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ABSTRACT

We study how equity analysts disclose different information to the public versus to fund managers to whom they are connected. We examine say-buy/whisper-sell behavior wherein analysts issue optimistic recommendations to attract retail investors while providing more accurate information to fund managers in private, so that fund managers sell the recommended stocks. We measure favor trading using fund managers' votes for analysts in a Chinese "star analyst" competition. Managers are more likely to vote for analysts who exhibit greater "say-buy/whisper-sell" behavior toward these managers. This suggests that analysts reduce the accuracy of their public recommendations, thereby maintaining the value of their private advice to funds. Our findings help explain several empirical puzzles about analyst public recommendations.

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1. Introduction

The study of how to sell information to market participants has deep theoretical roots dating back to Admati and Pfleiderer (1986, 1988) and Kyle (1985, 1989). In a model of a private information provider selling information to investors, García and Sangiorgi (2011) find that it is optimal for a provider to sell either relatively precise information to a small group of investors or relatively imprecise information to a large group of investors. In this paper, we test this prediction in the context of stock analysts in the Chinese market by examining whether analysts disclose less accurate information to the public than to a small group of institutional investors.

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

Such tension between analysts' different jobs suggests that analysts may disclose less accurate information to the public than to a small group of institutional investors. More accurate public recommendations make stock prices more efficient, which tends to reduce the expected profit to investors with private information. So accurate public disclosure can come at the expense of profits to analysts' private clients. Our purpose here is to test whether analysts strategically make inaccurate public recommendations to maintain the trading value of their private signals via say-buy/whisper-sell behavior.[1]

Say-buy/whisper-sell behavior is the issuance by analysts of optimistic recommendations to attract retail investors while privately providing more accurate information to fund managers, who then become more likely to sell. A famous example of say-buy/whisper-sell behavior from the U.S. occurred during the millennial Dot-com bubble, when Merrill Lynch's tech analyst Henry Blodget touted tech stocks publicly to investors while disparaging the same stocks privately, calling them "dogs" and worse in private e-mails (Tharp 2002).[2] More generally, say-buy/whisper-sell behavior need not take the explicit form of analysts advising connected fund managers to sell. Even without explicit trading advice, incrementally adverse private information from analysts can encourage selling.

To test our hypothesis that analysts use say-buy/whisper-sell behavior in disclosing accurate information privately to fund managers, we exploit the unique proprietary data on managers' voting to analysts in a "star analyst" competition in China. In this analyst competition, fund managers privately vote for analysts, and their votes determine star analysts.[3] Being a star analyst increases an analyst's reputation and leads to higher bonuses and greater

[1] 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.

[2] Later, Blodget resolved a settlement with SEC in which he neither admitted nor denied the regulator's 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. De Franco, Lu, and Vasvari (2007) document several other cases in which analysts' private negative signals were sent to institutions via email. However, in this paper, we do not take any stance on the issue of legality of this practice.

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

chances of promotion (Stickel 1992). If analysts provide useful information to fund managers, we expect that fund managers will reciprocate by giving a vote to the analysts.

We use say-buy/whisper-sell behavior to capture private information transmission from analysts to funds. We hypothesize that say-buy/whisper-sell behavior by analysts makes fund trading more profitable, making a fund manager more likely to vote for analysts who exhibit more say-buy/whisper-sell behavior with that manager.

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

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. Because the trade commission data is at the fund-brokerage level, we test our main hypothesis using more granular voting data at the fund manager-analyst level.

Next, we turn to the hypothesis that analysts use say-buy/whisper-sell behavior to provide information to fund managers that is incrementally informative relative to their public recommendations. Empirically, we measure whisper-sell (whisper-buy) behavior for any manager and analyst pairs as the percentage of the manager's sold (bought) stocks that are positively recommended by the analyst.[4,5] We find that an analyst's whisper-sell behavior is positively associated with the manager's vote for that analyst. An increase in whisper-sell behavior from the 25th percentile to the 75th percentile among the analyst industry peers is associated with a 10% increase, relative to the sample mean, in the probability of the manager voting for that analyst as his or her first choice. In regressions, we include controls that characterize analysts' public activities in that year, so we can differentiate managers who vote based on analysts' private communications from managers who vote based on analysts' public activities. The results suggest that analysts use say-buy/whisper-sell behavior to provide fund managers with more-accurate information about stock values than analysts include in their

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

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

public recommendations.

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

Conditions under which we expect private communications to be especially important are (1) when the manager has less investment skill in the industry and therefore relies more on outside information from analysts,[6] (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, (3) when the reputation costs of whispering sell are relatively low, and (4) when the benefit from misleading retail investors is greater.

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

In addition, we find that fund managers are more likely to vote for the analysts after managers find that the post-recommendation performance of the whisper-sell stocks is poor. This supports the hypothesis that there is private communication between analysts and fund

[6] This result is also inconsistent with the hypothesis that fund managers do not need private whispers from analysts, i.e., that managers are good at debiasing analysts' biased public recommendations using their own knowledge. If this hypothesis were true, we would expect the results to be stronger among the industries that fund managers overweight in their portfolios.

managers. If fund managers only learned from analysts' public recommendations, bad performance after positive recommendations would lead to a lower vote ranking of the analysts.

Furthermore, we 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 or analysts' access to firm management.

An alternative hypothesis is that fund managers vote for analysts because analysts only provide fund managers with industry knowledge and fund managers trade more stocks when managers are more informed about the analysts' industries. We address this alternative hypothesis by relating analysts' stock-specific knowledge with fund managers' trading decisions. If analysts inform managers of stock-specific information and analysts' stock-level knowledge varies within an industry, we expect that the informed fund managers would trade stocks of which the analysts have better and more accurate knowledge. So, our prediction is that analysts have more accurate knowledge of stocks traded by their voting managers than of other stocks not traded by their voting managers. This would be consistent with our hypothesis that analysts provide stock-specific private information to fund managers.

