Can star analysts make superior coverage decisions in poor information environment?*

Abstract

This study uses the quality of coverage decisions as a new metric to evaluate the performance of star and non-star analysts. We find that the coverage decisions of star analysts are better predictors of returns than those of non-star analysts. The return predictability of star analysts' coverage decisions is stronger for informationally opaque stocks. We further exploit the staggered short selling deregulations, Google's withdrawal, and the anti-corruption campaign as three quasi-natural experiments that create plausibly exogenous variations in the quality of information environment. These experiments show that the predictive power of star analysts' coverage decisions strengthens (weakens) following a sharp deterioration (improvement) in firms' information environment, consistent with the notion that star analysts possess superior ability to identify mispriced stocks. Overall, star analysts make better coverage decisions and play a superior role as information intermediaries, especially in poor information environment.

Keywords: star analysts, coverage decisions, return predictability, information environment

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1. Introduction

Do star analysts outperform non-star analysts? While evidence suggests star analysts make more accurate earnings forecasts and more valuable stock recommendations (Stickel, 1992; Desai et al., 2000; Loh and Stulz, 2011; Fang and Yasuda, 2014), institutional investors' rankings of analysts have been criticized as "popularity contests" where the rankings of analysts reflect the recognition of big brokerage houses rather than analysts' superior performance (Emery and Li, 2009; Brown et al., 2015). Unlike prior studies that compare analysts' performance based on "what analysts say" in earnings forecasts and recommendations, we evaluate analysts' performance based on "what analysts do" when allocating coverage across firms. The rationale behind our approach is that analysts with superior information processing skills are more able to make high quality coverage decisions by identifying stocks with better future performance (Lee and So, 2017). Hence, analyzing the information content of analysts' coverage decisions provides us with a unique opportunity to empirically assess whether star analysts possess superior skills.

Comparing the performance of star and non-star analysts based on their coverage decisions is arguably less biased and appealing for several reasons. First, analysts' earnings forecasts and recommendations could be biased due to the well-documented conflicts of interest[1], while coverage decisions reflect analysts' best efforts to cover stocks with greater prospects (McNichols and O'Brien, 1997; Hayes, 1998; Irvine, 2003; Lee and So, 2017). Second, resource-constrained analysts[2] have a strong preference for firms with better prospects, as such firms tend to have more easily forecasted earnings due to their desire to share information (Das et al., 2006).

[1] Specifically, analysts have the incentive to issue favorable stock recommendations, enabling them to gain access to private information from the firm (e.g., McNichols and O'Brien, 1997; Jegadeesh and Kim, 2009; Jegadeesh et al., 2004; Malmendier and Shanthikumar, 2014). In addition, analysts in a brokerage house which has an underwriting relationship with a particular firm tend to issue overly positive forecasts of the firm's earnings (e.g., Dugar and Nathan, 1995; Lin and McNichols, 1998; Dechow et al., 2000; Michaely and Womack, 1999; Agrawal and Chen, 2008; Huyghebaet and Xu, 2016).

[2] Analysts have limited time and attention, and therefore their coverage decisions can be viewed as constrained resource allocation (Lee and So, 2017; Harford et al., 2019).

Thus, the accuracy of "what analysts say" depends on "what analysts do" in the first place. Third, the decision to cover a firm reflects the analyst's true belief about the firm's future performance (see Kothari et al. (2016) for a review) and conveys this expected performance information to market participants. Thus, investigating "what analysts do" sheds new light on the relative performance of star and non-star analysts as information intermediaries in the capital markets.

Analysts are heterogeneous in their abilities to identify stocks with greater upside potential (e.g., Leone and Wu, 2007; Fang and Yasuda, 2014; Guan et al., 2019). Skilled analysts are more able to identify and cover underpriced stocks with superior future performance. In turn, the coverage decisions of skilled analysts would be informative for predicting returns (Hong, Lim and Stein, 2000; Lee and So, 2017), meaning a high quality of coverage decisions. In contrast, despite having the same incentive to cover stocks with great prospects, analysts with low ability may find it difficult to identify such stocks. Thus, the quality of coverage decisions can be used as a performance metric to evaluate the ability of star and non-star analysts to identify mispriced stocks.

To empirically gauge the quality of coverage decisions, we employ a novel model of analysts' coverage decisions developed by Lee and So (2017). In particular, we decompose coverage decisions into: (i) a mechanical component attributable to firm characteristics, and (ii) a component driven by analysts' expectations about firms' future performance, namely abnormal coverage. The high abnormal coverage of a stock indicates analysts' strong beliefs that the stock has a high future return (Lee and So, 2017). To the extent that star analysts possess superior information processing skills, the information embedded in the abnormal coverage of star analysts would be richer than that contained in the abnormal coverage of their non-star counterparts. Therefore, we expect the abnormal coverage of star analysts to be a stronger predictor than that of non-star analysts.

Our study focuses on star and non-star analysts' performance in China for three reasons.[3] First, the information environment of Chinese firms is characterized by a relatively low degree of voluntary disclosure and transparency (Morck et al., 2000; Piotroski et al., 2015). The opaque nature of the Chinese capital market makes it challenging for sell-side analysts to perform their information intermediary role (Chan and Hameed, 2006; Xu et al., 2013). Moreover, in the absence of strong law enforcement and investor protection, social connections, as an important informal institution in China (Gold et al., 2002), could influence analysts' opinions. For example, Chinese analysts tend to issue upwardly biased recommendations for stocks held by fund managers with whom they are connected (Gu et al., 2019). Thus, it is an empirical question as to how well analysts, star analysts in particular, perform as information intermediaries in such an institutional environment. Second, unlike the U.S. stock market where institutional investors are the dominant players (Aggarwal et al., 2011), retail investors own over 50% of Chinese shares and account for a majority of trading (Carpenter and Whitelaw, 2017; Jia et al., 2017). Retail investors who are typically less informed would demand more information from sell-side analysts. Thus, examining the information content of analysts' coverage decisions in the Chinese stock market is of particular interest to both academics and practitioners. Third, three quasi-natural experiments, including short-selling deregulation in China, Google's withdrawal from China, and the Chinese anti-corruption campaign (see section 4.3.2) enable us to tackle endogeneity problems.

We begin our analysis by constructing the abnormal coverage measure separately for star and non-star analysts. Following Lee and So (2017), we first calculate the raw coverage as the

[3] Several studies examine analyst forecast accuracy in China. He et al. (2019), Li et al. (2020) and Cao et al. (2020) find that Chinese analysts' facial structure and beauty are positively associated with the accuracy of earnings forecasts. Cheng et al. (2016) show that analysts who conduct corporate site visits have a greater increase in forecast accuracy than other analysts. However, these studies do not consider analysts' coverage decisions as a performance metric.

number of unique earnings forecasts summed across relevant analysts and forecasted periods (i.e., analyst-forecast pairs). We then estimate the abnormal component of the coverage as the residuals from monthly cross-sectional regressions of the raw coverage on firm characteristics (i.e., firm size, share turnover, and past performance). To examine the quality of the coverage decisions of star and non-star analysts, we evaluate the ability of abnormal coverage of each analyst group to predict returns. By sorting the sample stocks into deciles based on the abnormal coverage of each analyst group, we find that both the abnormal coverage of star analysts and that of non-star analysts predict returns in the next month, consistent with the notion that analysts' coverage decisions contain information about future firm performance.

To compare the return predictability of the abnormal coverage of star and non-star analysts, we perform the dependent double sorting. We first sort stocks into quartiles based on the abnormal coverage of star analysts and then within each quartile we sort the stocks into quartiles based on the abnormal coverage of non-star analysts (i.e., 4×4 portfolios). We find that after controlling for the abnormal coverage of star analysts the abnormal coverage of non-star analysts can no longer predict future returns, indicating that the coverage decisions of non-star analysts contain no incremental information over those of star analysts. We then reverse the order of the double sorting by first sorting based on the abnormal coverage of non-star analysts and then within each quartile sorting based on the abnormal coverage of star analysts. After controlling for the abnormal coverage of non-star analysts, the abnormal coverage of star analysts remains a strong predictor of future returns, indicating that the coverage decisions of star analysts contain incremental information over those of non-star analysts. To control for firm characteristics that may affect future returns, we run Fama-MacBeth regressions including both the coverage measures of star and non-star analysts. We find that only the coverage measure of star analysts is significantly positively related to future returns. Collectively, our evidence indicates that the abnormal coverage of star analysts is the dominant predictor of future returns, suggesting that star analysts possess better information processing skills than non-star analysts.

Next, we explore the mechanism through which the coverage decisions of star analysts predict returns. First, we examine whether star analysts are able to forecast improvements in firm fundamental performance. Consistent with the mispricing-based explanation, the coverage decisions of star analysts can predict two-year-ahead firm fundamental performance proxied by Piotroski's (2000) F-score and are positively associated with standardized unexpected earnings, analyst forecast revision and analyst forecast error. Second, we examine return predictability around earnings announcements. Investors may underreact to salient information about firm fundamentals conveyed by star analysts' coverage decisions. The resulting underpricing will be subsequently corrected when new information (e.g., earnings announcements) arrives and investors update their beliefs accordingly (e.g., Noh, So and Verdi, 2021). Consistent with this mechanism, we find that stocks with high abnormal coverage of star analysts have higher returns on earnings announcement days than on non-announcement days. Collectively, these results suggest that the return predictability of the abnormal coverage of star analysts is driven by investor underreaction to fundamental information.

We further explore the cross-sectional heterogeneity in the relationship between the coverage decisions of star analysts and future returns and expect that the information content of star analysts' coverage decisions depends on firms' information environment. In particular, an opaque information environment, which gives rise to more mispricing, provides star analysts with greater opportunities to exploit their information processing skills and, therefore, enriches the information content of their coverage decisions. In contrast, a transparent information environment, in which prices are more likely to reflect firms' intrinsic values, could pre-empt the information contained in star analysts' coverage decisions (e.g., Frankel et al., 2006; Loh and

Stulz, 2011; 2018). Consistent with this conjecture, we find that the return predictability of the coverage decisions of star analysts is stronger for informationally opaque stocks (i.e., smaller firms, firms without institutional ownership, and firms with higher return volatility).

However, the observed cross-sectional differences might be biased due to the endogenous nature of our measures of information opacity (e.g., firm size). To mitigate this concern, we exploit three quasi-natural experiments that exogenously change firms' information environment: (i) the Chinese pilot program of short selling, (ii) Google's withdrawal from China, and (iii) the Chinese anti-corruption campaign. The analysis of the short selling pilot program is relevant because when a firm's stock becomes shortable, the potential short selling threats would curb managers' incentives to misinform investors and improve the firm's information environment (Massa et al., 2015; Fang et al., 2016; Tsai et al., 2021). Similarly, the anti-corruption campaign could improve firms' information environment by enhancing legal enforcement (Shleifer and Vishny, 1997; La Porta et al., 1998) and accounting information quality (Zhang, 2018; Hope et al., 2020). In contrast, Google's withdrawal from mainland China increases investors' information acquisition and processing costs (Xu et al., 2021), and deteriorates firms' information environment. We use these three experiments to investigate the impact of exogenous changes in information environment on the return predictability of the coverage decisions of star analysts.

We show that the ability of the coverage decisions of star analysts to predict returns weakens considerably following the relaxation of short selling restrictions and after the anti-corruption campaign. However, the return predictability of the coverage decisions of star analysts strengthens significantly after the exit of Google from mainland China. The results of these experiments indicate that the coverage decisions of star analysts better predict future returns in poor information environment, consistent with the notion that star analysts possess superior ability to identify mispriced stocks.

In additional analyses, we revisit the relation between the coverage decisions of non-star analysts and future returns in an attempt to explain why such relation disappears after controlling for the coverage measure of star analysts. We conjecture that non-star analysts may follow the coverage decisions of star analysts with high media visibility (e.g., Cooper et al., 2001; Groysberg and Healy, 2013; Rees et al., 2015). Consistent with this conjecture, we find that the return predictability of the coverage decisions of non-star analysts is subsumed by the lagged coverage measure of star analysts. This finding provides suggestive evidence that non-star analysts are able to predict returns because they follow the coverage decisions of star analysts.

We also consider two alternative explanations for the return predictability of star analysts' coverage decisions. First, star analysts may communicate with their institutional clients about stock picking ideas. When institutional investors change their positions accordingly, the price pressure from the institutional investors may drive the return predictability of the coverage decisions of star analysts. Inconsistent with this explanation, our results remain after adding controls for lagged and forward changes in institutional ownership. The second alternative explanation is that attention seeking behaviors of undervalued firms, rather than the superior ability of star analysts, may drive the return predictability. In particular, undervalued firms may attempt to enhance firm valuation by actively seeking the coverage of star analysts. It is thus possible that analysts piggyback coverage decisions on the undervaluation signals from the firms. Following prior studies (e.g., So et al., 2021), we use the growth in share repurchase and the net insider purchase ratio as two proxies for attention seeking behaviors of undervalued firms. We find that the return predictability of the coverage decisions of star analysts does not depend on firms' attention seeking behaviors.

Our final tests leverage the U.S. data to examine the generalizability of our results and to contribute directly to the long-standing debate on the relative performance of star and non-star analysts first documented in the U.S. (e.g., Stickel, 1992). By performing similar empirical analyses as those on the Chinese data, we find that star analysts in the U.S. are able to make superior coverage decisions which are predictive of future returns. Overall, we provide compelling evidence that star analysts outperform their non-star peers as financial intermediaries in two of the most important capital markets in the world.

Our study makes two contributions that advance our understanding of the information intermediary role of analysts. This study is the first to evaluate the performance of star and non-star analysts based on a new performance metric - the quality of coverage decisions. Our approach to comparing star and non-star analysts' performance represents a departure from, and an important complement to, prior studies focusing on earnings forecasts and stock recommendations (e.g., Stickel, 1992; Emery and Li, 2009; Xu et al., 2013; Fang and Yasuda, 2014; Guan et al., 2019). We reveal that the coverage decisions of star analysts are better predictors of stock returns in the cross-section, indicating that star analysts outperform their non-star peers. Furthermore, the return predictability of star analysts' coverage decisions is stronger when opaque information environment prevails and creates hurdles for their non-star peers to make informative coverage decisions, supporting the notion that the informativeness of analysts' output varies with the quality of information environment (Loh and Stulz, 2018). Thus, our study sheds light on whether and when star analysts outperform their non-star peers.

Second, a growing literature shows that analysts' output can predict future returns (Das et al., 2006; Jung et al., 2015; Lee and So, 2017).[4] We contribute to this strand of research by showing that the coverage decisions of star analysts exhibit particularly strong return predictability. This implies that star analysts can identify mispricing arising from discrepancies

[4] Exogenous coverage termination and initiation also affect future returns (Hong and Kacperczyk, 2010; Kelly and Ljungvist, 2012; Li and You, 2015).

between prices and fundamental values (e.g., Fama, 1965; Crane and Crotty, 2020), and are therefore able to convey timely, accurate, and unbiased information through their coverage decisions. However, investors seem to underreact to such information that is perhaps less salient than other explicit investment advice (e.g., Jegadeesh et al., 2004; Hirshleifer et al., 2009; Giglio and Shue, 2014; Lee and So, 2017). Our study, together with Xu et al. (2013) who document a negative relation between star analysts' coverage and stock price synchronicity, indicates that star analysts are able to produce firm-specific information. We make a step forward by examining the return predictability of star analysts' coverage and thereby provide new evidence on star analysts' ability to identify mispriced stocks. Our evidence suggests that the mispricing signals embedded in the star analysts' coverage decisions can be useful to investors in making better informed investment decisions, ultimately contributing to market efficiency.

