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 July 2022

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 July 2022
JEL No. G12,G14,G2,G23,G24,G3,M41

ABSTRACT

We examine how sell-side equity analysts strategically disclose information of differing quality to the public versus the buy-side mutual fund managers to whom they are connected. We consider cases in which analysts recommend that the public buys a stock, but some fund managers sell it. We measure favor trading using mutual fund managers’ votes for analysts in a Chinese “star analyst” competition. We find that managers are more likely to vote for analysts who exhibit more “say-buy/whisper-sell” behavior with these managers. This suggests that analysts introduce noise in their public recommendations, making the more-precise information provided to their private clients more valuable. Analysts’ say-buy/whisper-sell behavior results in information asymmetry: the positive-recommendation stocks bought by the managers who vote for the analysts outperform the stocks sold by these managers after the recommendation dates. Our findings help explain several puzzles regarding analysts’ 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

Do analysts produce information and generate value for trading? The answers to this question so far have been mixed. On the one hand, recent literature has found that analysts' favorable recommendations about a stock are followed by *negative* anomaly returns (Engelberg, McLean, and Pontiff 2020; Guo, Li, and Wei 2020). On the other hand, the literature focusing on private connections has found that sell-side analysts provide useful information to fund managers via networks (Cohen, Frazzini, and Malloy 2008; Busse, Green, and Jegadeesh 2012; Brown, Wei, and Wermers 2014; Gu et al. 2019).

These findings suggest that there is a tension between analysts' jobs delivering public information to the market versus delivering private information to their clients. To address this tradeoff more directly, we examine here whether analysts deliver information of different quality to private clients and public audiences. As a *Euromoney* article states, "[R]etail investors . . . didn't seem to realize . . . that you had to call analysts to get their private views, not merely read their reports" (Euromoney.com 2003). Occasionally there is information leakage, so that mismatches between analysts' public versus private communications come to light. During the millennial Dot-com bubble, Merrill'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).[1] We provide evidence here suggesting a general patten of analysts providing different messages to public and private audiences, and we explore the economic incentives behind such analysts' behavior.

Analysts have incentives to disclose different information to private clients and public audiences. More precise public disclosures make stock prices more efficient, which tend to reduce the expected profit to investors with private information (Kyle 1985, 1989). So public disclosure can come at the expense of profits to analysts' private clients. Therefore, analysts must strike a balance between the precision of the information they disclose and the number of

[1] Later, Blodget resolved a settlement with SEC in which he neither admitted nor denied the regulators' allegations of securities fraud. The case was brought to SEC's attention in part because of the subsequent collapse of touted tech stocks. Under less extreme circumstances, such activities may be under the radar of enforcement agencies. This suggests that the practice of providing different messages to different audiences may be common. However, in this paper, we do not take any stance on the issue of legality of this practice.

investors they inform. In a model of a private information provider selling information to investors, García and Sangiorgi (2011) show that the provider will sell relatively precise information to a small group of investors (corresponding to mutual fund managers in this paper) or sell relatively imprecise information to a large group of investors (corresponding to public audiences).[2] That is to say, analysts strategically add noise in their public recommendations to maintain the trading value of their private signals.[3]

This incentive to provide different information to different audiences helps us understand several important facts, some puzzling, about analyst recommendations. One is that government regulations aimed at improving the authenticity and integrity of analyst behavior have been of limited effectiveness.[4] Kadan et al. (2009) analyzes the effect of the Global Analyst Research Settlements on the informativeness of analyst recommendations. They find that, contrary to the intention of the settlements, the overall informativeness of analyst recommendations subsequently declined.[5] Our findings can help explain that finding: if analysts benefit from selling private information to their clients, they are reluctant to improve the informativeness of their public recommendations at the expense of compromising the profitability of their private information.

Our findings can also help explain why analysts' public recommendation performance do not seem to influence their career outcomes (Mikhail, Walther, and Willis 1999; Hong and Kubik 2003; Emery and Li 2009). If analysts' public recommendations do not reveal their true beliefs about stocks, such recommendations may not be the best way to evaluate the performance of an analyst.

Analyst recommendations provide public signals, available to the empiricist, about analyst

---

[2] Some early theoretical work on information sales delivers similar insights, including Admati and Pfleiderer (1986, 1888), Kyle (1985, 1989), and Cespa (2008).

[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] For instance, during the early 2000s, the U.S. Securities and Exchange Commission (SEC) caught analysts at Merrill Lynch putting rosy recommendations on internet startup companies and later disclosing different opinions in their private email correspondence.

[5] Kadan et al. (2009) find that to respond to the public criticism of analysts' optimistic recommendations, the analysts increased the informativeness of their positive recommendations. However, on the other hand, they decreased the informativeness of their negative recommendations.

assessments of the value of investing in a stock.[6] It is much harder to identify or measure the private information that analysts pass on to fund managers, since researchers do not observe the timing and content of private communications. To identify private information given to fund managers, we focus on situations in which analysts publicly recommend a particular stock to *buy* but fund managers who are connected to the analyst *sell* that stock; in short, say-buy/whisper sell behavior.[7]

Consider the following example. An analyst issues the same "buy" rating to the public on Stock A and Stock B. Meanwhile, the analyst has more-precise information about these two stocks; for example, Stock A is better than Stock B, and privately discloses this information to his or her clients (e.g., mutual fund managers).[8] To the extent that the managers trade based on such private information, if they ever held Stock B in their portfolios, they would tilt their portfolios from Stock B toward Stock A. Therefore, we treat Stock A as the whisper-buy stocks and Stock B as the whisper-sell stocks.[9] Whisper-sell stocks are crucial for testing the hypothesis that analysts disclose different quality information to different audiences.

Whisper-sell stocks is not a perfect indicator of disclosure inconsistencies on the part of analysts. In some cases, fund managers may happen to be independently pessimistic, and sell stocks that were positively recommended by analysts. To ensure that whisper-sell stocks capture private communications rather than mere coincidences, we exploit a form of quid pro quo behavior between analysts and fund managers using a "star analyst" competition in China. In this analyst competition, fund managers vote for analysts, and their votes determine star analysts;[10] being a star analyst increases an analyst's reputation and leads to higher bonuses

[6] Analysts may disclose information through means other than stock recommendations, such as earnings forecasts. However, stock recommendations directly reflect analysts' opinions on investment strategies whereas there is lack of a clear mapping between earnings forecasts and investment strategies.

[7] Since most of analyst recommendations are positive in the Chinese market, we focus only on say-buy/whisper-sell behavior. On the other hand, since mutual funds cannot short-sell, fund managers mostly focus on buying high-value stocks before the private information is incorporated into prices, rather than short-selling low-value stocks.

[8] There are other forms of private information communications between analysts and their clients. For example, analysts may give some information exclusively to their clients without any disclosure to the public (Li, Mukherjee, and Sen 2021). Analysts may also give fund managers the same information as their public reports but give it in advance of the public release. The form of communication being considered in this paper is the one that we can empirically identify.

[9] Empirically, we infer managers' trading from the two recent holdings disclosures and measure whisper-sell behavior as the fraction of the manager's selling stocks that are positively recommended by the analyst. We use managers' 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.

[10] This ranking procedure is very similar to the U.S. counterpart of *Institutional Investor* analyst ranking in which the ranking

and greater chances of promotion (Stickel 1992). Analysts, thus, are motivated to curry favor with fund managers by providing private information on stocks in exchange for votes (e.g., Green 2006; Irvine, Lipson, and Puckett 2006). Therefore, the main testable prediction of this paper is that the analyst's whisper-sell behavior positively correlates with the fund manager's voting for that analyst.

The prediction of a positive relationship between whisper-sell behavior and favorable manager voting distinguishes our private-communication hypothesis from alternative hypotheses about the causes of analyst behavior. Under the private-communication hypothesis in which analysts provide private information to their connected fund managers, whisper-sell behavior encourages a manager to vote for an analyst.[11] This differs from existing literature on fund managers acting based on analysts' public recommendations. Consider two alternative scenarios that a manager learns only public information from the analyst and that the manager and the analyst make independent decisions based on the same external signals. Under these scenarios, whisper-sell behavior would *discourage* the manager from voting for the analyst, in contrast with our hypothesis, because it implies that the manager disagrees with the analyst's opinions inferred from their public recommendations.

The empirical analysis starts by verifying the informativeness of managers' votes by linking their votes with their trade allocation decisions. Previous literature 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). Building on these insights, 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.

Next, we turn to the main hypothesis that analysts provide private and more-precise

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.

[11] It is possible that fund managers may identify analysts' overly optimistic recommendations and sell these stocks by analyzing various analyst recommendation biases documented by academics. However, in this case, it is unlikely that managers would credit analysts for simply issuing biased public recommendations.

information to fund managers. We find that an analyst's whisper-sell behavior positively correlates 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 leads to a 10% increase 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 provide fund managers with more-precise information about stock values than they include in their public recommendations.

Other tests provide further evidence that is supportive of the private-communication hypothesis. We find that the effect of whisper-sell behavior on the voting rank is strengthened: (1) when the manager has less investment skill in the industry and therefore relies more on outside information from analysts, (2) when the manager has a preexisting business tie with the analyst's broker and therefore is more likely to have contact with the analyst, and (3) when the firm information environment is less transparent and information asymmetry is high, and therefore the reputation costs of whispering sell is relatively low.

In addition, we expect that if a fund manager ranks an analyst higher, which translates into a higher evaluation of the analyst due to the private information the analyst provided, the fund manager will engage in more private communications with the same analyst in the future. As with the prediction, we find that manager votes positively correlate with the extent of whisper-sell behavior for the same analysts in the subsequent year.

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 concerns that analysts' tendencies to recommend many stocks or to herd on recommendations made by peer analysts may mechanically lead to a higher measurement of whisper-sell behavior. We also rule out the case that our whisper-sell measures simply proxy for analysts' specific coverage of stocks held by fund managers.

Next, we explore the financial implications of the analysts' different disclosure strategies.

Specifically, we examine whether analyst public recommendations perform differently between the whisper-sell and whisper-buy stocks. We divide positive recommendations into three groups based on the average trade direction across funds whose managers vote for the analyst: fund-buy, fund-sell, and the rest (not trade).

We examine stock performance around public recommendation dates using a standard event-study approach. Given that these three groups are for positive recommendations, we observe positive price spikes on the recommendation dates across all groups. However, cross-sectionally, whisper-sell recommendations outperform whisper-buy recommendations after the recommendation dates. The difference in the cumulative abnormal returns is 0.46% over the window of −1 to 1 trading days, 2.47% over the window of 2 to 40 trading days, and 3.16% over the window of 41 to 220 trading days. Although we cannot observe the exact trading dates by the voting managers, to the extent that they trade stocks around the recommendation dates, the trading of the voting managers outperforms the trading strategy of simply following analysts' public recommendations. This finding is consistent with the conjecture that fund managers act on analysts' private information in addition to analysts' public recommendations.

Furthermore, the market still reacts positively to the whisper-sell recommendations around the announcement dates: the event-day abnormal returns from −1 to 1 trading days, on average, equal 1.05%, 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 do not distinguish between whisper-buy and whisper-sell stocks. The uninformed investors who buy unconditionally upon positive public recommendations would, on average, earn about 1.50% fewer returns from 2 to 40 trading days after the recommendation dates than the informed managers who only follow whisper-buy recommendations. We attribute such differences in investment returns among market participants to the information asymmetry caused by analysts' different information disclosure strategies.