We measure the analyst's stock-specific knowledge by the accuracy of earnings forecast they give to these stocks. Among stocks that are positively recommended by analysts, we define those that analysts' voting fund managers sell as "whisper-sell" stocks and the stocks that analysts' voting fund managers buy as "whisper-buy" stocks. We find that among the stocks the analyst recommends positively in a given semi-year, the analyst issues more accurate earnings forecasts on both whisper-sell and whisper-buy stocks than on other stocks that are not traded by their voting managers. Similarly, the analysts issue more reports and have more coverage experiences on whisper-sell and whisper-buy stocks, which indicates that they spend more effort in studying these stocks and thus are more likely to produce private information.

We further address the concern that analysts may use different optimism levels of their recommendations to distinguish whisper-sell stocks from whisper-buy stocks, so that retail investors can identify these stocks based on public information and our whisper-sell case would not actually be capturing private information. To test whether this is the case, we compare the probabilities of analysts issuing Strong Buy recommendations to whisper-buy and whisper-sell stocks. If there is no significant difference in the probabilities, it suggests that retail investors are unlikely to identify whisper-buy and whisper-sell stocks only based on analysts' public recommendations.

We find that for both whisper-sell and whisper-buy stocks, the probabilities of Strong Buy recommendation are equally 10% higher than other stocks that are not traded by analysts' voting managers. Taken together, this evidence suggests that analysts provide stock-specific private information to fund managers but do not disclose such information in their public recommendations to maintain the trading value of their private information.

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

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 1.24%, most of which are reversed in the following 40 trading days. This result suggests that at least some investors, likely retail investors, buy stocks upon positive recommendations and cannot distinguish between 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 in part to the information asymmetry caused by analysts' different information disclosure strategies.

This paper contributes to the broader literature that documents that analysts issue biased recommendations because of conflicts of interest.[7] One strand of this literature examines how analysts balance delivering valuable private information to clients versus making accurate public recommendations. Past work has documented that analysts create information asymmetry through tipping behavior---sharing their information with their clients before making it public (e.g., Irvine, Lipson, and Puckett 2006; Juergens and Lindsey 2009; Kadan, Michaely, and Moulton 2018; Even-Tov and Ozel 2021) or providing insider information to their clients without any public disclosure (Li, Mukherjee, and Sen 2021). Drawing on the insights of the information sales theory of Admati and Pfleiderer (1986, 1988), this paper documents another form of opportunistic analyst behavior: analysts reduce the accuracy of their public signals to preserve the trading value of their private information.

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

Our paper shares a similar insight with that of Malmendier and Shanthikumar (2014), who document "two-tongue" behavior of analysts who issue overly positive recommendations but

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

less optimistic forecasts to target different audiences. Complementing their paper, this paper shows that analysts disclose recommendations with different levels of accuracy to different audiences, and links such behavior to rewards (in the form of voting behavior) by private clients.

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

In contrast with these papers, we use managers' votes to measure managers' one-on-one evaluation of analysts. Moreover, we infer private communication through 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 to retail investors.

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

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

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

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

2.1 Say-buy/whisper-sell behavior

If managers act on analysts' private, more-accurate information in addition to public information, we may 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 presents better investment value than Stock B. The analyst does not want to fully disclose such accurate information to the public because if the public information is accurate 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). On the other hand, when the fund holds Stock B and has capital constraints, the informed manager is likely to buy Stock A and sell Stock B. Therefore, Stock A is the whisper-buy stock, whereas Stock B is the whisper-sell stock.[8] 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, whisper-sell stocks serve as a crucial identification strategy to rule out alternative hypotheses.

2.2 Main 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 scenario), 2) the manager learns public information from the analyst's public recommendations (the public-recommendation scenario), and 3) the analyst and the manager behave independently based on common external signals (the homophily scenario).

Whisper-buy behavior provides the same prediction under all scenarios; more whisper-buy

[8] 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.

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 scenarios. Under the public-recommendation or the homophily scenario, more whisper-sell behavior 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 scenario, 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 scenario: whisper-sell behavior* negatively *correlates with the manager's voting rank for the analyst.*

H1b: *Private-communication scenario: whisper-sell behavior* positively *correlates with the manager's voting rank for the analyst.*

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

Managers who have weak skills in a specific industry have more need for 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. We expect a stronger statistical relationship between whisper-sell behavior and voting rank among these manager-analyst pairs.

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

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

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

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

If analysts issue inaccurate public recommendations to promote trades of retail investors, they will benefit most when they target categories of stocks that are favored by retail investors.

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

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

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

If managers build their relationships with analysts based on their past encounters, we expect that managers will 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.

H7: *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-accurate 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 after the recommendation dates.

H8: *Whisper-buy recommendations outperform whisper-sell recommendations after the recommendation dates.*

3. Data

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

3.1 Voting data

The primary data we use come from the voting data of the "Crystal Ball Awards for Sell-Side Analysts" from 2010 to 2016 in China. This analyst competition is hosted by *Capital Week* magazine, which is the only media outlet authorized to publish listed firms' disclosures in China. Analysts (single or multiple analysts as a team) take part in the competition each year across 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 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 2,381 fund manager-year observations with nonmissing holding information; 2010 has the lowest number of managers at 213, and 2016 has the highest number of managers at 535. Our sample accounts for, on average, 34% of total active funds existing in that year; the percentages remain stable across years.[9]

We infer the fund trades based on fund disclosures of total portfolio holdings. In China, mutual funds must disclose their total asset holdings information semi-yearly, in the second and fourth quarters. All funds' fiscal years correspond to the calendar year. Funds also disclose their top-ten holdings quarterly. In our main results, we use fund trades implied from the semi-yearly holdings because we can access the total asset holdings of the funds. We also use quarterly holdings to produce robust results. Panel A of Table 2 shows the characteristics of active funds' holdings and implied trades in our sample. Active funds, on average, invest in 58.75 stocks across 16.90 industries. The relatively broad coverage of industries by fund managers suggests that they may not specialize in all the industries they invest in and therefore

[9] In Table A1, we compare the fund-year observations used in this study with the whole sample from the CSMAR database. There is no strong difference between the two samples in terms of fund characteristics. If anything, the funds included manage larger amounts of assets and have higher raw returns than the average fund during our sample period.

may seek advice and information from analysts who specialize in certain industries. Between two semi-yearly holding disclosures, fund managers implement significant portfolio changes, which results in, on average, 45.39 stocks with shares being increased and 49.49 stocks with shares being decreased, and a high turnover ratio of 57.58%.

