Analyzing the Analysts: Star Rankings and Analysts' Effort Allocation

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We examine the impact of vote solicitation restrictions on the inputs and outputs of sell-side analysts serving the needs of buy-side. We exploit a regulatory change taking place in China's securities market ("Security Analysts Participating in External Selection Standard", "SAPESS" hereafter), to investigate the underlying motives of sell-side analysts' behaviors. SAPESS was implemented in 2019, prohibiting solicitation by sell-side analysts of votes from the buy-side (such as fund managers) counting towards the annual ranking of the sell-side analysts. We find that affected brokerages reduce their spending on business entertainment expenses, sell-side analysts increase the frequency of site visits at companies that they cover, and increase their output of higher-quality industry reports but not company-specific reports. We also document that these changes mainly occur during the period when the voting for star analysts is ongoing. Our findings shed light on analysts' activities that are likely to be considered more valuable by the buy-side.

Keywords: Sell-side analyst, vote-solicitation, industry report, site visit

1. Introduction

A well-established literature on the role of financial analysts in capital markets and the relationship between institutional investors and financial analysts has focused on sell-side analysts catering to buy-side preferences (Jackson, 2005; Gu et al., 2013). Buy-side investors are a key audience of sell-side analysts' work because they are responsible for not only the allocation of trading commission fees to brokerages and analysts, but also voting in annual rankings of sell-side analysts (Stickel, 1992; Brown et al., 2015). Thus, sell-side analysts have a strong incentive to meet buy-side preferences and needs.

In many countries, periodic (usually annual) ranking surveys collect institutional investors' votes to identify sell-side analysts to be bestowed with titles such as "All-Star" or "Star" Analysts. Sell-side analysts who receive such ranking accolades enjoy significant improvements in their compensation and career prospects (Groysberg et al., 2011). In China, New Fortune magazine (hereafter N/F) conducts Star Analysts rankings annually. The base salary for top-ranked Star Analysts in China is around U.S. $1 million, which is extremely high relative to average wages in China (Li et al., 2020). In addition to various quantitative attributes such as earnings forecast accuracy, the voting process also requires assessments of voters' subjective and qualitative judgements about the sell-side analysts, such as their industry knowledge, accessibility, responsiveness, and specialist skills. This subjectivity can lead to vote manipulation, e.g., the voters can nominate those analysts who are close to them, or who transfer more benefits to them, whether observed or unobserved.

A related stream of literature considers analysts' lobbying behavior (Hong & Kubik, 2003). Due to the substantial benefits of being a ranked analyst, it may be tempting for some sell-side analysts and their employing brokerages to spend significant resources to solicit or lobby for buy-side votes by providing them with lavish perks. News stories are regularly reported in the media about such incidents and often draw attention from regulators and investors. In China's recently established capital markets, stories reported in the media sometimes even mention by name the brokerages engaging in or condoning vote solicitation by their analysts (e.g., Zhang, 2017). To the best of our knowledge, there has been no large-sample study on analyst vote-solicitation behavior and its effect on analyst research work to date.

In this paper, we exploit a setting in China involving a regulatory change to the star analyst voting regime to analyze differences in sell-side analysts' behaviors (and their employing brokerages) in response to such changes. The regulatory change was introduced one year after racy videos of analysts from a sell-side brokerage firm partying with a buy-side client went viral around the time of the launch of the 2018 ranking exercise by N/F, giving rise to serious public concern. The scandal was serious enough that the N/F Star Analysts voting was suspended in that year. Responding to this incident, the Securities Association of China (hereafter SAC) referred to "negative public opinion and unfair competitive behavior in the current selection process, which has affected the seriousness, fairness and professionalism of the rankings"[1] and introduced "Security Analysts Participating in External Selection Standard" (hereafter SAPESS) in 2019, which placed explicit restrictions on the soliciting of votes for star rankings by brokerages and analysts.

Consistent with anecdotal conjectures, we find that sell-side analysts conduct more site visits and produce higher-quality industry reports compared to firm reports when vote-solicitation is restricted. We conduct difference-in-differences analyses to differentiate sell-side analysts who are likely to be affected by the introduction of SAPESS (the "suspect" group) versus those less likely to be affected (the "non-suspect" group), and find that the effects

[1] https://www.bqprime.com/amp/china/chinese-brokerages-pull-out-of-scandal-plagued-analyst-contest

observed are entirely attributable to the former group. Moreover, the brokerages where the affected sell-side analysts work also display a pattern of reduced expenditure on entertainment activities following the implementation of the new rule, suggesting that resources were previously utilized at the brokerage level, and not just by individual analysts, to solicit buy-side votes. Further analyses also show that these changes are concentrated on the period when the voting for star analysts is ongoing.

This paper contributes to several streams of literature. First, we provide direct evidence on brokerage-level spending on vote-solicitation. There has only been scant evidence about brokerages' attitudes to analyst rankings. We exploit disclosure rules in China, whereby brokerages are required to disclose *Business entertainment expenditure* separately from other business and management fees when the item reaches certain materiality thresholds. We hand-collect relevant data and we document that brokerages also respond to changes in regulation that *prima facie* are aimed at curbing excesses that are typically ascribed to individual analysts soliciting votes.

Second, we highlight the salient features of sell-side analysts' work which are valued by the buy-side. In a related paper, Lobo et al. (2021) establishes that "star analyst rankings are largely popularity contests that induce analysts to allocate time and effort to attention grabbing and relationship building activities." With the implementation of SAPESS putting a stop to vote-solicitation activities by sell-side analysts and their employers, the resulting re-allocation of analysts' efforts is likely to indicate alternative ways for those analysts to impress their buy-side clients.

The rest of the paper proceeds as follows. Section 2 describes the institutional setting for determining sell-side star analysts ranking based on votes by the buy-side and a brief literature review. Section 3 develops the main hypotheses. Section 4 describes the main data sources and construction of variables used in the analysis. Empirical approaches, main findings and results are discussed in Section 5. Section 6 concludes.

2. Institutional Setting and Literature Review

Sell-side analysts with star analyst status enjoy significantly higher compensation and have greater influence (Groysberg et al., 2011; Jackson 2005), easier access to management (Leone and Wu 2007) and better job mobility (Clarke et al. 2007). In China, sell-side analysts having appeared on prestigious ranking lists for five years or more can earn more than $1 million a year while also-rans with equivalent experience reputedly earn around $75,000 per year.[2] Therefore, sell-side analysts have strong incentives to solicit votes from buy-side investors (Brown et al. 2015).

Similar to the All-Star Analysts ranking in the US, the N/F Star Analyst ranking exercise is the most influential among sell-side security analysts in mainland China. Starting from 2003, N/F has publicly ranked and rewarded top analysts in each industry each year except 2018. The N/F star ranking is considered to be more influential than those of other ranking organizations in China, such as the Crystal Ball ranking run by Capital Week since 2011, or the WIND Gold Medal recognition by WIND financial database since 2013. For example, in 2016, the N/F Contest received votes from more than 4,000 institutional investors while the Crystal Ball Contest collected votes from around 900 fund managers.[3] Each year, around September, N/F invites institutional investors, such as fund managers at mutual funds, insurance asset management companies, bank's fund subsidiary corporations, and asset management departments in brokerage firms, to nominate the top three to five analysts or analyst groups and

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[2] https://www.bqprime.com/china/chinese-brokerages-pull-out-of-scandal-plagued-analyst-contest

[3] The selection of WIND gold medal is based on sell-side analysts' influence on buy-side reflected in number of research reports or reading quantity, which is evaluated by the WIND financial database. There is no voting.

rank them within their industry sectors.[4] The ranking results are based on the sum of weighted votes from thousands of those qualified buy-side investors. The voting process is audited by Deloitte. Prior studies have widely used the N/F ranking results to distinguish the well-known and competitive analysts from others (e.g., Chen and Lu, 2017; Li et al., 2020).

Unsurprisingly, analysts and brokerage firms spend significant resources to cultivate and maintain good relationships with institutional investors who are likely to be invited to cast votes. Anecdotally, it is alleged that some analysts spend at least two months each year conducting large numbers of roadshows (running into triple digits) and treating buy-side investors to extravagant and lavish dinners with the objective of maintaining good relationships and obtaining their votes (Ying 2018). On September 18, 2018, a video clip was posted publicly online showing a dinner party at a high-end restaurant where a female analyst and a male fund manager seemed to hug and kiss inappropriately. After the release of the video, there was a rush of exodus from the N/F Contest by many high-profile brokerages seeking to distance themselves from such questionable practices, and N/F announced the suspension of the contest for that year on September 21, 2018.

In 2019, the N/F Contest restarted with a new self-regulatory selection rule, SAPESS, which was announced by SAC on October 8, 2019. Compared to the previous selection rules, SAPESS has two distinct elements. First, Article 12 of SAPESS stipulates stricter details about voting solicitation behaviors that are explicitly forbidden. For example, analysts and brokerages are prohibited from publishing or sending vote-solicitation information in the form of emails or various social media platforms such as WeChat or Weibo. Second, Article 15 of SAPESS prohibits brokerages from using the ranking system as a basis for analysts' salary

[4] In practice, the exact number of nominations varies with the number of signed-up analyst groups. For industries having more than 20 groups of candidates, voters usually rank top five analysts. For smaller industries, voters usually rank top three analysts.

incentives. Key provisions of SAPESS are summarized in Appendix A.

The introduction of SAPESS was intended to link votes for analysts' rankings to their true ability and performance rather than their vote solicitation efforts. The consequences of implementing such a rule give rise to several interesting empirical questions that we explore in this paper.

3. Hypothesis Development

Given the importance of appearing on a prestigious ranking list such as the N/F Star Analysts, especially in terms of job promotion and substantial compensation benefits (Li et al., 2020), we would expect analysts to devote substantial energy and resources to securing a rank. In the absence of any specific prohibition against canvassing or lobbying, it is believed that certain analysts engage extensively in vote solicitation during the voting period.

Since the implementation of SAPESS makes explicit the SAC restrictions on vote-solicitation activities and thus increases litigation risk of lobbying, the vote-solicitation behaviors would correspondingly be restricted. Therefore, the affected analysts' resources and time could be freed from vote-solicitation activities such as lavish dining, holding events, providing free travel perks, and other entertainment of buy-side managers. The suspected analysts' employing brokerages' expenditure on business entertainment would be expected to decrease following the implementation of SAPESS.

However, although SAPESS restricts sell-side analysts' vote solicitation, monitoring analysts' full-time behavior could be too costly to implement. Therefore, the SAPESS regulation and N/F rule change might not effectively prevent vote-solicitation activities, and thus the suspected analysts' employing brokerages' vote-solicitation expenditure may not change significantly following the implementation of SAPESS. Thus, we propose the following alternative hypotheses:

H1(a): The reduction in expenditure on business entertainment following the implementation of SAPESS is higher for brokerages that employ suspected analysts.

H1(b): The expenditure on business entertainment following the implementation of SAPESS is no different for brokerages that employ suspected analysts and those that do not.

The introduction of SAPESS in China also provides an opportunity to test how sell-side analysts reallocate their efforts when they are prohibited from engaging in lobbying. If suspected analysts engage in less vote-solicitation activities because of the implementation of SAPESS, resources and time would be saved from vote-solicitation. Besides, when vote-solicitation is restricted but being ranked as a Star Analysts is still highly desirable, achieving a N/F star analyst ranking should reflect more of the ranking's original intention, namely, to reward analysts who have conducted the best research during the past year. Therefore, suspected analysts could reallocate time and resources to activities that improve their research output after the implementation of SAPESS. Hence, we formulate our second hypothesis as follows:

H2: Following the introduction of SAPESS, the efforts to improve research output by suspected vote-soliciting analysts increase more than those by non-suspected vote-soliciting analysts.