Last, we test whether managers benefit from private communications with analysts. We find that fund managers are not only more likely to hold the stocks positively recommended by the analysts for whom the managers vote, which confirms existing literature (e.g., Cohen, Frazzini, and Malloy 2008; Gu et al. 2019), but also more likely to buy or sell them. Interestingly, the likelihood of selling stocks from voted-for analysts' positive recommendations is as high as that of buying these stocks. We also find that among fund managers' holdings, the whisper-sell stocks underperform whisper-buy stocks, consistent with our previous event study of stock recommendations. In sum, our evidence suggests that fund managers benefit from analysts' private information that is not fully revealed in analysts' public recommendations.

Our paper builds on literature that documents that analysts issue biased recommendations because of conflicts of interest. 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 2012), management relations (Das, Levine, and Sivaramakrishnan 1998; Lourie 2019), and trade generation (Irvine 2000, 2004; Jackson 2005; Cowen, Groysberg, and Healy 2006; Agrawal and Chen 2008). Complementing these papers, ours examines a new form of conflict of interest: the analysts' incentive to sell private information is at odds with the informativeness of their public recommendations. In addition, different from previous papers that say that analysts introduce directional biases in their recommendations, this paper shows that analysts introduce noise in their public recommendations to create value for their private information.

This paper shares a similar insight with Malmendier and Shanthikumar (2014), who show the "two-tongue" behavior of analysts who issue overly positive recommendations but less optimistic forecasts to target different audiences. Complementing their paper, this paper shows that analysts disclose information with different levels of precision to different audiences, and links such behavior to rewards (in the form of voting behavior) by private clients.

In addition, this paper's findings help in explaining partially several empirical facts about analyst recommendations: (1) widely distributed stock reports such as analyst recommendations have relatively low information content (Graham and Harvey 1996; Womack

1996; Metrick 1999; Barber et al. 2001; Antweiler and Frank 2004; Jegadeesh et al. 2004; Engelberg, Sasseville, and Williams 2012);[12] (2) analysts' public recommendation performance is not significantly linked to their career outcomes (Mikhail, Walther, and Willis 1999; Hong and Kubik 2003; Emery and Li 2009);[13] (3) past regulations did not effectively improve the informativeness of analysts' public recommendations (Kadan et al. 2009), and 4) analysts' public positive recommendations are more associated with overvalued stocks than undervalued stocks (Engelberg, McLean and Pontiff 2020; Guo, Li, and Wei 2020).

Many theoretical papers touch on the information sale problems pioneered by Admati and Pfleiderer (1986, 1988). In practice, an analyst's job of analyzing firms and publishing reports is one of selling private information. This paper's findings are specifically related to the model of García and Sangiorgi (2011) regarding optimal information sales. They show that a private information provider's optimal selling strategy is either: (1) to sell imprecise information to as many investors as possible, or (2) to sell precise information to as few investors as possible. This paper confirms their predictions by showing that analysts provide noisy information to the public and precise information to a small group of institutional investors.

This paper also contributes to the literature that examines the private connections among financial professionals (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

[12] Womack (1996) finds short-lived limited performance when following analyst buy recommendations. 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 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.

[13] Hong and Kubik (2003) find that analysts' high relative forecast accuracy and optimism positively correlate with good career outcomes. That implies that recommendation performance might not be an important factor for determining analysts' career outcomes. Mikhail, Walther, and Willis (1999) directly test this hypothesis and find that neither the absolute nor relative recommendation performance is significantly related to the probability of analyst turnover. Emery and Li (2009) study the determinants of the star analyst ranking in the United States and find that recommendation performance is not a significant factor.

as identified by social ties.

In contrast with these papers, ours takes advantage of novel data on managers' voting for analysts to identify sharper one-to-one connections between analysts and fund managers that can vary over time. Moreover, we look at cases in which managers diverge from analysts' public signals rather than cases in which managers follow analysts' signals, which brings an edge to our identification strategy. As a result, our paper reconciles the fact that analysts pass valuable information to fund managers with the puzzle that analysts' public recommendations do not add as much value.

The remainder of this paper is organized as follows. Section 2 develops testable 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 explores market price reactions to analysts' positive public recommendations. Section 7 provides further discussion, and Section 8 concludes.

2. Main testable hypotheses

In this section, we explain our empirical strategy for testing analysts' different disclosure strategies. We develop a series of hypotheses revolving around analysts' whisper-sell behavior to test whether analysts provide private and more-precise information to fund managers than they do to the public.

2.1 Whisper-sell and whisper-buy behavior

If managers act on analysts' private, more-precise information in addition to public information, we will observe managers' trading decisions diverging from the course suggested by analysts' public recommendations. For example, an analyst publicly assigns the same buy recommendation rating to Stocks A and B but privately informs the manager that Stock A is better than Stock B. [14] In turn, the informed manager is likely to buy Stock A and sell Stock B

[14] The analyst does not want to fully disclose the precise information because there is a free-rider problem among public investors: it is difficult for the analyst to benefit from his or her information-analyzing efforts from the free riders. Also, if the public information is precise enough, then the price will almost immediately realize the fundamental value such that nearly no one can benefit from trading on such information (Cespa 2008).

when the fund holds Stock B and has capital constraints. Therefore, Stock A is the whisper-buy stocks, whereas Stock B is the whisper-sell stocks. [15] Though we cannot directly observe the private communication between analysts and managers, we use the occurrence of whisper-sell and whisper-buy stocks to proxy for the extent of private communication between any manager-analyst pair. Moreover, as we will explain in the next subsection, the whisper-sell stocks serve as a crucial identification strategy to rule out alternative hypotheses.[16]

2.2 Testable hypotheses

For identification, we focus on whisper-sell behavior, since the contrasting 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 hypothesis), 2) the manager learns public information from the analyst's public recommendations (the public-recommendation hypothesis), and 3) the analyst and the manager behave independently based on common external signals (the homophily hypothesis).

Whisper-buy behavior provides the same prediction under all hypotheses; more whisper-buy behavior would have the manager give 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, whisper-sell behavior generates different predictions under different hypotheses. Under the public-recommendation or the homophily hypothesis, more whisper-sell behavior

[15] The above example illustrates a fully rational case in which whisper-sell and whisper-buy behavior can occur. Previous literature has revealed a variety of cases in which analysts issue overly optimistic stock recommendations that are not warranted by stock values because of conflict of interest they face. Whisper-sell and whisper-buy behavior is even more likely to occur in cases in which analysts issue optimistic recommendations in public while revealing genuine recommendations only to certain fund managers.

[16] In the literature, another way to distinguish the network effect from other confounding factors is to exploit the exogenous information shocks to some part of members in the network (see, e.g., Duflo and Saez 2003, Brown et al. 2008, Tucker 2008, Baily et al. 2018, and Baily et al. 2019). In contrast, in this paper, we introduce additional data of fund managers evaluating analysts via votes, which helps us identify whether fund managers are receiving private information from analysts.

suggests 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. Fund managers may, through their knowledge, filter and sell analysts' overly optimistic recommendations. Nonetheless, it is hard to believe that, without any direct inputs from analysts, fund managers would credit analysts with their biased public recommendations by giving a vote. On the other hand, under the private-communication hypothesis, more 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 behavior but also include whisper-buy behavior in regressions to control for the public-recommendation and homophily effects.

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

We develop further hypotheses assuming that analysts privately communicate with fund managers to corroborate our main hypothesis. Some managers may be more likely to engage in private communications with analysts or a specific group of analysts. One could expect a strengthened statistical relationship between whisper-sell behavior and voting rank among these manager-analyst pairs. We argue that managers who have weak skills in a specific industry have more need for analysts' information. Also, managers who have strong business ties with a broker are more likely to communicate privately with analysts working in that brokerage house.

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. Such behavior is likely to hurt the analyst's reputation when the quality of analysts' public recommendations is more verifiable. Also, in such an environment a given analyst may be able to generate little private information, which reduces the benefit to whispering sell. Therefore, analysts will be more likely to engage 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 managers build their relationships with analysts based on their past encounters, we expect that managers would advance their relationship with the analyst if the analyst's private information turns out to be useful. Therefore, if a manager votes for an analyst, we expect the manager to engage in more private communications with the same analyst in the future.

H5: If a manager ranks an analyst higher, the degree of whisper-sell behavior for the same manager-analyst pair will be higher in the subsequent year.

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

H6: *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, the measure for analysts' whisper-sell behavior in Section 3.3, and analyst characteristics in Section 3.4.

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 27 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 and/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 that 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 2,407 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 541. Our sample account for, on average, 34% of total active funds existing in that year; the percentages remain stable across years.[17]

We imply 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. However, 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 58.74 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, 45.3 stocks with shares being increased and 49.8 stocks with shares being decreased, and a high turnover ratio of 57.58%.

[Insert Table 2]

[17] In Appendix Table 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 the period.

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. Even though analysts issue reports as sole authors, they often incorporate their coworkers' opinions. Naturally, a team of 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. Because of this, the number of analysts reported in our paper is smaller than the number reported in other papers.

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 3,150 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 each year.

The recommendation and earnings forecast data are also from the CSMAR database. We assign a recommendation or 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.[18] 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). In China, most of the recommendations are Strong Buy and Buy; only 5% of total recommendations are Sell or Strong Sell. Because of this, we only study analysts' positive recommendations, mostly comprised of Strong Buy and Buy recommendations. Also, the percentage of upgrade recommendations is relatively small in the Chinese market (approximately 4.19% in our sample). Other data on stock returns and related variables are also from the CSMAR database.

[18] 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.

3.3 Whisper-sell (Whisper-buy) 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 *WhisperSell* and *WhisperBuy* for analyst *l* and fund *j* in semi-year *s*, as follows.

$$WhisperSell_{ljs} = \frac{\sum_{i \in A_{lhs} \cap B_{jhs}} |\min(v_{ijs} - v_{ijs-1}, 0)\, p_{is}|}{\sum_{i \in B_{jhs}} |\min(v_{ijs} - v_{ijs-1}, 0)\, p_{is}|}, \tag{1}$$

$$WhisperBuy_{ljs} = \frac{\sum_{i \in A_{lhs} \cap B_{jhs}} |\max(v_{ijs} - v_{ijs-1}, 0)\, p_{is}|}{\sum_{i \in B_{jhs}} |\max(v_{ijs} - v_{ijs-1}, 0)\, p_{is}|}, \tag{2}$$

where v_{ijs} is the number of shares of stock *i* held by fund *j* in semi-year *s*; p_{is} is the price of stock *i* at the end of semi-year *s*; A_{lhs} is the set of stocks, in industry *h*, that analyst *l* recommended as Buy, Strong Buy or upgrade from the last recommendation in semi-year *s*; B_{jhs} is the set of stocks, in industry *h*, that fund *j* traded during semi-year *s*. 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.[19]

For a numerical example, analyst *l* issued a positive recommendation on Stocks A and B in semi-year *s*. Meanwhile, fund *j* has sold three stocks among analyst *l*'s industry in semi-year *s*: Stocks B, C, and D. Assume that the estimated trading dollar volume, that is, the change in shares multiplied by the stock price, is equal across three stocks (B, C, and D). Therefore, *WhisperSell* would take the value of 1/3 for analyst *l* and fund *j* in semi-year *s*; under the private-communication hypothesis, a higher value of *WhisperSell* means that the analyst is likely to have more private communication with the manager.