[Insert Table 2]

On the other hand, we match the analysts in the voting data with their names and brokerage house names in the CSMAR database and adopt the analyst teams when we can successfully identify at least one of their team members. In China, a brokerage house typically assigns multiple analysts to form teamwork to cover one industry; on average, 34 brokerage houses take part in the competition each year. 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.

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 in the corresponding year.

The recommendation and earnings forecast data are also from the CSMAR database. We assign a recommendation or an earnings forecast to the analyst if at least one group member is listed as the issuer of that recommendation (or earnings forecast) in the CSMAR database.[10] Analyst recommendations in CSMAR are recorded using the standardized five-digit rating system similar to I/B/E/S, which goes from 1 (Strong Buy) to 5 (Strong Sell). Other data on stock returns and related variables are also from the CSMAR database.

3.3 Analyst public recommendations

Public recommendations made by analysts are one of the major focuses of this paper. In this paper, we examine 123,097 public recommendations issued by analysts who engage in analyst ranking competition in our sample from 2010 to 2016. Of those recommendations, 45.48% are Strong Buy; 49.44% are Buy; 4.97% are Hold; 0.03% are Sell; and 0.08% are Strong Sell. In terms of the rating changes, 7.55% are first-ever recommendations, 3.35% are upgrades, 82.91% are recommendations whose ratings are the same as the previous one, 1.94% are downgrades, and the rests are undefined.[11]

As compared with the U.S. market, the distribution of recommendations indicates that Chinese analysts tend to issue overly optimistic recommendations and tend to be reluctant to issue recommendation changes. This is consistent with our premise that analysts limit the informativeness of their public recommendations but use optimistic recommendations to generate retail trades. On the other hand, despite the fact that most recommendations are Buy and Strong Buy, Chinese analysts' recommendations are not pure noise. In our sample, Strong

[10] 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.
[11] The distribution is similar when using all recommendations from CSMAR database.

Buy (Buy) recommendations produce DGTW-abnormal returns of 1.55% (0.98%) over the −1 to +1 event window. This indicates that investors believe that analysts' Strong Buy and Buy recommendations contain some useful information.

3.4 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.

$$\text{WhisperSell}_{ljs} = \frac{\sum_{i \in \mathrm{A}_{lhs} \cap \mathrm{B}_{jhs}} |\min(v_{ijs} - v_{ijs-1}, 0)\, p_{is}|}{\sum_{i \in \mathrm{B}_{jhs}} |\min(v_{ijs} - v_{ijs-1}, 0)\, p_{is}|}, \tag{1}$$

$$\text{WhisperBuy}_{ljs} = \frac{\sum_{i \in \mathrm{A}_{lhs} \cap \mathrm{B}_{jhs}} |\max(v_{ijs} - v_{ijs-1}, 0)\, p_{is}|}{\sum_{i \in \mathrm{B}_{jhs}} |\max(v_{ijs} - v_{ijs-1}, 0)\, p_{is}|}, \tag{2}$$

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*. We do not observe the exact timing of managers' trades relative to analysts' recommendations. However, our hypotheses do not critically hinge on whether managers trade immediately at the time of the public recommendation days. Fund managers can profitably make use of analysts' private information at a horizon longer than just a few days around public recommendations. For robustness, we also construct the whisper-sell and whisper-buy measures using funds' quarterly disclosures of top-ten holdings.

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.[12]

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 scenario, 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-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.[13] 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

[12] 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.

[13] 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.

manager sells stocks for informational reasons; that is, they tilt the portfolio from some stocks to others for better future performance, rather than for liquidity reasons, such as fire sales or investment policy changes.

[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. This 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.

3.5 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. 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*).[14] 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 C of Table 2 shows the summary statistics on these analyst characteristics. The analysts in our sample, on average, cover 13.83 stocks and publish 38.65 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 D 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,

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

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*.

4. Votes as manager evaluations of analysts

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

To test this hypothesis, we collect information about the fund trade allocations in dollar value among brokers for each mutual fund and each year from the Wind Financial Database (WindDB).[15] 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

[15] 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.

estimate the ordinary least-squares (OLS) regressions as follows.

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

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) to (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.

By linking managers' votes with their real-world actions in allocating trade commissions between brokers, we provide evidence that managers' votes could be a good proxy for their evaluations of analysts' services. However, the commission data only associate brokers with funds. In the next section, we use more granular voting data that associates specific fund managers with brokers' analysts to test our main hypothesis.

5. Do managers vote for whisper-sell behavior?

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

$$\begin{aligned} \text{VoteRank}_{lmt} = \beta_0 + \beta_1 \text{WhisperSell}_{lmt} + \beta_2 \text{WhisperBuy}_{lmt} \\ + \gamma \text{Analyst Characteristics}_{lt} + \delta_{gk} + \varepsilon_{lmt}. \end{aligned} \tag{4}$$

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. If the analyst's private information drives the fund manager's selling decisions and the manager rewards the analyst with their vote, we expect a positive estimate on *WhisperSell* (*Hypothesis* 1).

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.

[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* (size of the analyst's brokerage house) is 0.281.[16] Important business relations (*TradeBroker*)

[16] Because we use the ranking value for all continuous variables, we can compare their magnitudes by simply comparing their coefficient estimates.

and previous star status (*PreAward*) are also associated with higher ranks.

Nrec_s (number of reports) has a positive and significant estimate of 0.466. This result suggests 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 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.[17] If the analyst's private information drives the

[17] 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.

fund manager's selling decisions and the manager rewards the analyst with their vote, we expect a positive relationship between *VoteRank* and *WhisperSell*. 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 use say-buy/whisper-sell behavior to provide fund managers with private information that is incrementally informative relative to analysts' public recommendations.

We also include *WhisperBuy* 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.