When SAPESS-affected sell-side analysts reallocate time and resources saved from restricted vote-solicitation to conducting site visits, they may direct their efforts towards the most worthwhile information mining and collection, which would reflect their preference between more micro firm information and more macro industry information, which would in tun be reflected in the report quality of firm reports versus industry reports published by those analysts. In surveys, buy-side investors and analysts consistently rank industry knowledge as the most important sell-side research attribute (Bradshaw, 2012). Therefore, SAPESS-affected analysts are likely to work harder on increasing their industry knowledge, which would then be reflected in improved quality of their industry reports. Thus, we hypothesize that:

H3: The increase in research quality of suspected vote-soliciting analysts following the implementation of SAPESS is higher for industry reports compared to firm-level reports.

4. Sample Description and Variable Construction

4.1 Data Sources

To identify the suspected analysts who are more likely to solicit votes for N/F star analyst ranking, and would therefore be more likely to be affected by SAPESS than other analysts, we obtain media news reports covering analysts' vote-solicitation behaviors with their brokerage names from Google and Chinese mainstream media including Caixin, Sina Finance, YiCai, Jiemian, and JC Economic Information. In addition, to identify star analysts, we collect N/F Star analyst name list for each year from N/F official website.

We obtain the initial brokerage-year and analyst-year samples with fundamental data from WIND and CSMAR databases, which are COMPUSTAT-style databases and widely used in China studies. The vote-solicitation cost variable is constructed based on manually collected data from brokerages' annual reports, which were initially downloaded from WIND, and complemented by each brokerage's official website. The time range is set between 2012 and 2021, we start from 2012 because brokerage's disclosure about vote-solicitation cost is relatively sparse before 2012. In robustness checks, we exclude observations from 2019, the year in which SAPESS was introduced and implemented.

The analysts' firm and industry in-depth reports are downloaded from a commercial data provider, Datayes. The time ranges are set to 2016-2018, and 2020-2021, because reports in Datayes before 2016 are relatively incomplete and untagged, and we exclude the SAPESS implementation year 2019 because data collection from Datayes is non-trivial. Datayes tags the report characteristics including issue date, analyst name, brokerage, recommendation rating, report type, target industry and target firm (if applicable) for each report. We make use of Datayes if the variable data are available. If the report characteristics information is missing from Datayes, we parse the report PDF file and extract the report characteristics by searching related keywords, and manually check the extracted information to minimize the possibility of making mistakes. The textual data cleaning process is described in more detail in Appendix C.

4.2 Variable Construction

To measure the effectiveness of SAPESS on brokerages and how sell-side analysts react to the implementation of SAPESS, we introduce the following variables.

(1) Cost

Cost represents each brokerage's expenditure on vote-solicitation activities. In China, brokerages disclose *Business entertainment expenditures* in a footnote when the item reaches materiality thresholds within Business and Management Fees (usually when the amount is no less than the top 10 items contained in the Business and Management Fees). We hand-collect the amount of the item *Business entertainment expenditures* ("ye wu zhao dai fei") in each brokerage's footnotes to their financial filings. *Business entertainment expenditures* contain the entertainment expenses at the brokerage level and is likely to include expenditure on analyst vote-solicitation activities. *Cost* is the log value of *Business entertainment expenditures*.

(2) Post

Post captures the effect of implementation of SAPESS. For sample years equal to or later than 2019, we set *SAPESS* =1. For sample year earlier than 2019, we set *SAPESS* = 0.

(3) Treat

To identify analysts who are more likely to be affected by SAPESS than other analysts, we use two dummy variables to indicate "suspect" analysts, i.e., those who are more likely to solicit votes for N/F Star Analyst ranking contest.

First, we investigate the implications of N/F star voting results. Analysts who have hopes of winning star status but have not yet established their capability and reputation relative to their competitors are viewed as likely vote-solicitors. According to industry anecdotes, analysts or analyst groups who can continuously win first place in the N/F Star Analyst ranking are viewed as outstandingly knowledgeable[5]. Since those analysts can top the star ranking and are acknowledged by the industry with their own outstanding knowledge and output, they should be relatively less motivated to solicit votes than other star winners. Furthermore, for analysts who have very little hope of being ranked star analysts, soliciting votes would be too costly to execute. Therefore, we use *Treat_star* to represent those analysts who successfully become the N/F Star Analyst but cannot continuously win first place of N/F Star Analyst ranking. In brokerage-level tests, we set *Treat_star* =1 for brokerages that employ analysts who win the star ranking during the fiscal year but cannot continuously win first place in N/F Star Analyst ranking, and *Treat_star* =0 otherwise. In analyst- and report-level tests, we set *Treat_star* =1 for analysts or report authors who win the star in the fiscal year but cannot continuously win first place in N/F Star Analyst ranking, and *Treat_star* =0 otherwise.

Second, we investigate the evidence recorded by news media. Brokerages and their employed analysts that have been reported by media as soliciting votes for N/F star analyst ranking are viewed as suspected vote-solicitors. We collect 56 pieces of media reports documenting sell-side analysts vote-solicitation activities along with their brokerages' names.

[5] For example, the analyst group for medicine and biology industry employed by Xinye Securities have long been ranked as the first place in the corresponding division of N/F star contest. This group of analysts had such high reputation that N/F kept the first place vacant rather than give it to other analysts when Xinye medicine and biology group of analysts were unable to participate in the ranking in 2021 for alleged violation of some political issues unrelated to the ranking process.

Therefore, we set *Treat_media* =1 for brokerages and their employed analysts that have been reported as participating in vote-solicitation activities by media, and *Treat_media* =0 otherwise.

(4) Effort

Effort represents each analyst's effort in his/her research work. We use the log value of each analyst's number of onsite and virtual site visits conducted in each fiscal year. In robustness checks, we consider only on-site site visits, *Effort_onsite*.

(5) Quality

Quality represents each analyst's research report quality. Since analysts in China are sometimes found to plagiarize other analysts' work, directly analyzing the content itself without comparison with other published reports would lead to bias (Chen et al, 2022). Also, among all sub-types of analyst reports including in-depth, short comments, news comments and regular reports, in-depth reports display the most analysts' knowledge. Therefore, we implement the methodologies in Hanley and Hoberg (2010) and Loughran and McDonald (2014) to perform textual analysis and calculate informativeness of each in-depth report, which is captured in the variable *Quality*.

Hanley and Hoberg (2010) provide a methodology to decompose a report's content into normatively standard and informative parts. The standard part can be interpreted as the degree to which an analyst report simply borrows or copies textual elements from related reports published previously. Referring to Hanley and Hoberg (2010), we can use the calculated informative content to quantify each report's excess information that cannot be explained by standard content factors. A description of how we process analyst report PDFs and count words for each report is provided in Appendix C.

We denote $words_{tot,i}$ as the words' vector for each report i to store words and wordcounts. We then normalize this vector to control for the size of the underlying report by dividing each count by the sum of all words' counts to get $norm_{tot,i}$. Note that word vectors for all analyst reports have the same length within the firm or industry type, as all words' vectors are based on the same global words list within the firm or industry type.

According to Hanley and Hoberg (2010), the standard content of an analyst report is related to (1) words used in other concurrent analyst reports, and (2) words used in other analyst reports covering the same industry for industry report or firms in the same industry for firm report. Hence, to estimate each report i's exposure to the content of other recently issued reports, we calculate the variable $norm_{rec,i}$, which is the average of the normalized content word vectors for the analyst reports that were issued in the 90 days preceding report i's issue date. The formula for $norm_{rec,i}$ is given by:

$$norm_{rec,i} = \frac{1}{k}\sum_{k=1}^{k} norm_{tot,k}$$

Similarly, to estimate the second component of the standard information content, the variable $norm_{ind,i}$ is calculated as the average of the normalized content word vectors for the analyst reports that were covering the same industry as report i covers, and were issued before the 90-day window but no later than 365 days to ensure the content do not overlap with the first standard information component. The formula for $norm_{ind,i}$ is given by:

$$norm_{ind,i} = \frac{1}{p}\sum_{p=1}^{p} norm_{tot,p}$$

For each analyst report, we then run the following first-stage regression in which one observation is one word:

$$norm_{tot,i} = \alpha_{rec,i}\, norm_{rec,i} + \alpha_{ind,i}\, norm_{ind,i} + \epsilon$$

The standard content variable is defined as follows:

$$\alpha_{standard,i} = \alpha_{rec,i} + \alpha_{ind,i}$$

$\alpha_{standard,i}$ measures the relative loading of standard content, and its interpretation is the proportion of standard words in analyst report i. The content not explained by standard content sources is the vector of the absolute value of the residuals, which is defined to be informative content. The informative content of report i is calculated as the sum of the absolute values of the residual calculated for each word, and $Quality$ takes the natural logarithm value of the informative content to better capture the change percentage in regression tests:

$$Quality = \ln\left(\alpha_{informative,i}\right) = \ln\left(\sum_{i} |\epsilon|\right)$$

(6) Control Variables

Based on prior studies, we include a range of controls that may explain our dependent variables. Appendix B provides definitions of all variables used in the paper. In brokerage-level tests, we control for brokerage characteristics and brokerages' in-service analysts' statistics (Jiang et al., 2016; Gu et al., 2019; Do and Zhang, 2020; Chiu et al., 2021; Coleman et al., 2022). We control star analyst number *StarNumber* to control peer pressure within a brokerage.

Given that the N/F star analyst ranking invites not only mutual fund managers, but also hedge fund, insurance managers, and other kinds of institutional investors, who would vote for star analysts and allocate commission fee to analysts, the total amount of commission fee is indicative of the business and revenue scale of brokerage firms that can be important sources supporting the reported entertainment fee. Therefore, we control for the total commission fee brokerage received.

In addition, we control for brokerage size (*BrokerSize*), merges and acquisitions (*MA*), and average values of in-service analysts' forecast numbers (*Mean_ForecastFreq*), working experience (*Mean_Experience*), sex ratio (*Maleratio*), and education (*Education*) for each brokerage in fiscal year *t*.

In analyst-level tests, we control both analyst and brokerage characteristics mostly the same as the brokerage level design by replacing mean value of analyst characteristics as the characteristics of the individual analyst. We exclude *MA* and *Commissionfee* which are aimed at controlling noise in *Cost* but are not directly related to *Effort*. Furthermore, we include the average value of analyst's covering firm size to control for firm size effect on *Effort* (Chan et al., 2019) and we use individual analyst forecast frequency to replace the brokerage mean value of revision time to control for analyst forecast report amount effect on *Effort*.

In analyst report-level tests, we basically follow the analyst-level design to include all the control variables that would not be omitted because of analyst fixed effect. Besides, we follow prior studies to control report length *Page* and report content sentiment *Tone* (De Franco et al., 2015).

5. *Research Design and Empirical Results*

5.1 Brokerage vote-solicitation cost

To test the impact of vote-solicitation restriction on brokerage and analyst behavior, we first conduct the difference-in-differences regression model (1) below to measure the effectiveness of SAPESS on effected brokerages' vote-solicitation spending for N/F star analyst ranking competition:

$$Cost_{i,t} = a + \beta_1 Post_{i,t} \times Treat_{i,t} + \beta_2 Post_{i,t} + \beta_3 Treat_{i,t} + \sum \mu Controls_{i,t} +$$

$$\sum \mu Brokerage_i + \sum \mu Year_t + u_{it} \tag{1}$$

The regression includes brokerage fixed effects and year fixed effects to control for any alternative explanations pertaining to static differences between brokerages and static differences between different fiscal years. We winsorize all continuous control variables at the top and bottom 1% to reduce the effect of extreme observations. To control for potential correlations among the residuals, we calculate clustered standard errors by brokerage (Petersen, 2009). The expected coefficient for β_1 is negative if hypothesis H1(a) is not rejected, or is not different from 0 if hypothesis H1(b) is not rejected.