2. Related literature and hypothesis

This paper evaluates the performance of star and non-star analysts based on the quality of their coverage decisions. Our study is motivated by Bradshaw's (2011) call for research on analysts' activity other than earnings forecasts and recommendations. Bradshaw (p3) states that: "our focus almost exclusively on earnings forecasts now obstructs the growth in our understanding of analysts' role … it is necessary for the literature to expand its focus on other activities performed by analysts and attempt to better model their incentives". In response to this, we assess analysts' performance by shifting the focus from what analysts 'say' through their advice to what analysts 'do' through their coverage decisions.[5] This section discusses the related theoretical and empirical literature to further motivate our study, and develops our central hypothesis.

[5]Analysts play three non-mutually exclusive roles: information discovery, information interpretation, and information dissemination (Bradshaw et al., 2017). The information discovery role means that analysts "gather a wide variety of

The issue of whether star analysts outperform their non-star counterparts is controversial. Several studies show that star analysts provide more accurate and timely earnings forecasts and that their earnings revisions have greater influences on stock prices (e.g., Stickel, 1992; Gleason and Lee, 2003; Xu et al., 2013). In addition, early evidence shows that the earnings forecasted by star analysts are less influenced by the mean consensus forecast, suggesting that these analysts are leaders in the profession (Stickel, 1990; 1992). Moreover, buy (sell) stock recommendations issued by star analysts yield more positive (negative) returns than those issued by non-star analysts (e.g., Loh and Stulz, 2011; Desai et al., 2000; Fang and Yasuda, 2014). However, analysts' rankings are often criticized as being "popularity contests" (e.g., Emery and Li, 2009; Brown et al., 2015). In particular, analysts at big brokerage houses, who have a large sales force to promote their work to institutional investors, have an advantage over those at small houses to be ranked as stars. This implies that the star status may reflect the recognition of big brokerage houses rather than analysts' superior performance. Consistent with this argument, Emery and Li (2009) find that star and non-star analysts perform indifferently in forecasting earnings and making investment recommendations. Thus, prior research on what analysts 'say' remains inconclusive as to whether star analysts are superior to their non-star counterparts in performing the information intermediary role.

However, the conventional approach to evaluating analysts' performance based on what they 'say' could be subject to the caveat that some analysts may intentionally provide biased predictions due to potential incentive problems (e.g., McNichols and O'Brien, 1997; Jegadeesh and Kim, 2009; Jegadeesh et al., 2004; Hu et al., 2021). In particular, analysts may issue

information not readily available to investors and efficiently process that information" (Ivković and Jegadeesh, 2004, p. 434). The information interpretation role refers to analysts' ability to "facilitate investors' understanding of the existing public information by analyzing and clarifying it and by offering their own opinions on issues raised through public disclosures" (Huang et al., 2018, p.2833). The information dissemination role entails broadcasting information and may be viewed as a case of low-level information interpretation (Huang et al., 2018). The role of analysts in our paper is more related to information discovery and interpretation.

upwardly biased earnings forecasts and recommendations to appease firm management to gain access to privileged information and ultimately increase revenues for their employers (e.g., via investment banking business).[6] Despite these economic incentives, some analysts may be reluctant to issue biased, optimistic views in order to preserve their reputations (e.g., Fang and Yasuda, 2009; Ljungqvist et al., 2006; Clarke et al., 2007; Bradley et al., 2012). To the extent that reputation is a portable and valuable asset for those seeking long-term career gains[7], star analysts who have strong incentives to preserve their reputations might be more likely to refrain from producing biased forecasts and recommendations. If this is the case, the observed difference in the performance between star and non-star analysts in terms of what they 'say' can be partly attributed to their heterogeneous incentives. Consequently, the value and accuracy of what analysts 'say' could be noisy signals about their skills.

Departing from the focus on what analysts 'say', this study compares the performance of star and non-star analysts on the basis of what analysts 'do'.[8] Specifically, we use the quality of coverage decisions, which reflects an analyst's best effort to cover firms with better prospects, as a new performance metric. Theoretically, Hayes (1998) models an analyst's incentive to cover a firm as an increasing function of the expected trading commissions to be generated from the firm. Her model implies that analysts, regardless of whether they are stars or non-stars, have strong incentives to initiate (drop) coverage on firms when they expect the firms to perform well (poorly). Consistent with these predictions, empirical evidence shows that analysts' coverage

[6] By doing so, analysts can increase their own compensation (e.g., Dugar and Nathan, 1995; Lin and McNichols, 1998; Dechow et al., 2000; Michaely and Womack, 1999; Agrawal and Chen, 2008; Malmendier and Shanthikumar, 2014; Huyghebaet and Xu, 2016).

[7] Anecdotal evidence suggests that being a star analyst increases the likelihood of becoming research directors and buy-side fund managers (e.g., Asquith et al., 2005; Groysberg et al., 2011).

[8] Nevertheless, to complement our main analysis, we compare the accuracy of the earnings forecasts made by star and non-star analysts. Following prior studies (e.g., Jacob et al., 1999; Clement, 1999), our measure of earnings forecast accuracy is constructed by comparing an analyst's one-year-ahead EPS forecast error for a particular firm to the average level of forecast error of all analysts who forecast the same firm's EPS during the same period. We find that star analysts provide more accurate earnings forecasts than non-star analysts, confirming that star analysts do a better job of forecasting earnings than their non-star counterparts.

decisions contain information about future firm performance. For instance, McNichols and O'Brien (1997) find that firms experience higher (lower) levels of profitability following analysts' coverage initiations (terminations). Das et al. (2006) also find that IPOs with abnormally high analyst coverage exhibit greater post-coverage returns and long-term operating performance. Irvine (2003) finds that an analyst's initiation of coverage, defined as her first recommendation to a firm, generates a higher return than the recommendation issued by an existing analyst who already covers the firm. Finally, in a comprehensive study on the information content of analysts' coverage decisions, Lee and So (2017) document that firms with abnormally high analyst coverage subsequently outperform those with abnormally low coverage and attribute their findings to analysts' ability to identify mispriced stocks.

In sum, analysts' choices of which firms to cover can be informative about the firms' future performance and the value-relevance of such information depends on the quality of analysts' coverage decisions. To the extent that star analysts possess better skills in processing value-relevant information and identifying mispriced stocks, they can make high quality coverage decisions. Therefore, we expect the coverage decisions of star analysts are better than those of their non-star counterparts at predicting returns. We state our central hypothesis as follows:

Hypothesis 1: The coverage decisions of star analysts have stronger predictive power for future returns than those of non-star analysts.

3. Institutional background, data description, and empirical model

3.1. Institutional background

This section describes the selection procedure of star analysts in China. Starting from 2003, the magazine of *The New Fortune* publishes the most influential rankings of financial analysts based on institutional investors' assessments of analysts' performance in the previous year (e.g., Xu et al., 2013; Gu et al., 2019; Li et al., 2020). *The New Fortune* requires institutional investors (buy-side firms) to nominate analysts who provide outstanding research to institutional clients.[9] The nomination process is similar to that of the U.S. All American Research Team published in the magazine of *Institutional Investor*, which is based on surveying institutional investors in all industries (Li et al., 2020). The surveys do not pre-select any analysts. Instead, respondents are required to provide the names of their nominated analysts. There is no restriction on the number of analysts to be nominated. If two or more analysts are nominated, respondents need to provide an explicit ranking. *The New Fortune* tallies the votes and selects the top five in their respective industry as star analysts. The entire selection process and the outcome are audited by a Big Four accounting firm, Deloitte. The number of star analysts increases from 26 to 316 over the period 2003-2017, whereas the turnover of star analysts in the ranking list is reasonably high. In our sample, only around 14% of star analysts maintain star status for more than two years, while 65% and 21% of star analysts are respectively first-time and second-time winners, indicating strong competition for being star analysts in China.

3.2. Data and sample

We obtain the information about firm fundamentals, stock returns, and analysts' coverage from the China Security Market and Accounting Research (CSMAR) database. We manually collect star analysts' names from the yearly issues of *The New Fortune* magazine and match analysts by name with the CSMAR database. Our sample includes firms with A-shares listed on the Shanghai and Shenzhen Stock Exchanges. Carpenter and Whitelaw (2017) suggest that some special features in the Chinese stock market (e.g., trading suspension, special treatment status for

[9] The buy-side firms involved in the voting of star analysts include banks, mutual funds, pension funds, insurance companies, private equity, and foreign investment funds (Li et al., 2020).

distressed stocks) should be controlled in empirical studies. We adopt the following sampling criteria: i) a stock must have more than 120 trading days in the prior 12 months; ii) stocks with special treatment (ST) are excluded from the sample[10]; and iii) shares of mutual funds and investment companies are also excluded.[11] However, following Lee and So (2017), to avoid unnecessarily censoring the sample against firms with low coverage, we include firms that are not followed by any analyst. Finally, our sample consists of 2,935 firms with 362,561 firm-month observations, largely representing the CSMAR universe, over the period 2004-2019. Figure 1 presents the number of firms in the full sample and the subsamples of firms covered by non-star and star analysts, and the number of firms with no coverage over the period from January 2004 to December 2019. The graph indicates that a relatively large number of firms have no analyst coverage and that the number of firms covered by star analysts is smaller than that covered by their non-star peers.

[Insert Figure 1 about here]

3.3. Estimating abnormal coverage of star and non-star analysts

This section describes how we measure the coverage decisions of star and non-star analysts based on the empirical framework of Lee and So (2017). We first separate all analysts into stars and non-stars. Specifically, an analyst's star status, published by *The New Fortune* at the end of the last year, holds from January to December of this year[12] (e.g., Fang and Yasuda, 2009; 2014). Following Lee and So (2017), we measure the raw coverage of star (non-star) analysts as the number of unique earnings forecasts summed across star (non-star) analysts and forecasted fiscal

[10] ST stocks are subject to daily price limits of ±5%, while other stocks have price limits of ±10%.
[11] These sample selection criteria reduce the number of firm-month (firm) observations by 25,262 (244), 23,232 (195) and 14,491 (88) respectively.
[12] The 2018 ranking list is missing in *The New Fortune*. To deal with this issue, an analyst's star status in 2017 lasts from January 2018 until December 2019. We find the similar results when we exclude the sample year of 2019.

period (i.e., analyst-forecast pairs) over a six-month period ending in month *t*, referred to as raw star (non-star) coverage and denoted as *StarCov* (*NStarCov*).[13] Our choice of a six-month period is to strike a balance between the inclusion of most forecast information produced by stars and that by non-stars. In particular, we calculate the mean numbers of months it takes for star and non-star analysts to revise their prior forecasts by pooling the data at the analyst-firm level (with 1.6 million observations). We find that on average star and non-star analysts revise their forecasts every 5.3 and 3.2 months, respectively. As such, the sum of earnings forecasts over the six-month period incorporates most of the forecast information of star and non-star analysts.

We employ the model of analysts' coverage decisions developed by Lee and So (2017) to estimate the abnormal coverage of star and non-star analysts. In particular, we regress their corresponding raw coverage on the expected components of coverage related to size, liquidity, and momentum in each month (Lee and So, 2017). We use the log one plus *StarCov* (*NStarCov*) to mitigate outliers. Specifically, we estimate the following two regressions to obtain abnormal star and non-star coverage for firm *i* in month *t*, respectively:

$$Log\left(1 + StarCov_{i,t}\right) = \beta_0 + \beta_1 Size_{i,t} + \beta_2 TO_{i,t} + \beta_3 MOM_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$Log\left(1 + NStarCov_{i,t}\right) = \delta_0 + \delta_1 Size_{i,t} + \delta_2 TO_{i,t} + \delta_3 MOM_{i,t} + \epsilon_{i,t} \quad (2)$$

where $Size_{i,t}$ is the log of market capitalization in month *t*, $TO_{i,t}$ is share turnover calculated as trading volume scaled by shares outstanding, and $MOM_{i,t}$ is the firm *i*'s cumulative market-adjusted returns. $TO_{i,t}$ and $MOM_{i,t}$ are measured over the prior 12 months ending in month *t*. The abnormal coverage of star analysts for each firm-month is defined as the regression

[13] Following Lee and So (2017), analyst forecast revisions are single counted. For example, if a stock is covered by a non-star analyst and a star analyst, the non-star analyst forecasts the stock's one-year ahead earnings, while the star analyst makes not only one-year ahead but also two-year ahead earnings forecasts. As such, the raw coverage of non-star analysts is counted as one, while that of star analysts is summed as two. For a given stock, the more earnings forecasts an analyst makes the more effort she devotes to forecasting. The Lee and So's (2017) approach to measuring analyst coverage is different from the conventional approach that is based on the number of analysts following a firm (e.g., Hong, Lim and Stein, 2000; Doukas et al., 2006; 2008).

residuals (i.e., $\widehat{\varepsilon_{i,t}}$) in Eq. (1) and denoted as *AStarCov*. Similarly, the abnormal coverage of non-star analysts is defined as the regression residuals (i.e., $\widehat{\epsilon_{i,t}}$) in Eq. (2) and denoted as *ANStarCov*. A higher value of *AStarCov* means that star analysts allocate abnormally high coverage to a particular firm given its profiles of size, liquidity, and past performance, which we hypothesize is indicative of star analysts' strong belief that the firm will have superior future performance. A similar interpretation can be applied to *ANStarCov*. In brief, *AStarCov* and *ANStarCov* reflect respectively star and non-star analysts' true beliefs about firms' future prospects, and allow us to compare the performance of star and non-stars based on the information content of these two coverage measures.[14]

Panel A of Table 1 shows the time-series average coefficients from the monthly Fama-MacBeth regressions. To facilitate the comparison of the coefficient estimates, each month we standardize all variables in Eq. (1) and Eq. (2) to have a zero mean and a standard deviation of one.[15] Columns (1) and (2) show that the coverage of star and non-star analysts is significantly and positively related to size and momentum, and negatively related to turnover. The coefficient on size is the largest, consistent with the notion that market capitalization is the dominant determinant of analyst coverage (e.g., Bhushan, 1989; O'Brien and Bhushan, 1990; Hong, Kubik

[14] A caveat of our approach lies in the fact that an analyst's coverage decision (i.e., what analysts do) is paired with an earnings forecast (i.e., what analysts say), making it difficult to disentangle the two effects. Nevertheless, our approach is distinctive in that we focus on what analysts do that is not expected (i.e., the abnormal component of analysts' coverage decisions). A positive (negative) earnings forecast is not necessarily associated with a high (low) level of abnormal analyst coverage, meaning that abnormal coverage may contain unique information that is not conveyed by earnings forecast.

[15] By re-scaling all variables, the coefficients become scale free and comparable across Eq. (1) and Eq. (2) (e.g., $\beta 1$ vs. $\delta 1$) (Bennett et al., 2003). The *t*-statistics of the standardized coefficients and R^2s of the standardized regressions are identical to their values calculated in raw data.

and Solomon, 2000). In addition, Column (3) shows that star analysts cover smaller stocks[16] and stocks with lower turnover and lower momentum, compared with their non-star counterparts.

It is worth noting that the signs of the coefficients on turnover and momentum are different between our study and the U.S. evidence in Lee and So (2017) that the analyst coverage of U.S. firms is positively (negatively) related to turnover (momentum). The negative association between turnover and analyst coverage contradicts the notion that analysts have the incentive to cover stocks that can generate large brokerage commissions. This negative association, however, is consistent with the findings of Andrade et al. (2013), who argue that stock turnover reflects the dispersion of investor beliefs, and the observed negative relationship between analyst coverage and stock turnover is consistent with analyst coverage coordinating beliefs across investors. In addition, the positive association between momentum and analyst coverage suggests that analysts prefer to cover better performing stocks (Lee and So, 2017).

