker	Broker×Year	Broker×Year Fund×Broker
Observations	15,328	15,328	15,328	15,328	15,328
Adjusted R^2	0.001	0.170	0.201	0.216	0.407

Table 4 Whisper-sell behavior and voting decisions

This table reports the effect of analysts' whisper-sell behavior on fund managers' voting decisions. The dependent variables from columns (1)–(7) are *VoteRank*, representing the manager's vote for the analyst (first choice = 5; second choice = 4; third choice = 3; fourth choice = 2; fifth choice = 1; no vote = 0). The dependent variables from columns (8)–(12) are indicator variables taking the value of one if the manager votes for that specific analyst as the manager's first choice, as at least the second choice, as at least the third choice, as at least the fourth choice, and as at least the fifth choice, respectively. Independent variables with the suffix *s* are the percentage rankings of the original values among the industry-year analyst groups (the highest-ranked = 1 and the lowest-ranked = 0). *FundSell* (*FundBuy*) measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. The other independent variables are previously defined in Table 2. *PeerVote* is the average voting rank across the fund manager's colleagues from the same fund company who do not invest in the analyst's industry. Analyst-year fixed, (fund) company-broker, or (fund) manager-broker fixed effects are included. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	VoteRank							*=First Choice*	*≤Second Choice*	*≤Third Choice*	*≤Fourth Choice*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FundSell	0.084***			0.079***								
	(0.021)			(0.019)								
FundBuy	0.132***			0.116***								
	(0.022)			(0.020)								
FundSell_s		0.096***	0.050***		0.082***	0.076***	0.061***	0.010***	0.014***	0.019***	0.019***	0.019***
		(0.023)	(0.015)		(0.021)	(0.022)	(0.014)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
FundBuy_s		0.152***	0.115***		0.121***	0.115***	0.068***	0.017***	0.022***	0.024***	0.029***	0.029***
		(0.021)	(0.015)		(0.020)	(0.021)	(0.013)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
InfoRatio_s	0.095**	0.095**		0.080 **	0.082**	0.084**	0.029	0.013***	0.015**	0.015*	0.019*	0.020*
	(0.042)	(0.042)		(0.040)	(0.040)	(0.040)	(0.019)	(0.005)	(0.007)	(0.009)	(0.010)	(0.011)
Risk_s	0.015	0.015		0.022	0.023	0.015	0.007	0.003	0.003	0.005	0.005	0.007
	(0.044)	(0.044)		(0.040)	(0.040)	(0.040)	(0.019)	(0.004)	(0.007)	(0.009)	(0.010)	(0.011)
Nrec_s	0.419***	0.404***		0.498***	0.489***	0.505***	0.157***	0.035***	0.064***	0.103***	0.130***	0.157***
	(0.086)	(0.086)		(0.083)	(0.083)	(0.083)	(0.042)	(0.010)	(0.015)	(0.018)	(0.021)	(0.023)
Nstock_s	0.030	0.011		−0.070	−0.078	−0.089	−0.103**	−0.017*	−0.015	−0.023	−0.012	−0.012
	(0.085)	(0.085)		(0.081)	(0.081)	(0.081)	(0.040)	(0.010)	(0.014)	(0.018)	(0.020)	(0.023)
Optism_recom_s	0.122***	0.122***		0.133**	0.128**	0.120**	0.044	0.012*	0.019*	0.027**	0.031**	0.040**

	(0.043)	(0.043)		(0.056)	(0.056)	(0.057)	(0.027)	(0.006)	(0.010)	(0.012)	(0.014)	(0.016)
Optism_feps_s	0.178***	0.177***		0.131***	0.130***	0.136***	0.042*	0.013**	0.019**	0.025***	0.035***	0.039***
	(0.047)	(0.047)		(0.042)	(0.042)	(0.041)	(0.021)	(0.005)	(0.008)	(0.009)	(0.011)	(0.012)
Upgrade_s	−0.156***	−0.157***		−0.151***	−0.151***	−0.137***	−0.077***	−0.014***	−0.025***	−0.034***	−0.039***	−0.040***
	(0.044)	(0.044)		(0.044)	(0.044)	(0.044)	(0.021)	(0.005)	(0.008)	(0.010)	(0.011)	(0.012)
Firmsize_s	−0.031	−0.037		−0.051	−0.058	−0.066	−0.053**	−0.011**	−0.018**	−0.013	−0.010	−0.006
	(0.046)	(0.046)		(0.045)	(0.045)	(0.045)	(0.022)	(0.006)	(0.008)	(0.010)	(0.011)	(0.012)
Attention_s	0.096**	0.096**		0.095**	0.098**	0.108***	0.048**	0.009*	0.015**	0.025***	0.024**	0.024**
	(0.042)	(0.042)		(0.040)	(0.040)	(0.040)	(0.020)	(0.005)	(0.007)	(0.009)	(0.010)	(0.011)
Experience_s	−0.089**	−0.089*		−0.067	−0.069	−0.076*	−0.021	−0.006	−0.009	−0.013	−0.019*	−0.021
	(0.045)	(0.045)		(0.045)	(0.045)	(0.044)	(0.022)	(0.005)	(0.008)	(0.010)	(0.011)	(0.013)
Brokersize_s	0.278***	0.275***		−0.011	−0.039	−0.123	−0.024	−0.000	−0.005	−0.006	−0.010	−0.018
	(0.048)	(0.048)		(0.075)	(0.075)	(0.076)	(0.036)	(0.008)	(0.013)	(0.017)	(0.019)	(0.021)
TradeBroker	0.061***	0.067***	0.040***	0.005	0.009	0.009	-0.003	0.001	0.002	0.003	0.002	0.001
	(0.013)	(0.013)	(0.008)	(0.010)	(0.010)	(0.015)	(0.007)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
PreAward	0.710***	0.709***		0.610***	0.608***	0.579***	0.233***	0.061***	0.103***	0.136***	0.151***	0.158***
	(0.038)	(0.038)		(0.038)	(0.039)	(0.039)	(0.021)	(0.005)	(0.007)	(0.009)	(0.010)	(0.010)
PeerVote							2.442***					
							(0.022)					
Fixed effects	-	-	Analyst× Year	Company× Broker	Company× Broker	Manager× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	271,551	271,551	271,551	271,551	271,551	271,551	271,551	271,551	271,551	271,551	271,551	271,551
Adjusted R^2	0.078	0.078	0.219	0.123	0.123	0.118	0.395	0.053	0.077	0.097	0.113	0.127