Table 1 shows the descriptive statistics for the base sample. Panels A, B and C document the descriptive statistics for brokerages, analysts, and analysts' reports, respectively. We set the same time window, fiscal year, for *Commissionfee* and *Cost*. Also, because not only mutual fund managers, but also all other buy-side investors as clients are potential voters for star analysts, we include the natural logarithm value of total commission fee received by the brokerage, which has reasonably larger average value than the commission fee measure used by previous studies focusing on mutual fund managers (Gu et al., 2019). In panel A of Table 1, *StarNumber* shows that more than half of the brokerages in the sample do not employ star analysts, and star analysts are relatively concentrated in a few brokerages (Coleman et al., 2022). *Education* distribution shows that the majority of financial analysts have Masters or PhD degree.

About one half of the brokerages in the sample provide services for mergers and acquisitions, which could add noise to brokerage-level business entertainment expenditures and should be controlled for in the regression. The mean value of *Mean_ForecastFreq* is around 32 times per year and has similar distribution as prior studies (Li et al., 2020). The mean value of the average analysts' experience is around 13 quarters, also similar to prior studies

(Chiu et al., 2021; Coleman et al., 2022). *BrokerSize* has similar distribution as prior literature (Gu et al., 2019). The mean and median value of *Maleratio* in sample brokerage is higher than 0.5 but lower than 0.8, which indicates that the analyst gender majority in China is male, but female proportion is relatively higher than in the U.S., consistent with prior literature (Li et al., 2020). Hence, we are unlikely to encounter selection bias in our sample.

Panel B of Table A shows descriptive statistics at the analyst level. The indicator variables for suspected analysts (i.e., those likely to be affected by the ranking exercise), *Treat_media* and *Treat_star,* follow similar distribution as the sample for the brokerage-level analyses. The mean value of *Treat_star* is lower than brokerage-level *Treat_star*, because *Treat_star* is based on analysts and more accurate when used at individual analyst level. Also, the mean value of *Treat_media* is higher than brokerage-level *Treat_media*, because *Treat_media* is based on brokerages that employ analysts and is somewhat more accurate when used at the brokerage level. The analysts and brokerages characteristics distributions are similar to those in brokerage-level tests. The analysts' covered firm size has similar distribution as prior studies (Chan et al., 2019). The analyst forecast frequency represents the number of analyst report that contains earnings forecast, the mean value of which is around 44, indicating that analysts publish a report containing earnings forecast around every 8 days on average.

Panel C of Table 1 shows the descriptive statistics for the base sample. The mean and median value of *Tone* is higher than 0.6, indicating that a majority of analyst reports contain positive sentiment, consistent with the well-known analysts' optimism phenomenon (e.g, Huang et al., 2014). The mean values of *ForecastFreq* and *Experience* are higher than the mean values in the analyst-level samples, indicating that in-depth reports come from analysts who are relatively more active and experienced.

We first examine the changes in brokerage vote-solicitation expenses upon SAPESS implementation for suspected vote-solicitation brokerages, compared to other brokerages. Panel A of Table 2 presents coefficient estimates of equation (1) for different *Treat* proxies and cluster options using the full sample. Column (1) shows the results without control variables. The coefficients on the interaction term are significantly negative. For example, *Treat_star* × *Post* in column (2) is -0.196, indicating that the incremental decrease in *Cost* for an average suspected vote-soliciting brokerage represents 17.80% of the pre-SAPESS level. This evidence supports our argument that suspected brokerages solicit votes for N/F star analyst ranking before SAPESS and spend less on entertaining their clients after restriction on vote-solicitation. Column (6) and (7) drop the year in which SAPESS first took effect. The implications are the same as in Column (2).

Apart from the coefficient of *Treat*×*Post*, we observe that *BrokerSize* and *Commissionfee* are positively correlated with *Cost*, which suggests that larger brokerages and brokerages that receive more commission fee have more resources and greater need to solicit votes. *Maleratio* is negatively correlated with *Cost*, which suggests that women are more likely than men to engage in vote-solicitation as a way of private activism (Coffé & Bolzendahi, 2010). *Mean_Experience* is negatively correlated with *Cost*, indicating that brokerages with more experienced analysts have less motivation to solicit votes.

One important assumption for the interpretation of the difference-in-differences estimates is the parallel trends assumption – both treatment and control brokerages would have exhibited a similar trend in *Cost* spending without the treatment effect (SAPESS implementation). While we cannot test this counterfactual, we follow the *Cost* and examine the pre-trend. To do so, we generate indicator variables, *Year2012*, *Year2013*, *Year2014*, *Year2015*, *Year2016*, *Year 2017*, *Year2019*, *Year2020*, *Year2021*, which take the value of 1 for the year 2012, 2013, 2014, 2015, 2016, 2017, 2019, 2020, 2021. Year 2018 is excluded because not any analyst wins a star that year so that no analyst is suspected to solicit votes for all samples and interaction term *Treat_star* × *Year2018* would be omitted in the regression. Accordingly, we exclude samples in year 2018 for estimation. In all specifications, we include brokerage level control variables, brokerage and year fixed effects, and cluster standard errors at the brokerage and year level.

Panel B of Table 2 presents the results. In column (1), we find that the coefficient on *Treat_star* × *Post* remains negative and statistically significant at 5% level. In addition, the coefficients on the interaction terms of *Treat_star* with all previous years' indicators are statistically insignificant, which implies that there is no difference in *Cost* spending between treatment and control brokerages and supports the parallel trend assumption. Column (2) provides the results of dynamic effects, where we replace *Treat_star* × *Post* by *Treat_star* × *Year2019*, *Treat_star* × *Year2020*, and *Treat_star* × *Year2021*, we find that the three interaction terms are negative, and statistically significant for *Treat_star* × *Year2020*, and *Treat_star* × *Year2021*, of which one interesting pattern is that the magnitudes and statistical significance of the coefficients are increasing. This is presumably because the enforcement and effect of SAPESS may have gradually increased overtime. Overall, the results suggest that the effects in vote-solicitation spending are persistent over the post period.

5.2 Analyst site-visit effort

If suspected analysts engage in less vote-solicitation activities because of the implementation of SAPESS, resources and time would be saved from vote-solicitation. Besides, when vote-solicitation as a shortcut to gain star analyst status is restricted, winning N/F Star Analyst ranking should depend more on the ranking's original intention, i.e., to reward analysts who are good at research. Therefore, suspected analysts are hypothesized to reallocate time and resource to activities that improve their research output after the implementation of SAPESS. Prior studies have found that site visits and private communication with covered firms provide more useful inputs to analysts than openly available information (Brown et al., 2015; Cheng et al., 2016; Han et al., 2018). Hence, we introduce the following test to examine the effect of SAPESS on suspected analysts' research efforts:

$$Effort_{i,t} = a + \beta_1 Post_{i,t} \times Treat_{i,t} + \beta_2 Post_{i,t} + \beta_3 Treat_{i,t} + \sum \mu Controls_{i,t} + \sum \mu Analyst_i + \sum \mu Brokerage_i + \sum \mu Year_t + u_{it} \quad (2)$$

The expected coefficient for β_1 in the model (2) is expected to be positive if hypothesis H2 is not rejected. The regression includes analyst fixed effect, brokerage fixed effects, and year fixed effects to control for alternative explanations pertaining to static differences between different analysts, brokerages, and fiscal years. We winsorize all continuous control variables at the top and bottom 1% to reduce the effect of extreme observations. To control potential correlations among the residuals, we calculate clustered standard errors by analyst, and calculate additional clustered standard errors by brokerage for robustness check (Petersen, 2009).

We examine the changes in analyst research effort upon SAPESS implementation for suspected vote-soliciting analysts, compared to other analysts. Panel A of Table 3 presents coefficient estimates of equation (2) on *Effort_OnSite* for different *Treat* proxies and cluster options using the full sample. The coefficients on the interaction term *Treat_star* × *Post* and *Treat_media* × *Post* are significantly positive. Column (1) reports the regression results without control variables, the coefficient of *Treat_star* × *Post* is 0.136, indicating that the incremental increase in on-site visit for an average suspected vote-soliciting analyst represents 14.57% of the pre-SAPESS level. In Column (4) to (6), we can observe that after adding control variables, controlling analyst, brokerage and year fixed effects and cluster effects on analyst and brokerage, the incremental increase in on-site visit for an average suspected vote-solicited analyst represents 19.72% of the pre-SAPESS level. This evidence supports our argument that suspected analysts solicit votes for N/F star analyst ranking before SAPESS and put more effort into research works after restriction on vote-solicitation.

Apart from the coefficient of *Treat×Post*, we observe that *BrokerSize* is positively correlated with *Effort_OnSite*, consistent with larger brokerages employing larger numbers of analysts who conduct more site visits. *CoverFirmSize* is negatively related to *Effort_OnSite*, suggesting that larger covered firms have more information available publicly, this analysts have less necessity to conduct on-site visits or, alternatively, that covering large firm occupy relatively more of analysts' time and resources, leaving them with less ability to conduct on-site visits when covering larger firms. *ForecastFreq* is positively correlated with *Effort_OnSite*, consistent with the idea that higher forecast frequency requires more timely information that can be gained from conducting site visits. As for *Gender* and *Master*, both are positively correlated with *Effort_OnSite*, which may reflect the fact that women are typically more homebound with housework duties than men and therefore have less time to conduct site visits at the covered firms (Du, 2021), and that analysts with masters and higher degrees work harder than bachelors. Lastly, *Experience* is negatively correlated with *Effort_OnSite*, indicating that more experienced analysts have more knowledge and understanding of the covered firm and the industry, and do not need to spend as much effort on site visits as more junior, less experienced analysts.

One important assumption for the interpretation of the difference-in-differences estimates is the parallel trends assumption – both treatment and control analysts would have exhibited a similar trend in site visit efforts without the treatment effect (SAPESS implementation). While we cannot test this counterfactual, we follow the *Effort_OnSite* and examine the pre-trend. To do so, we generate indicator variables, *Year2012*, *Year2013*, *Year2014*, *Year2015*, *Year2016*, *Year 2017*, *Year2019*, *Year2020*, *Year2021*, which take the value of 1 for the year 2012, 2013, 2014, 2015, 2016, 2017, 2019, 2020, 2021. Year 2018 is excluded because not any analyst wins a star that year so that no analyst is suspected to solicit votes for all samples and interaction term *Treat_star* × *Year2018* would be omitted in the regression. Accordingly, we exclude samples in year 2018 for estimation. In all specifications, we include analyst level control variables, analyst, brokerage and year fixed effects, and cluster standard errors at the brokerage and analyst level.

Panel B of Table 3 presents the results. In column (1), we find that the coefficient on *Treat_star* × *Post* remains positive and statistically significant at 1% level. In addition, the coefficients on the interaction terms of *Treat_star* with all previous years' indicators are statistically insignificant, which implies that there is no difference in site visit efforts between treatment and control analysts and supports the parallel trend assumption. Column (2) provides the results of dynamic effects, where we replace *Treat_star* × *Post* by *Treat_star* × *Year2019*, *Treat_star* × *Year2020*, and *Treat_star* × *Year2021*, we find that the three interaction terms are positive and statistically significant in 5% level or better, of which one interesting pattern is that the magnitudes and statistical significance of the coefficients are increasing. This is presumably because the enforcement and effect of SAPESS may have gradually increased overtime. Overall, the results suggest that the effects in analyst site visit efforts are persistent over the post period.