[Insert Table 1 about here]

3.4. Summary statistics

Panels B and C of Table 1 report the summary statistics and correlation matrix respectively. As shown in Panel B, on average a stock has 36.629 and 16.947 unique earnings forecasts issued by non-star and star analysts, respectively. The high coverage from non-star analysts reflects the fact that there are more non-star analysts than star analysts on the market. By construction, the averages of abnormal star and non-star analyst coverage (AStarCov and ANStarCov) are zero. Panel C presents the correlations among various coverage measures and other stock characteristics. The coverage of star analysts (StarCov) is positively associated with Size (0.354)

[16] Star analysts' preferences of smaller firms for coverage suggest that star analysts are confident about their skills in dealing with complex forecast tasks (e.g., Clement, 1999). Such preferences partly explain the findings of Stickel (1990; 1992) that star analysts forecast small firms' earnings more accurately than non-star analysts.

and MOM (0.068), and is negatively associated with TO (-0.098). The coverage of non-star analysts (NStarCov) shows a similar pattern of correlations with TO, Size and MOM as does StarCov. In addition, regarding the control variables used in the regression analysis (see Table 4), both StarCov and NStarCov are positively highly correlated with SUE and INST, while their correlations with LBM, VLTY, RR and ACC are relatively small. The correlation between the abnormal coverage of star and non-star analysts is 0.625, suggesting that some stocks have attracted abnormally high coverage from both star and non-star analysts. This phenomenon is perhaps not surprising, considering that the coverage decisions of star analysts (in the form of issuing new earnings forecasts to stocks) are public information and can be learned and followed by non-star peers.

4. Results

4.1. Abnormal coverage and future returns

In this section, we test our main hypothesis that the coverage decisions of star analysts are stronger predictors of future returns than those of non-star analysts. We begin our analysis by examining the return predictability of the abnormal coverage of star analysts and that of non-star analysts. We then evaluate the incremental ability of each abnormal coverage measure to predict returns. Finally, we use the Fama-MacBeth regressions with additional controls to test the return predictability of the two coverage measures.

4.1.1. Single sorting

Table 2 reports the time-series average of monthly returns across the deciles of the abnormal coverage of star and non-star analysts, respectively. The abnormal coverage in month *t* is used to predict returns in month *t+1*. The ‘High-Low’ column reports the return difference between a long position in the highest decile and a short position in the lowest decile of the respective measures of abnormal coverage. Panel A shows a positive relation between the abnormal coverage of star analysts (*AStarCov*) and future returns. Specifically, firms in the highest decile of *AStarCov* outperform those in the lowest decile by 0.801% per month (*t*-statistic=3.01) on an equal-weighted basis, and by 0.779% per month (*t*-statistic=2.38) on a value-weighted basis.

To control for asset pricing risk factors, we estimate risk-adjusted returns across the deciles of *AStarCov* as well as the long-short hedge portfolio by regressing monthly raw returns on the Fama-French three factors along with the momentum factor (e.g., Liu et al., 2019)[17]. Panel A also shows the equal- and value-weighted risk-adjusted returns (i.e., 4-factor alphas). The long-short *AStarCov* strategy yields an equal-weighted alpha of 0.826% (*t*-statistic=6.57) and a value-weighted alpha of 0.481% (*t*-statistic=4.39). Hence, the returns associated with *AStarCov* are robust to standard risk adjustments.

Panel B shows that firms with abnormally high coverage of non-star analysts significantly outperform those with abnormally low coverage of non-star analysts. The long-short *ANStarCov* strategy yields an equal-weighted alpha of 0.943% (*t*-statistic=5.91), and a value-weighted alpha of 0.395% (*t*-statistic=3.66). The above evidence suggests that both the abnormal coverage of star analysts and that of non-star analysts can predict returns, consistent with the notion that analysts' coverage decisions contain information about future firm performance (e.g., Hong, Lim and Stein, 2000; Lee and So, 2017).[18]

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[17] We thank Jiannan Liu for providing size and value factors in China.

[18] We perform a robustness check to rule out the possibility that our results are driven by look-ahead bias. In the abnormal coverage regressions, we recalculate the three explanatory variables, namely Size, TO and MOM, to make sure that they are known at t-6. Specifically, the dependent variable is the same as the one specified in the main text (i.e., analyst-earnings forecast pairs over the past six months). Size is measured by market cap in month t-6; turnover (TO) is measured by cumulative trading volume scaled by shares outstanding over the prior 12 months ending in month t-6; MOM is measured by cumulative returns over the prior 12 months ending in month t-6. Using these variables, in untabulated results (available upon request) we re-run the regressions and the findings are qualitatively similar to those reported in Panel A of Table 1 and Table 2.

[Insert Table 2 about here]

Thus far, we demonstrate that the two measures of abnormal coverage can predict one-month-ahead returns, but can they predict longer-term returns? Figure 2 plots equal-weighted monthly returns up to six months ahead yielded by the abnormal coverage strategies of star and non-star analysts (i.e., the long position in the highest decile and the short position in the lowest decile based on each abnormal coverage measure), respectively. The shaded bars indicate that the returns associated with these strategies are significant at the 10% level or better. The graph shows that the abnormal coverage strategy of star (non-star) analysts yields significantly positive returns over the next five (three) months. In sum, the abnormal coverage of both star and non-star analysts can predict returns, but the return predictability of the former persists longer.

[Insert Figure 2 about here]

4.1.2. Dependent double sorting

Our previous results show that the abnormal coverage of star analysts and that of non-star analysts predicts returns. In this sub-section, we assess the incremental ability of each abnormal coverage measure to predict returns. We use the dependent double sorting procedure to control for the rankings of one abnormal coverage measure when analyzing the return predictability of the other. Specifically, we first sort all firms into quartiles according to the abnormal coverage of non-star analysts (*ANStarCov*), and then within each *ANStarCov* quartile we further sort the firms into quartiles based on the abnormal coverage of star analysts (*AStarCov*) (i.e., 4×4 portfolios). By testing the difference in Fama-French 4-factor alphas between the lowest and the highest *AStarCov* portfolios in a given *ANStarCov* quartile, we can evaluate whether the return predictability of *AStarCov* depends on *ANStarCov*. In addition, we perform the *GRS* test (Gibbons et al., 1989) for the null hypothesis that the four differences in alphas across the four

ANStarCov quartiles are jointly equal to zero (e.g., Fama and French, 1996; 2017). To more clearly show whether *AStarCov* contains incremental information about future returns over *ANStarCov*, we calculate the 4-factor alpha for a given *AStarCov* portfolio which contains stocks across all quartiles of *ANStarCov* and compare the difference in alphas between the highest and the lowest *AStarCov* portfolios. This comparison is based on a set of *AStarCov* portfolios with dispersion in *ANStarCov*, and thus, the returns predicted by *AStarCov* are controlled for the effect of *ANStarCov*. Next, we reverse the order of the two sorts (i.e., sorting the sample firms first by *AStarCov* and then by *ANStarCov*) to test whether the return predictability of the abnormal coverage of non-star analysts depends on the rankings of the abnormal coverage of star analysts.

[Insert Table 3 about here]

Panels A1 and A2 of Table 3 present the 4-factor alphas on the equal- and value-weighted portfolios which contain stocks first sorted by *ANStarCov* and then by *AStarCov*, respectively. In Panel A1, the four differences in alphas across the four *ANStarCov* quartiles are all significantly positive at the 10% level or better. The *p*-value of the *GRS* test in the last row of the panel is zero to two decimal places and thus we can reject the null hypothesis with high confidence that the four differences in alphas are jointly equal to zero. The last Column of Panel A1, labelled as "Avg", reports the alphas for a given *AStarCov* quartile portfolio which includes stocks across different levels of *ANStarCov*. In this column, the difference of "H-L" in 4-factor alphas is 0.927% per month (*t*-statistic=4.53). Thus, controlling for the abnormal coverage of non-star analysts has little effect on the return predictability of the abnormal coverage of star analysts. Our results and inferences largely remain when we turn to an examination of the value-weighted risk-adjusted returns on the *AStarCov* portfolios in Panel A2. In sum, the ability of the abnormal coverage of star analysts to predict returns is independent of the rankings of the abnormal coverage of their non-star counterparts.

To test whether the reverse is true, we first sort firms into quartiles by *AStarCov* and then within each quartile we sort the firms into four groups by *ANStarCov*. Panels B1 and B2 report 4-factor alphas on the equal- and value-weighted portfolios, respectively. In Panel B1, the difference in alphas is only significantly positive in the highest *AStarCov* quartile. The *p*-value of the *GRS* test is 0.10 and we can only reject the null hypothesis that the differences in alphas across the *ANStarCov* quartiles are jointly equal to zero at the 10% level. The last Column of Panel B1 shows that the difference of "H-L" in the 4-factor alphas is 0.398% per month and marginally significant at the 10% level. Thus, controlling for the abnormal coverage of star analysts substantially reduces the return predictability of the abnormal coverage of non-star analysts. The results become even stronger when we move to alphas in the value-weighted portfolios in Panel B2 where none of the four differences in alphas is individually significant. The large *p*-value of the *GRS* test suggests that the four differences in alphas are not jointly significantly different from zero. In the last Column of Panel B2, the difference in alphas between the high and the low *ANStarCov* portfolios is statistically indifferent from zero (i.e., 0.125% per month with *t*-statistic=1.03).

Overall, the results indicate that the return predictability of the abnormal coverage of non-star analysts depends on the rankings of the abnormal coverage of star analysts. Put differently, a large part of the returns predicted by the abnormal coverage of non-star analysts is driven by a subset of stocks that have attracted high abnormal coverage of star analysts. These results lend strong support to the notion that the coverage decisions of star analysts contain incremental information about future firm performance over those of their non-star counterparts.

4.1.3. Multivariate regressions

In this section, we use Fama-MacBeth regressions to examine the information content of the coverage decisions of star and non-star analysts. Following Lee and So (2017), we use the raw analyst coverage as our main variable of interest in the multivariate regressions where we control for the expected components of analyst coverage (i.e. firm size, share turnover, past returns).[19] In this regression setting, the coefficients on the raw analyst coverage measures, namely *Log(1+StarCov)* and *Log(1+NStarCov)*, can be interpreted as the impact of the abnormal coverage of star analysts and that of non-star analysts, respectively, on future returns. To facilitate the interpretation of the estimated coefficients, we follow Lee and So (2017) and standardize all of the independent variables each month to a mean of zero and a standard deviation of one.

[Insert Table 4 about here]

Table 4 reports the regression results. In Columns (1)-(3), we control for firm size (*Size*), share turnover (*TO*), and past returns (*MOM*) only. Columns (1) and (2) show that the coefficients on *Log(1+StarCov)* and *Log(1+NStarCov)* are positive and significant, respectively. However, when both measures are included in the same model in Column (3), only the coefficient on the coverage measure of star analysts remains positive and significant. In Columns (4)-(6), we re-run the regressions with other commonly used predictors of returns as additional control variables, including book-to-market ratio (*LBM*), return volatility (*VLTY*), monthly return reversals (*RR*), standardized unexpected earnings (*SUE*), accruals (*ACC*) and institutional holdings (*INST*). Again, only the coefficient on the coverage measure of star analysts remains positive and significant across all specifications. These findings lend strong support to our main hypothesis that the coverage decisions of star analysts are more informative about firms' future performance. In terms of economic magnitude, Column (6) shows that the incremental return spread associated

[19] Our results are qualitatively similar when we use abnormal coverage in the multivariate regressions.

with the coverage measure of star analysts has a similar size to other well-known anomalies, such as the accrual anomaly (Sloan, 1996) and the idiosyncratic volatility anomaly (Ang et al., 2006).

4.2. Testing the mispricing-based explanation

4.2.1. Abnormal coverage and future firm fundamental performance

This section aims to shed light on the mechanisms through which the coverage decisions of star analysts perform better in predicting future returns than those of non-star analysts. In particular, the return predictability of star analysts' coverage decisions could stem from their superior ability to forecast improvements in firm fundamental performance that is not yet reflected in stock prices. This mispricing-based explanation for the return predictability of star analysts' coverage decisions suggests that star analysts are more able to forecast future firm fundamental performance than their non-star peers. To test our conjecture, we follow the literature (Lee and So, 2017; So et al., 2021) and employ four measures of firms' fundamental performance, namely F-score, standardized unexpected earnings, analyst forecast revision and analyst forecast error.

In Panel A of Table 5, we use a composite measure for the strength of firms' fundamentals namely F-score (Piotroski, 2000; Fama and French, 2006; Piotroski and So, 2012; Lee and So, 2017), as the dependent variable. We calculate F-scores for the sample firms each year.[20] A high F-score indicates strong fundamental performance. We regress one-year- and two-year-ahead F-score on *Log(1+StarCov)*, *Log(1+NStarCov)*, momentum, turnover, size, volatility, and book-to-market ratio. Column (1) in Panel A shows that both the coverage measures of star and non-star analysts can predict the one-year-ahead F-score, while only the coverage measure of

[20] Following Piotroski (2000) and Piotroski and So (2012), we construct F-score as the sum of nine binary signals that capture levels of, and changes in profitability (ROA, change in ROA, operating cash flow, accruals), financial leverage (changes in leverage, current ratio and the number of shares) and operating efficiency (changes in gross margin and asset turnover).

star analysts can predict the two-year-ahead F-score. This suggests that the coverage decisions of star analysts are better at predicting longer-term fundamental performance.

In Panel B of Table 5, we use three alternative measures of fundamental performance, namely standardized unexpected earnings (SUE)[21], analyst forecast revision (AFR) and analyst forecast error (AFE). SUE is defined as the realized earnings per share (EPS) minus EPS from four quarters prior divided by the standard deviation of this difference over the eight preceding quarters. AFR is defined as the difference between the latest consensus forecast and the consensus forecast measured at the end of fiscal year, divided by total assets per share. AFE is defined as actual EPS minus consensus forecast divided by total assets per share, where consensus forecast is calculated at the end of fiscal year. AFR and AFE capture investors' revisions of expectations about firms' performance under the premise of analysts' earnings forecasts being correlated with investors' expectations (Piotroski and So, 2012; So et al., 2021). Panel B shows that *Log(1+StarCov)* is significantly and positively associated with one-year-ahead SUE, AFR, and AFE. In contrast, *Log(1+NStarCov)* only has a significantly positive association with AFE, but has much weaker statistical and economic significance compared with the coefficient on *Log(1+StarCov)*. In sum, the results in this section suggest that the coverage decisions of star analysts are better at predicting future firm fundamental performance.