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) to (13), we relate *WhisperSell_s* to the managers' binary voting decisions, that is, whether the manager votes as the first choice, votes as the second choice or higher, votes as the third choice or higher, votes as the fourth choice or higher, or votes as the fifth choice or higher.[18] 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 being voted as the first choice; this translates into an approximately 10% increase relative to the unconditional probability of being voted as the first choice (5.03%).

5.3 Conditional effects of whisper-sell behavior

We explore the heterogenous effect of whisper-sell behavior on voting decisions and have five key findings. First, such whisper-sell-voting relationship should be more pronounced when managers have relatively low investment skills in the analysts' industries such that managers rely on outside knowledge from analysts (*Hypothesis* 2). Second, the relationship between

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

whisper-sell behavior and voting is strengthened when managers have an important business tie with the analysts' brokers and are more likely to communicate privately with the analysts (*Hypothesis* 3).

[Insert Table 5]

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

We define the manager's important partner brokers as those whose trade allocation percentages from the manager's fund in the previous year are above the sample median.[19] Columns (3) and (4) show that having an important business tie with the manager has a positive effect on the relationship between whisper-sell behavior and vote.

Third, a less transparent information environment may lead to more whisper-sell behavior because of less reputational concerns and of more benefits to finding private information (*Hypothesis* 4). To test this prediction, we first calculate stock-level information asymmetry using an average of the Z-score of four measures: (1) (inversely) number of analyst reports, (2) (inversely) number of covered analysts, (3) earnings forecast dispersion, and (4) stock idiosyncratic volatility. Then, we average the stock-level measure by industry, as the voting

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

regression is estimated at the industry dimension and define *InfoAsymmetry* as equal to one if the industry-level information asymmetry is above the median in the previous year. In columns (5) and (6), we find that the coefficient estimate on the interaction term between *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.

Fourth, analysts are more likely to engage in whisper-sell behavior for stocks that are preferred by retail investors. The reason for this is that for such stocks, overoptimistic analyst recommendations should induce more buy orders from retail investors. Based on the finding that retail investors are attracted to investing in lottery stocks (e.g., Kumar 2009; Hu, Lin, and Liu 2022), we use lottery stocks as a proxy for retail investor habitats. We define *Lottery* as equal to one if the proportion of lottery stock in that industry is above the median in the previous year. In column (7), we find that the coefficient on the interaction term between *WhisperSell_s* and *Lottery* is 0.159 and statistically significant. The coefficient is about twice as large as the unconditional estimate of the coefficient on *WhisperSell_s* (0.80). The result suggests that say-buy/whisper-sell behavior is more likely to occur among stocks that are attractive to retail investors.

Fifth, if fund managers sell the stocks based on analysts' private information, the managers will give a higher vote to the analysts when the managers see poor returns from such stocks. Accordingly, we calculate analysts' whisper-sell stocks' performance as the industry-adjusted abnormal return from the recommendation dates to the current semi-year-end. We include whisper-sell stocks' performance and its interaction with *WhisperSell_s* in our main regressions.

In column (9), we find that the coefficient on the interaction term between *WhisperSell_s* and whisper-sell stocks' performance is negative (−0.312) and statistically significant.[20] This suggests that when the average returns of whisper-sell stocks are one percent lower than zero, the sensitivity of votes on *WhisperSell_s* increases by 6.9% (0.312 * 0.01 / 0.045). This result indicates that fund managers are more likely to vote if they see poor returns from the whisper-sell stocks, even though these stocks are positively recommended in public.

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

5.4 Voting decisions and subsequent whisper-sell behavior

Do managers who rank analysts highly in the star analyst competition engage in more private communications with the same analysts in the future (*Hypothesis* 7)? 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. In column (1), we find that the coefficient on this year's voting rank is positive and statistically significant; the estimate (0.008) suggests that a one-unit increase in vote ranking will lead to an 8.4% increase in *WhisperSell* relative to the sample mean.[21] This result suggests that fund managers tend to use more private information

[20] For this test, we limit the manager-analyst observations to those with at least one whisper-sell stock in that year. Because of this, the total observations are reduced from 271,697 to 159,797.

[21] 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.

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) to (6), we use various specifications of fixed effects (company-broker, broker-year, industry-year, etc.), and the results are robust.

[Insert Table 6]

Taken together, these findings are consistent with analysts using say-buy/whisper-sell behavior to provide fund managers with private, more-accurate information.

5.5 Robustness checks

We run several robust checks. First, we construct the whisper-sell and whisper-buy measures using the quarterly disclosures of top-ten holdings. Though the measures are constructed with incomplete information of fund holdings,[22] in Table A2, we still find robust results for the same specifications as Table 4.

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

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

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

Compared to Eq. (1), *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.

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

The 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. (1) 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.[23] Alternatively, we assume that the chance of picking one stock is proportional to how many analysts of other brokers issued positive recommendations on the same stock.[24] By doing so, we further control for analysts' herding tendency, such as recommending popular large-cap stocks.

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[23] 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.

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

[Insert Table 7]

Table 7 replicates the main regressions of Table 4 using the alternative whisper-buy and whisper-sell measures defined above. Columns (1) and (2) use the whisper-sell measure based on the number of the analyst's whisper-sell stocks and the manager's selling stocks; the coefficient estimates are positive and statistically significant, in keeping with our main results. Furthermore, columns (3) to (6) use the measures in Eq. (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, we address the possibilities that the whisper-sell measure serves as a noisy proxy for the analyst's coverage in that specific fund manager's holdings, and that fund managers vote for the analysts because the analysts cover more of the stocks held by the fund. To distinguish our hypotheses from this account, we additionally control for analysts' fund-wise coverage in our main regressions. *FundCover* is defined as the fraction of the number of the fund manager's held stocks that are covered by the specific analyst.

Our tests are provided in columns (7) to (9). In column (7), 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 by analysts. However, in columns (8) and (9), when we include both *FundCover* and whisper-sell and whisper-buy measures, we find that the coefficient estimates on the whisper-sell and whisper-buy measures remain positive and statistically significant as in our main regressions, but the estimate on *FundCover* loses its statistical significance. This result suggests that it is the analysts' more-accurate information for trading that determines managers' voting decisions rather than the general coverage of stocks held by fund managers.