In Table 4, we present results using three different proxies for *Effort*. For concerns of noises in the SAPESS implementation year, we exclude samples of 2019, which would not change the implication of results when included. Column (1) and (2) use *Effort_VisitN* as dependent variable, and Column (5) and (6) use *Effort_Onsite* as dependent variable. The coefficients on the interaction *Treat_star* × *Post* in the regressions show that the incremental increase in site visits for an average suspected vote-soliciting analyst represents more than 10% of the pre-SAPESS level. Column (3) and (4) use *Effort_StockN* as dependent variable, and the coefficients of the interaction *Treat_star* × *Post* show that the incremental increase in site visits for an average suspected vote-soliciting analyst represents about 15.84% of the pre-SAPESS level. The coefficients of *Treat_media* × *Post* are also significantly positive.

5.3 Analyst report quality

While SAPESS-affected sell-side analysts allocate time and resources saved from restricted vote-solicitation to conduct site visits, they may also direct their efforts to more worthwhile information mining and collection, and reflect their preference between producing more micro firm information or more macro industry information, and also the informative portion of firm reports versus industry reports. In surveys, buy-side managers and analysts consistently rank industry knowledge as the most important sell-side research attribute (Bradshaw, 2012). Therefore, SAPESS-affected analysts are hypothesized to work harder on digging out industry knowledge, which could be reflected in increased quality of industry reports.

We run the following test for two separate samples of sell-side analyst outputs: in-depth industry reports and in-depth firm reports. We expect that the coefficient for β_1 for industry reports should be higher than β_1 for firm reports if hypothesis H3 is not rejected.

$$Quality_{i,t} = a + \beta_1 Post_{i,t} \times Treat_{i,t} + \beta_2 Post_{i,t} + \beta_3 Treat_{i,t} + \sum \mu Controls_{i,t} + \sum \mu Analyst_i + \sum \mu Brokerage_i + \sum \mu Industry_i + \sum \mu Year_t + u_{it} \quad (3)$$

We examine the changes in analyst report informative content (Hanley and Hoberg, 2010) upon SAPESS implementation for suspected vote-soliciting analysts, compared to other analysts, and the difference in informative content changes between industry report and firm report. Table 5 presents coefficient estimates of equation (3) on *Quality* for different *Treat* proxies and fixed effect combinations using industry in-depth reports and firm in-depth reports. Columns (1) to (4) present results without control variables, and the interaction coefficients' differences indicate that, compared to firm reports, the incremental increase in industry reports' *Quality* for an average suspected vote-soliciting analyst represents at least 2% of the pre-SAPESS level. Column (5) to Column (8) present results with control variables, with the coefficient of the interaction term *Treat_star* × *Post* indicating that the incremental increase in industry report *Quality* for an average suspected vote-soliciting analyst represents 3.25% of the pre-SAPESS level.

One important assumption for the interpretation of the difference-in-differences estimates is the parallel trends assumption – both treatment and control analysts would have exhibited a similar trend in report quality without the treatment effect (SAPESS implementation). While we cannot test this counterfactual, we follow the *Quality* and examine the pre-trend by industry and firm report type subtype. To do so, we generate indicator variables, *Year 2017*, *Year2020*, *Year2021*, which take the value of 1 for the year 2017, 2020, 2021. Year 2018 is excluded because not any analyst wins a star that year so that no analyst is suspected to solicit votes for all samples and interaction term *Treat_star* × *Year2018* would be omitted in the regression. Accordingly, we exclude samples in year 2018 for estimation. In all specifications, we include analyst and report level control variables, Industry and year fixed effects, and cluster standard errors at the brokerage, year, industry and analyst level.

Panel B of Table 5 presents the results. In column (1), we find that the coefficient on

Treat_star × *Post* for industry report remains positive and statistically significant at 5% level. In addition, the coefficients on the interaction terms of *Treat_star* with *Year2017* are statistically insignificant, which implies that there is no difference in analyst industry report *Quality* between treatment and control analysts and supports the parallel trend assumption. Column (2) provides the results of dynamic effects on industry report *Quality*, where we replace *Treat_star* × *Post* by *Treat_star* × *Year2020* and *Treat_star* × *Year2021*, we find that the two interaction terms are positive and statistically significant at 10% level or lower. However, the coefficient on *Treat_star* × *Post* in Column (3), and the coefficients of *Treat_star* × *Year2020* and *Treat_star* × *Year2021* in Column (4) for firm report are statistically insignificant, which indicates that SAPESS has a limited effect on firm report *Quality*. Overall, the results suggest that the effects in analyst industry report Quality are persistent over the post period, and analyst industry report *Quality* between treatment and control analysts supports the parallel trend assumption.

5.4 Voting period tests

According to New Fortune voting rules and Chen and Lu (2020), each year from August to October, New Fortune magazine would organize the N/F Analyst competition and collect votes from registered voters for each registered analyst and analyst group. Intuitively, vote-solicitation activities are supposed to arise most frequently around or during the voting period before being restricted by regulation. In this section, we examine this inference by demonstrating that the effects of SAPESS separately for the voting period and non-voting period. Specifically, we explore whether the decrease in vote-solicitation cost, increase in analyst effort, and increase in analyst industry report quality for suspected vote-solicitation brokerages and analysts mainly occur around or during voting periods after SAPESS implementation.

5.4.1 Brokerage vote-solicitation cost

Since scarcely do brokerage disclose their *Cost* by month or by quarter, to feasibly test whether the decrease in vote-solicitation *Cost* mainly exist around or during voting periods after SAPESS implementation, we manually recollect data of *Cost* from each brokerage's notes to the semiannual financial report as the First half year's *Cost*, and the Second half year's *Cost* equals to the *Cost* disclosed in the annual report minus the First half year's *Cost*. Because not every brokerage discloses *Business entertainment expenditures* in their semiannual financial reports, our sample size is decreased to 121 for both half year. Accordingly, we partition our sample into First half year and Second half year and then rerun equation (1) for each subsample separately.

We present the estimation results in Table 6. Same as the calculation for dependent variable *Cost* in Table 2, we first collected the value of *Business entertainment expenditures* for each half year of each brokerage, and then calculate the log value of *Business entertainment expenditures* as *Cost*. Therefore, economic significance of all coefficients can be interpreted in the same manner as described in the previous section. We use *Treat_media* as *Treat* variable because media coverage for brokerages' vote-solicitation captures the brokerage-level vote-solicitation behaviors more directly than suspected analysts' inference of suspected brokerage. We test the difference by comparing the coefficients of interaction term *Treat* × *Post* between Second half year and First half year subsamples. We find evidence supporting the argument that the decrease in vote-solicitation cost after SAPESS implementation for suspected brokerage mainly exists in the Second half year, when N/F organizes voting for star analysts.

The coefficient on the interaction term *Treat* × *Post* is more negative and only statistically significant at 1% level during Second half year. Differences between two subsamples are statistically significant at the 10% level, and the decrease percentage in vote-solicitation cost after SAPESS implementation for suspected brokerage in the Second half year is 24 times ((1-$e^{-0.410}$) /(1-$e^{-0.014}$)) as large as for the First half year. The results strengthen our inference that the effectiveness of SAPESS on brokerage vote-solicitation activities mainly take effects during voting period.

5.4.2 Analyst site-visit effort

We explore whether the increase in site-visit effort for suspected vote-solicitation analysts mainly exists around or during voting periods after SAPESS implementation. We recalculate analyst on-site visit times during the First half year and Second half year respectively, to compare the aggregate on-site visit times change in two periods with similar duration.

We estimate equation (2) for each subsample and present the estimation results in Table 7. Across the board, the results provide support for our inference that before the implementation of SAPESS, analysts spend time and resources on vote-solicitation during star analyst voting period to enhance the chance of winning the competition, however, as SAPESS came into effect, analysts reallocate their effort from soliciting votes to do more site visits. The coefficient on the interaction term *Treat* × *Post* is only positive and statistically significant at 1% level during Second half year. Differences between two subsamples are statistically significant at the 1% level, and the increase in site visit times after SAPESS implementation for suspected analyst in the Second half year is 26% of the site visit times in the Second half year during pre-SAPESS period. The results strengthen our inference that the effectiveness of SAPESS on analyst research work efforts mainly take place during voting period.

5.4.3 Analyst report quality

Given that the suspected analysts reallocate their resources and time from vote-solicitation activities to research work, we should expect to observe an increase in report quality, especially in the industry report, which contains more industry knowledge valued by buy-side clients. Therefore, we partition our analyst report samples according to whether the report is released in the voting period. In other words, report released from August to October are considered as voting period subsample, otherwise, the report is considered as non-voting period subsample. Consistent with the prior section, we rerun the equation (3) by report type and releasing period as four groups of subsamples, and the results are presented in Table 8.

Across the board, the results provide support for our inference that after the implementation of SAPESS, analysts reallocate their effort from soliciting votes to do more site visits and result in acquiring more industry knowledge. Comparing with the report released during voting period before SAPESS, the industry reports released during voting period after SAPESS have higher quality. The coefficient of the interaction term *Treat* × *Post* is only positive and statistically significant at 5% level for industry report during voting period after SAPESS. The increase in industry report quality after SAPESS implementation for suspected analysts in the voting period is 6% of the industry report quality in the voting period before SAPESS came into effect. Differences between industry reports released during the voting period and other subsamples are statistically significant at the 5% level, except for firm reports during non-voting period, with which difference is positive but not statistically significant. Overall, the results strengthen our inference that the suspected analysts reallocate their effort after SAPESS implementation and generate higher quality industry reports containing more industry knowledge during voting period.

5.5 Robustness check

Prior literature has established the job promotion and substantial compensation benefits of wining star analyst competition in analyst level (Groysberg et al., 2011; Li et al., 2020). In this section, we test a fundamental hypothesis for vote-solicitation incentive in brokerage level. One of the possible explanations for brokerages' willingness in paying for star analyst vote-solicitation is that vote-solicitation can increase possibility of wining star, and brokerage with more star analysts can attract higher commission fee from buy-side clients. Therefore, we implement tests to examine whether higher vote-solicitation cost led to higher star analyst ratio in the brokerage, and whether brokerage with more star analysts can receive more commission fee.

To begin with, we estimate the following regression model:

$$StarRatio_{i,t} = a + \beta_1 Cost_{i,t} + \sum \mu Controls_{i,t} + \sum \mu Brokerage_i + \sum \mu Year_t + u_{it} \quad (4)$$

Where *StarRatio* is the star analyst portion among all the analysts in each brokerage *i* as of year *t*. *Cost* uses the same definition as the log value of *Business entertainment fee* as used in prior sections. We include the same set of control variables as in equation (1), except for *BrokerSize*, which is contained in the dependent variable as the denominator.

Established on the prior section's suspected vote-solicitation brokerage indicator *Treat*, we expect β_1 to be positive and this positive relation between *Cost* and *StarRatio* only exists for suspected vote-solicitation brokerage. Therefore, we partition our sample by the value of *Treat*, to observe the effect of *Cost* on the portion of employed analysts wining star.

The estimation results for equation (4) using subsamples are presented in Table 9, Panel A. Column (1) to Column (4) provide estimation without brokerage-level control variables.

Column (5) and Column (6) provide estimation with brokerage-level control variables. Consistent with our prediction, in all subsamples where *Treat* =1, indicating that the brokerage is suspected to do vote-solicitation, *Cost* generate positive and statistically significant effect on the portion of brokerage employing analysts wining star. The coefficient for Cost equals to 0.119 in column (5), representing an increase of 5% percent in *Cost* would lead to an increase about 0.6% of employing analysts wining star. For subsamples where *Treat* = 0, indicating that the brokerage is not suspected to do vote-solicitation, *Cost* generate no statistically significantly positive effect on the portion of brokerage employing analysts wining star, which provide evidence for our identification of suspected vote-solicitating brokerages. Besides, we test whether this positive relation between *Cost* and *StarRatio* still exist after SAPESS by partition the samples into pre- and post- SAPESS periods, and found that for pre-SAPESS period *Treat* subsample, the coefficient of *Cost* equals to 0.130, significant at 10% level (t-value = 1.795). However, for post-SAPESS period treated subsample, the coefficient *Cost* equals to -0.028, not statistically significant (t-value = -0.167), not tabulated. Overall, these results suggest that brokerages spend more on vote-solicitation would have higher portion of analysts wining star in the current year when vote-solicitation is not restricted.