Table 5 Conditional effects of whisper-sell behavior on voting decisions

This table reports the conditional effect of analysts' whisper-sell behavior on fund managers' voting decisions. The dependent variable, *VoteRank*, represents the manager's vote for the analyst (first choice = 5; second choice = 4; third choice = 3; fourth choice = 2; fifth choice = 1; no vote = 0). *FundSell* (*FundBuy*) measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. Other control variables are the same as the previous tables. *IndustryWeight* is the fund manager's portfolio percentage in the analyst-specific industry in the previous year. *TradeBroker* is an indicator variable for an important business relationship between the analyst's brokerage house and the fund. *InfoAsymmetry* equals one if the industry average of information asymmetry score is above the median in the previous year. *Lottery* equals one if the industry average of being lottery stock is above the median in the previous year. *StockReturn* is the average industry-adjusted return of fund-sell stocks from the recommendation date to the current semi-year-end. Company-broker fixed effects are included in all regressions. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	VoteRank	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FundSell_s	0.163***	0.040***	0.064***	0.014***	−0.027	−0.007	0.027	0.007	0.045	0.009
	(0.027)	(0.007)	(0.022)	(0.006)	(0.040)	(0.011)	(0.030)	(0.008)	(0.028)	(0.008)
FundSell_s × *IndustryWeight*	−1.111***	−0.291***								
	(0.244)	(0.066)								
FundSell_s × *TradeBroker*			0.093***	0.026***						
			(0.035)	(0.010)						
FundSell_s × *InfoAsymmetry*					0.198***	0.048***				
					(0.056)	(0.015)				
FundSell_s × *Lottery*							0.156***	0.033**		
							(0.054)	(0.015)		
FundSell_s × *StockReturn*									−0.305**	-0.079**
									(0.142)	(0.038)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	271,551	271,551	271,551	271,551	271,551	271,551	271,551	271,551	159,790	159,790
Adjusted R^2	0.123	0.127	0.123	0.127	0.123	0.127	0.123	0.127	0.119	0.120

Table 6 Determinants of whisper-sell-prone analysts

This table reports the OLS regression of indicator variables for whisper-sell-prone analysts on analyst-year characteristics variables. Column (1) (2) defines the whisper-sell-prone analysts as those whose estimates of *FundSell* from the univariate regressions of manager voting decisions (*VoteRank*) fall under the top three (five) among analyst-industry peers. For analyst-year characteristics, *Nrec* is the number of reports issued by the analyst; *Nstock* is the number of stocks recommended by the analyst; *Attention* is the fraction of recommended stocks that are winners or losers; *Firmsize* is the average of the market cap of the analyst's recommended stocks. *InfoRatio* is the performance of the analyst's positive-recommendations mimicking portfolio; *Risk* is the industry beta of the analyst's positive-recommendations mimicking portfolio; *Optism_recom* is the recommendation optimism; *Upgrade* is the fraction of the recommendations that upgrade the existing recommendation rating; *Optism_feps* is earnings forecast optimism; *Accuracy_feps* is earnings forecast accuracy; *Experience* is the number of quarters since the analyst's first recommendation/earnings forecast in the CSMAR database; *Brokersize* is the number of active analysts in the analyst's brokerage house; *PreAward* is an indicator variable for winners in the previous year's competition. All dependent variables except for indicators are standardized. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	Whisper-sell-prone analysts	
	top three	*top five*
	(1)	(2)
Nrec	0.071***	0.079***
	(0.016)	(0.019)
Nstock	−0.063***	−0.075***
	(0.016)	(0.019)
Attention	0.005	−0.000
	(0.007)	(0.008)
Firmsize	0.001	0.011
	(0.007)	(0.008)
InfoRatio	0.003	0.002
	(0.007)	(0.008)
Risk	0.001	−0.000
	(0.007)	(0.008)
Optism_recom	0.012*	0.013
	(0.007)	(0.008)
Upgrade	−0.021	−0.032
	(0.024)	(0.029)
Optism_feps	−0.004	0.002
	(0.007)	(0.009)
Accuracy_feps	−0.004	−0.014
	(0.007)	(0.009)
Experience	0.006	0.006
	(0.007)	(0.008)
Brokersize	0.031***	0.042***
	(0.007)	(0.009)
PreAward	0.071***	0.091***
	(0.018)	(0.021)
Observations	3,146	3,146
Adjusted R^2	0.024	0.027

Table 7 Robustness tests on alternative whisper-sell measures

This table shows the robustness of whisper-sell and whisper-buy measures. The dependent variable, *VoteRank*, represents the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; fifth = 1; no vote = 0). "≤fifth Choice" is an indicator variable for a vote of the fifth choice or higher. *FundSell* (*FundBuy*) principally measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. "Stock count" corresponds to the measure that counts the number of stocks instead of the dollar trade volume of stocks. "Adjusted 1" corresponds to the measure that adjusts for the number of stocks the analyst recommends. "Adjusted 2" corresponds to the measure that adjusts for both the number of stocks the analyst recommends and the analyst's tendency for herding. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	Stock count		Adjusted 1		Adjusted 2	
	VoteRank	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)	(5)	(6)
FundSell	0.086***	0.023***	0.065***	0.016***	0.101***	0.025***
	(0.021)	(0.006)	(0.019)	(0.005)	(0.020)	(0.005)
FundBuy	0.129***	0.034***	0.101***	0.024***	0.148***	0.037***
	(0.021)	(0.006)	(0.020)	(0.006)	(0.020)	(0.006)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	271,551	271,551	271,551	271,551	271,551	271,551
Adjusted R^2	0.123	0.127	0.123	0.127	0.123	0.127

Table 8 Connected-manager trades and analyst reporting activities

This table reports the relationship between the analyst-voting managers' trades and the analyst's reporting activities. The dependent variable, *Accuracy_feps*, is earnings forecast accuracy. *Nrec* is the number of reports (recommendations or earnings forecasts) by the analyst on the stock during the semi-year. *Stkexp* is the stock-specific experience of the analyst, calculated as the number of quarters since the analyst issued the first report on that stock in the CSMAR database. *Strong Buy* is an indicator for Strong Buy recommendation. *Fund Buy* (*Fund Sell*) is the dummy variable taking the value of one if the average trade on the stock by the analyst-voting managers (*Portfolio_Chg*) is positive (negative). The reference group is the stocks that are not traded by these analyst-voting managers. Affiliation effect controls for the effect of the bank underwriting relationships. Analyst-semi-year fixed effects are included in all regressions. Analyst-semi-year observations with at least ten stocks are included in the analysis. Standard errors, clustered by analyst-semi-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels are indicated with ***, **, and *, respectively.