We first construct the measure at the fund-analyst level for each semi-year. In the regressions of manager voting decisions, we take an equal average of the fund-analyst–semi-

[19] There are other occasions where analysts' subtle actions may imply pessimistic beliefs. For example, a lack of updates after a company visit may indicate negative information (Chang, Chi, and Wu 2018). In unreported tests, we also exclude such occasions from our measurement and find robust results.

year percentages at the manager-analyst-year level. Each active equity mutual 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.[20] 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, he or she tilts the portfolio from some stocks to others for better future performance, rather than for liquidity reasons, such as fire sales or investment policy changes.

[Insert Table 2]

Table 2, Panel B reports the *WhisperSell* and *WhisperBuy* measures at the manager-analyst-year level. *WhisperSell* has a mean of 0.30 and a standard deviation of 0.34. That means there is significant variation across manager-analyst pairs as the 25th percentile is zero, whereas the 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 *WhisperBuy*, on average, to be much higher than *WhisperSell*. However, the mean of *WhisperBuy*, is approximately equal to the mean of *WhisperSell* (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.

3.4 Analyst characteristics

To examine why 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.

[20] 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.

Appendix A 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 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*).[21] To measure the popularity or name recognition of analysts, we also include measures for analysts' work experience (*Experience*), the size of analysts' 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*).

Panel B of Table 2 shows the summary statistics on these analyst characteristics. The analysts in our sample, on average, cover 13.83 stocks and publish 38.65 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, on average, do not generate significant positive returns against the industry benchmark; the average portfolio alpha is −0.30% per month.

Panel C of Table 2 reports the correlations between *WhisperSell* and the analyst characteristics variables. Overall, *WhisperSell* 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 *WhisperSell* than other analysts. Later, in Section 5.5, we will construct alternative measures to further neutralize such mechanical effects. The correlation between *WhisperSell* and *WhisperBuy* in our sample is not very high (estimate = 0.43), suggesting that *WhisperSell* contains different information from *WhisperBuy*.

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

4. Votes as manager evaluations of analysts

In this section, we examine whether managers' voting decisions reveal useful information about their evaluations of analysts. Drawing on previous literature on how institutions pay off brokers through trade commissions, we test whether a higher ranking from the manager for the broker's analysts is associated with higher future trade allocations.

4.1 Trade allocation

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) and that analysts' bonuses are often linked to trade commissions generated by their recommendations (Irvine 2000, 2004). Therefore, if managers vote for analysts because of the private information analysts provide, managers may make more trades with the analysts' brokers, suggesting a positive relationship between voting decisions and trade allocations.

To test this hypothesis, we collect information about the distribution of fund trade allocations in dollar value among individual brokers for each mutual fund and each year from the Wind Financial Database (WindDB).[22] We provide some descriptive analysis of the structure of fund-broker relationships in the Chinese market regarding trade allocation. We rank brokers for each fund and each year based on the percentage of trades they execute. Appendix Table 2 presents the transition matrix between the broker ranking for each year and the ranking for the same broker in the following year. Panel A uses all active funds with at least five partner brokers in the voting sample from 2010 to 2016.

[Insert Appendix Table 2]

We confirm two patterns in the Chinese data that are similar to data on U.S. funds. First, Chinese funds work with a small group of brokers consistently over time. Brokers who do not execute trades for a fund in a given year, on average, have a 95.3% probability of not executing

[22] 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.

trades for that fund in the following year, whereas brokers who execute trades in a given year are very likely (68.1% to 80.1% depending on rankings) to execute trades for that fund in the following year. Second, the rankings tend to fluctuate over time. For example, the first-ranked broker, on average, has only a 12.1% probability of maintaining the first ranking for the same fund in the next year, a 41.3% probability of remaining in the top five, a 26.9% probability of dropping out of the top five, and a 31.9% probability of not executing trades from the same fund. These results suggest that fund managers use trade allocations as leverage to incentivize brokers to provide better services. The results are similar when we use all active funds in the CSMAR database during the same period.

4.2 Do higher vote ranks go with greater trade allocations?

Next, we examine whether fund managers will allocate more trades to brokers whom they rank higher. We aggregate the voting rank at the fund-broker level by taking the average of the fund managers' voting ranks across all analysts of the same broker each year. Then, we estimate the ordinary least-squares (OLS) regressions as follows.

$$Ln\left(TradeShare_{gjt+1}\right) = \beta\Delta\overline{VoteRank}_{gjt} + \gamma Ln\left(TradeShare_{gjt}\right) + \varepsilon_{gjt+1}. \qquad (3)$$

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. The independent variable of interest, $\Delta\overline{VoteRank}_{gjt}$, 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)–(5), we add broker, broker-year, and broker-fund/broker-year fixed effects, respectively, and find robust results. Regarding the 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.

Because analysts' bonuses are often tied to trade commissions generated by their recommendations, the results suggest that managers' votes could be a good proxy for their evaluations of analysts' services.

5. Do managers vote for whisper-sell behavior?

Next, we test the main hypothesis that analysts provide more-precise information to fund managers than they do in their public recommendations. We test this hypothesis in Sections 5.1 and 5.2 by examining whether managers vote for analysts with more whisper-sell behavior. Then, we provide further evidence by exploiting the conditional effect of whisper-sell behavior in Section 5.3 and the relationship between voting decisions and future whisper-sell behavior in Section 5.4. We provide robustness checks in Section 5.5.

5.1 Determinants of manager voting decisions

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

$$\begin{aligned} VoteRank_{lmt} = \beta_0 + \beta_1 WhisperSell_{lmt} + \beta_2 WhisperBuy_{lmt} \\ + \gamma Analyst\ Characteristics_{lt} + \delta_{gk} + \varepsilon_{lmt}. \end{aligned} \tag{4}$$

The dependent variable (*VoteRank*) is fund manager *m*'s vote choice for analyst *l* in year *t*. The independent variables of interest, *WhisperSell* and *WhisperBuy*, and analyst characteristics variables are defined in detail in Section 3. For each continuous independent variable, we 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. δ_{gk} 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.[23]

[Insert Table 4]

We first explore what determines managers' votes by regressing *VoteRank* on various analyst characteristics. Emery and Li (2009), who study the U.S. analyst ranking, find that popularity or name recognition is an important factor in becoming a star analyst even compared with recommendation performance. We find similar results. For example, the coefficient on recommendation performance, *InfoRatio_s*, is 0.121, whereas the coefficient on *Brokersize_s* (the size of the analyst's brokerage house) is 0.281.[24] Important business relation (*TradeBroker*) and previous star status (*PreAward*) are also associated with higher ranks.

Nrec_s (number of reports) and *Nstock_s* (number of stocks) have positive and significant estimates of 0.459 and 0.074, respectively. These results suggest that fund managers recognize the analysts who put effort into analyzing companies in the industry (Jacob, Lys, and Neale, 1999).

The coefficient estimates of analyst optimism on recommendations (*Optism_recom_s*) and earnings forecasts (*Optism_feps_s*) are positive and statistically significant (0.124 and 0.180, respectively). The result for earnings forecasts is reminiscent of the finding by Hong and Kubik (2003) that analysts who provide relatively optimistic earnings forecasts are more likely to have favorable career outcomes. Similarly, we find that the coefficient on *Upgrade_s* is negative and statistically significant (−0.157). As upgrade recommendations reveal more information than

[23] The results are robust to different clusters, specifically, manager-year clusters, fund company-year clusters, and brokerage house-year clusters.

[24] Because we use the ranking value for all variables except for *TradeBroker* and *PreAward* which are dummy variables, we can compare their magnitudes by simply comparing their coefficient estimates.

level recommendations (Jegadeesh et al. 2004), fund managers appear to discourage analysts from providing too much information to the public.

We also control for analysts' preferences for recommending certain types of stocks. We find that managers favor analysts who recommend small firms—although the coefficient on *Firmsize_s* is statistically insignificant—and who recommend attention-grabbing stocks like past winners or losers.

5.2 Whisper-sell behavior and voting decisions

Next, we include *WhisperSell* in the regression to estimate the effect of analysts' whisper-sell behavior on managers' voting decisions.[25] If the analyst's private information drives the fund manager's selling decisions and the manager rewards the analyst with his or her vote, we expect a positive relationship between *VoteRank* and *WhisperSell* (*Hypothesis* 1). In column (2) of Table 4, we find that the coefficient on *WhisperSell* is 0.085, which is statistically significant at the 1% level. This result implies that analysts provide fund managers with private information that is different from analysts' public recommendations.

We also include *WhisperSell* in the regression and find that the coefficient is positive and statistically significant (estimate = 0.131). As stated in Section 2, this is also consistent with fund managers learning information from analysts' public recommendations and with fund managers recognizing the analysts who are similar to them. The inclusion of *WhisperBuy* helps control for these two effects.

In column (3), we find a similar result when we use the percentage ranking value of *WhisperSell*; the coefficient estimate on *WhisperSell_s* is 0.097 and is statistically significant. In column (4), 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 (5) for *WhisperSell* and column (6) for *WhisperSell_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.

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

In column (7), 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 (8), 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 *WhisperSell_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 (9)–(13), we relate *WhisperSell _s* to the managers' binary voting decisions, that is, whether the vote = the first choice, the vote <= the second choice, the vote <= the third choice, the vote <= the fourth choice, or the vote <= the fifth choice.[26] Results are consistent across all binary indicators. We find that whisper-sell behavior has a relatively strong effect on the first-choice vote. According to column (9), an increase in *WhisperSell_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's 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%).[27]

5.3 Conditional effects of whisper-sell behavior

We expect the effect of whisper-sell behavior on voting decisions to be more pronounced when managers: (1) have relatively low investment skill in the analysts' industries (*Hypothesis* 2), and (2) have an important business tie with the analysts' brokers (*Hypothesis* 3). Following 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. 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.[28]

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

[27] Tests using multiple logistic regression generate similar results. The tables are available upon request.

[28] 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 paid commissions and

[Insert Table 5]

Table 5 tests the hypotheses mentioned above. Column (1) shows that having a lower industry-wide ability (low portfolio weight) enhances the relationship between whisper-sell behavior and vote. This result makes sense because when fund managers optimally allocate their attention to the industries of which they have better knowledge (Van Nieuwerburgh and Veldkamp 2009, 2010), they tend to seek analysts' information from other industries to complement their existing knowledge. Column (3) shows that having an important business tie with the manager has a positive effect on the relationship between whisper-sell behavior and vote. Moreover, there are similar interaction results in columns (2) and (4) regarding whisper-buy measures, which is also consistent with analysts' providing useful (not necessarily private) information to fund managers.

In addition, 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 column (5), we find that the coefficient estimate on the interaction term between *WhisperSell_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. In column (6), we find that the estimate on the interaction term with the whisper-buy measure is less than that on the interaction term with the whisper-sell measure (0.071 versus 0.165). We argue that it is in part because whisper-buy behavior does not induce any reputational costs. Overall, these conditional tests further corroborate the private-communication hypothesis.

find similar results.