Secondly, we examine the effect of Star Analyst number on the commission fee received by brokerage by run the following regression model:

$$Commissionfee_{i,t} = a + \beta_1 StarNumber_{i,t} + \sum \mu Controls_{i,t} + \sum \mu Brokerage_i + \sum \mu Year_t + u_{it} \quad (5)$$

Where *Commissionfee* is the log value of commission fee received by each brokerage i as of year t. *StarNumber* uses the same definition as the number of analysts who win star in the brokerage in the current year as used in prior sections. We include the same set of control variables as in equation (1).

The estimation results for equation (5) are presented in Table 9 Panel B. Column (1) provides estimation without brokerage-level control variables. Column (2) provides estimation with brokerage-level control variables. The coefficient of *StarNumber* is positive and statistically significant at 1% level, indicating that among all the sample brokerages, the increase in star analyst number would increase the commission fee allocated by the buy-side clients to the analyst's employed brokerage. Overall, these results suggest that brokerages with more star analysts would receive more commission fee, which can be one possible explanation for brokerages' incentive to spend on vote-solicitation in star analyst competition.

6. Conclusion

This paper documents empirical evidence about how sell-side analysts and brokerages change their behaviors when vote-solicitation is restricted. The brokerages reduce their expenditure on business entertainment after SAPESS. The suspected analysts conduct more site visits than non-suspected analysts after SAPESS was introduced, and these efforts result in higher quality industry reports, which are viewed as the most important sell-side research attribute (Bradshaw 2012). We also find that these phenomena are mainly observed during the voting period for star analysts.

Our findings shed some light on the necessity of restricting some analysts' and brokerages' behavior. Under the restriction of vote-solicitation, brokerages and analysts change their behavior in a more desirable direction. Prior studies regard analysts star rankings as either a reasonable device to encourage analysts' efforts (Ljungqvist et al. 2007) or a beauty contest (Emery and Li 2009; Lobo et al. 2021). Beyond this dichotomy, our findings indicate that star rankings can play a better role with appropriate regulation, which could have important policy implications all around the world.

References

Bian, S., Jia, D., Li, F., Yan, Z. (2021), A New Chinese Financial Sentiment Dictionary for Textual Analysis in Accounting and Finance. Available at SSRN: https://ssrn.com/abstract=3446388 or http://dx.doi.org/10.2139/ssrn.3446388

Bradley, D., Gokkaya, S. and Liu, X. (2017), Before an Analyst Becomes an Analyst: Does Industry Experience Matter? The Journal of Finance, 72: 751-792. https://doi.org/10.1111/jofi.12466

Bradshaw, M. T. (2012). Discussion of "Analysts' industry expertise. Journal of Accounting and Economics 54(2–3), 121–131. https://doi.org/10.1016/j.jacceco.2012.09.003

Brown, L. D., Call, A. C. Clement, M. B. and Sharp, N. Y. (2015). "Inside the 'Black Box' of Sell-Side Financial Analysts." Journal of Accounting Research 53(1): 1–47. https://doi.org/10.1111/1475-679X.12067

Coffé, H., Catherine, B. (2010). Same Game, Different Rules? Gender Differences in Political Participation. Sex Roles 62: 318–333. https://doi.org/10.1007/s11199-009-9729-y

Coleman, B., Drake, M., Pacelli, J. et al. (2022). Brokerage relationships and analyst forecasts: evidence from the protocol for broker recruiting. Review of Accounting Studies. https://doi.org/10.1007/s11142-022-09682-4

Cheng, Q., Du, F., Wang, X. et al. (2016). Seeing is believing: analysts' corporate site visits. Review of Accounting Studies 21, 1245–1286. https://doi.org/10.1007/s11142-016-9368-9

Chen, Y., Guo, K., Wen, J. (2022). Why Do Investors Pay For Charlatan Analysts? Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4089930

Chan, K. C., Jiang, X., Wu, D., Xu, N., Zeng, H. (2019). When is the Client King? Evidence from Affiliated-Analyst Recommendations in China's Split-Share Reform. Contemporary Accounting Research, 1911-3846.12550–. https://doi:10.1111/1911-3846.12550

Clarke, J., Khorana, A., Patel, A., and Rau, P. R. (2007). The Impact of All-Star Analyst Job Changes on Their Coverage Choices and Investment Banking Deal Flow. Journal of Financial Economics 84(3): 713–37. https://doi.org/10.1016/j.jfineco.2005.12.010

Chen, S., Lu, R. (2020). The Impact of Star Analyst Awards on Equity Markets: A Regression Discontinuity Design Available at SSRN: https://ssrn.com/abstract=3678805 or http://dx.doi.org/10.2139/ssrn.3678805

Chiu, P. C., Lourie, Ben., Nekrasov, A., Teoh, S. H. (2021). Cater to Thy Client: Analyst Responsiveness to Institutional Investor Attention. Management Science 67(12): 7455-7471. https://doi.org/10.1287/mnsc.2020.3836

Du, M., (2021). Locked-in at Home: The Gender Difference in Analyst Forecasts after the COVID-19 School Closures Available at SSRN: https://ssrn.com/abstract=3741395 or http://dx.doi.org/10.2139/ssrn.3741395

De Franco, G., Hope, O.K., Vyas, D. and Zhou, Y. (2015). Analyst Report Readability. Contemporary Accounting Research 32: 76-104. https://doi.org/10.1111/1911-3846.12062

Do, T. P. T., Zhang, H. (2019). Peer Effects Among Financial Analysts. Contemporary Accounting Research 1911-3846.12523–. https://doi:10.1111/1911-3846.12523

Dong, Z., Paul S., Tassenberg, K., Melton, G., Dong H. (2021). Transformation from human-readable documents and archives in arc welding domain to machine-interpretable data, Computers in Industry, 128. https://doi.org/10.1016/j.compind.2021.103439

Emery, D., & Li, X. (2009). Are the Wall Street Analyst Rankings Popularity Contests? Journal of Financial and Quantitative Analysis, 44(2), 411-437. https://doi:10.1017/S0022109009090140

Groysberg, B., Healy, P. M., and Maber, D. A. (2011). What Drives Sell-Side Analyst Compensation at High-Status Investment Banks? Journal of Accounting Research 49(4): 969–1000. https://doi.org/10.1111/j.1475-679X.2011.00417.x

Gu, Z., Li, Z., Yang, Y. G., Li, G. (2019). Friends in Need Are Friends Indeed: An Analysis of Social Ties between Financial Analysts and Mutual Fund Managers. The Accounting Review (1): 153–181. https://doi.org/10.2308/accr-52160

Han, B., Kong D., Liu, S. (2018). Do Analysts Gain an Informational Advantage by Visiting Listed Companies? Contemporary Accounting Research https://doi:10.1111/1911-3846.12363

Hanley, K. W., Hoberg, G. (2010). The Information Content of IPO Prospectuses, Review of Financial Studies, 23(7), 2821–2864. https://doi.org/10.1093/rfs/hhq024

Hong, H., Kubik, J. D. (2003). Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. The Journal of Finance, 58(1), 313–351. https://doi:10.1111/1540-6261.00526

Huang, A. H., Zang, A. Y., Zheng, R. (2014). Evidence on the Information Content of Text in Analyst Reports. The Accounting Review 89 (6): 2151–2180. https://doi.org/10.2308/accr-50833

Jackson, A. R. (2005). Trade Generation, Reputation, and Sell-Side Analysts. The Journal of Finance 60(2): 673–717. https://doi.org/10.1111/j.1540-6261.2005.00743.x

Jiang, D., Kumar, A., Law, K.K.F. (2016). Political contributions and analyst behavior. Review of Accounting Studies 21, 37–88. https://doi.org/10.1007/s11142-015-9344-9

Leone, A. J., and Wu, J. S. (2007). What Does It Take to Become a Superstar? Evidence from Institutional Investor Rankings of Financial Analysts. https://papers.ssrn.com/abstract=313594

Li, C., Lin, AP., Lu, H. et al. (2020). Gender and beauty in the financial analyst profession: evidence from the United States and China. Review of Accounting Studies 25, 1230–1262. https://doi.org/10.1007/s11142-020-09542-z

Loughran, T. and McDonald, B. (2014). Measuring Readability in Financial Disclosures. The Journal of Finance, 69: 1643-1671. https://doi.org/10.1111/jofi.12162

Li, Q., Ma, M., Shevlin, T. (2021). The effect of tax avoidance crackdown on corporate innovation, Journal of Accounting and Economics, Volume 71, Issues 2–3. https://doi.org/10.1016/j.jacceco.2020.101382

Ljungqvist, A., Marston, F., Starks, L. T., Kelsey, D., Wei, H. Yan. (2007). Conflicts of interest in sell-side research and the moderating role of institutional investors, Journal of Financial Economics, Volume 85, Issue 2, 420-456. https://doi.org/10.1016/j.jfineco.2005.12.004

Liu, S., He, T. & Dai, J. (2021). A Survey of CRF Algorithm Based Knowledge Extraction of Elementary Mathematics in Chinese. Mobile Networks and Applications 26, 1891–1903. https://doi.org/10.1007/s11036-020-01725-x

Lobo, G. J.. Y. Tan, Y. Wen, and H. Zhao. (2020). How Do Star Analyst Rankings Influence Analysts' Forecast Performance? Available at SSRN: https://ssrn.com/abstract=3537330 or http://dx.doi.org/10.2139/ssrn.3537330

Petersen M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, Review of Financial Studies Volume 22, Issue 1, Pages 435–480. https://doi.org/10.1093/rfs/hhn053

Stickel S. E. (1992). Reputation and Performance Among Security Analysts, The Journal of Finance 47(5), 1811–1836. https://doi:10.1111/j.1540-6261.1992.tb04684.x

Ying, J. (2018). The post-N/F era: Brokerage firm's performance evaluation mechanism and the true value of road shows. China Business Network. https://www.yicai.com/news/100037755.html

Zhang, H. (2017). New Fortune vote-solicitation season: brokerages use the name of research to travel and shop abroad. Sina Finance. http://finance.sina.com.cn/stock/quanshang/qsyj/2017-08-28/doc-ifykiuaz1482276.shtml

Appendices

A. Partial translation of vote-solicitation restriction sections of SAPESS

Article 4: Brokerages should evaluate the rankings they participate in. The evaluation concerns key matters listed in the following table, including but not limited to whether the ranking organizer is a contracting institution of the "Analyst Rankings Organizer Discipline", the ranking organization, the rigor of the evaluation methods, and the fairness of the ranking results, etc. For rankings that do not meet the evaluation requirements, brokerages should refuse participation.

Ranking Evaluation Key Matters (Only directly related to Vote-Solicitation)

Number	Evaluation Content	Key Matters
1	Ranking Organization	(6) The organizer should have set up relevant rules and procedures to ensure the rigor of the ranking process, to prevent soliciting votes, and the occurrence of improper participation prohibited by Article 11, Article 12, and Article 14 of this specification.
2	Participant Condition	(2) For those who have been restricted from participating in the ranking by regulatory authorities or associations due to regulation violations, the ranking organizer should have clear rules on restricting their participation in the ranking. (4) For those who solicited votes, and participating in the ranking in improper ways prohibited by Articles 11, 12, and 14 of this specification, the ranking should cancel or restrict them from participating in the ranking competition.