	Accuracy_feps	*Nrec*	*Stkexp*	*Strong Buy*
	(1)	(2)	(3)	(4)
Fund-Buy Recommendation	−0.0126**	0.289***	0.522***	0.099***
	(0.006)	(0.026)	(0.076)	(0.007)
Fund-Sell Recommendation	−0.0135**	0.251***	0.656***	0.100***
	(0.006)	(0.025)	(0.077)	(0.008)
Affiliation effect	Yes	Yes	Yes	Yes
Fixed effects	Analyst× semi-year	Analyst× semi-year	Analyst× semi-year	Analyst× semi-year
Observations	32,173	32,173	32,173	32,173
Adjusted R^2	0.029	0.149	0.424	0.464

Table 9 Return performance around analyst recommendations

This table reports the mean of cumulative abnormal returns over different event windows around analysts' positive recommendations. In each semi-year, positive recommendations are divided into three groups, "Fund Sell," "Not Trade," and "Fund Buy," based on the average fund trades across the managers who vote for the analysts in that year. Recommendations are assigned into the "Fund Buy" ("Fund Sell") group if the average fund trade is positive (negative) and into the "Not Trade" group if the stock is not traded by the analyst-voting fund managers. The column titles specify the event windows around recommendation dates, whereas the row titles specify the groups of recommendations. "% of Obs." specifies the percentage of recommendations in each group. Abnormal returns are calculated as DGTW-adjusted returns following the instruction from DGTW (1991) in Panel A and as market-adjusted returns in Panel B. *t*-statistics adjusted for cross-sectional and serial correlations are shown below in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

Panel A: DGTW-adjusted returns

		Event windows around analyst recommendations				
	% of Obs.	[−120, −41]	[−40, −2]	[−1, 1]	[2, 40]	[41, 220]
Fund Buy	33.6%	2.79***	3.24***	1.70***	1.03*	2.93**
		(3.34)	(6.51)	(5.59)	(1.90)	(2.10)
Not Trade	34.1%	−0.03	1.28***	1.14***	−1.03***	−0.88
		(−0.06)	(3.16)	(5.09)	(−3.21)	(−0.82)
Fund Sell	32.3%	4.11***	1.67**	1.24***	−1.37**	−0.20
		(5.02)	(2.92)	(4.37)	(−2.39)	(−0.12)
Fund Buy − Fund Sell	-	−0.83	1.86***	0.45***	2.44***	3.16***
		(−1.35)	(7.81)	(7.19)	(12.53)	(10.28)

Panel B: Market-adjusted returns

		Event windows around analyst recommendations				
	% of Obs.	[−120, −41]	[−40, −2]	[−1, 1]	[2, 40]	[41, 220]
Fund Buy	33.6%	5.96***	4.66***	1.86***	3.11***	4.18*
		(6.01)	(8.75)	(5.92)	(4.11)	(1.89)
Not Trade	34.1%	2.97**	3.09***	1.33***	0.91**	1.96
		(2.52)	(7.23)	(5.13)	(2.17)	(1.11)
Fund Sell	32.3%	6.80***	2.53***	1.37***	0.00	−0.21
		(5.86)	(4.29)	(4.55)	(0.01)	(−0.09)
Fund Buy − Fund Sell	-	−0.36	2.47***	0.49***	3.11***	4.16***
		(−0.51)	(9.58)	(8.39)	(8.09)	(9.71)

Appendix

Table A.1 Construction of analyst characteristics

Variable	Definition
InfoRatio	Performance of an analyst's positive recommendations. For each analyst each year, we construct a long portfolio based on the analyst's positive recommendations. We adjust the portfolio daily and include a stock the next day of the analyst's Buy or Strong Buy recommendation. The stock remains in the portfolio until the sooner of the following three events: 1) downgrade to Hold, Sell, or Strong Sell, 2) the year-end, 3) three months since the latest Buy or Strong Buy recommendation. Then, we calculate the value-weighted daily portfolio returns. *InfoRatio* is the regression alpha of the excess daily returns of the analyst's recommendation-mimicking portfolio on the daily industry value-weighted returns (Emery and Li 2009).
Risk	Aggressiveness of an analyst's positive recommendations. We use the beta from the above regression of positive-recommendations mimicking portfolio returns (Emery and Li 2009).
Nrec	Number of reports (recommendations or earnings forecasts) issued by the analyst in that year (Jacob, Lys, and Neale 1999).
Nstock	Number of different stocks recommended by the analyst in that year (Jacob, Lys, and Neale 1999).
Optism_recom	Analyst optimism of recommendations. Each recommendation's optimism is defined as the recommendation rating (Strong Buy = 5; Buy = 4; Hold = 3; Sell = 2; Strong Sell = 1) minus the consensus rating of all recommendations in the same quarter. To construct a yearly measure, we take an average across all recommendations issued by the analyst in that year.
Upgrade	Proportion of the analyst's recommendations that are upgrades in that year (Elton, Gruber, and Grossman 1986; Jegadeesh et al. 2004).
Optism_feps	Analyst optimism of earnings forecasts. For each earnings forecast, following Hong and Kubik (2003), we first rank ascendingly all earnings forecasts in the same quarter. Then, we calculate *Optism_feps* as the percentage ranking of the earnings forecast minus 0.5 (the highest-ranked = 0.5 and the lowest-ranked = −0.5). To construct a yearly measure, we take an average across all earnings forecasts issued by the analyst in that year.

Accuracy_feps	For each analyst earnings forecast report, its accuracy is defined as the absolute value of the difference between forecast EPS and the actual EPS. Like *Optism_feps*, we first descendingly rank the raw measure of all earnings forecasts in the same quarter and then give *Accuracy_feps* the value of the percentage ranking of the raw measure minus 0.5 (the highest-ranked = 0.5 and the lowest-ranked = −0.5). To construct a yearly measure, we take an average across all earnings forecasts issued by that analyst in that year.
Firmsize	Average of the market cap of stocks recommended by the analyst in that year.
Attention	Proportion of the recommended stocks that are winners or losers, defined as the top or bottom quintile based on past 12-month returns as of the previous quarter-end, respectively.
Experience	Number of quarters since the analyst first issued a report recorded in the CSMAR database.
Brokersize	Number of active analysts in the analyst's brokerage house in that year.
TradeBroker	An indicator variable taking the value of one if the analyst works in one of the manager's important brokers, identified as executing more than 3.1% (sample median among non-zero values) of trades from the manager's fund in the previous year.
PreAward	An indicator variable taking the value of one if the analyst won a title (ranked as the top three or five depending on industry) in the previous year's competition.