[Insert Table 5 about here]

4.2.2. Returns around earnings announcements

Our findings so far show that star analysts' coverage decisions convey salient information about firms' future fundamentals. Specifically, the return predictability of abnormal star coverage could

[21] In untabulated results, the coverage measure of non-star analysts can predict one-quarter-ahead SUE, suggesting that non-star analysts are able to predict short-term fundamental performance.

represent mispricing due to investor underreaction to such information. Under this explanation, undervalued stocks will subsequently experience a price correction that occurs when new information (e.g., earnings announcements) is made public and investors update their beliefs about firms' future performance (e.g., Noh, So and Verdi, 2021). Therefore, the abnormal returns predicted by star analysts' coverage decisions would concentrate on future earnings announcement dates. In particular, stocks with higher (lower) levels of abnormal star coverage would have predictably higher (lower) returns on earnings announcement days than on non-announcement days. To test this conjecture, we follow Engelberg et al. (2018) and estimate the following panel model based on stock-day observations:

$$\begin{aligned} DRet_{i,t} = \alpha_t &+ \beta_1 H\_AStarCov_{i,t} + \beta_2 L\_AStarCov_{i,t} + \beta_3 H\_ANStarCov_{i,t} + \beta_4 L\_ANStarCov_{i,t} \\ &+ \beta_5 H\_AStarCov_{i,t} \times Eday_{i,t} + \beta_6 L\_AStarCov_{i,t} \times Eday_{i,t} \\ &+ \beta_7 H\_ANStarCov_{i,t} \times Eday_{i,t} + \beta_8 L\_ANStarCov_{i,t} \times Eday_{i,t} \\ &+ \beta_9 \sum_{j=1}^{10} \gamma_i LagRet_{i,t-j} + \beta_{10} \sum_{j=1}^{10} \delta_i LagRet_{i,t-j}^2 + \beta_{11} \sum_{j=1}^{10} \rho_i Vol_{i,t-j} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where the dependent variable is the daily returns (*DRet*) in basis point. *H_AStarCov* and *L_AStarCov* (*H_ANStarCov* and *L_ANStarCov*) are dummy variables indicating whether a stock belongs to the top and bottom abnormal star (non-star) coverage deciles, respectively, at the beginning of each month. By construction, the value of the above four dummy variables remains the same throughout a month (i.e., the four portfolios are re-balanced each month). *Eday* is a dummy variable that takes the value of one for the three-day window around an earnings announcement day for firm *i*, and zero otherwise. Control variables include lagged values of the last 10 days of returns (*LagRet*), volatility proxied by return squared (*LagRet*^{2}), and trading volume (*Vol*). We also control for day fixed effects (α_t) that capture the impact of the common factors (e.g. macroeconomic variables) on daily stock returns. Specifically, we include n-1 dummy variables based on n (i.e. 3890) trading days over the sample period.

Our main variable of interest in Eq. (3) is the interaction term, *H_AStarCov*Eday*. A positive coefficient (β_5) indicates that the returns to the top abnormal star coverage portfolio are higher on information days relative to non-information days. Table 6 shows that the coefficient on *H_AStarCov*Eday* is positive and statistically significant.[22] This evidence implies that the price of undervalued stocks, which attract abnormally high star analysts' coverage, is subsequently corrected around future earnings announcement dates, consistent with the notion that the return predictability of star analysts' coverage decisions represents mispricing.

[Insert Table 6 about here]

4.3. Cross-sectional heterogeneity

4.3.1. Information opacity

In this section, we explore the cross-sectional variations in the relation between the coverage measure of star analysts and future returns. The purpose of this analysis is to examine whether the ability of the coverage decisions of star analysts to predict returns depends on firms' information environment. In particular, a firm's transparent information environment, which allows investors to draw better inferences about the firm's intrinsic value, is likely to pre-empt the information contained in the coverage decisions of star analysts (e.g., Frankel et al., 2006). In contrast, information opacity, which may make it difficult for investors to value firms,[23] provides skilled analysts with greater opportunities to identify mispriced stocks. To the extent that star analysts

[22] The R-square of 43% is higher than that in the U.S. market (Lee et al, 2019) as stock prices move together more in China than in the U.S. (Morch et al., 2000).

[23] For example, large trading costs preventing investors from fully incorporating their expectations into prices (e.g., Shleifer and Vishny, 1997; Lam and Wei, 2011), investors having difficulties in gathering information (e.g., Garleanu and Pederson, 2013), investors' limited attention (e.g., Merton, 1987) and differences in opinion slowing down the price adjustment process (e.g., Chen et al., 2002; Zhang, 2006).

possess superior information processing skills, we expect the coverage measure of star analysts to be a stronger predictor of returns in informationally opaque environments.

Following Loh and Stulz (2011; 2018), we use firm size, institutional ownership, and return volatility as proxies for information opacity. Small firms, firms with low institutional ownership and firms with high return volatility tend to suffer more from information asymmetry. We group stocks into two size (volatility) groups based on the median of firm size (return volatility) in June each year and each variable's rankings are carried over from July of one year to June of next year (e.g., Fama and French, 1996). We also separate stocks with and without institutional ownership in each month.[24] We then run Fama-MacBeth regressions within each group and report the time-series average coefficients on *Log(1+StarCov)* and *Log(1+NStarCov)*. Table 7 shows that the coefficient on *Log(1+StarCov)* is significantly positive only in the subsamples with small-cap, high volatility, and no institutional ownership. These results suggest that the return predictability of coverage decisions reflects analysts' skills in identifying mispriced stocks.

[Insert Table 7 about here]

4.3.2. Exogenous shocks to information environment

A potential limitation of the above cross-sectional analysis is that our proxies for the quality of information environment might be endogenous to abnormal coverage. In the presence of endogeneity, for example, the estimated moderating effect of firm size on the link between coverage decisions and future returns could be biased. To mitigate such concern, we exploit three quasi-natural experiments that exogenously change the quality of firms' information

[24] Institutional ownership is not included as a control variable in this cross-sectional test.

environment, namely the Chinese short selling deregulations, Google's withdrawal from China, and the Chinese anti-corruption campaign.[25]

The Chinese short selling deregulations are staggered and generate exogenous shocks to firms' information environment. Specifically, the Chinese Securities Regulatory Commission (CSRC) launched the initial pilot program on March 31 2010, allowing 90 constituent stocks (comprising the Shanghai Stock Exchange 50 Index and the Shenzhen Stock Exchange 40 Index) on a designated list to be sold short. The designated list has been subsequently revised and the number of stocks on the list has increased over the period 2011-2016. As of December 2016, the designated list contained 950 shortable stocks. When short selling constraints are relaxed, the resulting short selling threats play a disciplinary role in improving accounting quality by mitigating managers' incentives to misinform investors (Massa et al., 2015; Fang et al., 2016; Tsai et al., 2021). The improved information environment, in turn, reduces mispricing as well as the ability of the coverage decisions of star analysts to predict returns.[26]

[25] To validate these experiments, we verify whether the shock leads to significant changes in information environment. As shown in Appendix 2, it is comforting to see that the treated firms that experience an improvement (deterioration) in information environment, in all the three experiments, have significantly lower (higher) stock price synchronicity, higher (lower) stock turnover, and less (more) price delay (see the caption of Appendix 2 for the definitions of these variables, namely *PriceSync*, *Turnover*, *PriceDelay1*, and *PriceDelay2*). This means that as these experiments improve (deteriorate) information environment, firm-specific information can be capitalized into stock prices in a more (less) timely manner (e.g., Roll, 1988; Gul et al., 2010), stocks become more (less) liquid (e.g., Milgrom and Stokey, 1982; Liu, 2006; Xu et al., 2021), and the speed at which prices incorporate market-wide information increases (decreases) (e.g., Hou and Moskowitz, 2005; Xu et al., 2021). Overall, these findings confirm the three experiments are associated with significant changes in information environment quality and price efficiency.

[26] Short sellers are typically informed traders with private information and the ability to identify not only overvalued but also undervalued stocks (e.g., Boehmer et al., 2010; Boehmer et al., 2020). When stocks can be easily shorted, market participants can observe the undervaluation signals generated by short sellers who avoid shorting some stocks. Boehmer et al. (2010) document that lightly shorted stocks (i.e., stocks with low short interest) have significant positive returns that are larger (in absolute value) than the negative returns on heavily shorted stocks. Their evidence suggests that the absence of short interest may be a strong indicator of private good news. The transmission of good news from short sellers to the market is only possible when short selling constraints become less binding. In our short selling experiment, the lifting of short selling constraints allows such transmission to occur. To the extent that investors exploit the undervaluation signals conveyed by low short interest (and given that investors have access to the short interest information with a one-day lag from the official websites of the Shanghai and Shenzhen stock exchanges), we would expect underpricing to be less prevalent and consequently fewer opportunities for analysts to initiate coverage on undervalued stocks.

To test our proposition, we use a difference-in-differences (DiD) approach. Specifically, we define six event dates[27] on which the CSRC announces the revisions of the designated list. The variable of *Treated1* is equal to one if a stock is added to the list, and zero otherwise. We also construct a post-event variable of *Post1*, which is equal to one if firm-month observations are one year after the announcement of the designated list, and zero otherwise. For example, the first list is announced on March 31 2010. The pre-event period is from March 2009 to February 2010 and the post-event period is from March 2011 to February 2012.[28] Finally, we compile the panel data set with 156,321 firm-month[29] observations and estimate the following panel regression:

$$\begin{aligned} Ret_{i,t+1} = \alpha &+ \beta_1 Treated1_{i,t} + \beta_2 Post1_{i,t} + \beta_3 Log\ (1+StarCov)_{i,t} \\ &+ \beta_4 Log(1+StarCov)_{i,t} \times Post1_{i,t} \times Treated1_{i,t} + \beta_5 Log(1+NStarCov)_{i.t} \\ &+ \beta_6 Log(1+NStarCov)_{i,t} \times Post1_{i,t} \times Treated1_{i,t} + \beta_7 Treated1_{i,t} \times Post1_{i,t} \\ &+ \beta_8 Log(1+StarCov)_{i,t} \times Post1_{i,t} + \beta_9 Log(1+NStarCov)_{i,t} \times Post1_{i,t} \\ &+ \beta_{10} Log(1+StarCov)_{i,t} \times Treated1_{i,t} + \beta_{11} Log(1+NStarCov)_{i,t} \times Treated1_{i,t} \\ &+ \delta Control_{i,t} + Industry_{i,t} + Year_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where the dependent variable is firm *i*'s return in the next month. The interaction term (*Log(1+StarCov)*Post1*Treated1*) is of our main interest and its coefficient captures the change in the ability of star analysts to predict the treated firms' returns after the short selling deregulations. We control for industry (i.e., 20-industry classification by the China Securities Regulatory Commission (CSRC)) and year fixed effects. Panel A of Table 8 shows that the coefficient on *Log(1+StarCov)*Post1*Treated1* is negative (-0.371) and significant at less than

[27] These dates are Mar. 31, 2010, Dec. 5, 2011, Jan. 31, 2013, Sep. 16, 2013, Sep. 22, 2014, and Dec. 12, 2016. (see http://www.sse.com.cn/disclosure/magin/announcement/ and http://www.szse.cn/main/disclosure/rzrqxx/ywgg/)

[28] The announcement year of the short selling deregulations is removed from the sample because the relaxation of the short selling constraints may not have an immediate effect on firm information environment and stock prices (e.g. Massa et al., 2015).

[29] 106 firms are subsequently removed from the designated list by the Shanghai and Shenzhen stock exchanges, meaning that short selling restrictions are re-imposed on these firms. We exclude these firms in our DiD analysis because they do not remain in the treatment group for the entire post-treatment period.

5% level, while that on *Log(1+NStarCov)*Post1*Treated1* is statistically insignificant. This finding suggests that the predictive power of the coverage decisions of star analysts for returns weakens following the exogenous improvement in information environment.[30]

[Insert Table 8 about here]

Next, we exploit Google's withdrawal from China, which exogenously deteriorates firms' information environment, as the second quasi-natural experiment. Google's search engine was first launched in China in 2006 but pulled out abruptly from mainland China in 2010. This unexpected exit of the searching business represents a negative shock that limits investors' ability to acquire and process information via internet searching. Consequently, the investors incur higher information acquisition and processing costs, which may in turn hinder stock price efficiency (Drake et al., 2012; Hoopes et al., 2015). Indeed, Xu et al. (2021) document that Google's withdrawal is associated with a lower price adjustment to information, higher stock price crash risk, and lower stock liquidity. The deteriorated information environment, in turn, increases mispricing as well as the ability of the coverage decisions of star analysts to predict returns.

We test the above proposition in a difference-in-differences (DiD) framework. Following Xu et al. (2021), we define the treatment firms (*Treated2*) as those whose stock tickers have a higher search volume index (SVI)[31] than the sample median in 2009. These firms are classified into the treatment group considering that firms with higher pre-treatment search volume should be most affected by the withdrawal, because investors of such firms rely more on Google for information gathering before the withdrawal. We also construct a post-event variable of *Post2*,

[30] The coefficient on Log(1+StarCov) is negative and statistically insignificant (*t*-statistic=-0.70). This result could be due to multicollinearity problems associated with interaction terms, leading to biased coefficient estimates and inflated standard errors. In untabulated results, we remove all the interaction terms in Eq. (4) and only keep Log(1+StarCov), Log(1+NStarCov) and control variables. We find that the coefficient on Log(1+StarCov) is positive and statistically significant, consistent with our baseline results in section 4.1.3.

[31] We thank the authors of Xu et al. (2021) for generously sharing the search volume index (SVI) of Google.

which is equal to one for firm-month observations after Google's withdrawal (i.e. 2011-2013), and zero for the observations before the withdrawal (i.e. 2007-2009). Specifically, we compile the panel data set with 116,683 firm-month observations and estimate Eq. (4) using *Treated2* and *Post2* instead of *Treated1* and *Post1* as the treatment and post-event indicators, respectively.[32]

The results are presented in Panel B of Table 8 where the dependent variable is a firm's return in the next month. The coefficient on the interaction term (*Log(1+StarCov)*Post2*Treated2*) captures the change in the ability of star analysts to predict the returns of the treated stocks after Google's withdrawal. The coefficient on *Log(1+StarCov)*Post2*Treated2* is 0.535 and statistically significant, while that on *Log(1+NStarCov)*Post2*Treated2* is insignificant. This finding suggests the predictive power of the coverage decisions of star analysts becomes stronger following the exogenous deterioration in information environment, consistent with the argument that poor information environment is associated with more opportunities for skilled analysts to identify mispriced stocks.

Finally, we utilize the anti-corruption campaign in China, launched by the Chinese president Jinping Xi on 4th December 2012, as an exogenous shock to firms' accounting information quality. Corruption undermines regulatory monitoring and legal enforcement and, in turn, weakens investor protection and exacerbates managerial agency problems (e.g., Shleifer and Vishny, 1997; La Porta et al., 1998). This campaign does not only have a profound effect on the behavior of government officials[33], but also the quality of corporate governance. The campaign reduces firms' incentives to engage in accounting manipulations and improves financial reporting quality (Zhang, 2018; Hope et al., 2020). To the extent that the campaign improves firms'

[32] In this regression, *Post2* is absorbed into the year fixed effects.
[33] In the year after the launch of the campaign, 182,000 government officials were disciplined for corruption or abuse of power (Lin et al., 2018).

information environment and reduces the likelihood of mispricing, the ability of the star analysts' coverage decisions to predict returns would weaken after the campaign.

In our test, we construct a moderating variable, *AntiCorruption*, that takes the value of one for firm-month observations in the post-campaign period (i.e., 2013-2015), and zero for observations in the pre-campaign period (i.e., 2010-2012). Panel C of Table 8 shows that the coefficient on *Log(1+StarCov)*AntiCorruption* is -0.386 and statistically significant, while that on *Log(1+NStarCov)*AntiCorruption* is insignificant. This finding indicates that the predictive power of star analysts' coverage decisions weakens after the anti-corruption campaign, consistent with the evidence from the short selling experiment, suggesting that the improved information environment reduces the opportunities for skilled analysts to identify mispriced stocks.

In sum, the three experiments suggest that the ability of star analysts to predict returns depends on the quality of information environment. The stronger return predictability of star analysts' coverage decisions when information environments are poor reflects these analysts' superior skills in processing information and identifying mispriced stocks. The evidence supports the notion that analysts' output becomes more important in times of information shortage (Loh and Stulz, 2018). For investors, the signals contained in the coverage decisions of star analysts are particularly useful when investing in informationally opaque stocks.