Article 6: Brokerages and analysts should consciously resist rankings that have conflicts of interest, lack of fairness or impartiality, and seriously affect the independence of analysts.

Article 7: After the ranking process or the announcement of the ranking results, if there is any violation of fairness or impartiality in the rankings, the brokerage shall withdraw from the ranking promptly and make an announcement.

Article 10: Brokerages and analysts shall strictly abide by laws, regulations, regulatory requirements, and self-discipline rules of SAC, participating in the rankings in accordance with the principles of honesty, integrity, self-discipline, and fair competition, and shall not influence the ranking results by improper ways.

Article 11: It is strictly forbidden for analysts to treat or benefit voters and other people who may have an impact on the results of the ranking in various forms, including providing cash, gifts, travel, red envelopes, entertainment and fitness training, or other flexible ways to interest tunnelling.

Article 12: It is strictly forbidden for brokerages and analysts to publish or send vote-solicitation information in various forms, including but not limited to emailing vote-solicitation information or publishing vote-solicitation information on various social media such as WeChat groups, WeChat Moments, etc., or using nickname or nickname annotations of WeChat, Weibo, blog, or sending vote-solicitation information when providing research services, etc.

Vote-solicitation information refers to information sent to voters to invite or ask the voters to vote for analysts or brokerage's candidates, which includes containing the name or logo of the ranking competition or the ranking organizer, and entry number of the participants in the research report, publicity, the above-mentioned social media, and other materials. Besides, the use of "please vote for X", "vote", "on the ranking list" and other words, and other information designed to lobby and influence voters to vote for analysts or brokerage candidates are also viewed as vote-solicitation information.

Article 14: The materials sent by brokerages and analysts for ranking competition shall be reviewed by the compliance department of the brokerage. The content of introduction and self-recommendation materials should be objective and authentic, and the trend or increase of a certain or some securities recommended in the past should not be used to prove analyst's performance.

Article 17: Brokerages should strengthen the management of analysts' participation in the ranking activities, keep abreast of and grasp the situation of analysts' participation in the ranking, and if brokerages find that analysts participate in the ranking in an improper way, they should deal with relevant personnel and report the results to the SAC.

Article 18: For brokerages that fail to perform management duties as required, the SAC will take self-regulatory management measures such as warnings and orders for rectification, or disciplinary actions within the industry such as circular criticism, public condemnation, and suspension of the rights of some members, depending on the severity of the circumstances.

For analysts who participate in the ranking through unfair competition, the association will take self-regulatory management measures such as warnings and orders for rectification, or disciplinary actions such as public criticism, suspension of practice or cancellation of practice certificates in the industry, depending on the severity of the circumstances.

B. Variable definitions

Variable	Definition	Source
Dependent Variables		
Cost	Cost of vote-solicitation: log of the “Business entertainment expenditures” in each brokerage’s notes to financial reporting, which contains the expenditure of vote-solicitation activities entertaining clients	WIND, brokerages official websites
Effort_OnSite	Analyst Effort: log of analyst on-site visit times	WIND
Effort_VisitN	Analyst Effort: log of analyst visit times	WIND
Effort_StockN	Analyst Effort: log of analyst visit stock number	WIND
Quality	Natural logarithm value of informative content of analyst report (Hanley and Hoberg, 2010)	Datayes
Key Independent Variables		
Treat_star	Suspected brokerages (analysts) that solicite votes for N/F star analyst ranking:*Treat_star* =1 for brokerages (analysts) that have (have been) N/F Star Analysts but not continuously win the first place of the ranking, as the treatment group, and *Treat_star*=0 otherwise, as the control group	N/F
Treat_media	Suspected brokerages (analysts) that solicite votes for N/F star analyst ranking: *Treat_media* =1 for brokerages (analysts) that have (have been) N/F Star Analysts but not continuously win the first place of the ranking, as the treatment group, and *Treat_media* =0 otherwise, as the control group	Google and Chinese mainstream media including Caixin, Sina Finance, YiCai, Jiemian, JC Economic Information
Post	Implementation of SAPESS: *Post* =1 if time is in or after 2019, *Post* =0 if time is before 2019	CSMAR, WIND

Control Variables		
BrokerSize	Log of number of analysts in the brokerage who publish at least 1 analyst report in the year	CSMAR
Mean_ForecastFreq	Mean value of analysts' forecast numbers in brokerage in the fiscal year	CSMAR
Mean_Experience	Mean value of analysts' experience in brokerage, count in seasons	CSMAR
Maleratio	Ratio of male analysts in brokerage	CSMAR
Education	Ratio of analysts who has Master degree or PhD degree in brokerage	CSMAR
StarNumber	Number of analysts who win star in brokerage during the fiscal year	CSMAR
Commissionfee	Log of total commission fee that brokerage received from buy-side for brokerage service	WIND
MA	Indicator variable equals to 1 if there is a merger or acquisition during the fiscal year. Otherwise, the variable equals to 0	CSMAR
CoverFirmSize	Mean value of log of firms' total assets book value in analyst's portfolio	CSMAR
ForecastFreq	Number of earnings forecast report issued by analyst in the year	CSMAR
Experience	Analyst experience: number of seasons starting from analyst first report publishment date	CSMAR
Gender	Analyst gender: *Gender*=1 if analyst is male, *Gender* =0 if analyst is female	CSMAR
Master	Master degree analyst: *Master* =1 if analyst's highest degree is master, *Master* =0 otherwise	CSMAR
PhD	PhD degree analyst: *PhD* =1 if analyst's highest degree is PhD, *PhD* =0 otherwise	CSMAR
Tone	Sentiment score of the analyst report, we count positive and negative words based on Bian et al. (2021)'s Chinese sentiment dictionary, *Tone* = (Number of Positive words - Number of Positive words)/(Number of Positive words + Number of Positive words)	Datayes
Page	Log of report page number	Datayes

“log of v.” in this table indicates natural logarithm value of (1+ v.) unless otherwise specified

C. Textual data processing

C1. Textual data cleaning

We extract text from each analyst report PDF by Python modules PDFplumber and PDFMiner in most cases, which are widely used packages in PDF textual analysis (Dong et al, 2021; Chen et al, 2022). We use Regular Expression to exclude common messy code generated from report PDF converting process. Besides, we hand copy the text from PDF to machine-interpretable text when Python fails to extract the text out. We remove graphics, exhibits and all other non-text items. Also, we remove the appendix section of analyst reports, because that the expressions in this section are the same within reports published by each brokerage and follow a similar pattern among different brokerages, the appendix section would affect the calculation of our informative content.

Since Chinese is not an inflected language and does not have white spaces between words, we then employ a widely used Python module Jieba in accurate mode to split Chinese words without removing the inflectional endings of words (Du et al., 2021). Before splitting the words by Jieba, we add financial word and phrase dictionary developed by Sogou, and Chinese Financial Sentiment Dictionary developed by Bian et al. (2021) into Jieba, enabling Jieba to preferentially recognize and cut sentences into financial words or phrases which are frequently used in analyst reports. Then we use Jieba to split the texts into words, after which we count the words for each report and filter stop words, punctuation, numbers, and analyst contact information. Stop words are words in texts that do not contain actual meaning, mainly including generally articles, auxiliary verbs, conjunctions, prepositions, and pronouns. The stop words dictionary we use here is a simple combination without duplication of stop word dictionaries respectively developed by Baidu, Sichuan University Machine Learning Intelligence Lab and Harbin Institute of Technology (Liu et al., 2021).

We rely on Datayes if the report type data is available. The industry reports are tagged as 4 types: in-depth report, industry news, regular report, and short comment. And the firm reports are tagged as 6 types: in-depth report, site-visit notes, performance comment, event comment, first-time covering, and IPO comment. But if the report type information is missing in Datayes, then we parse the report PDF and extract the report type information by searching related keywords, and manually check the extracted information to minimize the possibility of making mistakes. For example, if the keyword "in-depth industry report" in Chinese exists in a report preceding other type-related keywords, then we tag the report as an in-depth industry report.

C2. Construction of global word dictionary for words vectors

Following Loughran and McDonald (2014), we only keep reports having total number of words no less than 2000. And we only include reports that have (1) at least one other report that was published ninety days prior to the current report's publishing date and (2) at least one other report in the same industry as the current report that was published at least ninety-one days prior to but no later than one year before the current report's publishing date (Hanley and Hoberg, 2010).

Because we compare the reports' informative content change within its type, we use two global word dictionaries for firm and industry in-depth reports respectively constructed by the samples of each type's reports. We firstly summarize counts for each word from all reports of firm (or industry) in-depth reports, then following Hanley and Hoberg (2010), we keep words that have total counts not less than 5 times. Besides, we only keep words that have record in the Contemporary Chinese Dictionary (7th edition), or Sogou financial words dictionary, or Chinese Financial Sentiment Dictionary developed by Bian et al. (2021). Then we calculate TF-IDF for each word in each report following Loughran and McDonald (2016), and keep the representative 50 words that have the highest TF-IDF in each report. Finally, we set all representative words together without duplication and obtain two global word dictionaries for words vectors within firm or industry in-depth reports respectively.

Table 1
Descriptive Statistics

This table presents the summary statistics for variables used in the empirical analyses. *Cost* is the vote-solicitation activities spending. *Treat_star* and *Treat_media* both proxy for suspected vote-soliciting brokerage or analyst. *ForecastFreq* is the forecast frequency of analysts. *Mean_ForecastFreq* is the average value of *ForecastFreq* of analysts in the brokerage. *Experience* is analyst experience counted by seasons. *Mean_Experience* is the average value of analyst *Experience* in the brokerage. *Maleratio* is the portion of male analysts in the brokerage. *Education* is ratio of analysts who has Master degree or PhD degree in brokerage. *StarNumber* is number of analysts who win star in brokerage during the fiscal year. *Commissionfee* is the log value of total commission fee that brokerage received from buy-side. *BrokerSize* is the number of analysts in the brokerage who publish at least 1 analyst report in the year. *MA* is indicator variable equals to 1 if there is a merger or acquisition during the fiscal year. *Effort_Onsite*, *Effort_VisitN*, and *Effort_StockN* all proxy for research work effort by analysts, in On-site site visit, all kinds of site visit, and site visit firm number separately. *CoverFirmSize* is the mean value of log of firms' total assets book value in analyst's portfolio. *Gender* equals to 1 if the analyst is male. *Master* and PhD proxy for analyst education background. *Tone* is analyst report sentiment score, *Page* is the log value of analyst report page number. Appendix B provides detailed definitions for the variables.