Internet Appendix

A. Fund sample comparison

We compare the fund-year observations used in this study with the whole sample from the CSMAR database. There is no strong difference between the two samples in terms of fund characteristics. If anything, the funds included manage larger amounts of assets and have higher raw returns than the average fund during our sample period.

[Insert Table IA.1]

B. Robustness test of fund allocation decisions to brokers

We also use a ranking value of *TradeShare* as the dependent variables in Table 3. First, we rank *TradeShare* across all non-zero brokerages for each fund, and then convert the rankings into a numerical measure that ranges from zero to one (the same procedure as we use for other measures in the paper). All zero *TradeShare* gets a value of zero. Table IA.2 shows robust results.

[Insert Table IA.2]

C. Tests using quarterly top-10 holdings data

We construct whisper-sell and whisper-buy measures using the quarterly disclosures of top-ten holdings, though the measures are constructed with incomplete information of fund holdings. Because the quarterly disclosure only includes top-ten holdings, we regard buying stocks as those whose numbers of held shares increase or whose rankings enter the top ten and selling stocks as those whose numbers of held shares decrease or whose rankings drop out of the top ten. We find robust results in Table IA.3.

[Insert Table IA.3]

D. Robustness of whisper-sell measures

D.1 Effect of within-semiyear turnovers

We use the change in holding shares between two semi-year reports to infer the fund manager's investment views on the stock; a decrease in holding shares means the fund manager holds a negative view of the stock. However, there is a possibility that the fund manager may have changed his/her view within the semi-year, leading to within-semi-year turnovers.

One potential situation corresponds to the cases in which the fund manager first buys and then sells shares within a semi year. Although this case shows that the fund manager is, on average, pessimistic about the stock within the semi-year, it is possible that the analyst's positive recommendation could only happen when the fund manager bought the shares. This causes measurement errors. To show that our results are not solely driven by this mismeasurement, we adopt your suggestion to exclude the stocks when the analyst recommendations occur only in the first three months of the semi-year. Table IA.4 reports the results for this variant of whisper-sell measure. We find consistent results that the coefficients on whisper-sell measures are positive and statistically significant.

[Insert Table IA.4]

Another potential case of within-semi-year turnover is that the fund manager first sells and then buys the stock. This could mean that the fund manager shifts his/her pessimistic view to an optimistic one. It is possible that the analyst's positive recommendation only coincided with the fund manager's buying the stock, which is another source of mismeasurement. To partially address this concern, we only focus on the cases of full position exits. The action of selling all the holding shares not only implies a strong pessimistic belief but also excludes the case of buying shares after selling them. Table IA.5 reports the results using the whisper-sell measure based only on stock exists. The results are robust.

[Insert Table IA.5]

D.2 Impact of earnings forecast optimism

Analysts may convey their pessimistic beliefs through their earnings forecast while issuing positive recommendations. To alleviate this concern, we exclude positive recommendations with relatively pessimistic earnings forecasts. In particular, we exclude the positive recommendations in that semi-year if the analyst issues an earnings forecast whose EPS is below the median of other forecasts in that quarter. Table IA.6 reports the regressions of whisper-sell measure based on this subsample of positive recommendations. The main results are robust, which suggests that fund managers' selling decisions of analysts' positive recommendations is unlikely solely due to managers learning from analysts' earnings forecasts.

[Insert Table IA.6]

E. Analyst coverage

We address the possibilities that the whisper-sell measure serves as a noisy proxy for the analyst's coverage in that specific fund manager's holdings, and that the fund manager votes for the analyst because the analyst covers more of the stocks held by the fund. To distinguish our hypotheses from this account, we additionally control for the analyst's fund-wise coverage in our main regressions. *FundCover* is defined as the fraction of the number of the fund manager's held stocks that are covered by the specific analyst.

[Insert Table IA.7]

Our tests are provided in Table IA.7. In column (1), we first only include *FundCover* but not whisper-sell and whisper-buy measures. The coefficient estimates on *FundCove*r are positive and statistically significant, seemingly suggesting that fund managers appreciate more specific stock coverage by analysts. However, in columns (1) and (2), when we include both *FundCover* and whisper-sell and whisper-buy measures, we find that the coefficient estimates on the whisper-sell and whisper-buy measures remain positive and statistically significant as in our main regressions, but the estimate on *FundCover* loses its statistical significance. This result suggests that it is the analysts' more-accurate information for trading that determines managers' voting decisions rather than the general coverage of stocks held by fund managers.

F. Analyst site visits

It is interesting to explore the possibility that fund managers may vote for analysts who have private connections with firm managers (Cohen, Frazzini, and Malloy 2010; Bradley, James, and Williams 2022). Such a possibility is compatible with our hypotheses. This paper mainly focuses on the interaction between analysts and fund managers, recognizing that there are different possible sources of analyst private information. Nonetheless, we can further control for analysts' connection with firm management and examine to what extent fund managers value such connections in their votes.

To do so, we use analysts' site visits to the firm as a proxy for their connections with the firm management. We collect the site visit information from 2012 to 2016 from CSMAR and associate analysts' site visits with fund managers' traded stocks.[39] *FirmConnection* measures the fraction of the number of the fund manager's traded stocks to which the analyst has site visits in that semi-year.

The results are reported in Table IA.8. We find that the coefficient on *FirmConnection* is positive and statistically significant, suggesting that the firm manager votes for the analyst more favorably if the analyst has more connections with firm management. On the other hand, the coefficients on whisper-sell and whisper-buy measures remain positive and statistically significant, consistent with our main results.

[Insert Table IA.8]

G. Voting decisions and subsequent whisper-sell behavior

Does the manager who ranks analysts highly in the star analyst competition engage in more private communications with the same analysts in the future? To test this hypothesis, we relate the voting rank to *FundSell* for the same manager-analyst pair in the following year.

[39] Shenzhen Stock exchange requires its listed firm to report the information on institutional investors' site visits to the firms starting 2009. CSMAR database starts to collect the data since 2012.