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

To do so, we use analysts' site visits to the firm as a proxy for their connections with the firm management. We collect the site visit information from 2012 to 2016 from CSMAR and associate analysts' site visits with fund managers' traded stocks.[25] *FirmConnection* measures the fraction of the number of the fund manager's traded stocks to which the analyst has site visits in that semi-year.

The results are reported in columns (10) and (11). We find that the coefficient on *FirmConnection* is positive and statistically significant, suggesting that firm managers vote for the analysts more favorably if the analysts have more connections with firm management. On the other hand, the coefficients on whisper-sell and whisper-buy measures remain positive and statistically significant, consistent with our main results.

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

6. Further evidence on private information transmission

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

6.1 Do analysts provide accurate private information to fund managers?

Our hypotheses are based on the premise that fund managers vote for the analysts because analysts give accurate and valuable information of stocks to fund managers for profitable trading. In this subsection, we perform further tests of that premise. If analysts give stock-level private information to fund managers and analysts' stock-level knowledge varies across analysts' covered stocks, then fund managers will trade stocks of which analysts have more-accurate information. We measure the accuracy of analysts' information by their earnings forecast accuracy. Therefore, we predict that analysts issue more accurate earnings forecast to whisper-sell and whisper-buy stocks than to other stocks that fund managers chose not to trade.

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

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.

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

$Fund_{lis}$ 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*.[26] 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, $Fund_{lis}$.

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

[26] 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.

sample, 33.62% of positive recommendations are whisper-buy recommendations, whereas 33.32% of them are whisper-sell recommendations; the remaining are not-trade recommendations.

[Insert Table 8]

In Table 8, we examine the relationship between analyst earnings forecast accuracy and voting managers' trading decisions in the cross-section of analysts' positive recommendations.[27] In the regressions, we include analyst-semi-year fixed effects such that we only draw comparisons between stocks in the same industry that are recommended by the same analyst. The result, in column (1), indicates that analyst earnings forecast accuracy is higher on stocks that are traded (bought or sold) by the analyst's voting managers than on stocks that are not traded by these managers, suggesting that the analysts have more-accurate information on these traded stocks than on other stocks covered by the same analysts. 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. These results are consistent with analysts providing more-accurate stock-specific information to fund managers, instead of providing only industry-wide knowledge to fund managers.

We also examine whether analysts reveal whisper-buy and whisper-sell stocks in their public recommendation decisions. In column (4), we find that both whisper-buy and whisper-

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

sell stocks are equally 10% more likely to be recommended as Strong Buy. Overall, the evidence suggests that analysts provide information to fund managers that is more accurate than the information reflected in their public recommendations.

6.2 Return performance of stock recommendations

In this subsection, we compare the recommendation performances of whisper-sell and whisper-buy stocks. We hypothesize that the positive recommendations of whisper-buy stocks outperform the positive recommendations of whisper-sell stocks under the premise that fund managers trade these stocks based on analysts' more-accurate private information (*Hypothesis* 8). In other words, we expect that fund managers' informed trading of analysts' recommended stocks generate higher returns than unconditionally following analysts' public recommendations. We analyze the return performance around recommendation dates from −120 to 220 trading days using an event-study approach.

Fig. 1 presents the means of DGTW (1997)-adjusted daily returns around the public recommendation dates by different groups of positive recommendations. Consistent with the previous studies, the market, on average, reacts positively to analysts' positive recommendations for all three groups of positive recommendations. For example, according to Panel A of Table 9, fund-buy recommendations over the −1 to +1 event window experience 1.70% of cumulative abnormal returns (CAR), whereas fund-sell recommendations experience 1.24%.[28] The fact that fund-sell recommendations have positive event-date abnormal returns

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

and are followed by negative returns of –1.37% from 2 to 40 trading days suggests that at least some investors do not access analysts' private information and thereby unconditionally follow the analysts' positive recommendations. The results are similar when we use industry-adjusted abnormal returns.

[Insert Figure 1]

[Insert Table 9]

These recommendations differ consistently and significantly in CARs around the recommendation dates. According to Panel A of Table 9, the CAR for fund-buy recommendations minus that for fund-sell recommendations is 1.86% from −40 to −2 trading days, 2.44% from 2 to 40 trading days, and 3.15% from 41 to 220 trading days.[29] 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.[30] The overall persistent pattern of fund-buy recommendation outperforming fund-sell recommendations suggests that whisper-buy stocks are better investment than whisper-sell stocks.

Next, we calculate the difference in investment performance between informed versus uninformed investors. Assume conservatively that analyst-voting fund managers buy the stocks one trading day after positive public recommendations. Because informed fund managers will

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

[30] 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).

invest only in fund-buy recommendations, their buying strategy generates an average CAR of 1.04% over 2 to 40 trading days after the public recommendations. On the other hand, uninformed investors cannot distinguish whisper-buy and whisper-sell stocks, and hence can only buy positive recommendations unconditionally. Accordingly, their average investment returns would be 1.04% * 33.6% + (−1.04%) * 34.1% + (−1.37%) * 32.3% = −0.45%. In other words, analysts' differentiation of information disclosure toward different audiences generates differential investment returns of about 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.[31]

We acknowledge that in this event study setting of public recommendations, we observe stock returns and fund managers' trading contemporarily, which leaves room for alternative interpretations. We run several robustness tests to address some most likely alternative hypotheses. First, we ensure that managers' buying and selling decisions are not based on managers' differentiation of Strong Buy and Buy recommendations (see Figure A1). Second, we control for funds' momentum trading. For example, after a positive earnings surprise, an analyst might start to issue a positive recommendation, and meanwhile, funds start to increase holdings after a price run-up (Griffin, Harris, and Topaloglu 2003; Sias 2004). We address this concern by partitioning our sample into quintiles based on CARs from −40 to −2 trading days. In Table A3, we find consistent differences in post-recommendation CARs between fund-buy

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

and fund-sell recommendations across all quintiles; that is, the return patterns cannot be fully explained by fund momentum trading based on price movement leading to analyst recommendations.