Variables	N	Mean	SD	P10	Median	P90
Panel A: Brokerage level						
Cost	301	17.944	0.884	16.689	18.018	19.043
Treat_star	301	0.236	0.425	0.000	0.000	1.000
Treat_media	301	0.654	0.476	0.000	1.000	1.000
Mean_ForecastFreq	301	31.901	16.850	11.923	31.217	53.100
Mean_Experience	301	12.897	3.784	8.495	12.983	16.859
Maleratio	301	0.718	0.124	0.613	0.714	0.839
Education	301	0.936	0.084	0.875	0.949	1.000
StarNumber	301	8.914	15.420	0.000	0.000	33.000
Commissionfee	301	21.424	1.069	20.079	21.451	22.750
BrokerSize	301	3.615	0.852	2.303	3.807	4.554
MA	301	0.515	0.501	0.000	1.000	1.000
Panel B: Analyst level						
Effort_Onsite	9173	1.447	0.697	0.693	1.386	2.398
Effort_VisitN	9173	1.741	0.697	0.693	1.792	2.708
Effort_StockN	9173	1.608	0.624	0.693	1.609	2.485
Treat_media	9173	0.752	0.432	0.000	1.000	1.000
Treat_star	9173	0.175	0.380	0.000	0.000	1.000
StarNumber	9173	13.565	19.161	0.000	5.000	45.000
BrokerSize	9173	3.977	0.582	3.178	4.060	4.595
CoverFirmSize	9173	23.623	1.476	22.043	23.381	25.467
FroecastFreq	9173	44.372	42.438	4.000	32.000	103.000
Experience	9173	13.227	11.301	1.608	9.746	29.618
Gender	9173	0.727	0.445	0.000	1.000	1.000
Master	9173	0.864	0.342	0.000	1.000	1.000
PhD	9173	0.077	0.267	0.000	0.000	0.000
Panel C: Report level						
Quality	12,992	0.413	0.163	0.207	0.406	0.627
Treat_star	12,992	0.080	0.271	0.000	0.000	0.000
Treat_media	12,992	0.483	0.500	0.000	0.000	1.000
Tone	12,992	0.649	0.200	0.362	0.701	0.847
Page	12,992	3.260	0.413	2.708	3.258	3.738
ForecastFreq	12,992	75.775	62.979	12.000	60.000	165.000
Experience	12,992	20.214	13.546	4.690	17.677	40.395
CoverFirmSize	12,992	24.069	1.490	22.578	23.721	25.987
StarNumber	12,992	6.424	12.914	0.000	0.000	20.000
BrokerSize	12,992	3.680	0.632	2.833	3.850	4.317

Table 2
Brokerage Vote-solicitation Cost

This table presents the results that examine the effect of SAPESS on vote-solicitation *Cost* of suspected brokerages. Dropping singleton observations does not affect significance or conclusions. t-statistics is in the parentheses, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed). Appendix B provides detailed definitions for the variables.

Panel A: Main effects

Dep. Variable:	*Cost*						
Sample:	Full sample (1)	Full sample (2)	Full sample (3)	Full sample (4)	Full sample (5)	Drop 2019 (6)	Drop 2019 (7)
Treat_star × Post	-0.322*	-0.196***	-0.196*			-0.226***	
	(-1.701)	(-2.671)	(-1.696)			(-2.682)	
Treat_media × Post				-0.192***	-0.192*		-0.240***
				(-3.083)	(-1.756)		(-3.294)
Treat_star	0.535***	-0.009	-0.009			-0.023	
	(4.852)	(-0.177)	(-0.114)			(-0.444)	
Post	0.214						
	(1.556)						
BrokerSize		0.105**	0.105	0.077*	0.077	0.098**	0.068
		(2.550)	(1.534)	(1.811)	(1.062)	(2.179)	(1.469)
Mean_ForecastFreq		-0.001	-0.001	-0.001	-0.001	-0.002	-0.001
		(-0.883)	(-0.665)	(-1.014)	(-0.701)	(-1.108)	(-0.884)
Mean_Experience		-0.021***	-0.021	-0.023***	-0.023	-0.022***	-0.025***
		(-3.111)	(-1.421)	(-3.473)	(-1.612)	(-3.098)	(-3.461)
MaleRatio		-0.129	-0.129	-0.179	-0.179	-0.176	-0.251
		(-0.685)	(-0.345)	(-0.954)	(-0.501)	(-0.843)	(-1.204)
Education		0.431	0.431	0.431	0.431	0.245	0.284
		(1.622)	(1.535)	(1.626)	(1.405)	(0.835)	(0.973)
StarNumber		-0.002	-0.002	-0.002	-0.002	-0.002	-0.003*
		(-1.396)	(-1.378)	(-1.471)	(-1.113)	(-1.208)	(-1.654)
Commissionfee		0.966***	0.966***	0.971***	0.971***	0.967***	0.975***
		(11.465)	(6.407)	(11.495)	(6.315)	(10.551)	(10.639)
MA		-0.022	-0.022	-0.040	-0.040	-0.023	-0.041
		(-0.591)	(-0.371)	(-1.108)	(-0.715)	(-0.578)	(-1.041)
Constant	17.770***	-3.077*	-3.077	-2.975*	-2.975	-2.883	-2.852
	(246.975)	(-1.708)	(-1.003)	(-1.662)	(-0.961)	(-1.476)	(-1.469)
Fixed Effect	No	Year, Brokerage	Year, Brokerage	Year, Brokerage	Year, Brokerage	Year, Brokerage	Year, Brokerage
Cluster	No	No	Brokerage	No	Brokerage	No	No
Observations	301	301	301	301	301	267	267
Adjusted R-squared	0.042	0.939	0.938	0.939	0.939	0.936	0.936

Panel B: Parallel trend and dynamic effects

This panel presents the results of parallel trend and dynamic effects of SAPESS on Cost for suspected brokerages. Since no analyst is suspected to solicit votes in 2018 due to suspension of N/F star analyst competition, the year 2018 observations are omitted for estimation of parallel trend. Dropping singleton observations does not affect significance or conclusions. t-statistics is in the parentheses, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed). Controls = Y means that in brokerage level, the regressions use the same controls as previous tests in brokerage level, including *BrokerSize, Mean_ForecastFreq, Mean_Experience, MaleRatio, Education, StarNumber, Commissionfee, and MA*.

Dep. Variable:	*Cost*	
	(1)	(2)
Treat_star × *Year2012*	0.080	0.084
	(1.151)	(0.957)
Treat_star × *Year2013*	0.196	0.195
	(1.581)	(1.554)
Treat_star × *Year2014*	0.003	0.003
	(0.037)	(0.037)
Treat_star × *Year2015*	-0.133	-0.133
	(-0.900)	(-0.878)
Treat_star × *Year2016*	-0.156	-0.156
	(-0.830)	(-0.806)
Treat_star × *Year2017*	-0.191	-0.186
	(-1.563)	(-1.525)
Treat_star × *Post*	-0.272**	
	(-2.520)	
Treat_star × *Year2019*		-0.201
		(-1.326)
Treat_star × *Year2020*		-0.266*
		(-2.173)
Treat_star × *Year2021*		-0.352**
		(-3.186)
Constant	-5.365*	-5.571*
	(-1.897)	(-1.942)
Controls	Y	Y
Fixed Effects	Year, Brokerage	Year, Brokerage
Clusters	Year, Brokerage	Year, Brokerage
Observations	271	271
Adjusted R-squared	0.938	0.937

Table 3
Analysts' Onsite Visits

This table presents the results that examine the effect of SAPESS on effort in site visiting by suspected vote-solicitation analyst. Replacing *Treat_Star* by *Treat_Media* does not affect conclusions. Dropping singleton observations does not affect significance or conclusions. t-statistics is in the parentheses, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed). Appendix B provides detailed definitions for the variables.

Panel A: Main effects

Dep. Variable:	*Effort_OnSite*				
	(1)	(2)	(3)	(4)	(5)
Treat_star × Post	0.136***	0.123***	0.180***	0.180***	0.180***
	(2.915)	(3.323)	(3.749)	(3.487)	(3.675)
Treat_star	0.061*	0.017	0.008	0.008	0.008
	(1.851)	(0.642)	(0.242)	(0.222)	(0.206)
StarNumber		0.000	-0.000	-0.000	-0.000
		(0.571)	(-0.012)	(-0.012)	(-0.012)
BrokerSize		0.077***	0.050	0.050	0.050
		(2.932)	(1.504)	(1.413)	(1.127)
CoverFirmSize		-0.110***	-0.042***	-0.042***	-0.042***
		(-22.927)	(-3.783)	(-3.508)	(-3.416)
FroecastFreq		0.003***	0.003***	0.003***	0.003***
		(17.435)	(14.481)	(12.709)	(9.107)
Experience		-0.008***	-0.031***	-0.031***	-0.031***
		(-12.384)	(-3.172)	(-2.738)	(-3.900)
Gender		0.094***			
		(6.250)			
Master		0.080***			
		(2.779)			
PhD		0.050			
		(1.376)			
Constant	1.426***	3.543***	2.483***	2.483***	2.483***
	(291.006)	(23.200)	(7.909)	(7.355)	(7.981)
Fixed Effect	Analyst, Brokerage, Year	Brokerage, Year	Analyst, Brokerage, Year	Analyst, Brokerage, Year	Analyst, Brokerage, Year
Cluster	Analyst, Brokerage	No	No	Analyst	Analyst, Brokerage
Observations	9,173	9,173	9,173	9,173	9,173
Adj. R-squared	0.405	0.188	0.429	0.428	0.428

Panel B: Parallel trend and dynamic effects

This panel presents the results of parallel trend and dynamic effects of SAPESS on research work efforts for suspected analysts. Since no analyst is suspected to solicit votes in 2018 due to suspension of N/F star analyst competition, the year 2018 observations are omitted for estimation of parallel trend. Dropping singleton observations does not affect significance or conclusions. t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controls = Y means that in analyst level, the regressions use the same controls as previous tests in analyst level, including *BrokerSize, Experience, Education, StarNumber, CoverFirmSize,* and *FroecastFreq.*

Dep. Variable:	*Effort_OnSite*	
	(1)	(2)
Treat_star × Year2012	-0.106	-0.105
	(-0.930)	(-0.928)
Treat_star × Year2013	-0.001	-0.001
	(-0.014)	(-0.010)
Treat_star × Year2014	0.083	0.083
	(1.348)	(1.358)
Treat_star × Year2015	0.104*	0.104*
	(1.722)	(1.728)
Treat_star × Year2016	-0.065	-0.066
	(-1.142)	(-1.148)
Treat_star × Year2017	-0.063	-0.064
	(-1.038)	(-1.053)
Treat_star × Post	0.172***	
	(3.155)	
Treat_star × Year2019		0.132**
		(2.198)
Treat_star × Year2020		0.183***
		(2.822)
Treat_star × Year2021		0.238***
		(3.016)
Constant	2.927***	2.924***
	(8.149)	(8.221)
Controls	Y	Y
Fixed Effects	Year, Brokerage,Analyst	Year, Brokerage,Analyst
Clusters	Brokerage,Analyst	Brokerage,Analyst
Observations	6,658	6,658
Adjusted R-squared	0.428	0.428

Table 4
Analysts' Site Visits – Total site visit number or Site visit Firm number

This table presents the results that examine the effect of SAPESS on effort in three types of site visiting by suspected vote-solicitation analyst. For concerns of noises in SAPESS implementation year, 2019 samples are excluded. Column (1) and Column (2) use total site visit number as dependent variable, Column (3) and Column (4) use site visit firm number as dependent variable, Column (5) and Column (6) use on site visit number as dependent variable. Dropping singleton observations does not affect significance or conclusions. t-statistics is in the parentheses, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed). Appendix B provides detailed definitions for the variables.