Table IA.9 reports the regression results. In column (1), we find that the coefficient on this year's voting rank is positive and statistically significant; the estimate (0.008) suggests that a one-unit increase in vote ranking will lead to an 8.4% increase in *FundSell* relative to the sample mean.[40] This result suggests that fund managers tend to use more private information from the analysts after ranking them higher compared to other analysts in the same industry. In column (2), we include both *FundSell* and *FundBuy* in the current year as a control and the indicator for the manager's important partner brokers (*TradeBroker*). The coefficient estimate of *TradeBroker* is positive, meaning that a preexisting business relationship also predicts a higher degree of private information communication. The estimate of the voting rank remains positive and statistically significant. In columns (3) to (6), we use various specifications of fixed effects (company-broker, broker-year, industry-year, etc.), and the results are robust.

[Insert Table IA.9]

H. Calculation of recommendation returns

This subsection details how we constructed Table 9, which concerns recommendation performance around recommendation dates using an event study approach. Since multiple recommendations are made on numerous days, the returns for stocks for which the event windows overlap in calendar time would be correlated. To allow for this cross-sectional dependence in the statistical tests, we follow the approach in Jegadeesh (2000). For each group (fund-buy, no-trade, and fund-sell), we first compute the average CAR for all recommendations in each calendar month. The average abnormal return for each category is the weighted average of the abnormal returns for the monthly cohorts in the sample, where the weights are proportional to the number of observations in the respective cohorts. Specifically,

$$\overline{CAR} = \omega' CAR, \tag{H.1}$$

[40] The average *FundSell* for the same manager-analyst pairs drops significantly next year from 0.30 to 0.095. We argue that it is likely due to managers shifting their holdings across industries as we find that adding the industry-year fixed effects significantly increase the R-squared of the regressions.

where $\overline{CAR}$ is the average cumulative abnormal return, ω the vector of weights where the jth element is the ratio of the number of observations in month j divided by the total number of observations over the sample period, and CAR the vector of average CAR where the element CAR_j is the average CAR for the month-j cohort. For the difference between the fund-buy and fund-sell groups, we first calculate the difference in the average CAR between fund-buy and fund-sell in month j, then calculate the time-series weighted average with the weight for month j being proportional to the average of the numbers of fund-buy recommendations and fund-sell recommendations in month j.

The variance of $\overline{CAR}$ is given by

$$Var(\overline{CAR}) = \omega' V_C \omega, \tag{H.2}$$

where V_C is the variance-covariance matrix of $\overline{CAR}$. Since the CAR intervals for different monthly cohorts overlap, we allow for the first- through sixth-order serial covariance of monthly average CAR to be nonzero and set the higher-order serial covariances to equal zero. To be specific, let $\nu_{i,j}$ be the ijth element of V_C. The estimator for V_C is

$$\begin{aligned} \nu_{i,j} &= (CAR_i - \overline{CAR})^2 \;\; \forall\, i = j, \\ &= (CAR_i - \overline{CAR})\big(CAR_j - \overline{CAR}\big) \;\; \forall\, 1 \le |i - j| \le 6, \\ &= 0 \text{ otherwise.} \end{aligned} \tag{H.3}$$

I. Robustness of the event study test of analyst positive recommendations

We acknowledge that in this event study setting of public recommendations, we observe stock returns and fund managers' trading contemporarily, which leaves room for alternative interpretations. We run several robustness tests to address some most likely alternative hypotheses. First, we ensure that managers' buying and selling decisions are not based on managers' differentiation of Strong Buy and Buy recommendations (see Figure IA.1).

[Insert Figure IA.1]

Second, we control for funds' momentum trading. For example, after a positive earnings surprise, an analyst might start to issue a positive recommendation, and meanwhile, funds start to increase holdings after a price run-up (Griffin, Harris, and Topaloglu 2003; Sias 2004). We address this concern by partitioning our sample into quintiles based on CARs from −40 to −2 trading days. In Table IA.10, we find consistent differences in post-recommendation CARs between fund-buy and fund-sell recommendations across all quintiles; that is, the return patterns cannot be fully explained by fund momentum trading based on price movement leading to analyst recommendations.

[Insert Table IA.10]

J. Fund performance

To show that private communication from analysts helps with fund performance, we adopt the regression setup used in Cohen, Frazzini, and Malloy (2008) and Gu et al. (2019). Our strategy is to see, among the stock holdings of a specific fund at a given semi year-end, the stocks that are recommended by the fund manager's voted-for analysts generate better posterior performance than other stocks. In this setting, we can have a clear benchmark to measure the benefit of private communication with firm-semi-year fixed effects. The specific regression goes as follows:

$$DGTW\ return_{i,j,s+1} = VoteTies_{i,j,s} + Control\ Variables + \varepsilon_{i,j,s+1}, \tag{J.1}$$

where $DGTW\ return_{i,j,s+1}$ is the DGTW-adjusted returns over the following quarter of stock i in fund j's holdings at the end of semi-year s; $VoteTies_{i,j,s}$ is an indicator variable equal to one if stock i is recommended in semi-year s as positive by any of the analysts for whom fund j's manager(s) vote in that year. In addition, we control for various firm characteristics such as industry-wide analyst recommendation (*Indsutry_recom*), firm size (*Size*), book-to-market ratio (*BM*), and stock returns in the past 12 months (*Return*).

[Insert Table IA.11]

According to column (2) with fund-year fixed effects, we find that fund managers enjoy 86.0 basis points more returns from stocks that are linked to their voted-for analysts than other stocks in their holdings. This result is consistent with our conjecture that voted analysts give private information to fund managers such that those recommended stocks in the fund's portfolios deliver better performance than other stocks. Note that fund managers do not include all their voted-for analysts' positively recommended stocks in their portfolios. These partial stock selections are arguably private information from the analysts. On the other hand, following the consensus analyst recommendations (*Indsutry_recom*) does not contribute to any superior stock performance.

Furthermore, in columns (3) and (4), we include an indicator for the fund decreasing the holding shares of the stock in semi-year s (*Sell*) and its interaction with *VoteTies*. We expect that those stocks of which the managers decrease the shares may perform less than other stocks also recommended by the same analysts. The estimates on the interaction term are negative (−0.668 in column (3) and −0.544 in column (4) with fixed effects) and statistically significant. These results suggest that among the stock holdings linked to their voted-for analysts, the stocks that managers choose to sell underperform the stocks that managers choose to buy or keep. The results are generally consistent with our finding at the stock-recommendation level that fund-sell stock recommendations underperform fund-buy stock recommendations.