4.4. Further analyses

4.4.1. Further tests on the information content of non-star analysts' coverage decisions

This section further explores why the coverage measure of non-star analysts fails to predict returns after controlling for the coverage measure of star analysts. The single sorting results show that the coverage measure of non-star analysts significantly predicts returns, while this predictability disappears after controlling for the coverage measure of star analysts. This evidence implies that the coverage decisions of non-star analysts contain information about future firm performance, but such information is largely embedded in the coverage decisions of star analysts. This implication is plausible as previous studies show that star analysts often disseminate their coverage information through business press and TV (e.g., Cooper et al., 2001; Groysberg and Healy, 2013; Rees et al., 2015). The great exposure of star analysts to the media makes it possible for non-star analysts to easily observe and follow the coverage decisions of star analysts, which could be the reason why the coverage measure of non-star analysts also predicts returns. If this argument holds, not only would the lagged coverage measure of star analysts predict returns but also subsume the return predictability of the contemporaneous coverage measure of non-star analysts. To test this, we reconstruct the two coverage measures (*Log(1+NStarCov_3m)* and *Log(1+StarCov_3m)*) by aggregating unique analyst-forecast pairs over the past three months. By holding this period constant, we are able to compare the return predictability of the three-month lagged value of *Log(1+StarCov_3m)* (i.e. *Lag3_log(1+StarCov_3m)* with that of the contemporaneous coverage measure of non-star analysts*)* in the Fama-MacBeth regressions.

Columns (1) and (2) in Panel A of Table 9 show that *Lag3_Log(1+StarCov_3m)* and *Log(1+NStarCov_3m)* can individually predict returns. However, when the two coverage measures are jointly included in the regressions, only is the coefficient on *Lag3_log(1+StarCov_3m)* significant, suggesting that the return predictability of non-star analysts' coverage decisions is subsumed by the lagged coverage decisions of star analysts. A plausible explanation of this finding is that non-star analysts may follow the coverage decisions of star analysts and consequently incremental information content in the abnormal coverage of non-star analysts is very limited. To further verify this explanation, we perform a direct test on whether the coverage decisions of star analysts lead those of non-star analysts. Panel B of Table 9 shows that the coefficient on *Lag3_Log(1+StarCov_3m)* is 0.583, which is highly significant and the largest (in absolute value) among the four coefficients in the standardized Fama-MacBeth regressions[34].

Overall, these findings indicate that non-star analysts are able to predict future returns largely because non-star analysts follow the coverage decisions of star analysts. Furthermore, the dissemination of expected performance information across analysts provides suggestive evidence that star analysts are able to identify mispriced stocks in a timely fashion and such superior ability is likely to be recognized by their non-star peers (Leone and Wu, 2007).

[Insert Table 9 about here]

4.4.2. Alternative explanations

This section examines two alternative explanations for the return predictability of star analysts' coverage decisions. First, star analysts may communicate the stock picking ideas and their coverage decisions to their institutional clients who then change positions accordingly. The resulting price pressure from institutional investors may drive the return predictability of star analysts' coverage decisions. To account for this possibility, we control for the lagged and forward changes in institutional ownership (Δ*INST_Lag* and Δ*INST_Lead*) in regressions. In Column (1) of Table 10, we reestimate the empirical model presented in Column (6) Table 4, and additionally control for Δ*INST_Lag*. Column (1) shows that the coefficient on *Log(1+StarCov)* remains positive and significant after controlling for lagged changes in institutional ownership. The result still holds after controlling for forward changes in institutional ownership in Column (2). These results mitigate the concern that our evidence reflects price pressure from institutional investors.

[34] One should be careful in interpreting our result in Panel B. Despite using the 3-month lagged value of Log(1+StarCov_3m) in our empirical model, endogeneity may still prevail and prevent us from revealing the causal effect of star analysts' coverage decisions on the subsequent non-star analysts' coverage decisions.

Second, underpriced firms may attempt to enhance firm valuation by actively seeking the coverage of star analysts and investors' attention. To the extent that the attention seeking behaviors of firms signal the undervaluation of firm stocks, analysts have an opportunity to piggyback coverage decisions on the undervaluation signals. Consequently, the return predictability of analyst coverage can only be attributed to the piggybacking behavior rather than analysts' ability to identify undervalued stocks. If this alternative explanation holds, the return predictability of star analysts' coverage decisions would be stronger when high abnormal star analyst coverage coincides with attention seeking behaviors. Following prior studies (e.g., So et al., 2021), we use two proxies for attention seeking behaviors, namely the growth in share repurchases and the net insider purchase, capturing the undervaluation signals transmitted to the market. The growth in share repurchases is defined as a change in cash outflow from share repurchase scaled by the beginning-of-period total assets. The net insider purchase is defined as the difference between the number of insider purchases and sales scaled by the total number of insider transactions over the past 12-month period (e.g., Lakonishok and Lee, 2001; Cziraki et al., 2021)[35]. Then, we construct two dummy variables, Δ*Repurchase_H* and *InsiderBuy_H*, indicating whether a stock is in the top tercile of the growth in share repurchases and corporate insider purchases, respectively. We examine whether the return predictability of *Log(1+StarCov)* and *Log(1+NStarCov)* depends on the two indicators of undervaluation signals. Columns (3), (4) and (5) show that the moderating effects of Δ*Repurchase_H* and *InsiderBuy_H* are insignificant. Collectively, these results suggest that the return predictability of star analysts' coverage is not due to the attention seeking behaviors of underpriced firms.

[35] Using the net insider purchase ratio limits the number of our sample firms in our analysis, because a firm must have a non-missing value for either inside purchase or inside sale in the past 12 months. Instead, we can construct an alternative dummy variable, indicating whether the number of inside purchase is greater than that of inside sale. Our results are qualitatively similar when using the alternative dummy variable.

[Insert Table 10 about here]

4.4.3. Corresponding U.S. evidence

Next, we compare the return predictability of star and non-star analysts' coverage decisions for the U.S. market. This extended analysis aims to examine the generalizability of our Chinese evidence and contribute directly to the long-standing debate on the relative performance of star and non-star analysts first documented in the U.S. (e.g., Stickel, 1992; Desai et al., 2000; Emery and Li, 2009; Loh and Stulz, 2011; Fang and Yasuda, 2014; Brown et al., 2015). We compare the quality of the coverage decisions of U.S. star and non-star analysts by implementing single sorting, dependent double sorting, and multivariate analysis. To perform these tests, we construct the sample as follows. Analyst coverage data is from IBES. The information about All-American star analysts is from the *Institutional Investor* magazine.[36] We merge the analyst data with share price information from CRSP. We eliminate firms with share codes other than 10 or 11 (US-based common shares) and firms with share prices below $1. We obtain accounting data from Compustat. The sample includes 1,821,150 firm-month observations between 1984 and 2017.

In Panel A of Table 11, we estimate the abnormal coverage of the U.S. star and non-star analysts. We regress raw star (non-star) coverage on the contemporaneous market capitalization (*Size*), share turnover (*TO*), and momentum (*MOM*). Columns (1) and (2) show that the coverage of star and non-star analysts is significantly and positively related to size and turnover, and negatively related to momentum. The coefficients on these three determinants of analyst coverage are consistent with the initial finding of Lee and So (2017).

We use the residuals from the regressions in Columns (1) and (2) respectively as measures of the abnormal coverage of star and non-star analysts. We then compare the return predictability

[36] We thank Jonathan Clarke and Jeffery Pontiff for generously sharing the list of U.S. star analysts up to 2017.

of the abnormal coverage of star and non-star analysts. Panels B and C of Table 11 show the time-series average of monthly returns across the deciles of the abnormal coverage of star and non-star analysts, respectively.[37] The evidence suggests that both the abnormal coverage of star analysts and that of non-star analysts can predict returns, consistent with our Chinese evidence.

We perform dependent double sorting in Panel D of Table 11. Panel D1 presents the equal- and value-weighted risk-adjusted returns associated with the first sort of *ANStarCov* and the second sort of *AStarCov*. For brevity, we do not report returns for all 16 portfolios.[38] Instead, Panel D1 presents risk-adjusted returns to each *AStarCov* based quartile portfolio which includes stocks across different levels of *ANStarCov*. The last column of this sub-panel ("H-L") shows the differences in 4-factor alpha between the highest and the lowest *AStarCov* portfolios and the corresponding *t*-statistics. The difference in risk-adjusted returns, based on both equal-weighted and value-weighted portfolios, is significantly positive (i.e., 0.835% per month (*t*-statistic=7.92) on an equal-weighted basis and 0.274% per month (*t*-statistic=3.29) on a value-weighted basis). These results suggest that the return predictability of the abnormal coverage of star analysts is independent of the rankings of the abnormal coverage of non-star counterparts.

In Panel D2, we reverse the two sorts by first sorting the sample stocks on *AStarCov* into quartiles and then sorting the stocks on *ANStarCov* in each *AStarCov* quartile. The difference in risk-adjusted return is significantly positive only for the equal-weighted portfolios (i.e., 0.518% per month (*t*-statistic=6.67)). In contrast, the difference in the value-weighted returns becomes small and insignificant (i.e., 0.08% per month (*t*-statistic=1.05)). This evidence suggests that the return predictability of the abnormal coverage of non-star analysts depends on the rankings of the abnormal coverage of star analysts, indicating limited incremental predictive power of the

[37] In Online Appendix 1, we report the returns for all single-sorted decile portfolios (in the same format as Table 2).
[38] In Online Appendix 2, we report the returns for all 16 double-sorted portfolios (in the same format as Table 3).

coverage decisions of non-star analysts. In general, consistent with our Chinese evidence, the coverage decisions of star analysts contain incremental information about future firm performance over those of their non-star counterparts.

To further compare the incremental information content of the coverage decisions of star and non-star analysts, we run Fama-MacBeth regressions as described in section 4.1.3.[39] Columns (1) and (2) in Panel E of Table 11 show that both *Log(1+StarCov)* and *Log(1+NStarCov)* are significantly and positively associated with the monthly returns in month *t+1*, consistent with the single sorting results in Panels B and C. However, in Column (3) where both *Log(1+StarCov)* and *Log(1+NStarCov)* are included, with a full set of control variables, only the coefficient on *Log(1+StarCov)* remains significantly positive (i.e., 0.216 with a *t*-statistic of 6.06), while the coefficient on *Log(1+NStarCov)* becomes statistically insignificant, with a *t*-statistic of 0.48. This evidence based on the full model in Column (3) confirms that the return predictability of the coverage decisions of star analysts is stronger than that of their non-star counterparts. To conclude, consistent with our Chinese evidence, the U.S. evidence confirms that star analysts are able to make superior coverage decisions which are predictive of future stock returns.

[Insert Table 11 about here]

4.5. Robustness checks

In Table 12, we conduct a range of robustness checks. First, to examine whether our results are robust to the subsample of firms with analysts following, we re-run the regressions using two subsamples: the first subsample includes stocks covered by at least one analyst, and the second

[39] We also control for the earnings announcement month (EAM) of U.S. firms that may drive returns (Lee and So, 2017). EAM is a dummy variable that equals one when a firm announces earnings, and zero otherwise. In our previous analysis of Chinese firms, EAM is too homogeneous to be included in the Fama-MacBeth regressions due to the fact that all Chinese firms have same fiscal year/quarter ends.

consists of stocks covered by more than three analysts. Columns (1) and (2) in Panel A show that the coefficient on *Log(1+StarCov)* is significantly positive for both subsamples.

Second, we include brokerage size as an additional control. Prior studies show that large brokerage houses are more prestigious and offer greater resources to analysts, resulting in the forecasts of large houses being more accurate than those of small houses (Clement, 1999; Jacob et al., 1999; Malloy, 2005; Hong and Kubik, 2003; Crane and Crotty, 2020). To the extent that star analysts work in relatively large houses, an omitted variable bias may arise. To address this concern, we control for the coverage of big brokerage houses by adding dummy variables (*Top3* and *Top5*) that denote whether a firm is covered by the top 3 or top 5 largest brokerage houses in terms of the number of analysts employed in each year (Clement, 1999). Columns (1) and (2) in Panel B show that the coefficient on the coverage measure of star analysts remains positive and significant after controlling for *Top3* and *Top5* respectively. Thus, the return predictability of star analysts' coverage decisions is not driven by the coverage of big brokerage houses.

Third, we examine whether our results are sensitive to alternative measures of abnormal analyst coverage. In our main analysis, abnormal coverage is measured by the residuals from a relatively parsimonious model with three stock characteristics (*Size*, *TO*, *MOM*). As a robustness check, we add three additional firm characteristics (i.e., book-to-market, return volatility, and return on assets) in Eq. (1) and Eq. (2), and use the regression residuals as alternative measures of abnormal coverage. Panel C shows that there is roughly a 1% increase in R^2 when an additional explanatory variable is included in the model. Based on these alternative measures of abnormal coverage, the equal-weighted (EW) and value-weighted (VW) risk-adjusted returns of the hedge portfolio, consisting of a long position in stocks with the highest abnormal coverage decile and a short position in stocks with the lowest abnormal coverage decile, are significantly positive across all models, confirming our evidence is robust to alternative abnormal coverage measures.

Finally, the 4-factor model may not fully capture the expected returns. To address this concern, we report the characteristics-adjusted returns (Daniel et al., 1997) (hereafter DGTW returns) on the value-weighted and equal-weighted portfolios. We first calculate the DGTW returns and then the stocks are singly sorted by abnormal star and non-star coverage respectively. Panel D shows that the long-short *AStarCov* strategy yields a monthly equal-weighted (value-weighted) DGTW return of 0.528% (0.642%). The returns based on a long-short *ANStarCov* strategy is relatively lower, with a monthly equal-weighted (value-weighted) DGTW return of 0.483% (0.485%). Therefore, our finding is robust to the alternative measure of abnormal returns.

[Insert Table 12 about here]

5. Conclusion

It remains inconclusive as to whether star analysts outperform their non-star counterparts as financial intermediaries. Our study contributes to this debate by using a new performance metric, namely the quality of analysts' coverage decisions, to compare the performance of star and non-star analysts. We find that the coverage decisions of star analysts are stronger predictors of returns than those of non-star analysts, suggesting that star analysts possess superior information processing skills. We also find that the return predictability of the coverage decisions of star analysts is stronger for informationally opaque stocks. Further analysis reveals that such return predictability weakens following the short selling deregulations and after the anti-corruption campaign in China, both of which exogenously improve firms' information environment, and strengthens after the exit of Google from mainland China, which deteriorates firms' information environment. The evidence based on these three quasi-natural experiments indicates that the return predictability of star analysts' coverage decisions stems from their superior ability to identify mispriced stocks. Overall, our results suggest that star analysts are better at performing the information intermediary role. By conveying value-relevant information above and beyond that reflected in prevailing prices through coverage decisions, star analysts can facilitate the allocation of investors’ capital to its best use and ultimately help improve market efficiency.

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Appendix 1 Variable definitions

This table presents the definitions of the main variables used in the empirical analysis.