In sum, we find that among analysts' public positive recommendations, whisper-buy stocks persistently outperform whisper-sell stocks. 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. 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

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

The first set of implications concerns the ability of researchers to infer analyst ability from the performance of their public recommendations. If 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).

The second concerns the information content of stock recommendations. Consistent with theoretical research, our evidence suggests that analysts substitute between the profitability of the private information that they provide to private clients, and the informativeness of the public recommendation that analysts provide. Our argument is that it is in analysts' interests to limit the informativeness of their public signals. Our findings help explain the fact that publicly disseminated stock recommendations have relatively low information content (Graham and Harvey 1996; Metrick 1999; Barber et al. 2001; Antweiler and Frank 2004; Jegadeesh et al. 2004; Engelberg, Sasseville, and Williams 2012).[32]

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 prioritized so that investors have better knowledge of the informativeness of analyst recommendation ratings.

A caveat is that the insights we provide here are applicable to markets where retail investors

[32] 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. On the other hand, Womack (1996) finds analysts' recommendations are informative and are followed by return drifts. Crane and Crotty (2020) find that U.S. analysts' recommendation revisions are informative.

attend to analysts' recommendations credulously, and this credulity generates significant trades. Several authors have provided evidence that this is the case in U.S. markets, at least in the past (Cowen, Groysberg, and Healy 2006; De Franco, Lu, and Vasvari 2007; Malmendier and Shanthikumar 2007).

8. Conclusion

Inspired by the theoretical models of information sales (Cespa 2008; García and Sangiorgi 2011), we test whether financial analysts use say-buy/whisper-sell behavior to reduce the accuracy of the recommendations provided to a large group of retail investors and communicate more-accurate information to a small group of investors (mutual fund managers). In particular, analysts issue optimistic recommendations on a wide range of stocks to incite retail investor purchases, but analysts limit the informativeness of their public recommendations to maintain the trading value of their private advice to funds. We test such a hypothesis by examining the relationship between analysts' say-buy/whisper-sell behavior and fund managers' votes.

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 hypothesis that analysts use say-buy/whisper-sell behavior to give fund managers private and more-accurate information than analysts give to the general public in their public recommendations. We further find that among the analysts' positive public recommendations, the stocks bought by the managers who vote for the analysts outperform the stocks sold by these managers, consistent with managers receiving more-accurate information. We find that 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 balance the informativeness of their public recommendations against the trading value of the private information they provide to their private clients, resulting in say-buy/whisper-sell behavior. Analysts' whisper-sell behavior means that they limit the informativeness of public recommendations even under the pressure of government regulation. Furthermore, since analysts' public recommendations do not reveal analysts' true beliefs about stocks, the performance of analysts' public recommendations is an imperfect indicator of analysts' abilities and career prospects. The phenomenon that an information provider produces less-accurate public signals to create the value of their private signals may be present in other contexts such as voting recommendations of advisory firms and credit ratings.

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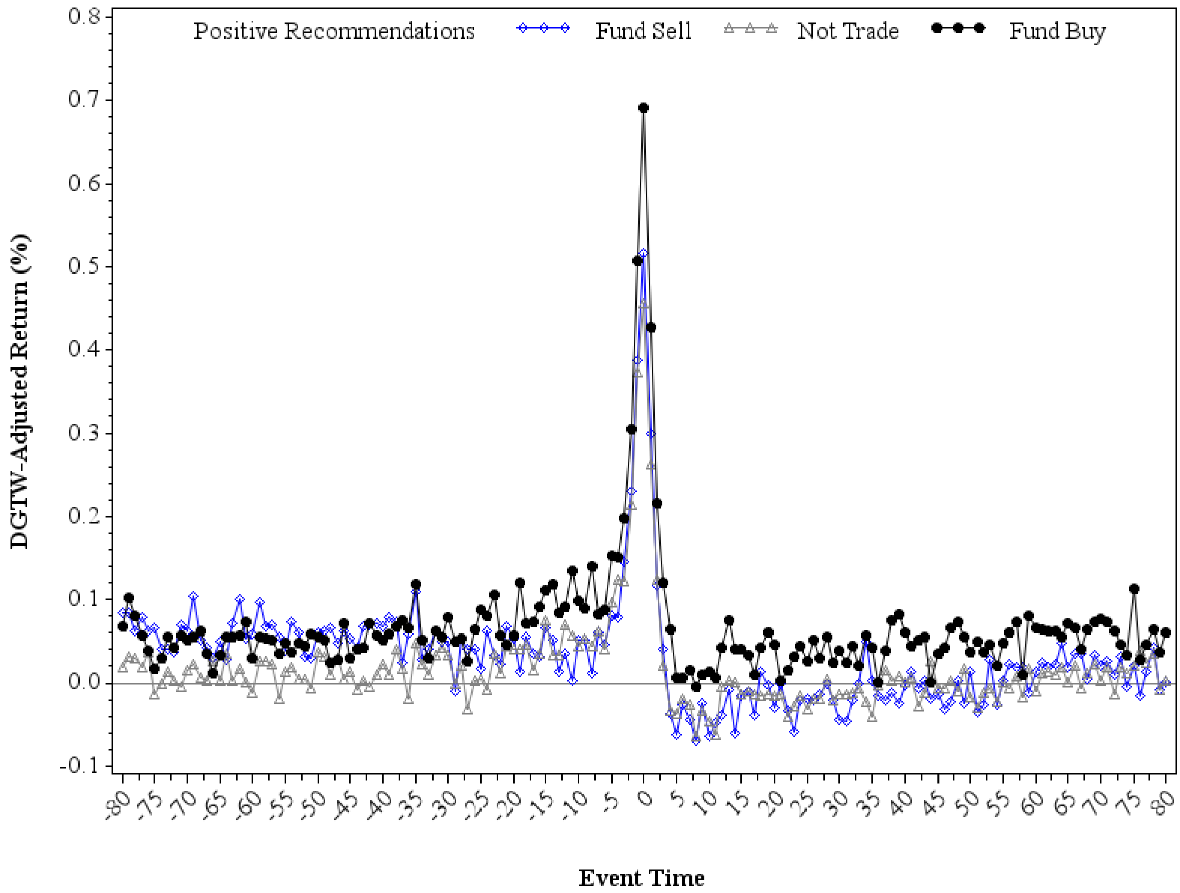
Figures