References

Bradley, Daniel, Russell Jame, and Jared Williams, 2022. Non-Deal Roadshows, Informed Trading, and Analyst Conflicts of Interest. *Journal of Finance* 77, 265–315.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008. The small world of investing: board connections and mutual fund returns. *Journal of Political Economy* 116, 951–979.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2010. Sell-side school ties. *Journal of Finance* 65, 1409–1437.

Griffin, John M., Jeffrey H. Harris, and Selim Topaloglu, 2003. The dynamics of institutional and individual trading. *Journal of Finance* 58, 2285–2320.

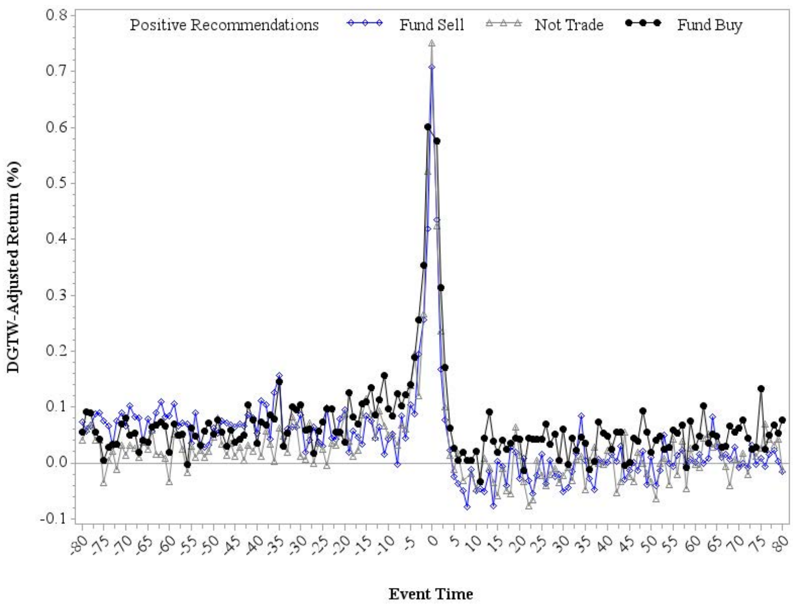
Jegadeesh, Narasimhan, 2000. Long-term performance of seasoned equity offerings: benchmark errors and biases in expectations. *Financial Management*, 5–30.

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

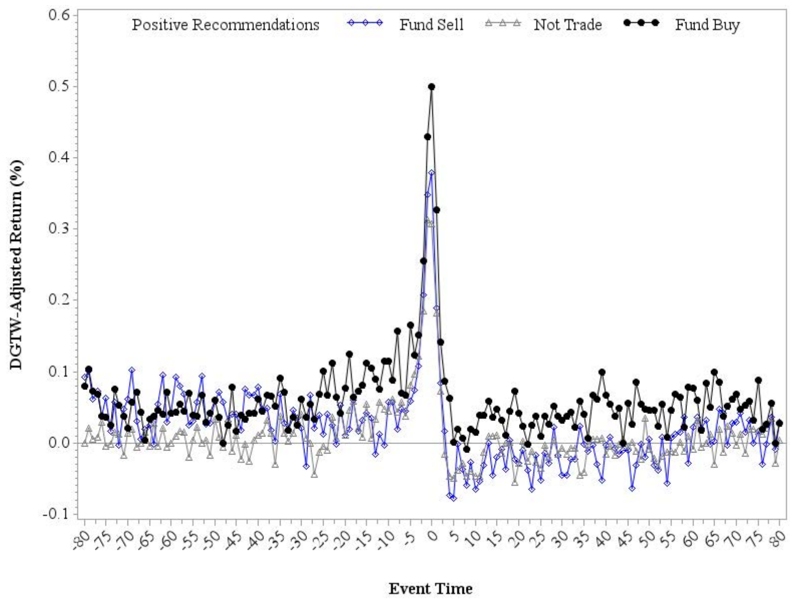
Internet Appendix Figures

Figure IA.1 Abnormal daily returns around positive recommendations by fund trades

This figure presents the mean of abnormal daily returns around positive recommendations by the direction of the average trades by funds whose managers vote for the analyst. The upper (lower) panel refers to Strong Buy (Buy) recommendations. "Fund Buy" ("Fund Sell") refers to the recommendations for which the average trades of the stock across the funds whose managers vote for the analyst are positive (negative). "Not Trade" recommendations are those for which the stocks are not traded by the analyst-voting fund managers. Abnormal return is measured by the difference between the raw return and the DGTW benchmark return. The figure shows an event window of −80 to 80 trading days.



Upper panel: Strong Buy recommendations



Lower panel: Buy recommendations

Internet Appendix Tables

Table IA.1 Characteristics of active funds included

This table compares the fund-year observations included in this study with the whole sample from the CSMAR database from 2010 to 2016. We use 3,132 fund-year observations (or 2,391 manager-year observations) for which we have the manager votes, whereas the whole CSMAR sample has 7,506 fund-year observations. Total net assets is the average of the total net assets of the fund at the end of each quarter. Annualized turnover ratio is the annual turnover ratio of the fund in that year. Annualized raw return is the raw return of the fund annualized from the average of quarterly returns over the past eight quarters. Annualized flow is the flow of the fund during the year annualized from quarterly flows. Annualized volatility is the annualized standard deviation of the quarterly raw returns of the fund over the past eight quarters.