Variable	Definition	Source
StarCOV	Unique star analyst-forecast pairs summed over the prior six-month period ending at the end of month *t*.	CSMAR
NStarCOV	Unique non-star analyst-forecast pairs summed over the prior six-month period ending at the end of month *t*.	CSMAR
AStarCOV	Residuals from a monthly regression of star coverage on firms' contemporaneous log market capitalization (Size), share turnover (TO), and momentum (MOM).	CSMAR
ANStarCOV	Residuals from a monthly regression of non-star coverage on firms' contemporaneous log market capitalization (Size), share turnover (TO), and momentum (MOM).	CSMAR
Size	Market capitalization in logarithm form in month *t*	CSMAR
TO	Share turnover aggregated over the prior 12-month period ending in month *t*. Share turnover is defined as the number of shares traded over share outstanding.	CSMAR
MOM	Cumulative market-adjusted returns measured over the prior 12-month period ending in month *t*.	CSMAR
LBM	Log of one plus a firm's book-to-market ratio.	CSMAR
VLTY	Volatility is calculated as the standard deviation of monthly return over the prior 12 months ending in month *t*	CSMAR
RR	Monthly return reversals defined as the return in month *t*.	CSMAR
SUE	Standardized unexpected earnings, defined as the realized earnings per share (EPS) minus EPS from four quarters prior divided by the standard deviation of this difference over the prior eight quarters.	CSMAR
ACC	Net income minus cash flows from operations scaled by lagged total assets.	CSMAR
INST	Institutional ownership defined as a fraction of share outstanding.	CSMAR
Post1	A dummy variable that is equal to one if a sample month is one year after the announcement of the designated short selling list, and zero otherwise.	CSRC website
Treated1	A dummy variable that is equal to one if a stock is added to the revised designated short selling list, and zero otherwise.	CSRC website
Post2	A dummy variable that is equal to one for firm-month observations after Google's withdrawal (i.e. 2011-2013), and zero for the observations before the withdrawal (i.e. 2007-2009).	
Treated2	A dummy variable that is equal to one if a stock ticker has a higher search volume index (SVI) than the sample median in 2009, and zero otherwise	Xu et al. (2021)
AntiCorruption	A dummy variable that is equal to one for firm-month observations after the anti-corruption campaign in China (i.e. 2013-2015), and zero for observations before the campaign (i.e. 2010-2012).	
Top3	A dummy variable that is equal to one if a firm is covered by the largest three brokerage houses in terms of the number of analysts employed in each year, and zero otherwise.	CSMAR
Top5	A dummy variable that is equal to one if a firm is covered by the largest five brokerage houses in terms of the number of analysts employed in each year, and zero otherwise.	CSMAR

Appendix 2 Validation tests of three quasi-natural experiments

This table presents tests that validate whether the treated firms in the three experiments, namely short selling deregulation (Panel A), Google's withdrawal (Panel B) and anti-corruption campaign (Panel C), experience a significant change in the quality of information environment. We use four proxies for the quality of information environment, including stock price synchronicity (PriceSync), stock turnover (Turnover) and two price delay measures (PriceDelay1 and PriceDelay2). PriceSync is measured by $log\left(\frac{R^2}{1-R^2}\right)$ (Roll, 1988), where the R^2 is obtained from regressing a stock's daily returns on the market return, lagged market return, the industry return and lagged industry return (e.g., Gul et al., 2010). Turnover is defined as the annual average of monthly turnover (i.e. the monthly share trading volume scaled by the number of tradable shares over the month) (e.g., Liu, 2006). PriceDelay1 and PriceDelay2 are constructed following models 2 and 3 in Hou and Moskowitz (2005). The larger values of PriceDelay1 and PriceDelay2 mean that there are more delays in the incorporation of market-wide information into a stock price. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Panel A: Short selling deregulation and firm information environment

	(1)	(2)	(3)	(4)
Dep. variable	PriceSync	Turnover	PriceDelay1	PriceDelay2
Post1×Treated1	-0.216***	0.028***	-0.051*	-0.066*
	(-8.97)	(3.02)	(-1.85)	(-1.95)
Controls	Y	Y	Y	Y
Industry effects	Y	Y	Y	Y
Year effects	Y	Y	Y	Y
R^2 (%)	0.304	0.277	0.195	0.262
Obs.	145,300	156,321	152,301	152,301

Panel B: Google's withdrawal and firm information environment

	(1)	(2)	(3)	(4)
Dep. variable	PriceSync	Turnover	PriceDelay1	PriceDelay2
Post2×Treated2	0.061***	-0.065***	0.026***	0.016***
	(2.61)	(-4.59)	(4.56)	(3.45)
Controls	Y	Y	Y	Y
Industry effects	Y	Y	Y	Y
Year effects	Y	Y	Y	Y
R^2 (%)	0.220	0.411	0.120	0.182
Obs.	109,802	116,683	115,537	115,537

Panel C: Anti-corruption campaign and firm information environment

	(1)	(2)	(3)	(4)
Dep. variable	PriceSync	Turnover	PriceDelay1	PriceDelay2
AntiCorruption	-0.268***	0.207***	-0.032*	-0.231*
	(-20.57）	(20.99)	(-1.70)	(-1.91)
Controls	Y	Y	Y	Y
Industry effects	Y	Y	Y	Y
Year effects	Y	Y	Y	Y
R^2 (%)	0.105	0.212	0.012	0.008
Obs.	126,576	132,977	130,746	130,746

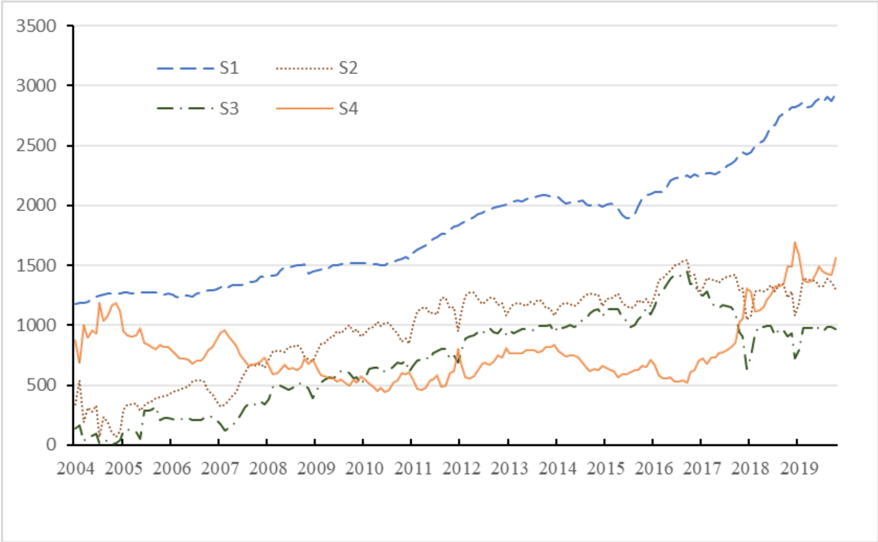

Figure 1 The number of sample firms

This figure depicts the number of our sample firms in each month over the period from January 2004 to December 2019. In particular, S1 shows the number of firms regardless of analyst coverage. S2 and S3 show the number of firms covered by non-star and star analysts, respectively. S4 shows the number for firms without analyst coverage.

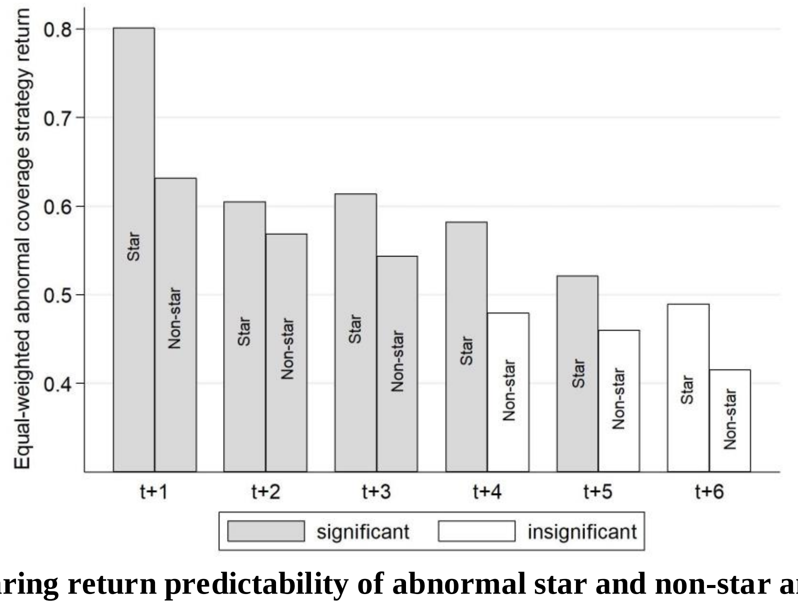

Figure 2 Comparing return predictability of abnormal star and non-star analyst coverage

This graph plots equal-weighted future returns from abnormal star and non-star coverage strategies. The returns to the abnormal star (non-star) coverage strategy is yielded by the long position in the highest decile of *AStarCOV* (*ANStarCOV*) and the short position in the lowest decile of *AStarCOV* (*ANStarCOV*). *AStarCOV* (*ANStarCOV*) is the residual from a monthly regression of raw star (non-star) coverage on firms' contemporaneous log market capitalization (*Size*), share turnover (*TO*) and momentum (*MOM*). *TO* and *MOM* are defined as trading volume scaled by shares outstanding and cumulative market-adjusted returns, respectively, over the prior 12 months ending in month *t*. The returns are reported in percentage. The grey shadow indicates that the return is statistically significant at the 10% level or better.

Table 1 Estimating abnormal coverage of star and non-star analysts and summary statistics

This table shows the regressions estimating abnormal analyst coverage in Panel A and the summary statistics of main variables and correlation matrix in Panels B and C respectively. Panel A presents the time-series average coefficients from regressing raw star (non-star) coverage on firms' contemporaneous log market capitalization (*Size*), share turnover (*TO*), and momentum (*MOM*). All variables in this regression are standardized each month to have a zero mean and a standard deviation of one. *TO* and *MOM* are defined as trading volume scaled by shares outstanding and cumulative market-adjusted returns, respectively, over the prior 12 months ending in month *t*. *StarCOV* (*NStarCOV*) is defined as the number of unique star (non-star) analyst-forecast pairs summed over a six-month period ending at the end of month *t*. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively. The sample consists of 362,561 firm-month observations over the period 2004-2019. Panel B reports the summary statistics and Panel C presents the pairwise correlation matrix.

Panel A: Estimating abnormal star and non-star analyst coverage			
	(1)	(2)	(3)
Dep. variable	*Log(1+StarCov)*	*Log(1+NStarCov)*	Coeff. Difference: (1)-(2)
Size	0.366***	0.409***	-0.043***
	(23.27)	(24.34)	(-8.92)
TO	-0.065***	-0.046***	-0.019***
	(-11.95)	(-6.81)	(-8.74)
MOM	0.061***	0.066***	-0.005*
	(5.38)	(6.30)	(-1.89)
R^2 (%)	27.34	31.65	
Obs.	362,561	362,561	

Panel B: Summary statistics						
Variable name	Obs.	Mean	Std. Dev.	P25	Median	P75
StarCov	362,561	16.947	47.188	0.000	0.000	9.000
NStarCov	362,561	36.629	84.231	0.000	0.000	31.000
AStarCov	362,561	0.000	1.329	-0.891	-0.168	0.689
ANStarCov	362,561	0.000	1.549	-1.177	-0.052	1.088
Size	362,561	15.318	1.592	14.606	15.279	16.033
TO	362,561	4.917	4.051	2.114	3.838	6.602
MOM	362,561	0.055	0.452	-0.185	0.004	0.237
LBM	362,561	0.485	0.158	0.373	0.509	0.615
VLTY	362,561	0.133	0.123	0.087	0.117	0.159
RR	362,561	0.014	0.146	-0.068	0.002	0.082
SUE	362,561	0.084	0.978	-0.014	0.055	0.120
ACC	362,561	0.028	0.080	-0.015	0.023	0.081
INST	362,561	0.038	0.067	0.049	0.067	0.117

Panel C: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. StarCov	1												
2. NStarCov	0.662	1											
3. AStarCov	0.568	0.420	1										
4. ANStarCov	0.341	0.530	0.625	1									
5. Size	0.354	0.408	0.000	0.000	1								
6. TO	-0.098	-0.110	0.000	0.000	-0.117	1							
7. MOM	0.068	0.090	0.000	0.000	0.133	0.177	1						
8. LBM	0.001	0.015	0.034	0.045	0.066	-0.187	-0.111	1					
9. VLTY	-0.021	-0.015	-0.033	-0.041	0.002	0.226	0.672	-0.076	1				
10. RR	0.012	0.012	-0.018	-0.019	0.051	-0.032	0.314	-0.070	0.066	1			
11. SUE	0.252	0.319	0.185	0.212	0.375	-0.098	0.099	-0.022	-0.053	0.008	1		
12. ACC	0.060	0.064	0.032	0.040	0.063	-0.015	0.037	0.019	0.011	0.004	0.103	1	
13. INST	0.307	0.335	0.202	0.211	0.296	-0.060	0.146	0.030	0.014	0.043	0.180	0.054	1

Table 2 Returns and alphas on portfolios of stocks singly sorted by abnormal coverage

This table reports returns and alphas in percentage on portfolios of stocks singly sorted by the abnormal coverage of star analysts (*AStarCov*) or the abnormal coverage of non-star analysts (*ANStarCov*). *AStarCov* and *ANStarCov* are based on the residuals from monthly regressions of raw star and non-star coverage, respectively, on firms' contemporaneous log market capitalization (Size), share turnover (*TO*), and momentum (*MOM*). *TO* and *MOM* are defined as trading volume scaled by shares outstanding and cumulative market-adjusted returns, respectively, over the prior 12 months ending in month *t*. The raw star (non-star) coverage is defined as the number of unique star (non-star) analyst-earnings forecast pairs summed over the prior six-month period ending at the end of month *t*. We form the decile portfolios by sorting stocks on *AStarCov* and *ANStarCov*, respectively, in ascending order. Portfolio 1 (10) is with the lowest (highest) *AStarCov* or *ANStarCov*. Panel A reports the value-weighted (VW) and equal-weighted (EW) average monthly returns and the Fama-French 4-factor adjusted alphas for the portfolio of stocks sorted by *AStarCov*. Similarly, Panel B reports the results based on *ANStarCov*. The last two columns present the differences in monthly returns and the differences in Fama-French 4-factor adjusted alphas between portfolios 10 and 1 and the corresponding *t*-statistics are reported in parentheses. The last row in each panel reports the average observations in a portfolio over the sample period from 2004-2019.