5.4 Voting decisions and subsequent whisper-sell behavior

Do managers who rank analysts highly in the star analyst competition based on useful information analysts have given them engage in more private communications with the same analysts in the future (*Hypothesis* 5)? To test this hypothesis, we relate the voting rank to *WhisperSell* for the same manager-analyst pair in the following year.

Table 6 reports the regression results. According to Panel A, 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 *WhisperSell* relative to the sample mean.[29] 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 *WhisperSell* and *WhisperBuy* 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)–(6), we use various specifications of fixed effects (company-broker, broker-year, industry-year, etc.), and the results are robust.

[Insert Table 6]

In Panel B of Table 6, we replicate the same regressions using *WhisperBuy* instead of *WhisperSell* and find a similar positive effect of the voting rank on future *WhisperBuy* for the same analyst-manager pairs. Taken together, these findings are consistent with analysts providing fund managers with private, precise information.

5.5 Robustness checks

We run several robust checks. One is to construct the whisper-sell and whisper-buy measures using the quarterly disclosures of top-ten holdings. Though the measures are

[29] The average *WhisperSell* 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.

constructed with incomplete information of fund holdings,[30] in Appendix Table 3, we still find robust results for the same specifications as Table 4.

[Insert Appendix Table 3]

Another set of robustness checks uses several alternative whisper-sell measures. First, we calculate a parsimonious version of *WhisperSell* that is insensitive to trade turnover.

$$WhisperSell_{ljs}^{count} = \frac{\sum_{i \in A_{lhs} \cap B_{jhs}} I\left(v_{ijs} - v_{ijs-1} < 0\right)}{\sum_{i \in B_{jhs}} I\left(v_{ijs} - v_{ijs-1} < 0\right)}, \tag{5}$$

Compared to Eq. (2), *WhisperSell*^{count} of Eq. (5), using the indicator function I (.), counts the number of stocks actively sold by fund managers and the number of whisper-sell stocks and does not weight stocks by the trading volume.

$$WhisperSell_{ljs}^{adjusted} = WhisperSell_{ljs} - \frac{\sum_{i \in B_{jhs}} \omega_{is}^{l} \left|\min\left(v_{ijs} - v_{ijs-1}, 0\right) p_{is}\right|}{\sum_{i \in B_{jhs}} \left|\min\left(v_{ijs} - v_{ijs-1}, 0\right) p_{is}\right|}. \tag{6}$$

Second, alternative measures control for the mechanical effect that recommending more stocks or herding with other analysts will lead to higher values of *WhisperSell*. In Eq. (6), we subtract the expectation of *WhisperSell* of Eq. (2) under the assumption that analysts randomly recommend stocks. The variable ω_{is}^{l} refers to the probability of analyst l positively recommending stock i in semi-year s, given the number of positive recommendations. 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.[31] Alternatively, we assume that the chance of picking one stock is proportional to how many analysts of other brokers issued positive

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

[31] In particular, the probability of picking stock i from industry h by analyst l, ω_{is}^{l}, equals $1 - \left(1 - \frac{1}{\#(i \in industry\ h)}\right)^{\#(A_{lhs})}$ where $\#(i \in industry\ h)$ counts the number of stocks in industry h and $\#(A_{lhs})$ counts the number of stocks in industry h that analyst l recommends as positive in semi-year s. Put differently, we calculate ω_{is}^{l} 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.

recommendations on the same stock.[32] 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 whisper-sell stocks and manager's selling stocks; the coefficient estimates are positive and statistically significant, confirming our main results. Moreover, we tweak the count-based measure to only count, for the numerator, the whisper-sell stocks of which the fund manager completely exists the positions. Because the complete exists are more in line with managers selling stocks based on stock information, we find that the estimate is larger in column (3) than that on the measure counting for all whisper-sell stocks in column (2) (0.103 versus 0.87).

Furthermore, columns (4) to (8) use the measures in Eq. (6) that adjust for the expectations. 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, one may concern that fund managers vote for the analysts because the analysts cover more of the stocks held by the fund, but fund managers make trading decisions using their own judgments. Under this hypothesis, the whisper-sell measure serves as the noised proxy for the analysts' coverage in that specific fund manager's holdings. To distinguish our story from this, we create a new measure, *FundCover*, specifically for analysts' fund-wise coverage; it is defined as the fraction of the number of the fund manager's held stocks that are covered by the specific analyst. In column (9), we first only include *FundCover* but not whisper-sell and whisper-buy measures. The coefficient estimates on *FundCover* are positive and statistically significant, seemingly suggesting that fund managers appreciate more specific stock coverage

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

by analysts. However, in columns (10) and (11), 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 *Cover* loses its statistical significance. This result suggests that it is the more-precise information analysts provide to fund managers that determines their voting decisions rather than the general coverage of stocks held by fund managers.

6. How market prices react to analysts' recommendations

In this section, we study how the market reaction to analysts' positive public recommendations differs between whisper-buy and whisper-sell stocks. Through this, we answer the questions as to whether investors other than those connected managers can access analysts' private information and, if not, how much returns uninformed traders miss out on due to this information asymmetry.

6.1 Whisper-sell versus whisper-buy recommendations

We first identify the whisper-sell and whisper-buy stocks among analysts' positive public recommendations by measuring in what direction the managers who vote for the analysts, 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.

$$Portfolio\_Chg_{ils} = \frac{\sum_{j \in Fund_{lis}} a_{ijs}}{\sum_{j \in Fund_{lis}} 1},$$
$$\text{where } a_{ijs} = \frac{(v_{ijs} - v_{ijs-1})p_{is}}{(mv_{jhs-1} + mv_{jhs})/2}. \tag{7}$$

$Fund_{lis}$ 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_{jhs-1}, in industry h in semi-year s-1 and s.[33] 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, $Fund_{lis}$.

Portfolio_Chg takes the value of zero if no managers who vote for the analyst ever traded that stock. *Portfolio_Chg* is further winsorized at the 1st and the 99th percentiles. Positive (negative) values of *Portfolio_Chg* suggest average buying (selling) decisions made by analyst-voting managers.

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. For multiple recommendations on the same stock by the same analyst in the same semi-year, we only include the earliest one.[34] In the sample, 33.62% of positive recommendations are fund-buy recommendations, whereas 33.32% of them are fund-sell recommendations; the remaining are not-trade recommendations.

6.2 Stock recommendation performance

According to *Hypothesis* 6, the fund-buy recommendations (whisper-buy stocks) outperform fund-sell recommendations (whisper-sell stocks), due to the private information received by fund managers. To test this hypothesis, we analyze the return performance around recommendation dates from −120 to 220 trading days using an event-study approach.

Fig. 1 presents the means of DGTW-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, fund-buy

[33] 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.

[34] Similar results obtain if we include all the analysts' positive recommendations of the same stocks in each semi-year.

recommendations over the −1 to +1 event window experience 1.70% of cumulative abnormal returns (CAR), whereas fund-sell recommendations experience 1.24%.[35] The fact that fund-sell recommendations have positive event-date abnormal returns and are followed by negative returns of –1.34% 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 8]

These recommendations differ consistently and significantly in CARs around the recommendation dates. According to Table 8, the CAR for fund-buy recommendations minus that for fund-sell recommendations is 1.86% from −40 to −2 trading days, 2.47% from 2 to 40 trading days.[36] 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. 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). The overall results suggest that fund-buy recommendations outperform fund-sell recommendations. Although we cannot observe the exact trading dates by the voting managers, to the extent that they trade stocks around the recommendation dates, the trading of the voting managers outperforms the trading strategy of simply following analysts' public recommendations.

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 they will invest only in fund-

[35] To address the cross-sectional dependence issue that arises because of multiple recommendations on many 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 Appendix B for the detailed procedure.

[36] Note that in Table 8, 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.

buy recommendations, their buying strategy generates an average CAR of 1.09% 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 investment returns would be 1.09% * 33.62% + (−1.00%) * 34.06% + (−1.34%) * 32.32% = −0.41%. In other words, analysts' differentiation of information disclosure toward different audiences generates differential investment returns of 1.50% 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.

6.3 Robustness checks

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 rule out some most likely alternative hypotheses. First, the returns differences could be due to the price impact of institutional trading rather than the changes in fundamentals revealed in analysts' recommendations. We examine long-term returns (from 41 trading days up to one year) after the recommendations; return reversals would indicate potential price impact. However, we still find fund-buy recommendations outperform fund-sell recommendations by 3.16% over that longer horizon; the spread mostly comes from fund-buy recommendations keeping earning positive abnormal returns of 3.05%. The finding is more consistent with fund managers trading on stock information changes than fund managers' trading affects stock returns.

Second, we ensure that managers' buying and selling decisions are not based on managers' differentiation of Strong Buy and Buy recommendations. We run the analysis on Strong Buy and Buy recommendation groups separately and show the results in Fig. A1. We find the return differences associated with fund trade exist in both subsamples, which means that the results cannot be solely explained by fund managers buying Strong Buy stocks and selling Buy stocks.

[Insert Figure A1]

Third, it could be that funds' momentum trading drives the return patterns. 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 Appendix Table 4, 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 recent price movement.

[Insert Appendix Table 4]

In sum, we find that among analysts' public positive recommendations, fund-buy recommendations (whisper-buy stocks) persistently outperform fund-sell recommendations (whisper-sell stocks). Specifically, fund-sell recommendations show positive event returns that quickly reverse afterward, suggesting that many investors, likely retail investors, are not capable of distinguishing between the whisper-buy and whisper-sell stocks among the same analysts' positive recommendations.

7. Discussion

7.1 Do managers benefit from private communications?

Given our finding that managers tend to vote for analysts who provide private information as proxied for by whisper-sell behavior, it is interesting to test whether and how managers benefit from private communications. Does whisper-sell behavior improve managers' portfolio holdings? Previous literature has proxied for connections between analysts and fund managers by education and workplace ties (Cohen, Frazzini, and Malloy 2008; Gu et al. 2019). Here we use managers' votes to identify their connections with certain analysts.

To test whether managers are likely to hold stocks that are recommended by their connected analysts, following Gu et al. (2019), we estimate the following OLS regression model:

$$Holdings_{ijs} = VoteTies_{ijs} + Control\ Variables + \varepsilon_{ijs}, \quad (8)$$

where $Holdings_{ijs}$ is an indicator equal to one if stock i is among fund j's holdings at the end of semi-year s;[37] $VoteTies_{ijs}$ 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 (*Industry_recom*), firm size (*Size*), book-to-market ratio (*BM*), and stock returns in the past 12 months (*Return*).

[Insert Table 9]

Panel A of Table 9 reports the regression estimates of Eq. (8). In both columns (1) and (2) with fixed effects, the coefficients on *VoteTies* are positive and significant at the 1% level. The estimate in column (2) with fixed effects suggests an increase of 90.1 basis points in the probability of holding a stock when the stock is recommended as positive by the manager's voted-for analysts.[38] Since we include the industry-wide analyst recommendation in the regression, this effect is not driven by fund managers' herding to respond to consensus sell-side analyst recommendations (Busse, Green, and Jegadeesh 2012; Brown, Wei, and Wermers 2014).