	Mean		Median	
	Obs. included	Obs. in CSMAR	Obs. included	Obs. in CSMAR
Ln(Total net assets) (Yuan millions)	6.74	6.63	6.91	6.75
Annualized turnover ratio (%)	107.9%	107.1%	98.7%	94.5%
Annualized raw return (%)	11.3%	9.67%	10.8%	7.8%
Annualized flow (%)	5.0%	28.3%	-18.7%	-16.4%
Annualized volatility (%)	46.0%	40.8%	43.7%	36.6%

Table IA.2 Voting decisions and future trade allocations-robustness check

This table reports the effect of fund managers' voting decisions on their trade allocations to the brokers in subsequent years. *TradeShare* is the percentage share (from 0 to 100) of trades allocated from the fund to the broker in the subsequent year. *TradeShare_s* is the percentage rankings of *TradeShare* among the industry-year analyst groups (the highest-ranked = 1 and the lowest-ranked = 0). $\Delta\overline{VoteRank}$ is the change in the average vote ranking to the broker's analysts from the fund's managers in the current year. The trade share measure in the current year is also included as a control. Standard errors, clustered by broker and fund, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	TradeShare_s t+1				
	(1)	(2)	(3)	(4)	(5)
$\Delta\overline{VoteRank}\ t$	0.0177***	0.0132**	0.0099*	0.0136**	0.0133**
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
TradeShare_s t		0.338***	0.312***	0.314***	−0.088***
		(0.011)	(0.012)	(0.012)	(0.015)
Fixed effects	-	-	Broker	Broker×Year	Broker×Year Fund×Broker
Observations	15,328	15,328	15,328	15,328	15,328
Adjusted R^2	0.001	0.091	0.123	0.139	0.294

Table IA.3 Main regressions using quarterly disclosures of holdings

This table replicates the main Table 4, except that the whisper-sell and whisper-buy measures are constructed based on the quarterly disclosures of top-ten fund holdings. Specifically, *FundSell* (*FundBuy*) is defined as the fraction of the number of the manager's selling (buying) stocks that are positively recommended by the analyst. For top-ten fund holdings, the buying (selling) stocks are defined as those whose shares increase (decrease) or climb up to (drop out of) the top-ten list. Independent variables with the suffix *s* are the percentage rankings of the original values among the industry-year analyst groups (the highest-ranked = 1 and the lowest-ranked = 0). Other control variables are the same in Table 4. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	VoteRank	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)
FundSell	0.038**	0.009*		
	(0.015)	(0.004)		
FundBuy	0.151***	0.039***		
	(0.026)	(0.007)		
FundSell_s			0.087***	0.019**
			(0.031)	(0.009)
FundBuy_s			0.159***	0.041***
			(0.030)	(0.008)
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	218,420	218,420	218,420	218,420
Adjusted R^2	0.123	0.126	0.123	0.126

Table IA.4 Whisper-sell measure—Exclusion of early recommendations

This table shows the robustness of whisper-sell and whisper-buy measures. The dependent variable, *VoteRank*, represents the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; fifth = 1; no vote = 0). "≤fifth Choice" is an indicator variable for a vote of the fifth choice or higher. *FundSell* (*FundBuy*) principally measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. Independent variables with the suffix *s* are the percentage rankings of the original values among the industry-year analyst groups (the highest-ranked = 1 and the lowest-ranked = 0). The whisper-sell and whisper-buy measures used here exclude the analyst-stocks if the analyst only issues positive recommendations of the stocks in the first half of the semi-year. Other control variables are the same as the main regressions. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	VoteRank	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)
FundSell	0.120***	0.034***		
	(0.025)	(0.006)		
FundBuy	0.151***	0.037***		
	(0.025)	(0.006)		
FundSell_s			0.115***	0.030***
			(0.024)	(0.007)
FundBuy_s			0.133***	0.032***
			(0.023)	(0.006)
Other controls	Yes	Yes	Yes	Yes
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	271,551	271,551	271,551	271,551
Adjusted R2	0.123	0.128	0.123	0.127

Table IA.5 Whisper-sell measure—Full exist

This table shows the robustness of whisper-sell and whisper-buy measures. The dependent variable, *VoteRank*, represents the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; fifth = 1; no vote = 0). "≤fifth Choice" is an indicator variable for a vote of the fifth choice or higher. *FundSell* (*FundBuy*) principally measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. Independent variables with the suffix s are the percentage rankings of the original values among the industry-year analyst groups (the highest-ranked = 1 and the lowest-ranked = 0). The whisper-sell and whisper-buy measures used here count for only full stock exits for *FundSell* and new stock positions for *FundBuy*. Other control variables are the same as the main regressions. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	VoteRank	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)
FundSell	0.078***	0.022***		
	(0.020)	(0.007)		
FundBuy	0.129***	0.035***		
	(0.022)	(0.007)		
FundSell_s			0.077***	0.019***
			(0.022)	(0.006)
FundBuy_s			0.117***	0.031***
			(0.021)	(0.006)
Other controls	Yes	Yes	Yes	Yes
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	271,551	271,551	271,551	271,551
Adjusted R2	0.123	0.128	0.123	0.127

Table IA.6 Whisper-sell measure—Exclusion of pessimistic earnings forecasts

This table shows the robustness of whisper-sell and whisper-buy measures. The dependent variable, *VoteRank*, represents the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; fifth = 1; no vote = 0). "≤fifth Choice" is an indicator variable for a vote of the fifth choice or higher. *FundSell* (*FundBuy*) principally measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. Independent variables with the suffix *s* are the percentage rankings of the original values among the industry-year analyst groups (the highest-ranked = 1 and the lowest-ranked = 0). The whisper-sell and whisper-buy measures used here exclude the analyst-stocks if the analyst issues an earnings forecast below the median forecast. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	VoteRank	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)
FundSell	0.108***	0.033***		
	(0.030)	(0.008)		
FundBuy	0.122***	0.032***		
	(0.032)	(0.009)		
FundSell_s			0.074***	0.020***
			(0.024)	(0.007)
FundBuy_s			0.073***	0.018***
			(0.022)	(0.006)
Other controls	Yes	Yes	Yes	Yes
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	271,551	271,551	271,551	271,551
Adjusted R^2	0.122	0.127	0.122	0.127

Table IA.7 Whisper-sell measure and analyst coverage

This table shows the robustness of whisper-sell and whisper-buy measures with the influence of analyst coverage. The dependent variable, *VoteRan*k, represents the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; fifth = 1; no vote = 0). "≤fifth Choice" is an indicator variable for a vote of the fifth choice or higher. *FundSell* (*FundBuy*) principally measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. Independent variables with the suffix s are the percentage rankings of the original values among the industry-year analyst groups (the highest-ranked = 1 and the lowest-ranked = 0). *FundCover* measures the fraction of the number of fund stock holdings that are covered by the analyst. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	VoteRank	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)
FundSell		0.065***	0.016***
		(0.021)	(0.006)
FundBuy		0.107***	0.027***
		(0.020)	(0.006)
FundCover	0.179***	0.045	0.015
	(0.040)	(0.041)	(0.012)
Other controls	Yes	Yes	Yes
Fixed effects	Company× Broker	Company× Broker	Company× Broker
Observations	271,551	271,551	271,551
Adjusted R2	0.123	0.123	0.127