Dep. Variable:	*Effort_VisitN*		*Effort_StockN*		*Effort_Onsite*	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat_star × Post	0.152**		0.147***		0.206***	
	(2.568)		(2.820)		(3.111)	
Treat_media × Post		0.102*		0.126**		0.097
		(1.808)		(2.570)		(1.601)
Treat_star	0.026		-0.005		0.010	
	(0.715)		(-0.146)		(0.259)	
Treat_media		-0.082		-0.063		-0.150*
		(-1.226)		(-1.049)		(-1.870)
StarNumber	-0.001	-0.000	-0.000	0.000	-0.000	0.001
	(-1.298)	(-0.615)	(-0.351)	(0.054)	(-0.153)	(0.665)
BrokerSize	0.064*	0.081**	0.051	0.067*	0.044	0.071*
	(1.729)	(2.040)	(1.457)	(1.803)	(1.114)	(1.754)
CoverFirmSize	-0.037***	-0.037***	-0.032***	-0.032***	-0.047***	-0.047***
	(-2.793)	(-2.804)	(-2.620)	(-2.645)	(-3.563)	(-3.562)
FroecastFreq	0.003***	0.003***	0.002***	0.002***	0.003***	0.003***
	(10.246)	(10.138)	(9.810)	(9.641)	(10.948)	(10.801)
Experience	-0.033***	-0.035***	-0.030***	-0.033***	-0.028**	-0.032***
	(-3.240)	(-3.475)	(-3.443)	(-3.798)	(-2.518)	(-2.779)
Constant	2.690***	2.703***	2.475***	2.466***	2.593***	2.618***
	(7.478)	(7.501)	(7.503)	(7.529)	(7.107)	(7.193)
Fixed Effect	Analyst, Brokerage, Year	Analyst, Brokerage, Year	Analyst, Brokerage, Year	Analyst, Brokerage, Year	Analyst, Brokerage, Year	Analyst, Brokerage, Year
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst
Observations	7,840	7,840	7,840	7,840	7,840	7,840
Adjusted R-squared	0.497	0.496	0.490	0.490	0.436	0.435

Table 5
Analyst report Quality

This table presents the results that examine the effect of SAPESS on report quality by suspected vote-solicitation analyst. Dropping singleton observations does not affect significance or conclusions. Diff. of Industry and Firm is calculated as the difference in coefficients between interactions of industry report and firm report using Stata package *bdiff*, repeated 1000 times. Dropping singleton observations does not affect significance or conclusions.t-statistics is in the parentheses, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed). Appendix B provides detailed definitions for the variables.

Panel A: Main effects

Dep. Variable:	*Quality*							
Report type:	Industry	Firm	Industry	Firm	Industry	Firm	Industry	Firm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Diff. of Industry and Firm	0.057*** (p=0.000)		0.020*** (p=0.000)		0.032** (p=0.031)		0.032*** (p=0.000)	
Treat_star × Post	0.040***	-0.017			0.020**	-0.012		
	(3.263)	(-1.133)			(2.439)	(-0.503)		
Treat_media × Post			0.016**	-0.004			-0.000	-0.032*
			(2.114)	(-0.641)			(-0.036)	(-1.919)
Treat_star	-0.021**	-0.011			-0.033**	-0.008		
	(-2.450)	(-0.966)			(-2.156)	(-0.422)		
Treat_media			-0.017***	-0.003			0.014	0.032***
			(-3.596)	(-0.648)			(0.825)	(2.833)
Tone					-0.073***	0.079***	-0.073***	0.078***
					(-5.793)	(2.928)	(-5.916)	(2.934)
Page					-0.112***	-0.119***	-0.112***	-0.119***
					(-12.551)	(-7.966)	(-12.798)	(-7.883)
FroecastFreq					0.000	0.000**	0.000	0.000**
					(0.675)	(2.434)	(0.310)	(2.206)
Experience					-0.001	-0.008	-0.000	-0.009
					(-0.129)	(-1.063)	(-0.035)	(-1.217)
CoverFirmSize					-0.000	-0.008	-0.000	-0.009
					(-0.005)	(-1.168)	(-0.018)	(-1.267)
StarNumber					0.001**	0.001	0.000	0.001
					(2.296)	(1.148)	(1.306)	(1.346)
BrokerSize					-0.016	0.001	-0.016	-0.000
					(-1.104)	(0.092)	(-1.024)	(-0.021)
Constant	0.330***	0.498***	0.335***	0.499***	0.802***	1.170***	0.784***	1.195***
	(175.761)	(290.260)	(130.701)	(217.318)	(3.629)	(5.126)	(3.531)	(5.153)
Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Brokerage Fixed Effect	N	N	N	N	Y	Y	Y	Y
Analyst Fixed Effect	N	N	N	N	Y	Y	Y	Y
Brokerage Cluster	N	N	N	N	Y	Y	Y	Y
Analyst Cluster	N	N	N	N	Y	Y	Y	Y
Industry Cluster	N	N	N	N	Y	Y	Y	Y
Observations	6,546	6,446	6,546	6,446	6,546	6,446	6,546	6,446
Adjusted R-squared	0.026	0.023	0.027	0.022	0.305	0.286	0.305	0.287

Panel B: Parallel trend and dynamic effects

This panel presents the results of parallel trend and dynamic effects of SAPESS on report quality for suspected analysts by report type. Since no analyst is suspected to solicit votes in 2018 due to suspension of N/F star analyst competition, the year 2018 observations are omitted for estimation of parallel trend. Dropping singleton observations does not affect significance or conclusions. t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Controls = Y means that in report level, the regressions use the same controls as previous tests in report level, including *Treat_star, Tone, Page, BrokerSize, Experience, Education, Gender, Education, StarNumber, CoverFirmSize,* and *FroecastFreq*.

Dep. Variable:	*Quality*			
Report Type:	Industry		Firm	
	(1)	(2)	(3)	(4)
Treat_star × *Year2017*	0.018	0.018	0.008	0.008
	(1.019)	(0.971)	(0.526)	(0.545)
Treat_star × *Post*	0.050**		-0.008	
	(4.046)		(-0.622)	
Treat_star × *Year2020*		0.050**		0.001
		(4.619)		(0.056)
Treat_star × *Year2021*		0.050*		-0.018
		(2.933)		(-1.319)
Constant	0.939***	0.939***	0.895***	0.894***
	(9.584)	(9.557)	(12.080)	(12.147)
Observations	4,619	4,619	4,471	4,471
Adjusted R-squared	0.171	0.171	0.116	0.116
Controls	Y	Y	Y	Y
Fixed effect	Year, Industry	Year, Industry	Year, Industry	Year, Industry
Cluster	Year, Brokerage, Analyst, Industry	Year, Brokerage, Analyst, Industry	Year, Brokerage, Analyst, Industry	Year, Brokerage, Analyst, Industry

Table 6
Voting period tests – Brokerage vote-solicitation cost

This table presents the results that examine the effect of SAPESS on vote-solicitation cost by suspected vote-solicitation brokerages using First half year and Second half year subsamples. *Treat* uses *Treat_media*. Dropping singleton observations does not affect significance or conclusions. Diff. of Industry and Firm is calculated as the difference in coefficients between interactions of industry report and firm report using Stata package *bdiff*, repeated 1000 times. Dropping singleton observations does not affect significance or conclusions.t-statistics is in the parentheses, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed). Appendix B provides detailed definitions for the variables.

Dep. Variable:	*Cost*	
Period:	First half year	Second half year
	(1)	(2)
Diff. Second-First	-0.396* (p=0.081)	
Treat× *Post*	-0.014	-0.410***
	(-0.070)	(-3.602)
Constant	17.750***	1.130
	(12.774)	(0.309)
Observations	121	121
Adjusted R-squared	0.903	0.903
Controls	Y	Y
Year FE	Year, Brokerage	Year, Brokerage
Cluster	Brokerage	Brokerage

Table 7
Voting period tests – Analyst site-visit

This table presents the results that examine the effect of SAPESS on report quality by suspected vote-solicitation analyst using First half year and Second half year subsamples. Dropping singleton observations does not affect significance or conclusions. Diff. of Industry and Firm is calculated as the difference in coefficients between interactions of industry report and firm report using Stata package *bdiff*, repeated 1000 times. Dropping singleton observations does not affect significance or conclusions.t-statistics is in the parentheses, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed). Appendix B provides detailed definitions for the variables.

Dep. Variable:	*Effort_Onsite*	
Period:	First half year	Second half year
	(1)	(2)
Diff. of Second and First	0.308***(p=0.000)	
Treat_star × *Post*	-0.077	0.231***
	(-1.535)	(4.492)
Constant	1.005***	1.860***
	(3.038)	(5.373)
Observations	9,184	9,184
Adjusted R-squared	0.347	0.268
Controls	Y	Y
Fixed Effect	Year, Brokerage, Analyst	Year, Brokerage, Analyst
Cluster	Analyst	Analyst

Table 8
Voting period tests – Report Quality

This table presents the results that examine the effect of SAPESS on report quality by suspected vote-solicitation analyst comparing subsamples result by industry or firm reports and voting or non-voting periods. Dropping singleton observations does not affect significance or conclusions. Diff. of Industry and Firm is calculated as the difference in coefficients between interactions of industry report and firm report using Stata package *bdiff*, repeated 1000 times. Dropping singleton observations does not affect significance or conclusions.t-statistics is in the parentheses, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed). Appendix B provides detailed definitions for the variables.

Dep. Variable:	*Quality*			
Report type:	Industry		Firm	
Period:	Voting period	non-Voting period	Voting period	non-Voting period
	(1)	(2)	(3)	(4)
Diff. of Industry-voting period		0.063**	0.099**	0.053
and the column's group		(p=0.049)	(p=0.043)	(p=0.240)
Treat_star × Post	0.060**	-0.003	-0.039	0.007
	(3.885)	(-0.072)	(-1.036)	(0.218)
Constant	0.641*	0.593**	0.918*	1.100***
	(2.477)	(3.751)	(2.201)	(9.278)
Observations	1,807	4,491	1,174	4,560
Adjusted R-squared	0.333	0.333	0.405	0.318
Controls	Y	Y	Y	Y
Fixed Effect	Year×Brokerage, Analyst, Industry	Year×Brokerage, Analyst, Industry	Year×Brokerage, Analyst, Industry	Year×Brokerage, Analyst, Industry
Cluster	Year, Brokerage, Analyst	Year, Brokerage, Analyst	Year, Brokerage, Analyst	Year, Brokerage, Analyst

Table 9
Robustness check – Vote-solicitation incentive in Brokerage level

This table presents the results that examine the effect of Cost spending on the ratio of analysts wining star in the current year. Dropping singleton observations does not affect significance or conclusions. Controls = Y means that in brokerage level, the regressions use the same controls as previous tests in brokerage level, including *Mean_ForecastFreq, Mean_Experience, MaleRatio, Education, Commissionfee, MA*. Dropping singleton observations does not affect significance or conclusions.t-statistics is in the parentheses, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed). Appendix B provides detailed definitions for the variables.

Panel A: Cost effect on wining star analysts

Dep. Variable:	*StarRatio*					
Group:	Treat_Star=1	Treat_Star=0	Treat_Media=1	Treat_Media=0	Treat_Star=1	Treat_Star=0
	(1)	(2)	(3)	(4)	(5)	(6)
Cost	0.155***	-0.020	0.078**	-0.040*	0.119**	-0.073**
	(2.686)	(-0.677)	(2.495)	(-1.860)	(2.103)	(-2.066)
Constant	-2.602**	0.471	-1.222**	0.694*	-12.654***	-1.090
	(-2.476)	(0.880)	(-2.143)	(1.891)	(-3.055)	(-1.030)
Controls	N	N	N	N	Y	Y
Fixed effect	Year,Brokerage	Year,Brokerage	Year,Brokerage	Year,Brokerage	Year,Brokerage	Year,Brokerage
Observations	71	230	197	104	71	230
Adjusted R-squared	0.813	0.701	0.691	0.141	0.856	0.751

Panel B: Wining star analysts effect on commission fee

Controls = Y means that in brokerage level, the regressions use the same controls as previous tests in brokerage level, including *BrokerSize, Mean_ForecastFreq, Mean_Experience, MaleRatio, Education, Commissionfee, MA.*

Dep. Variable:	*Commissionfee*	
	(1)	(2)
StarNumber	0.006***	0.003***
	(4.855)	(2.785)
Constant	21.372***	21.062***
	(1,441.915)	(90.362)
Controls	N	Y
Fixed effect	Year,Brokerage	Year,Brokerage
Observations	301	301
Adjusted R-squared	0.972	0.975