In addition to the portfolio holdings as examined by previous literature, we also examine fund managers' buying and selling decisions separately. We find that voted-for analysts' positive recommendations increase the probability of buying that stock by 67.5 basis points (column (4) with fixed effects) or selling that stock by 141.4 basis points (column (6) with fixed effects). It, to some degree, surprises us that the probability of managers selling stocks from these positive recommendations is higher than that of managers buying stocks. Overall, the fact that fund managers are both likely to buy or sell stocks from connected analysts'

[37] To be consistent with our criterion of sampling fund-semi-year holdings, the sample contains all fund-stock pairs in the industries of which the funds both bought and sold at least one stock, respectively, in that semi-year. In some specifications, we include fund-year and industry-year fixed effects, and we cluster standard errors by fund and year.

[38] The economic magnitude estimate we obtain is higher than the estimates from Gu et al. (2019) of 25.5 basis points because we limit our samples to industries in which the fund made portfolio shifts in that semi-year.

positive recommendations is consistent with fund managers' acting on analysts' private information in addition to analysts' public recommendations.

Next, we explore whether managers earn higher returns from the holdings linked to their voted-for analysts. Following Cohen, Frazzini, and Malloy (2008) and Gu et al. (2019), we measure the holdings performance as the stock's DGTW-adjusted returns over the following quarter. Panel B of Table 9 shows the regression estimates. According to column (2) with fixed effects, we find that fund managers enjoy 51.6 basis points more returns from stocks that are linked to their voted-for analysts than other stocks in their holdings. On the other hand, following the consensus analyst recommendations (*Industry_recom*) does not add to any superior fund performance.

Furthermore, in columns (3) and (4), we include an indicator for the fund selling the stock in semi-year *s* (*Fund Sell*) and its interaction with *VoteTies*. The estimates on the interaction term are negative (−0.576 in column (3) and −0.615 in column (4) with fixed effects) and marginally significant in column (3). These results suggest that among the stock holdings linked to their voted-for analysts, the stocks that managers sell underperform the stocks that managers buy or keep. We note that the performance based on fund holdings may not accurately measure funds' trading performance as the actual trades may occur a few weeks or even months before the dates when fund holdings are reported. The results, nonetheless, are generally consistent with our finding in Section 6 that at the stock-recommendation level, whisper-sell stocks underperform whisper-buy stocks. In sum, the evidence regarding managers' portfolio decisions supports our hypothesis that analysts disclose more-precise information to fund managers than they disclose to the public.

7.2 Do fund managers initiate interaction with analysts?

So far, we have examined the hypothesis that stock information flows from analysts to fund managers. However, it could be those fund managers who get the information first want to sell the stocks and ask the analysts to issue positive recommendations for purposes of price manipulation.[39] Another similar scenario is that the fund managers who consider selling

[39] This scenario is plausible on theoretical grounds because analysts' positive recommendations, on average, have positive

communicate with their connected analysts about any fundamental-related information to help them make decisions. However, these manager-initiated actions are more likely to occur when the managers have extensive knowledge about the sold stocks. Our results in Section 5.3 indicate that whisper-sell behaviors are more likely to occur when the managers have relatively limited knowledge about the stocks as proxied for by low industry weight in their portfolios.

[Insert Appendix Table 5]

We provide further evidence that supports the argument that it is the analysts who have private information on the stocks. In Appendix Table 5, we examine the relationship between analyst earnings forecast accuracy and voting managers' trading decisions in the cross-section of analysts' positive recommendations. The result 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 analysts have more-precise information on these traded stocks than on other nontraded stocks. This result is hard to reconcile with the collusion account because, in the case of collusion, the managers have no incentive to inform analysts of the firms' earnings forecasts. This result is also consistent with Harford et al. (2019), who find that analysts make more accurate earnings forecasts for stocks that are important to institutional investors.

Likewise, analysts cover 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. Overall, the evidence suggests that the precise information that leads to fund managers' trading is more likely to come from analysts than from fund managers themselves. Nonetheless, the existing evidence does not rule out the possibility that fund managers know the information first.

7.3 New insights on analyst recommendations

---

abnormal returns on the event dates; uninformed investors naively buying upon analyst positive recommendations provides liquidity to informed fund managers who want to sell the stocks.

Our finding in this paper that analysts add noise to their public recommendations to create value for private information given to fund managers provides novel insights about analyst recommendations. First are implications for how to infer analyst ability from the performance of their public recommendations. If analysts intentionally include relatively low-value stocks in their positive recommendations, as epitomized by whisper-sell stocks, one could not measure analysts' true abilities by simply measuring the performance of their public recommendations. In this light, this paper's findings can help explain the insignificant relationship between analysts' recommendation performance and career outcomes (Mikhail, Walther, and Willis 1999; Hong and Kubik 2003; Emery and Li 2009).

Second, we have provided evidence suggesting that analysts substitute between the profitability of the private information that they provide to private clients, and the informativeness of the public information that analysts provide. Our argument is that it is in analysts' interests to limit the informativeness of their public signals. This helps explain the fact that widely distributed stock reports such as analyst recommendations have relatively low information content (Graham and Harvey 1996; Womack 1996; Metrick 1999; Barber et al. 2001; Antweiler and Frank 2004; Jegadeesh et al. 2004; Engelberg, Sasseville, and Williams 2012).

Third, our findings help explain why legal settlements that were intended to improve the informativeness of analyst recommendations have had limited effectiveness, as found by Kadan et al. (2009). If analysts have an interest in selling private information to their clients, they are reluctant to improve the informativeness of their public recommendations at the cost of compromising the profitability of their private information. In our opinion, investor education should be more prioritized so that investors have better knowledge of the informativeness of analyst recommendation ratings.

Fourth, recent literature has found that analysts' positive recommendations are associated more with overvalued stocks than with undervalued stocks, which seems likely to harm the performance of these recommendations (Engelberg, McLean, and Pontiff 2020; Guo, Li, and Wei 2020). The authors attribute this phenomenon to unskillful analysts who are incapable of incorporating the information in anomaly signals when making recommendations. Our findings suggest an alternative but not exclusive explanation: that analysts can distinguish between overvalued and undervalued stocks, but choose to exclude this information in producing their public recommendations. Issuing positive recommendations on overvalued stocks not only can generate trades from uninformed investors but also preserves the value of more-precise information for trading by informed managers.

8. Conclusion

Inspired by the theoretical models of information sales (Cespa 2008; García and Sangiorgi 2011), we test whether financial analysts strategically adjust the quality of the information that they disclose to different audiences. Specifically, we test whether analysts reveal more-precise information to fund managers than to the public by examining analysts' say-buy/whisper-sell behavior.

Using data on managers' votes for star analysts, which reflect fund managers' evaluations of analysts, 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 conjecture that managers receive private and different information from analysts than the analysts give to the general public, but inconsistent with the conjectures that managers only learn from analysts' public recommendations and/or managers and analysts receive similar public signals. 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-precise information. Analysts' strategy of disclosing information of different quality to different audiences gives rise to information asymmetry that creates a performance advantage to informed managers over uninformed investors.

Our empirical findings suggest that analysts trade off between the informativeness of their public recommendations and the trading value of the private information they provide to their private clients, resulting in say-buy/whisper-sell behavior. The incentive to do so limits the informativeness of public recommendations even under the pressure of government regulation. This provides a possible explanation for evidence that analysts include overvalued stocks in their public recommendations. 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 adds noise to the public signals in order to create the value of their private signals can be observed in other contexts such as voting recommendations of advisory firms and credit ratings.

References

Admati, Anat R., and Paul Pfleiderer, 1986. A monopolistic market for information. *Journal of Economic Theory* 39, 400–438.

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.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel, 2018. The economic effects of social networks: evidence from the housing market. *Journal of Political Economy* 126, 2224–2276.

Bailey, Michael, Drew M. Johnston, Theresa Kuchler, Johannes Stroebel, and Arlene Wong, 2019. Peer effects in product adoption (No. w25843). *National Bureau of Economic Research*.

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.

Brown, Jeffrey R., Zoran Ivković, Paul A. Smith, and Scott Weisbenner, 2008. Neighbors matter: causal community effects and stock market participation. *Journal of Finance* 63, 1509–1531.

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.

Chang, Danting, Yeguang Chi, and Fei Wu, 2018. No signal is bad signal: analyst silence after on-site visit. *Working paper*, Shanghai Jiao Tong 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.

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.

Duflo, Esther, and Emmanuel Saez, 2003. The role of information and social interactions in retirement plan decisions: evidence from a randomized experiment. *Quarterly Journal of Economics* 118, 815–842.

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, R. David McLean, and Jeffrey Pontiff, 2020. Analysts and anomalies. *Journal of Accounting and Economics* 69, 101249.

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.

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

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

Gu, Zhaoyang, Zengquan Li, and Yong George Yang, 2012. 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.

Guo, Li, Frank Weikai Li, and KC John Wei, 2020. Security analysts and capital market anomalies. *Journal of Financial Economics* 137, 204–230.

Harford, Jarrad, Feng Jiang, Rong Wang, and Fei Xie, 2019. Analyst career concerns, effort allocation, and firms' information environment. *Review of Financial Studies* 32, 2179–2224.

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.

Jackson, Andrew R., 2005. Trade generation, reputation, and sell-side analysts. *Journal of Finance* 60, 673–717.

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.

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

Kyle, Albert S., 1989. Informed speculation with imperfect competition. *Review of Economic Studies* 56, 317–355.

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

Manski, Charles F., 1993. Identification of endogenous social effects: the reflection problem. *Review of Economic Studies* 60, 531–542.

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.

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

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/

Tucker, Catherine, 2008. Identifying formal and informal influence in technology adoption with network externalities. *Management Science* 54, 2024–2038.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2009. Information immobility and the home bias puzzle. *Journal of Finance* 64, 1187-1215.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2010. Information acquisition and under-diversification. *Review of Economic Studies* 77, 779-805.