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

	Ln(TradeShare) t+1				
	(1)	(2)	(3)	(4)	(5)
$\Delta\overline{VoteRank}$ *t*	0.0505**	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 choice = 5; second choice = 4; third choice = 3; fourth choice = 2; fifth choice = 1; no vote = 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 choice = 5; second choice = 4; third choice = 3; fourth choice = 2; fifth choice = 1; no vote = 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 tables. *IndustryWeight* is the fund manager's portfolio percentage in the analyst-specific industry in the previous year. *TradeBroker* is an indicator variable for an important business relationship between the analyst's brokerage house and the fund. *InfoAsymmetry* equals one if the industry average of information asymmetry score is above the median in the previous year. *Lottery* equals one if the industry average of being lottery stock is above the median in the previous year. *StockReturn* is the average industry-adjusted return of whisper-sell stocks from the recommendation date to the current semi-year-end. Company-broker fixed effects are included in all regressions. Standard errors, clustered by analyst-year, are shown below coefficient estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated with ***, **, and *, respectively.

	VoteRank	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WhisperSell_s	0.162***	0.040***	0.065***	0.015***	-0.022	-0.006	0.027	0.008	0.045	0.009
	(0.026)	(0.007)	(0.022)	(0.006)	(0.040)	(0.011)	(0.030)	(0.008)	(0.028)	(0.008)
WhisperSell_s × *IndustryWeight*	−1.085***	−0.283***								
	(0.241)	(0.065)								
WhisperSell_s × *TradeBroker*			0.092***	0.026***						
			(0.035)	(0.010)						
WhisperSell_s × *InfoAsymmetry*					0.193***	0.047***				
					(0.055)	(0.015)				
WhisperSell_s × *Lottery*							0.159***	0.034**		
							(0.054)	(0.015)		
WhisperSell_s × *StockReturn*									−0.312**	-0.080**
									(0.143)	(0.038)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker	Company× Broker
Observations	271,697	271,697	271,697	271,697	271,697	271,697	271,697	271,697	159,797	159,797
Adjusted R^2	0.123	0.128	0.123	0.127	0.123	0.128	0.123	0.127	0.120	0.121

Table 6 Voting decisions and future whisper-sell behavior

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

	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)
WhisperBuy 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

Table 7 Robustness tests on alternative whisper-sell measures

This table shows the robustness of whisper-sell and whisper-buy measures. The dependent variable, *VoteRank*, represents the manager's vote for the analyst (first = 5; second = 4; third = 3; fourth = 2; 5th = 1; no vote = 0). "≤fifth Choice" is an indicator variable for a vote of the 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 count" corresponds to the measure that counts the number of stocks instead of the dollar trade volume of stocks. "Adjusted 1" corresponds to the measure that adjusts for the number of stocks the analyst recommends. "Adjusted 2" corresponds to the measure that adjusts for both the number of stocks the analyst recommends and the analyst's tendency for herding. *FundCover* measures the fraction of the number of fund stock holdings that are covered by the analyst. *FirmConection* measures the fraction of the number of fund-traded stocks of which the analysts have site visit to the firms. For columns (10) and (11), the sample period starts from 2012 due to the data availability. 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 count		Adjusted 1		Adjusted 2		Original				
	VoteRank	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*VoteRank*	*≤Fifth Choice*	*VoteRank*	*≤Fifth Choice*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
WhisperSell	0.087***	0.023***	0.066***	0.016***	0.102***	0.025***		0.063***	0.016***	0.092***	0.024**
	(0.021)	(0.006)	(0.021)	(0.006)	(0.020)	(0.005)		(0.020)	(0.006)	(0.022)	(0.006)
WhisperBuy	0.128***	0.033***	0.100***	0.024***	0.147***	0.036***		0.106***	0.027***	0.135***	0.036***
	(0.021)	(0.007)	(0.021)	(0.006)	(0.020)	(0.006)		(0.015)	(0.006)	(0.023)	(0.007)
FundCover							0.154***	0.042	0.013		
							(0.032)	(0.030)	(0.008)		
FirmConection										0.211**	0.057**
										(0.084)	(0.023)
Other controls	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	220,128	220,128
Adjusted R^2	0.124	0.128	0.123	0.127	0.123	0.127	0.123	0.123	0.128	0.118	0.113

Table 8 Connected-manager trades and analyst reporting activities

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

	Accuracy_feps	*Nrec*	*Stkexp*	*Strong Buy*
	(1)	(2)	(3)	(4)
Fund Buy	−0.0126**	0.335***	0.434***	0.099***
	(0.006)	(0.026)	(0.078)	(0.007)
Fund Sell	−0.0133**	0.257***	0.640***	0.100***
	(0.006)	(0.025)	(0.076)	(0.008)
Affiliation effect	Yes	Yes	Yes	Yes
Fixed effects	Analyst× semi-year	Analyst× semi-year	Analyst× semi-year	Analyst× semi-year
Observations	32,195	32,195	32,195	32,195
Adjusted R^2	0.029	0.149	0.424	0.464

Table 9 Return performance around analyst recommendations

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

Panel A. DGTW-adjusted return

		Event windows around analyst recommendations				
	% of Obs.	[−120, −41]	[−40, −2]	[−1, 1]	[2, 40]	[41, 220]
Fund Buy	33.6%	2.79***	3.24***	1.70***	1.04*	2.93**
		(3.34)	(6.51)	(5.60)	(1.90)	(2.09)
Not Trade	34.1%	−0.03	1.28***	1.13***	−1.04***	−0.88
		(−0.06)	(3.15)	(5.08)	(−3.19)	(−0.82)
Fund Sell	32.3%	4.11***	1.47**	1.24***	−1.37***	−0.19
		(5.02)	(2.92)	(4.37)	(−2.38)	(−0.12)
Fund Buy − Fund Sell	-	−0.83	1.86***	0.45***	2.44***	3.15***
		(−1.35)	(7.80)	(7.22)	(12.52)	(10.07)