Panel A: Returns and alphas across the deciles of the abnormal coverage of star analysts (*AStarCov*)

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low	
EW return	1.269	1.549	1.452	1.477	1.487	1.545	1.714	1.748	1.915	2.070	0.801	(3.01)
EW 4-factor alpha	-0.099	0.014	0.077	-0.064	0.035	0.051	0.101	0.351	0.497	0.728	0.826	(6.57)
VW return	1.346	1.590	1.509	1.503	1.527	1.593	1.771	1.730	1.966	2.125	0.779	(2.38)
VW 4-factor alpha	-0.058	0.049	0.044	0.042	0.046	0.059	0.07	0.085	0.211	0.423	0.481	(4.39)
Obs.	189	189	188	189	189	189	189	189	189	189		

Panel B: Returns and alphas across the deciles of the abnormal coverage of non-star analysts (*ANStarCov*)

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low	
EW return	1.376	1.426	1.492	1.472	1.516	1.558	1.635	1.926	1.897	2.008	0.632	(1.97)
EW 4-factor alpha	-0.221	0.006	-0.159	-0.127	0.017	0.134	0.179	0.357	0.547	0.723	0.943	(5.91)
VW return	1.506	1.526	1.533	1.508	1.581	1.608	1.678	1.900	1.943	2.068	0.562	(1.78)
VW 4-factor alpha	-0.072	-0.051	0.034	0.037	0.052	0.063	0.068	0.086	0.147	0.323	0.395	(3.66)
Obs.	189	189	189	189	189	188	189	189	189	189		

Table 3 Risk-adjusted returns on portfolios of stocks dependently sorted by the abnormal star and non-star coverage

This table reports the Fama-French 4-factor risk-adjusted returns (alphas) in percentage per month. In Panel A, we first sort all firms into quartiles according to the abnormal coverage of non-star analysts (*ANStarCov*), and then within each *ANStarCov* quartile we further sort the firms into quartiles to form the four portfolios based on the abnormal coverage of star analysts (*AStarCov*). *AStarCov* and *ANStarCov* are based on the residuals from monthly regressions of raw star (non-star) coverage on firms' contemporaneous log market capitalization (Size), share turnover (*TO*), and momentum (*MOM*). *TO* and *MOM* are defined as trading volume scaled by shares outstanding and cumulative market-adjusted returns, respectively, over the prior 12 months ending in month *t*. Panels A1 and A2 report the alphas for the 16 equal- and value-weighted portfolios in month *t+1*, respectively. The row of "H-L" presents the differences in alphas between the highest and lowest *AStarCov* portfolios conditional on each *ANStarCov* quartile and the corresponding *t*-statistics. The last columns labelled as "Avg." of Panel A1 and A2 report the alphas for a given *AStarCov* quartile portfolio which includes stocks across different levels of *ANStarCov*. In Panel B, we reverse the order of the two sorts. Specifically, we sort the sample firms first by *AStarCov* and then within each *AStarCov* quartile we sort the firms by *ANStarCov*. Panels B1 and B2 report the alphas for the 16 equal- and value-weighted portfolios in month *t+1*, respectively. The last columns labelled as "Avg" of Panel B1 and B2 report the alphas for a given *ANStarCov* quartile portfolio which includes stocks across different levels of *AStarCov*. The last row of each sub-panel shows *p*-values of the *GRS* statistic (Gibbons et al., 1989) for the null hypothesis that the four differences in the alphas across four *ANStarCov* or *AStarCov* portfolios are jointly equal to zero. The sample consists of 362,561 firm-month observations over the period 2004-2019. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Abnormal non-star coverage as the first sort and abnormal star coverage as the second sort

	Panel A1 Equal-weighted returns Quartiles of *ANStarCov*				
AStarCov	1 (Low)	2	3	4 (High)	Avg.
1 (low)	-0.071	-0.083	0.020	0.546	0.238
2	-0.196	0.215	-0.178	1.179	0.492
3	0.586	0.738	1.156	1.404	0.995
4 (high)	0.721	0.303	0.461	1.608	1.165
H-L	0.792***	0.386*	0.441*	1.062***	0.927***
t-statistic	(2.82)	(1.70)	(1.92)	(4.86)	(4.53)
p (*GRS*):	0.00				

	Panel A2 Value-weighted returns Quartiles of *ANStarCov*				
AStarCov	1 (Low)	2	3	4 (High)	Avg.
1 (low)	-0.315	-0.193	-0.025	0.306	-0.005
2	-0.367	-0.315	-1.034	1.039	0.336
3	-0.272	-0.289	-0.147	0.392	0.060
4 (high)	0.325	0.294	0.531	1.404	0.865
H-L	0.641***	0.487**	0.556**	1.098***	0.869***
t-statistic	(2.87)	(2.35)	(2.23)	(5.89)	(6.27)
p (*GRS*):	0.00				

Panel B: Abnormal star coverage as the first sort and abnormal non-star coverage as the second sort

	Panel B1 Equal-weighted returns Quartiles of *AStarCov*				
ANStarCov	1 (Low)	2	3	4 (High)	Avg.
1 (low)	-0.067	-0.013	0.531	0.554	0.244
2	0.017	-0.054	0.856	1.081	0.549
3	0.276	0.350	0.802	1.038	0.657
4 (high)	0.191	0.316	0.786	1.091	0.641
H-L	0.263	0.329	0.255	0.537**	0.398*
t-statistic	(1.65)	(1.59)	(1.32)	(2.41)	(1.87)
p (*GRS*):	0.10				

	Panel B2 Value-weighted returns Quartiles of *AStarCov*				
ANStarCov	1 (Low)	2	3	4 (High)	Avg.
1 (low)	-0.051	0.029	0.392	0.604	0.277
2	-0.024	-0.092	-0.166	0.208	0.092
3	-0.039	0.150	0.490	0.593	0.277
4 (high)	0.128	0.162	0.535	0.674	0.401
H-L	0.179	0.133	0.144	0.071	0.125
t-statistic	(1.51)	(1.62)	(1.39)	(0.55)	(1.03)
p (*GRS*):	0.31				

Table 4 Fama-MacBeth regressions

This table presents monthly average coefficients from Fama-MacBeth regressions of returns in month *t+1* on *Log(1+StarCov), Log(1+NStarCov)* and other control variables. All independent variables in this regression are standardized in each month to have a zero mean and a standard deviation of one. *StarCov* (*NStarCov*) is defined as the number of unique star (non-star) analyst-forecast pairs summed over the six-month ending at the end of month *t*. *Size* is a firm's log market capitalization in month *t*. *TO* and *MOM* are defined as share turnover and momentum, both of which are measured over the prior 12-month period ending in month *t*. *VLTY* is calculated as the standard deviation of monthly return over the prior 12 months ending in month *t* and *LBM* is calculated as the log of one plus a firm's book-to-market ratio. *RR* is monthly return reversals defined as the return in month *t*. *SUE* is a firm's standardized unexpected earnings, defined as the realized earnings per share (EPS) minus EPS from four quarters prior divided by the standard deviation of this difference over the prior eight quarters. *ACC* is the difference between net income and cash flows from operations scaled by lagged total assets. *INST* denotes firms' institutional ownership as a fraction of share outstanding. *t*-statistics are reported in parentheses after Newey-West adjustments. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively. The sample consists of 362,561 firm-month observations over the period 2004-2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Log(1+StarCov)	**0.534*** **		**0.299** **	**0.592*** **		**0.377*** **
	(5.69)		**(1.98)**	**(6.84)**		**(2.61)**
Log(1+NStarCov)		**0.523*** **	0.247		**0.574*** **	0.236
		(5.11)	(1.53)		**(5.87)**	(1.25)
Size	-0.983***	-0.988***	-0.987***	-0.973***	-0.971***	-0.949***
	(-7.07)	(-7.15)	(-7.16)	(-8.30)	(-8.17)	(-8.23)
TO	-0.847***	-0.847***	-0.838***	-0.704***	-0.711***	-0.701***
	(-8.28)	(-8.30)	(-8.44)	(-8.88)	(-8.92)	(-8.97)
MOM	0.425***	0.426***	0.425***	0.518***	0.519***	0.519***
	(6.65)	(6.65)	(6.64)	(6.45)	(6.45)	(6.45)
LBM				0.046	0.052	0.046
				(0.57)	(0.64)	(0.56)
VLTY				-0.287***	-0.284****	-0.282***
				(-3.33)	(-3.31)	(-3.31)
RR				-0.703***	-0.708***	-0.703***
				(-10.26)	(-10.29)	(-10.26)
SUE				0.149	0.149	0.150
				(1.47)	(1.51)	(1.55)
ACC				-0.396**	-0.398**	-0.396**
				(-2.33)	(-2.34)	(-2.37)
INST				0.023	0.022	0.023
				(1.29)	(1.21)	(1.29)
Cons	1.573*	1.574*	1.577*	1.550	1.557	1.554
	(1.69)	(1.69)	(1.69)	(1.61)	(1.61)	(1.61)
R^2 (%)	7.82	7.95	8.10	11.64	11.74	11.90

Table 5 Predicting firm fundamental performance

This table reports the results on the association between abnormal analyst coverage and firm fundamental performance. We run Fama-MacBeth regressions where all variables are standardized in each month to have a zero mean and a standard deviation of one. Panel A uses one-year- and two-year-ahead F-scores (Piotroski, 2000; Piotroski and So, 2012) as the dependent variable. We construct F-score as the sum of nine binary signals that capture levels of, and changes in profitability, financial leverage and operating efficiency. In Panel B, we use three alternative measures of fundamental performance, including one-year-ahead standardized unexpected earnings (SUE), analyst forecast revision (AFR) and analyst forecast error (AFE). SUE is defined as the realized earnings per share (EPS) minus EPS from four quarters prior divided by the standard deviation of this difference over the eight preceding quarters. AFR is defined as the difference between the latest consensus forecast and the consensus forecast measured at the end of fiscal year, divided by total assets per share. AFE is defined as actual EPS minus consensus forecast divided by total assets per share, where consensus forecast is calculated at the end of fiscal year. *StarCov* (*NStarCov*) is defined as the number of unique star (non-star) analyst-forecast pairs summed over the six-month period ending at the end of month *t*. We include a set of control variables, namely momentum, turnover, size, volatility, and book-to-market ratio. The coefficients on these control variables are omitted for brevity. Appendix 1 provides the details of these control variables. *t*-statistics are reported in parentheses. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Panel A: F-score

	(1)	(2)
Dep. variable	*One-year-ahead F-score*	*Two-year-ahead F-score*
Log(1+StarCov)	**0.056****	**0.059*****
	(2.53)	**(2.67)**
Log(1+NStarCov)	**0.047****	0.031
	(2.12)	(1.18)
Controls	Y	Y
R^2 (%)	3.04	2.43
Obs.	350,299	338,644

Panel B: Alternative measures of fundamental performance

	(1)	(2)	(3)
Dep. variable	*SUE*	*AFR*	*AFE*
Log(1+StarCov)	**0.185****	**0.031*****	**0.067*****
	(2.05)	**(3.61)**	**(3.09)**
Log(1+NStarCov)	-0.110	-0.002	**0.026***
	(-1.44)	(-0.35)	**(1.75)**
Controls	Y	Y	Y
R^2 (%)	7.36	2.35	9.26
Obs.	274,084	263,748	267,347

Table 6 Return around earnings announcement dates

This table reports the results of the return predictability of star and non-star analyst coverage around the futures earnings announcement dates using the daily data. Following the research design of Engelberg et al. (2018), we run a panel regression where the dependent variable denoted as *DRet* is daily return and is rescaled by multiplying 100. *H_AStarCov* (*L_AStarCov*) is a dummy variable that takes the value of one if a stock belongs to the top (bottom) abnormal star coverage decile at the beginning of each month and zero otherwise. Similarly, we construct the dummy variables of *H_ANStarCov* and *L_ANStarCov* indicating whether a stock belongs to the top and bottom abnormal non-star coverage deciles, respectively, at the beginning of each month. By construction, the value of the above four dummy variables remains the same throughout a month. *Eday* is a dummy variable that takes the value of one for the three-day window around an earnings announcement day (i.e., days $t-1$, t, and $t+1$) for firm *i* and zero otherwise. Control variables include lagged values of the last 10 days of returns (*LagRet*), volatility proxied by return squared (*$LagRet^2$*), and trading volume (*Vol*). We also control for day fixed effects (α_t). For brevity, the coefficients on the control variables are omitted. *t*-statistics are in parentheses. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Dep. variable	*DRet*
High_AStarCov	0.041***
	(7.72)
Low_AStarCov	0.004
	(1.03)
High_ANStarCov	0.020***
	(3.61)
Low_ANStarCov	-0.017***
	(-3.59)
High_AStarCov*Eday	**0.101*** **
	(4.18)
*Low_AStarCov*Eday*	0.017
	(0.82)
*High_ANStarCov*Eday*	0.006
	(0.29)
*Low_ANStarCov*Eday*	0.002
	(0.11)
Controls	Y
Day fixed effects	Y
R^2 (%)	43.44
Obs.	3,845,508

Table 7 Cross-sectional heterogeneity

This table reports the times-series average coefficients estimated from the Fama-MacBeth regressions based on the subsamples of small and large firms, firms with and without institutional ownership, and firms with high and low return volatility. Specifically, stocks are ranked by the median of firm size and volatility in June each year and each variable's rankings are carried over from July of one year to June of next year (Fama and French, 1996). We also group stocks with and without institutional ownership (*INST*) in each month. The dependent variable is the return in month *t+1*. The independent variables are *Log(1+StarCov)*, *Log(1+NStarCov)*, firm size, share turnover, momentum, book-to-market, volatility, returns in month *t*, standardized unexpected earnings, accruals, and institutional ownership. Appendix 1 provides the details of these control variables. *StarCov* (*NStarCov*) is defined as the number of unique star (non-star) analyst-forecast pairings summed over the prior six-month period ending at the end of month *t*. All independent variables in this regression are standardized in each month to have a zero mean and a standard deviation of one. The coefficients on the control variables are omitted for brevity. *t*-statistics are reported in parentheses after Newey-West adjustments. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively. The sample consists of 362,561 firm-month observations over the period 2004-2019.

	Small	Large
Log(1+StarCov)	**0.405****	0.197
	(2.57)	(1.03)
Log(1+NStarCov)	0.051	0.037
	(0.28)	(0.17)
Controls	Y	Y
Cons	0.872	2.129***
	(1.15)	(2.73)
R^2 (%)	8.96	15.79
Obs.	179,312	183,249
	High volatility	Low volatility
Log(1+StarCov)	**0.337***	0.131
	(1.84)	(0.62)
Log(1+NStarCov)	0.234	0.085
	(1.10)	(0.35)
Controls	Y	Y
Cons	1.699**	1.444
	(2.19)	(1.56)
R^2(%)	13.12	18.59
Obs.	183,534	179,027
	Without INST	INST
Log(1+StarCov)	**0.310***	0.222
	(1.71)	(1.38)
Log(1+NStarCov)	0.105	0.204
	(0.48)	(1.06)
Controls	Y	Y
Cons	4.121**	2.361***
	(2.26)	(3.09)
R^2 (%)	11.41	15.81
Obs.	149,609	212,952

Table 8 Evidence from three quasi-natural experiments

This table reports the results based on three quasi-experiments that exogenously change firms' information environment. The dependent variable is the return in month *t+1*. The independent variables are *Log(1+StarCov)*, *Log(1+NStarCov)*, firm size, share turnover, momentum, book-to-market, volatility, returns in month *t*, standardized unexpected earnings, accruals, and institutional ownership. Appendix 1 provides the details of these control variables. *StarCov* (*NStarCov*) is defined as the number of unique star (non-star) analyst-forecast pairings summed over the prior six-month period ending at the end of month *t*. All independent variables except for dummy variables in this regression are standardized in each month to have a zero mean and unit standard deviation. In Panel A, we exploit the Chinese pilot program of short selling that improves information environment. We define six event dates when the CSRC announced the revision of the designated list of shortable stocks. These dates are March 31, 2010, December 5, 2011, January 31, 2013, September 16, 2013, September 22, 2014, and December 12, 2016. *Treated1* is equal to one if a stock is added to the list, and zero otherwise. We also construct a post-event variable of *Post1*, which is equal to one if a sample month is over a one-year period since the designated list is announced, and zero otherwise. For example, the first list is published on March 31 2010. The pre-event period is from March 2009 to February 2010 and the post-event period is from March 2011 to February 2012. In this way, we define other pre- and post-events surrounding the announcement dates of the designated list. Finally, we compile the panel data set with 156,321 firm-month observations over the period 2009-2018. In Panel B, we exploit Google's withdrawal from mainland China in 2010 that deteriorates information environment. In this test, *Treated2* is equal to one if a stock ticker has a higher search volume index (SVI) than the sample median in 2009, and zero otherwise. *Post2* is equal to one for firm-month observations after Google's withdrawal (i.e. 2011-2013), and zero for the observations before the withdrawal (i.e. 2007-2009). We have 116,683 firm-month observations over the period 2007-2013. In Panel C, we exploit the anti-corruption campaign in China. *AntiCorruptio*n is equal to one for firm-month observations in the post-campaign period (i.e. 2013-2015), and zero in the pre-campaign period (i.e. 2010-2012). We have 132,977 observations over the period 2010-2015. *t*-statistics are reported in parentheses. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Panel A: Short selling deregulation	
Log(1+StarCov)×Post1×Treated1	**-0.371****
	(-2.20)
Log(1+NStarCov)×Post1×Treated1	0.182
	(1.57)
Log(1+StarCov)×Post1	-0.051
	(1.13)
Log(1+NStarCov)×Post1	0.056
	(0.45)
Log(1+StarCov)×Treated1	0.087
	(1.01)
Log(1+NStarCov)×Treated1	-0.005
	(-0.04)
Post×Treated1	0.001
	(0.01)
Post1	1.430***
	(10.64)
Treated1	1.906***
	(11.83)
Log(1+StarCov)	-0.099
	(-0.70)
Log(1+NStarCov)	0.109
	(1.06)
Controls	Y