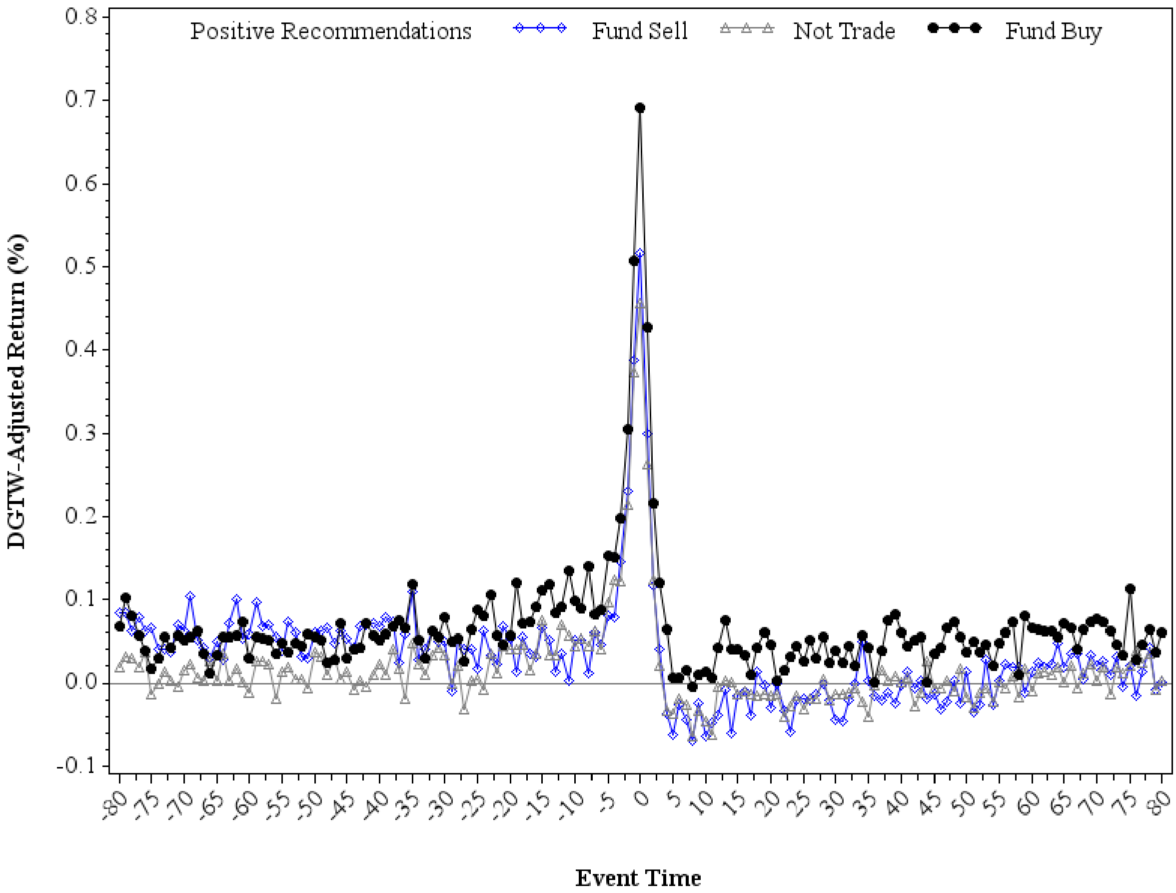
Where is all the buy-side outrage? 2003, February 1. *Euromoney.com*. https://www.euromoney.com/article/b1320pqt1qmzs0/wheres-the-buy-side-outrage

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, Buy, or Upgrade. “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.



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 who disclosed their holdings 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	446	27.1%
2011	585	523	240	34.3%	506	475	437	31.2%
2012	1,013	664	295	35.1%	608	580	549	45.0%
2013	1,015	630	296	30.2%	559	538	473	44.9%
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	2,381	34.0%	3,640	3,428	3,150	39.5%

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, *WhisperSell* (*WhisperBuy*) 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, Buy, or Upgrade without subsequent downgrade within the same semi-year. Variables presented in Panel C are analyst-year–specific measures. In total, there are 3,150 analyst-year observations. *InfoRatio* is return performance of the analyst's public recommendations issued in that year. *Risk* is the industry beta of the analyst's public recommendations in that year. *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 forecast) 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 winners or losers. *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 A. 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
WhisperSell	271, 697	0.30	0.34	0.00	0.18	0.50
WhisperBuy	271, 697	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, 150	−0.30	1.07	−1.02	−0.28	0.44
Risk	3, 150	1.01	0.18	0.95	1.02	1.08
Nrec	3, 150	38.65	32.86	16	30	52
Nstock	3, 150	13.83	8.89	8	12	18
Optism_recom	3, 150	0.05	0.31	−0.22	0.09	0.29

Optism_feps	3, 150	0.03	0.13	−0.06	0.02	0.10
Upgrade	3, 150	0.04	0.06	0	0.02	0.05
Firmsize	3, 150	16.70	0.98	16.05	16.55	17.11
Attention	3, 150	0.35	0.17	0.25	0.33	0.44
Experience	3, 150	9.52	7.58	3.67	8.33	13.67
Brokersize	3, 150	72.81	42.74	44	64	89
PreAward	3, 150	0.21	0.41	0	0	0

Panel D: Correlations

	VoteRank	*WhisperSell*	*WhisperBuy*	*InfoRatio*	*Risk*	*Nrec*	*Nstock*	*Op._recom*	*Op._feps*	*Upgrade*	*Firmsize*	*Attention*	*Experience*	*Brokersize*	*Trade Broker*	*PreAward*
VoteRank	1															
WhisperSell	0.10	1														
WhisperBuy	0.10	0.43	1													
InfoRatio	0.02	0.01	0.05	1												
Risk	0.01	−0.02	−0.00	−0.04	1											
Nrec	0.13	0.25	0.25	−0.09	0.02	1										
Nstock	0.10	0.19	0.20	−0.09	0.04	0.86	1									
Optism_recom	0.03	−0.02	−0.02	0.01	0.06	−0.07	−0.10	1								
Optism_feps	0.06	−0.02	−0.02	−0.01	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	0.03	0.00	−0.06	−0.11	0.01	−0.04	−0.03	1					
Attention	−0.00	0.05	0.04	−0.02	0.03	-0.05	−0.06	0.03	0.06	0.01	0.01	1				
Experience	0.01	0.04	0.05	−0.03	−0.05	0.08	0.03	−0.06	−0.07	0.02	0.07	−0.05	1			
Brokersize	0.12	0.13	0.12	−0.03	0.02	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	−0.03	0.02	0.24	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 voting decisions on trade allocations to the broker 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 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)
$\Delta\overline{VoteRank}\ t$	0.0505**	0.0364*	0.0287*	0.0434**	0.0388***
	(0.0228)	(0.0186)	(0.0163)	(0.0160)	(0.0138)
Ln(TradeShare) t		0.495***	0.468***	0.470***	−0.0548***
		(0.0329)	(0.0166)	(0.0165)	(0.0171)
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)–(8) are *VoteRank*, representing the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; fifth = 1; otherwise 0). The dependent variables from columns (9)–(13) 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). *WhisperSell* (*WhisperBuy*) 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)	(13)
WhisperSell		0.085***			0.080***								
		(0.021)			(0.019)								
WhisperBuy		0.131***			0.115***								
		(0.022)			(0.020)								
WhisperSell_s			0.097***	0.050***		0.083***	0.077***	0.061***	0.010***	0.015***	0.019***	0.019***	0.020***
			(0.023)	(0.015)		(0.021)	(0.022)	(0.014)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
WhisperBuy_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	0.121***	0.118***	0.118***		0.119***	0.121***	0.123***	0.039*	0.015***	0.021***	0.023**	0.030***	0.032***
	(0.043)	(0.043)	(0.043)		(0.040)	(0.040)	(0.040)	(0.020)	(0.005)	(0.007)	(0.009)	(0.010)	(0.011)
Risk_s	−0.016	−0.017	−0.016		−0.014	−0.013	−0.019	−0.003	0.001	−0.002	−0.003	−0.005	−0.004
	(0.044)	(0.043)	(0.043)		(0.041)	(0.041)	(0.041)	(0.020)	(0.005)	(0.007)	(0.009)	(0.010)	(0.011)
Nrec_s	0.466***	0.423***	0.408***		0.499***	0.490***	0.505***	0.158***	0.035***	0.064***	0.103***	0.130***	0.157***
	(0.085)	(0.086)	(0.085)		(0.083)	(0.083)	(0.082)	(0.042)	(0.010)	(0.015)	(0.018)	(0.021)	(0.023)
Nstock_s	0.074	0.031	0.012		−0.066	−0.075	−0.085	−0.103**	−0.016*	−0.014	−0.022	−0.011	−0.011
	(0.085)	(0.085)	(0.086)		(0.081)	(0.081)	(0.081)	(0.040)	(0.010)	(0.014)	(0.018)	(0.020)	(0.023)
Optism_recom_s	0.124***	0.122***	0.122***		0.132**	0.126**	0.119**	0.043	0.012*	0.018*	0.027**	0.031**	0.039**

	(0.044)	(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	0.180***	0.179***	0.178***		0.132***	0.132***	0.137***	0.042**	0.013**	0.019**	0.025***	0.036***	0.040***
	(0.047)	(0.047)	(0.047)		(0.042)	(0.042)	(0.041)	(0.021)	(0.005)	(0.008)	(0.009)	(0.010)	(0.012)
Upgrade_s	−0.157***	−0.155***	−0.156***		−0.151***	−0.151***	−0.138***	−0.077***	−0.014***	−0.025***	−0.034***	−0.039***	−0.040***
	(0.044)	(0.044)	(0.044)		(0.044)	(0.044)	(0.043)	(0.021)	(0.005)	(0.008)	(0.010)	(0.011)	(0.012)
Firmsize_s	−0.020	−0.034	−0.041		−0.054	−0.060	−0.068	−0.053**	−0.011**	−0.018**	−0.014	−0.011	−0.006
	(0.046)	(0.045)	(0.046)		(0.044)	(0.044)	(0.044)	(0.022)	(0.006)	(0.008)	(0.010)	(0.011)	(0.012)
Attention_s	0.100**	0.098**	0.099**		0.099**	0.101**	0.111***	0.049**	0.009*	0.016**	0.025***	0.025**	0.025**
	(0.042)	(0.042)	(0.042)		(0.040)	(0.040)	(0.040)	(0.020)	(0.005)	(0.007)	(0.009)	(0.010)	(0.011)
Experience_s	−0.091**	−0.091**	−0.090**		−0.070	−0.072	−0.079*	−0.022	−0.006	−0.010	−0.014	−0.020*	−0.021*
	(0.045)	(0.045)	(0.045)		(0.045)	(0.045)	(0.044)	(0.022)	(0.005)	(0.008)	(0.010)	(0.011)	(0.013)
Brokersize_s	0.281***	0.278***	0.274***		−0.019	−0.047	−0.131*	−0.026	−0.001	−0.006	−0.008	−0.012	−0.020
	(0.048)	(0.048)	(0.048)		(0.075)	(0.075)	(0.076)	(0.036)	(0.008)	(0.013)	(0.017)	(0.019)	(0.021)
TradeBroker	0.071***	0.063***	0.068***	0.042***	0.008	0.012	0.010	-0.002	0.001	0.003	0.003	0.003	0.002
	(0.013)	(0.012)	(0.013)	(0.008)	(0.009)	(0.009)	(0.015)	(0.007)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
PreAward	0.715***	0.710***	0.708***		0.610***	0.608***	0.578***	0.232***	0.061***	0.103***	0.136***	0.151***	0.158***
	(0.038)	(0.038)	(0.038)		(0.038)	(0.039)	(0.039)	(0.021)	(0.005)	(0.007)	(0.009)	(0.010)	(0.010)
PeerVote								2.441***					
								(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	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697
Adjusted R^2	0.077	0.079	0.078	0.219	0.123	0.123	0.118	0.395	0.053	0.077	0.098	0.114	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 = 5; second = 4; third = 3; fourth = 2; fifth = 1; otherwise 0). 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). *WhisperSell* (*WhisperBuy*) 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 regressions. *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 average information asymmetry score across stocks for that industry is above the median in the previous year. 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	*VoteRank*	*VoteRank*	*VoteRank*	*VoteRank*	*VoteRank*
	(1)	(2)	(3)	(4)	(5)	(6)
WhisperSell_s	0.162***	0.139***	0.064***	0.070***	0.133***	0.137***
	(0.026)	(0.025)	(0.022)	(0.022)	(0.032)	(0.029)
WhisperBuy_s	0.124***	0.176***	0.121***	0.106***	0.123***	0.110***
	(0.020)	(0.026)	(0.020)	(0.021)	(0.020)	(0.031)
WhisperSell_s × *IndustryWeight*	−1.085***	−0.723***				
	(0.241)	(0.211)				
WhisperBuy_s × *IndustryWeight*		−0.743***				
		(0.221)				
WhisperSell_s × *TradeBroker*			0.095***	0.067*		
			(0.035)	(0.034)		
WhisperBuy_s × *TradeBroker*				0.074**		
				(0.035)		
WhisperSell_s × *InfoAsymmetry*					0.193***	0.165***
					(0.055)	(0.045)
WhisperBuy_s × *InfoAsymmetry*						0.071
						(0.047)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	271,697	271,697	271,697	271,697	271,697	271,697
Adjusted R^2	0.123	0.124	0.123	0.123	0.123	0.123

Table 6 Voting decisions and future whisper-sell behavior

This table reports the effect of voting decisions on the subsequent whisper-sell (whisper-buy) behavior in Panel A (B). The dependent variable in Panel A (B) is *WhisperSell* (*WhisperBuy*) for the same analyst and manager in the subsequent year. *WhisperSell* (*WhisperBuy*) measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. *VoteRank* is the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; fifth = 1; otherwise 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.