Table IA.8 Whisper-sell measure and analyst site visits

This table shows the robustness of whisper-sell and whisper-buy measures with the influence of analyst sit visits. The dependent variable, *VoteRank*, represents the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; fifth = 1; no vote = 0). "≤fifth Choice" is an indicator variable for a vote of the fifth choice or higher. *FundSell* (*FundBuy*) principally measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. Independent variables with the suffix *s* are the percentage rankings of the original values among the industry-year analyst groups (the highest-ranked = 1 and the lowest-ranked = 0). *FirmConection* measures the fraction of the number of fund-traded stocks of which the analysts have site visits to the firms. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	VoteRank	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)
FundSell	0.092***	0.024**		
	(0.022)	(0.006)		
FundBuy	0.137***	0.036***		
	(0.023)	(0.007)		
FundSell_s			0.070***	0.015**
			(0.025)	(0.007)
FundBuy_s			0.116***	0.029***
			(0.023)	(0.006)
FirmConection	0.211**	0.057**	0.225**	0.061***
	(0.085)	(0.023)	(0.084)	(0.023)
Other controls	Yes	Yes	Yes	Yes
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	220,050	220,050	220,050	220,050
Adjusted R^2	0.112	0.118	0.111	0.117

Table IA.9 Voting decisions and future whisper-sell behavior

This table reports the effect of voting decisions on the subsequent whisper-sell behavior. The dependent variable is *FundSell* for the same analyst and manager in the subsequent year. *FundSell* measures the percentage of the fund manager's sold stocks that are also among the analyst's positive stock recommendations. *VoteRank* is the manager's vote for the analyst (first choice = 5; second choice = 4; third choice = 3; fourth choice = 2; fifth choice = 1; no vote = 0). *TradeBroker* is an indicator variable for an important business relationship between the analyst's brokerage house and the fund. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	FundSell t+1					
	(1)	(2)	(3)	(4)	(5)	(6)
VoteRank t	0.008***	0.003***	0.003***	0.002***	0.002***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FundSell t		0.067***	0.066***	0.052***	0.056***	0.044***
		(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
FundBuy t		0.125***	0.124***	0.112***	0.112***	0.099***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
TradeBroker t			0.05**	0.001	0.001	0.001
			(0.002)	(0.003)	(0.001)	(0.001)
Fixed effects	-	-	-	Company× Broker	Company× Broker Broker× Year	Company× Broker Industry× Year
Observations	271,551	271,551	271,551	271,551	271,551	271,551
Adjusted R^2	0.002	0.060	0.060	0.060	0.087	0.130

Table IA.10 Performance around analyst recommendations—controlling for momentum trading

This table reports the means of cumulative abnormal returns based on DGTW benchmark over different event windows around recommendations by the quintiles based on the CARs over the −40 to −2 days period. Positive recommendations are assigned into three groups, "Fund Sell," "Not Trade," and "Fund Buy," based on the average trades across funds whose managers vote for the analysts in that year. The column titles specify the event windows, whereas the row titles specify the groups of recommendations. *t*-statistics adjusted for cross-sectional and serial correlations are shown below in parentheses.

Pre-recommendation return quintiles	Low		2		3		4		High	
Event window	[-1, 1]	[2, 40]	[-1, 1]	[2, 40]	[-1, 1]	[2, 40]	[-1, 1]	[2, 40]	[-1, 1]	[2, 40]
Fund Buy	1.74	2.23	1.52	1.52	1.62	0.07	1.60	0.27	1.88	0.96
	(5.54)	(3.03)	(6.32)	(2.75)	(5.69)	(0.10)	(5.56)	(0.31)	(4.09)	(1.78)
Not Trade	1.13	−0.99	1.03	−0.20	1.00	−0.98	0.91	−1.45	1.52	−1.57
	(4.71)	(−2.68)	(4.28)	(−0.61)	(5.15)	(−1.91)	(3.41)	(−1.73)	(5.06)	(−3.51)
Fund Sell	1.21	−1.33	1.19	−0.85	1.06	-2.36	1.21	−0.74	1.47	−1.66
	(4.47)	(−2.68)	(3.91)	(−2.68)	(4.51)	(−1.91)	(3.38)	(−0.47)	(4.00)	(−2.60)
Fund Buy- Fund Sell	0.55	3.66	0.35	2.54	0.51	2.19	0.38	0.74	0.43	2.61
	(8.42)	(5.95)	(2.59)	(7.98)	(4.85)	(3.81)	(2.10)	(1.65)	(8.29)	(5.78)

Table IA.11 Voted-for analysts and fund performance

This table reports how fund managers benefit from private communication with the analysts they vote for. The sample includes all stock holdings reported in each semi-year report for the voting funds. The dependent variables are DGTW-adjusted returns of the stock holdings over the following quarter. *VoteTies* is an indicator variable equal to one if the stock is recommended as positive by any of the analysts for whom the fund's managers vote. *Sell* is an indicator variable equal to one if the fund decreases its holdings of the stock in the past semi-year. *Industry_recom* is the number of analysts, counted at the broker level, who positively recommended the stock. *Firm Size* is the market cap of the stock. *BM* is the book-to-market ratio. *Return* is the cumulative return over the past 12 months. Fund-year fixed effects are included in some specifications. Standard errors are clustered by fund and year. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	DGTW returns (%)	*DGTW returns* (%)	*DGTW returns* (%)	*DGTW returns* (%)
	(1)	(2)	(3)	(4)
VoteTies	0.720***	0.860**	0.851***	0.969***
	(0.205)	(0.246)	(0.178)	(0.235)
Sell			0.530	0.271
			(0.533)	(0.357)
VoteTies × *Sell*			−0.668**	−0.544**
			(0.294)	(0.196)
Industry_recom	0.005	0.053	0.004	0.053
	(0.051)	(0.074)	(0.050)	(0.073)
Firm Size	−0.655	−1.002*	−0.656	−1.001*
	(0.480)	(0.429)	(0.476)	(0.428)
BM	−1.692**	−1.283	−1.700*	−1.283
	(0.780)	(1.068)	(0.778)	(1.068)
Return	2.080***	1.264*	2.090***	1.266*
	(0.794)	(0.526)	(0.802)	(0.523)
Fixed effects	-	Fund×Year	-	Fund×Year
Observations	254,762	254,762	254,762	254,762
Adjusted R^2	0.007	0.031	0.007	0.031