Panel B. Industry-adjusted return

		Event windows around analyst recommendations				
	% of Obs.	[−120, −41]	[−40, −2]	[−1, 1]	[2, 40]	[41, 220]
Fund Buy	33.6%	0.60	2.04***	1.62***	0.06	−2.51
		(0.48)	(5.82)	(5.72)	(0.10)	(−0.82)
Not Trade	34.1%	−0.63	0.88***	1.13***	−1.06***	−4.13**
		(−0.96)	(4.60)	(5.15)	(−3.34)	(−2.03)
Fund Sell	32.3%	1.12	0.16	1.16***	−2.75***	−5.93*
		(0.91)	(0.34)	(4.60)	(−3.85)	(−1.87)
Fund Buy − Fund Sell	-	−0.17	2.19***	0.46***	2.80***	3.33***
		(−0.32)	(8.79)	(6.73)	(7.36)	(9.46)

Online 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 optimism, relative to the consensus, of recommendations and earnings forecasts, respectively.[33] 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

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

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.

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 *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 *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

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

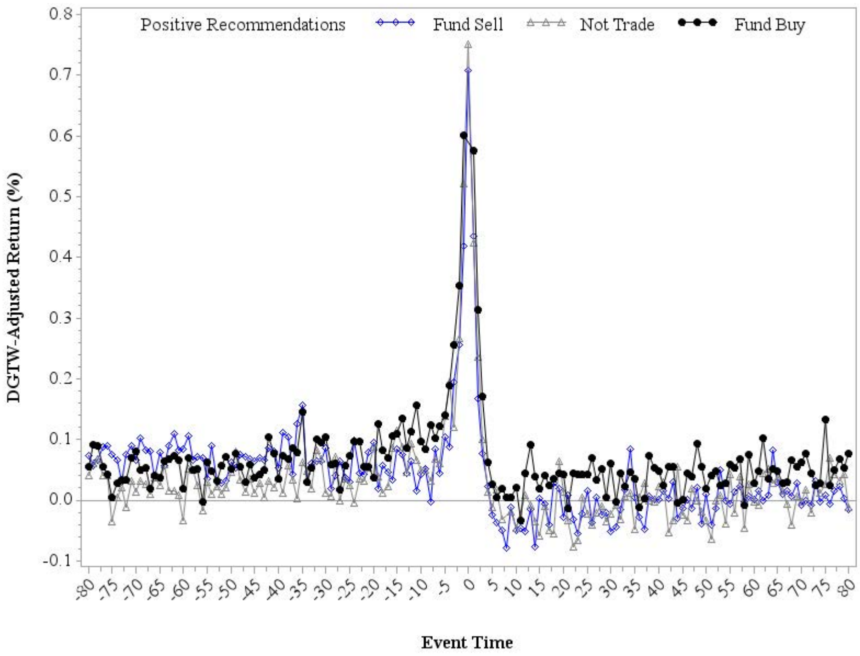
where V_C is the variance-covariance matrix of $\overline{CAR}$. Since the CAR intervals for different monthly cohorts overlap, we allow for the first- through sixth-order serial covariance of monthly average CAR to be nonzero and set the higher-order serial covariances to equal zero. To be specific,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

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

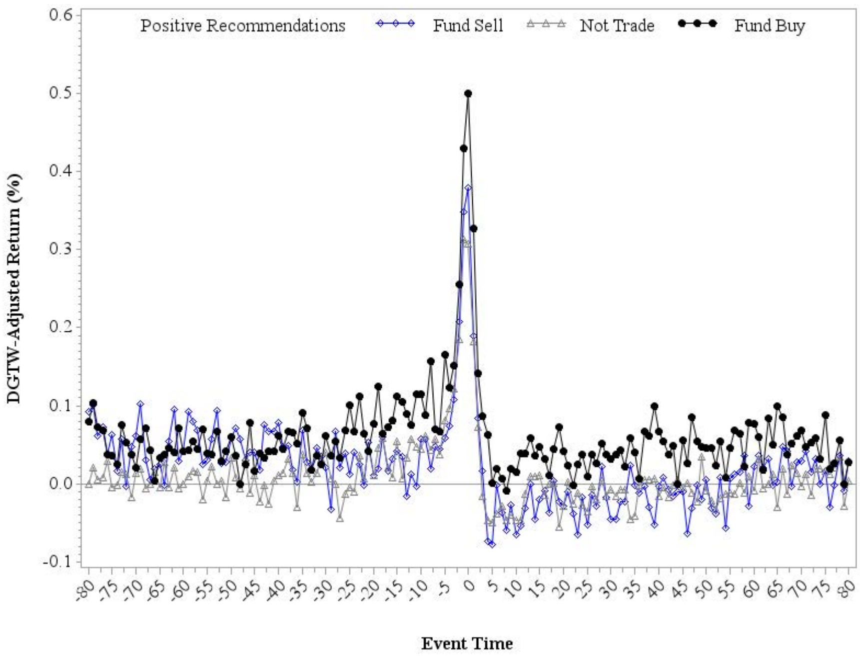
Online Appendix Figures

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

Online 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 (or 2,381 manager-year observations) for which we have the manager votes, whereas the whole CSMAR sample has 7,506 fund-year observations. Total net assets is the average of the total net assets of the fund at the end of each quarter. Annualized turnover ratio is the annual turnover ratio of the fund in that year. Annualized raw return is the raw return of the fund annualized from the average of quarterly returns over the past eight quarters. Annualized flow is the flow of the fund during the year annualized from quarterly flows. Annualized volatility is the annualized standard deviation of the quarterly raw returns of the fund over the past eight quarters.

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

Table A2 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 A3 Return performance around analyst recommendations: controlling for price momentum

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

Pre-recommendation return quintiles	Low		2		3		4		High	
Event window	[-1, 1]	[2, 40]	[-1, 1]	[2, 40]	[-1, 1]	[2, 40]	[-1, 1]	[2, 40]	[-1, 1]	[2, 40]
Fund Buy	1.74	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)