Panel A: Whisper-sell behavior

	WhisperSell 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)
WhisperSell t		0.067***	0.066***	0.052***	0.056***	0.044***
		(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
WhisperBell 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	271,697	271,697	271,697	271,697	271,697	271,697
Adjusted R^2	0.002	0.060	0.060	0.060	0.087	0.130

Panel B: Whisper-buy behavior

	WhisperBuy t+1					
	(1)	(2)	(3)	(4)	(5)	(6)
VoteRank t	0.008***	0.004***	0.004***	0.003***	0.002***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
WhisperSell t		0.069***	0.069***	0.069***	0.069***	0.069***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
WhisperBuy t		0.089***	0.088***	0.072***	0.075***	0.058***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
TradeBroker t			0.006***	0.00004	0.002	0.003*
			(0.002)	(0.003)	(0.001)	(0.002)
Fixed effects	-	-	-	Company× Broker	Company× Broker Broker× Year	Company× Broker Industry× Year
Observations	271,697	271,697	271,697	271,697	271,697	271,697
Adjusted R^2	0.002	0.039	0.039	0.041	0.067	0.110

Table 7 Robustness tests on alternative whisper-sell measures

This table replicates the regressions in columns (6) and (13) of Table 4 using alternative measures for whisper-sell and whisper-buy behavior. The dependent variable, *VoteRank*, represents the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; 5th = 1; otherwise 0). "<=fifth Preference" is an indicator variable for a vote of fifth choice or higher. *WhisperSell* (*WhisperBuy*) principally measures the percentage of the fund manager's sold (bought) stocks that are also among the analyst's positive stock recommendations. "Original" corresponds to the main measure used in Table 4. "Stock count1" corresponds to the measure that counts the number of stocks instead of the dollar trade volume of stocks; "Stock count2" is a revised version of "Stock count1" in which the numerator only counts the complete stock exists. "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. *FundCover* measures the fraction of the number of fund stock holdings that are covered by the analyst. 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.

	Stock count1		Stock count 2		Adjusted 1		Adjusted 2		Original		
	VoteRank	*<=Fifth Choice*	*VoteRank*	*<=Fifth Choice*	*VoteRank*	*<=Fifth Choice*	*VoteRank*	*<=Fifth Choice*	*VoteRank*	*VoteRank*	*<=Fifth Choice*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
WhisperSell	0.087***	0.023***	0.103***	0.029***	0.066***	0.016***	0.102***	0.025***		0.063***	0.016***
	(0.021)	(0.006)	(0.019)	(0.005)	(0.021)	(0.006)	(0.020)	(0.005)		(0.020)	(0.006)
WhisperBuy	0.128***	0.033***	0.143***	0.037***	0.100***	0.024***	0.147***	0.036***		0.106***	0.027***
	(0.021)	(0.007)	(0.024)	(0.007)	(0.021)	(0.006)	(0.020)	(0.006)		(0.015)	(0.006)
FundCover									0.154***	0.042	0.013
									(0.032)	(0.030)	(0.008)
Other	Yes	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	Company× Broker
Observations	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697
Adjusted R^2	0.124	0.128	0.123	0.128	0.123	0.127	0.123	0.127	0.123	0.123	0.128

Table 8 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). *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.

		Event windows around analyst recommendations				
	% of Obs.	[−120, −41]	[−40, −2]	[−1, 1]	[2, 40]	[41, 220]
Fund Buy	33.62%	2.79***	3.24***	1.70***	1.04**	3.05***
		(3.35)	(6.52)	(5.60)	(1.90)	(2.18)
Not Trade	34.06%	−0.04	1.28***	1.14***	−1.03***	−0.85
		(−0.07)	(3.16)	(5.08)	(−3.19)	(−0.78)
Fund Sell	32.32%	4.11***	1.67***	1.24***	−1.37***	−0.09
		(5.02)	(2.92)	(4.37)	(−2.39)	(−0.05)
Fund Buy − Fund	-	−0.83	1.86***	0.45***	2.44***	3.16***
		(−1.35)	(7.80)	(7.22)	(12.53)	(8.76)

Table 9 Voted-for analysts' recommendations and fund decisions

This table reports how fund managers benefit from private communication with analysts they vote for. Panel A reports the effect of the voted-for analysts' recommendations on the manager's holdings/trading decisions, and Panel B reports holdings performance from these recommended stocks. In Panel A, the dependent variables in columns (1) and (2) are the indicator variables for holding the stock as disclosed in the fund's half-year-end report; columns (3) and (4) (5 and 6) show the indicator variable for increasing (decreasing) the holdings of the stock between two half-year-end holding reports. The sample for Panel A contains all fund-stock pairs from the industries in which the funds both buy and sell stocks. In Panel B, the dependent variables in columns (1)–(4) 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. *Fund Sell* is an indicator variable equal to one if the fund decreases its holdings of the stock. *Industry_recom* is the number of analysts, counted at the broker level, that positively recommend 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 and industry-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.

Panel A: Fund manager's holdings/trading decisions

	Holdings=1	*Holdings=1*	*Buy=1*	*Buy=1*	*Sell=1*	*Sell=1*
	(1)	(2)	(3)	(4)	(5)	(6)
VoteTies (×100)	1.203***	0.901***	0.862***	0.675***	1.648***	1.414***
	(0.247)	(0.241)	(0.150)	(0.144)	(0.218)	(0.200)
Industry_recom (×100)	0.844***	0.767***	0.569***	0.526***	0.541***	0.505***
	(0.103)	(0.096)	(0.066)	(0.059)	(0.051)	(0.051)
Firm Size (×100)	1.301***	1.976***	0.882***	1.276***	0.981***	1.359***
	(0.252)	(0.342)	(0.180)	(0.228)	(0.259)	(0.281)
BM (×100)	0.771***	0.363*	0.466***	0.329*	0.359**	0.018
	(0.207)	(0.170)	(0.142)	(0.141)	(0.150)	(0.106)
Return (×100)	0.696	1.159***	0.789***	1.268***	−0.110	−0.420
	(0.436)	(0.170)	(0.293)	(0.182)	(0.401)	(0.372)
Fixed effects	-	Fund×Year Industry×Year	-	Fund×Year Industry×Year	-	Fund×Year Industry×Year
Observations	2,517,883	2,517,883	2,517,883	2,517,883	2,517,883	2,517,883
Adjusted R^2	0.071	0.101	0.044	0.062	0.045	0.067

Panel B: Fund manager holdings performance				
	DGTW returns (%) Among holdings	*DGTW returns* (%) Among holdings	*DGTW returns* (%) Among holdings	*DGTW returns* (%) Among holdings
	(1)	(2)	(3)	(4)
VoteTies	0.945**	0.516**	1.043**	0.623**
	(0.447)	(0.196)	(0.457)	(0.175)
Fund Sell			0.619	0.601
			(0.479)	(0.375)
VoteTies ×Fund Sell			−0.574*	−0.615
			(0.314)	(0.359)
Industry_recom	-0.016	0.041	−0.016	0.041
	(0.068)	(0.085)	(0.068)	(0.085)
Firm Size	−0.502	−0.678	−0.504	−0.681
	(0.530)	(0.466)	(0.529)	(0.466)
BM	−0.147	0.031	−0.148	0.032
	(0.198)	(0.301)	(0.197)	(0.299)
Return	2.036***	−0.131	2.046***	−0.122
	(0.480)	(0.796)	(0.489)	(0.799)
Fixed effects	-	Fund×Year Industry×Year	-	Fund×Year Industry×Year
Observations	114,139	114,139	114,139	114,139
Adjusted R^2	0.006	0.121	0.006	0.121

Appendix

A. Construction of analyst characteristics

InfoRatio. To measure the performance of analyst recommendations every year, we first construct a recommendation portfolio. The recommendation portfolio takes long (short) positions on the stocks as long as the analyst's outstanding recommendation, starting from the year, is Strong Buy or Buy (Strong Sell or Sell). Stocks are removed from the portfolio once the rating changes to Hold. *InfoRatio* is the regression alpha of the daily returns of the analyst's recommendation portfolio on the daily industry index returns. For most cases, we use the industry index returns as the performance benchmark because we focus on the analysts' abilities to pick stocks within the industry.

Risk. To measure the aggressiveness of an analyst's recommendations, we use the beta from the above regression of recommendation portfolio returns (Emery and Li 2009).

Nrec & ***Nstock***. *Nrec* is the number of reports (recommendations or earnings forecasts) issued by that analyst in that year. *Nstock* is the number of different stocks recommended by that analyst in that year. Jacob, Lys, and Neale (1999) use *Nrec* and *Nstock* to proxy for analysts' effort and industry knowledge.

Optism_recom & ***Optism_feps.*** We measure the analyst's optimism, relative to the consensus, for recommendations and earnings forecasts, respectively. [40] 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. 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 for *Optism_recom and Optism_feps,* we take an average across all recommendations and earnings forecasts, respectively, issued by that analyst in that year.

Upgrade. *Upgrade* is the fraction of recommendations that are upgrades in that year. Previous research has shown that recommendation revisions are more informative than level recommendations (Elton, Gruber, and Grossman 1986; Jegadeesh et al. 2004). We use this measure to proxy for the analyst's willingness to reveal more information to the public.

[40] We do not include the measure of analyst forecast precision in the main regression because this information is not available at the time of voting.

***Bold_feps* & *Accuracy_feps*.** For each analyst earnings forecast report, its boldness is defined as the absolute value of the difference between forecast EPS and the average forecast EPS in the same quarter; its accuracy is defined as the absolute value of the difference between forecast EPS and the actual EPS. Like *Optism_feps*, we first ascendingly rank the raw measure of all earnings forecasts in the same quarter and then give *Bold_feps* or *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 for *Bold_feps* or *Accuracy_feps,* we take an average across all earnings forecasts issued by that analyst in that year. Note that because actual EPSs are always reported in firm annual announcements that are issued in the next year, we do not include *Accuracy_feps* in the regressions for managers' voting decisions.

***Firmsize* & *Attention*.** *Firmsize* is the average of the market cap of stocks recommended by that analyst in that year. *Attention* is the fraction of the recommended stocks that are winners or losers, defined as the top or bottom quintile of past 12-month returns as of the previous quarter-end, respectively. We use this to measure the analyst's preference for attention-grabbing or hot topic stocks.

***Experience*, *Brokersize*, *TradeBroker*, and *PreAward*.** We use three measures for analysts' name recognition or popularity. *Experience* is the number of quarters since the analyst first issued a report recorded in the database. *Brokersize* is the number of active analysts in the analyst's brokerage house in that year. *TradeBroker* is 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* is 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.

B. Calculation of recommendation returns

This subsection details how we constructed Table 8, 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,

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

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

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

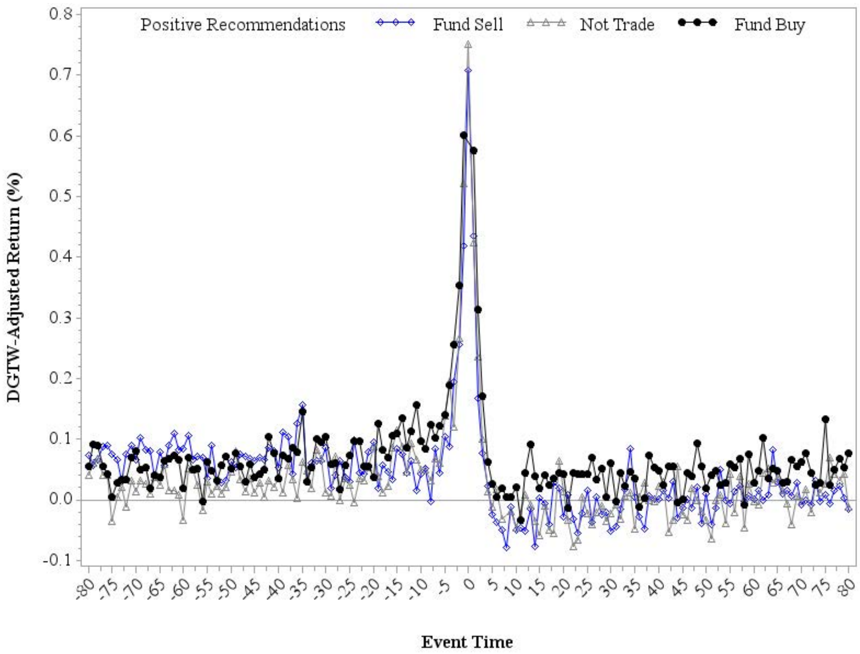
where V_C is the variance-covariance matrix of $\overline{CAR}$. Since the CAR intervals for different monthly cohorts overlap, we allow for the first- through sixth-order serial covariance of monthly average CAR to be nonzero and set the higher-order serial covariances to equal zero. To be specific,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

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

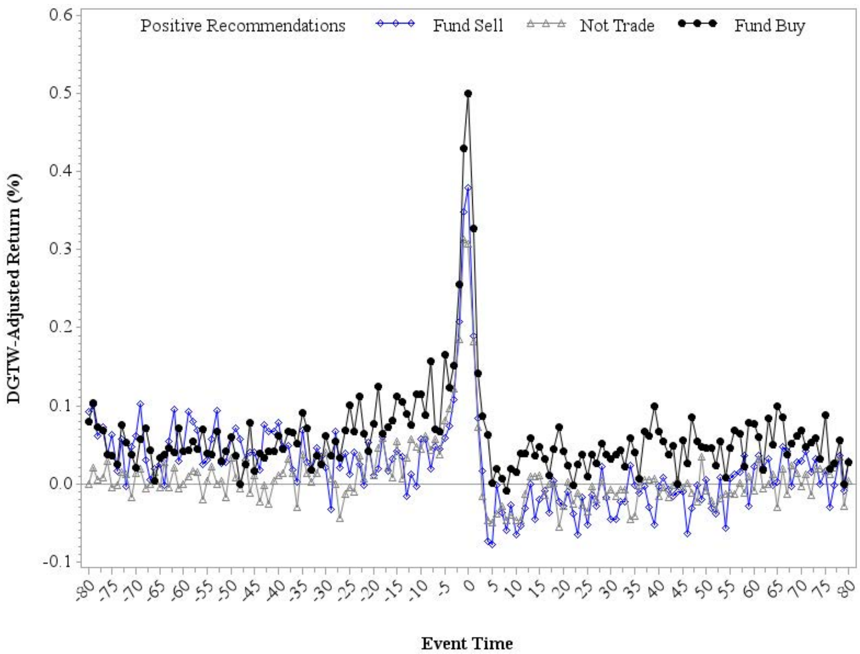
Appendix Figures

Figure A1 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

Appendix Tables

Table A1 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 for which we have the manager votes, whereas the whole sample has 7,506 observations. Total net assets is the average of the total net assets of the fund at the end of each quarter. Annual 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
Annual 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 A2 Transition matrix of broker ranks on trade allocations

This table presents the transition matrix of the probability of the broker rankings, in terms of the share of trade allocations, in the next year based on the rankings in the current year from 2010 to 2016. Panel A includes all active funds of managers in the voting database, whereas Panel B includes all active funds in the CSMAR database. Fund-year observations with less than five working brokers are excluded. For each fund, all brokers in that year are descendingly ranked based on the share of the fund's trades allocated to that broker. The broker rankings are classified into seven categories: 1, the first rank (the highest trade allocation share); 2, the second rank; 3, the third rank; 4, the fourth rank; 5, the fifth rank, >5, a rank greater than five; No allocation, no trade allocated.

Panel A: Active funds in the voting sample							
Broker ranks in the current year	Broker ranks on trade allocations in the next year						
	1	2	3	4	5	>5	No allocation
1	12.1%	8.5%	7.5%	7.2%	6.0%	26.9%	31.9%
2	9.1%	10.0%	8.0%	7.0%	6.1%	31.5%	28.3%
3	7.3%	7.9%	7.9%	7.6%	6.3%	34.9%	28.0%
4	6.4%	6.7%	7.7%	7.8%	6.2%	37.8%	27.5%
5	5.8%	5.5%	6.8%	7.3%	7.2%	43.2%	24.3%
>5	3.1%	3.3%	3.4%	3.7%	4.2%	62.4%	19.9%
No allocation	0.5%	0.5%	0.5%	0.4%	0.3%	2.5%	95.3%

Panel B: Active funds in the whole sample from CSMAR							
Broker ranks in the current year	Broker ranks on trade allocations in the next year						
	1	2	3	4	5	>5	No allocation
1	11.9%	9.5%	7.9%	7.5%	6.0%	26.7%	30.5%
2	9.4%	10.6%	8.3%	7.3%	6.2%	30.2%	28.0%
3	7.7%	8.4%	8.2%	7.8%	6.6%	34.4%	26.9%
4	6.7%	7.4%	7.8%	7.9%	6.4%	37.4%	26.4%
5	5.7%	5.4%	7.1%	7.0%	7.6%	43.0%	24.3%
>5	3.3%	3.5%	3.7%	3.9%	4.3%	61.9%	19.5%
No allocation	0.5%	0.5%	0.4%	0.4%	0.3%	2.3%	95.5%

Table A3 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, *WhisperSell* (*WhisperBuy*) is defined as the fraction of the number of the manager's selling (buying) stocks that are whisper-sell (whisper-buy) stocks 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)
WhisperSell	0.043***	0.010**		
	(0.014)	(0.004)		
WhisperBuy	0.128***	0.035***		
	(0.021)	(0.006)		
WhisperSell _s			0.079***	0.017**
			(0.027)	(0.008)
WhisperBuy_s			0.154***	0.043***
			(0.026)	(0.007)
InfoRatio_s	0.130***	0.034***	0.131***	0.034***
	(0.042)	(0.012)	(0.042)	(0.012)
Risk_s	−0.010	−0.003	−0.010	−0.003
	(0.043)	(0.012)	(0.043)	(0.012)
Nrec_s	0.484***	0.154***	0.472***	0.152***
	(0.085)	(0.024)	(0.086)	(0.024)
Nstock_s	−0.061	−0.010	−0.065	−0.011
	(0.083)	(0.023)	(0.083)	(0.023)
Optism_recom_s	0.113*	0.035*	0.111*	0.034**
	(0.058)	(0.016)	(0.058)	(0.016)
Optism_feps_s	0.119***	0.036***	0.118***	0.036***
	(0.043)	(0.012)	(0.043)	(0.012)
Upgrade_s	−0.163***	−0.044***	−0.163***	−0.044***
	(0.045)	(0.013)	(0.045)	(0.013)
Firmsize_s	−0.058	−0.006	−0.065	−0.008
	(0.046)	(0.013)	(0.046)	(0.013)
Attention_s	0.108**	0.027**	0.109**	0.028**
	(0.042)	(0.012)	(0.042)	(0.012)
Experience_s	−0.071	−0.021	−0.075	−0.021*
	(0.046)	(0.013)	(0.046)	(0.013)
Brokersize_s	−0.018	−0.012	−0.035	−0.017
	(0.077)	(0.022)	(0.077)	(0.022)
TradeBroker	0.011	0.001	0.012	0.002

	(0.011)	(0.003)	(0.011)	(0.003)
PreAward	0.606***	0.156***	0.604***	0.156***
	(0.039)	(0.010)	(0.040)	(0.010)
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	218,535	218,535	218,535	218,535
Adjusted R^2	0.123	0.126	0.123	0.126

Table A4 Return performance around analyst recommendations: controlling for momentum

This table reports the means of CARs 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	0.45	1.62	2.78	1.46	2.41	1.62	0.64	1.79	1.10
	(4.56)	(0.54)	(5.78)	(3.70)	(6.63)	(4.34)	(5.36)	(0.83)	(5.32)	(1.44)
Not Trade	1.44	−1.58	1.07	−0.65	0.97	−0.45	1.01	−1.56	1.08	−1.56
	(4.74)	(−2.58)	(4.27)	(−1.79)	(3.74)	(−0.86)	(4.59)	(−2.21)	(3.03)	(−1.61)
Fund Sell	1.41	−1.26	1.12	−1.19	1.01	−0.85	0.99	−2.16	1.11	−0.80
	(4.22)	(−1.92)	(4.12)	(−2.52)	(4.90)	(−2.31)	(4.54)	(−1.77)	(2.88)	(−1.16)
Fund Buy- Fund Sell	0.36	1.92	0.52	3.93	0.41	3.09	0.56	2.54	0.69	1.64
	(2.80)	(3.09)	(3.82)	(4.42)	(4.76)	(4.33)	(5.97)	(4.96)	(4.08)	(4.08)

Table A5 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. *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 on the analyst's reporting activities. Analyst-semi-year fixed effects are included in all regressions. 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*
	(1)	(2)	(3)
Fund Buy	−0.0151***	0.335***	0.434***
	(0.006)	(0.026)	(0.078)
Fund Sell	−0.0137**	0.257***	0.640***
	(0.006)	(0.025)	(0.076)
Affiliation effect	Yes	Yes	Yes
Fixed effects	Analyst× semi-year	Analyst× semi-year	Analyst× semi-year
Observations	31,128	31,128	31,128
Adjusted R^2	0.030	0.151	0.426

Appendix References

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

Elton, Edwin J., Martin J. Gruber, and Seth Grossman, 1986. Discrete expectational data and portfolio performance. *Journal of Finance* 41, 699–713.

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

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.