Industry effects	Y
Year effects	Y
R^2 (%)	10.53
Obs.	156,321
Panel B: Google's withdrawal	
Log(1+StarCov)×Post2×Treated2	**0.535***
	(1.78)
Log(1+NStarCov)×Post2×Treated2	0.128
	(0.43)
Log(1+StarCov)×Post2	-0.403
	(-1.34)
Log(1+NStarCov)×Post2	0.042
	(0.15)
Log(1+StarCov)×Treated2	-0.307
	(-1.37)
Log(1+NStarCov)×Treated2	-0.127
	(-0.75)
Post2×Treated2	0.070
	(0.72)
Treated2	-0.414***
	(-5.40)
Log(1+StarCov)	0.258
	(0.87)
Log(1+NStarCov)	0.080
	(0.34)
Controls	Y
Industry effects	Y
Year effects	Y
R^2 (%)	12.26
Obs.	116,683
Panel C: Anti-corruption campaign	
Log(1+StarCov)×AntiCorruption	**-0.386****
	(-1.98)
Log(1+StarCov)	0.355**
	(2.35)
Log(1+NStarCov)×AntiCorruption	-0.024
	(-0.12)
Log(1+NStarCov)	0.250*
	(1.67)
Controls	Y
Industry effects	Y
Year effects	Y
R^2 (%)	3.28
Obs.	132,977

Table 9 Further analysis: Information content of non-star analyst coverage

Panel A presents monthly average coefficients from Fama-MacBeth regressions of returns in month *t+1* on the coverage measure of non-star analysts (*Log(1+NStarCov_3m))* and the lagged coverage measure of star analysts *(Lag3_Log(1+StarCov_3m)*. *Lag3_Log(1+StarCov)* is the 3-month lagged value of *Log(1+StarCov_3m))*. *StarCov_3m* (*NStarCov_3m*) is defined as the number of unique star (non-star) analyst-forecast pairings summed over the prior 3-month period. We include a set of control variables, namely *Size*, *TO*, *MOM*, *VLTY*, *LBM*, *SUE*, *ACC*, *RR*, and *INST*. Appendix 1 provides the details of these control variables. The coefficients on these control variables are omitted for brevity. Panel B reports the relationship between lagged star coverage and contemporaneous non-star coverage. Specifically, we present the time-series average coefficients from regressing non-star coverage on lagged star coverage, firms' contemporaneous log market capitalization (Size), share turnover (*TO*) and momentum (*MOM*). *TO* and *MOM* are defined as trading volume scaled by shares outstanding and cumulative market-adjusted returns, respectively, over the prior 12 months ending in month *t*. All variables in this regression are standardized each month to have a zero mean and unit standard deviation. *t*-statistics are reported in parentheses after Newey-West adjustments. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively. The sample consists of 362,561 firm-month observations over the period 2004-2019.

Panel A: Controlling for the past star analyst coverage

	(1)	(2)	(3)
Log(1+NStarCov_3m)	0.572**		0.343
	(2.16)		(1.44)
Lag3_Log(1+StarCov_3m)		0.591**	0.445*
		(2.31)	(1.81)
Controls	Y	Y	Y
Cons	1.675	1.593	1.636
	(1.65)	(1.60)	(1.61)
R^2 (%)	12.04	12.24	13.37

Panel B: The relationship between lagged star coverage and non-star coverage

Dep. variable	*Log(1+NStarCov_3m)*
Lag3_Log(1+StarCov_3m)	**0.583*** **
	(9.90)
Size	0.407***
	(6.89)
TO	-0.008
	(-1.03)
MO	0.311***
	(4.46)
R^2 (%)	51.30

Table 10 Further analysis: Alternative explanations

This table reports the results of Fama-MacBeth regressions to examine whether the return predictability of abnormal coverage decisions is subject to alternative explanations. To control for the price pressure from institutional investors, we add the lagged (Δ*INST_Lag*) and forward (Δ*INST_Lead*) changes in institutional ownership in the regressions. Δ*INST_Lag* measures change in mutual fund holding in latest available quarter period. Δ*INST_Lead* measures the change in mutual fund holding in the next quarter period. We use two proxies for attention seeking behaviors, namely the growth in share repurchase and the net insider purchase ratio. The growth in share repurchases is defined as a change in cash outflow from share repurchase scaled by the beginning of period total assets. The net insider purchase ratio is defined as the difference between the number of insider purchases and sales scaled by the total number of insider transactions over the past 12-month period (e.g., Lakonishok and Lee, 2001; Cziraki et al., 2021). Firms are ranked and assigned into tercile groups based on the growth in share repurchases and the net insider purchase ratio. Δ*Repurchase_H* is equal to one if firms are in the top tercile and zero otherwise. Similarly, *InsiderBuy_H* is equal to one if firms are in the top tercile and zero otherwise. Control variables include variables in column 6 of Table 4. All explanatory variables are standardized as zero mean and one standard deviation within each cross-section. *t*-statistics are reported in parentheses after Newey-West adjustments. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Log(1+StarCov)	0.394**	0.332**	0.385**	0.420**	0.268*
	(2.58)	(2.06)	(2.49)	(2.18)	(1.83)
Log(1+NStarCov)	0.262	0.282	0.223	0.278	0.182
	(1.30)	(1.36)	(1.04)	(1.18)	(0.86)
Δ*INST_Lag*	0.548***	0.567***			
	(7.48)	(7.36)			
Δ*INST_Lead*		0.370***			
		(4.89)			
*Log(1+StarCov)*ΔRepurchase_H*			-0.031		-0.034
			(-0.23)		(-0.12)
*Log(1+StarCov)*InsiderBuy_H*				-0.102	-0.001
				(-1.60)	(-0.11)
*Log(1+NStarCov)*ΔRepurchase_H*			0.045		0.046
			(0.35)		(0.18)
*Log(1+NStarCov)*InsiderBuy_H*				0.052	0.002
				(0.64)	(1.38)
Controls	Y	Y	Y	Y	Y
R^2 (%)	11.95	12.07	12.27	10.67	17.92
Obs.	362,561	362,561	362,561	97,805	97,805

Table 11 Corresponding U.S. evidence

This table reports the results from the U.S. market. Panel A shows times-series average coefficients from regressing raw star (non-star) coverage on three expected components, namely log market capitalization (*Size*), share turnover (*TO*), and momentum (*MOM*). The three variables in this regression are standardized each month to have a zero mean and a standard deviation of one. *TO* and *MOM* are defined as trading volume scaled by shares outstanding and cumulative market-adjusted returns, respectively, over the prior 12 months ending in month *t*. *StarCov* (*NStarCov*) is defined as the number of unique star (non-star) analyst-forecast pairs summed over the 90 trading days ending in month *t*. Panels B and C present the value-weighted (VW) and equal-weighted (EW) average monthly returns and the Fama-French 4-factor alphas on the value-weighted and equal-weighted portfolios based on abnormal star or non-star coverage. Abnormal star and non-star coverage is based on the residuals of the regressions shown in Columns (1) and (2) of Panel A, respectively. The sample stocks are ranked by each of abnormal measures in an ascending order to form decile portfolios. The last two columns present the differences in monthly returns and the differences in alphas with respect to the Fama-French 4-factor model between portfolios 10 and 1 and the corresponding *t*-statistics. Panel D reports the risk-adjusted returns to the portfolios which are formed based on dependent sorts of abnormal star (*AStarCov*) and non-star (*ANStarCov*) coverage. Specifically, the sample firms are first sorted by *ANStarCov* into quartiles and then within each *ANStarCov* quartile we sort the firms by *AStarCov*. For brevity, we do not report returns for all 16 portfolios. Instead, Panel D1 presents risk-adjusted returns to each *AStarCov* based quartile portfolio which includes stocks across different levels of *ANStarCov*. The last column of this sub-panel ("H-L") shows the differences in 4-factor alpha between the highest and the lowest *AStarCov* portfolios and the corresponding *t*-statistics. In Panel D2, we reverse the two sorts by first sorting the sample stocks on *AStarCov* into quartiles and then sorting the stocks on *ANStarCov* in each *AStarCov* quartile. Panel E reports the time-series average coefficients of Fama-MacBeth regressions. The dependent variable is raw monthly returns in month t+1. To facilitate interpretation, all independent variables in this regression are standardized each month to have a zero mean and unit standard deviation. *t*-statistics are reported in parentheses after Newey-West adjustments. ∗∗∗, ∗∗, and ∗ indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Panel A: Estimating abnormal star and non-star analyst coverage

	(1)	(2)	(3)
	Log(1+StarCov)	Log(1+NStarCov)	Coeff. Difference: (1)-(2)
Size	0.653***	0.649***	0.004
	(221.48)	(201.24)	(1.44)
TO	0.092***	0.192***	-0.100***
	(66.84)	(78.14)	(-35.18)
MOM	-0.103***	-0.112***	0.009***
	(-58.27)	(-63.21)	(5.54)
R^2 (%)	45.20	49.60	

Panel B: Monthly returns based on the single sort of abnormal star coverage

AStarCov	1 (Low)	10 (High)	H-L	*t*-statistic
EW return	0.987	2.444	1.456	(6.90)
4-factor alpha	-0.045	1.607	1.653	(9.67)
VW return	0.876	1.429	0.553	(2.32)
4-factor alpha	-0.095	0.423	0.518	(4.05)

Panel C: Monthly returns based on the single sort of abnormal non-star coverage

ANStarCov	1 (Low)	10 (High)	H-L	*t*-statistic
EW return	0.980	1.921	0.940	(4.06)
4-factor alpha	-0.049	1.139	1.188	(7.56)
VW return	0.955	1.196	0.240	(0.82)

4-factor alpha	-0.002	0.353	0.356	(2.60)	
Panel D: Monthly returns based on dependent sorts between abnormal star and non-star coverage					
	Panel D1: Sorting first on *ANStarCov* and then on *AStarCov*				
AStarCov	1 (Low)	2	3	4 (High)	H-L
4-factor alpha EW	-0.001	0.115	0.302	0.835	0.835
t-statistic	(-0.02)	(2.05)	(3.71)	(8.43)	(7.92)
4-factor alpha VW	-0.057	0.062	0.095	0.217	0.274
t-statistic	(-1.74)	(1.48)	(1.98)	(3.54)	(3.29)
	Panel D2: Sorting first on *AStarCov* and then on *ANStarCov*				
ANStarCov	1 (Low)	2	3	4 (High)	H-L
4-factor alpha EW	0.075	0.214	0.314	0.594	0.518
t-statistic	(1.50)	(3.62)	(5.57)	(6.58)	(6.67)
4-factor alpha VW	-0.001	0.028	0.049	0.079	0.08
t-statistic	(-0.15)	(0.50)	(0.82)	(1.19)	(1.05)

Panel E: Fama-MacBeth regressions

	(1)	(2)	(3)
Log(1+StarCov)	0.306***		0.216***
	(8.49)		(6.06)
Log(1+NStarCov)		0.227***	0.002
		(5.38)	(0.48)
Size	-0.484***	-0.426***	-0.618***
	(-5.74)	(-5.34)	(-7.38)
TO	-0.331***	-0.350***	-0.329***
	(-3.89)	(-4.24)	(-6.96)
MOM	0.179**	0.175**	0.259***
	(2.19)	(2.11)	(2.68)
LBM			0.144***
			(2.77)
VLTY			-0.185**
			(1.96)
RR			-0.581***
			(8.20)
EAM			0.030*
			(1.84)
SUE			0.200***
			(4.49)
ACC			-0.367**
			(-2.53)
INST			0.133**
			(2.16)
Cons	1.267***	1.262***	1.271***
	(4.61)	(4.60)	(4.83)
R^2 (%)	2.763	2.794	5.238

Table 12 Robustness checks

This table reports the results of robustness tests. Columns (1) and (2) in Panel A report the results based on subsamples with at least one covering analyst and with more than three covering analysts, respectively. Columns (1) and (2) in Panel B report the results with additional control variables of *Top3* and *Top5*. *Top3* (*Top5*) is equal to one if a firm is covered by the largest three (five) brokerage houses in each year, and zero otherwise. Panel C reports the results based on alternative measures of abnormal analyst coverage. In addition to size, momentum, and turnover, we add log book-to-market (LBM), return volatility (VLTY), and return on assets (ROA) in Eq. (1) and Eq. (2), and use the regression residuals as alternative measures of abnormal coverage. R-square is reported for each model. The equal-weighted (EW) and value-weighted (VW) risk-adjusted returns of the hedge portfolio are reported in the right columns. Panel D reports the equal-weighted (EW) and value-weighted (VW) characteristic-adjusted (DGTW) returns (Daniel et al., 1997) of the hedge portfolio, consisting of a long position in stocks with the highest abnormal coverage decile and a short position in stocks with the lowest abnormal coverage decile. The coefficients on control variables are omitted for brevity. *t*-statistics are reported in parentheses after Newey-West adjustments. ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Panel A: Subsample with analysts following

	(1)	(2)
	Analyst coverage>0	Analyst coverage>3
Log(1+StarCov)	0.354**	0.360**
	(2.33)	(2.38)
Log(1+NStarCov)	0.246	0.253
	(1.30)	(1.37)
Controls	Y	Y
R^2 (%)	11.49	11.66
Obs.	195,001	174,954

Panel B: Control for the coverage of large brokerage houses

	(1)	(2)
Log(1+StarCov)	0.354**	0.353**
	(2.26)	(2.24)
Log(1+NStarCov)	0.234	0.237
	(1.27)	(1.25)
Top3	0.106***	
	(3.16)	
Top5		0.121***
		(3.32)
Controls	Y	Y
R^2 (%)	12.00	12.01
Obs.	362,561	362,561

Panel C: Alternative measures of abnormal star and non-star coverage

	R^2 (%)	EW Alpha High-Low	VW Alpha High-Low
Dependent variable: Log(1+StarCov)			
Size, TO, MOM, and LBM	28.21	0.767 (6.03)	0.368 (4.56)
Size, TO, MOM, LBM and ROA	29.37	0.748 (5.76)	0.294 (3.43)
Size, TO, MOM, LBM, ROA and VLTY	30.00	0.683 (5.17)	0.267 (2.95)
Dependent variable: Log(1+NStarCov)			
Size, TO, MOM, and LBM	33.14	0.789 (5.99)	0.297 (3.55)
Size, TO, MOM, LBM and ROA	34.63	0.712 (4.62)	0.232 (2.47)
Size, TO, MOM, LBM, ROA and VLTY	35.56	0.696 (4.31)	0.245 (2.61)

Panel D: DGTW returns

	EW	VW
	High-Low	High-Low
Abnormal star coverage	0.528 (3.31)	0.642 (4.97)
Abnormal non-star coverage	0.483 (3.55)	0.485 (3.62)

Online Appendix for

"Can star analysts make superior coverage decisions in poor information environment?"

Online Appendix 1: US evidence - returns and alphas on portfolios of stocks singly sorted by abnormal coverage

Online Appendix 2: US evidence - risk-adjusted returns on portfolios of stocks dependently sorted by the abnormal star and non-star coverage

Online Appendix 1: US evidence - returns and alphas on portfolios of stocks singly sorted by abnormal coverage

This table reports returns and alphas in percentage per month on portfolios of U.S. stocks singly sorted by the abnormal coverage of star analysts (*AStarCov*) or the abnormal coverage of non-star analysts (*ANStarCov*). *AStarCov* and *ANStarCov* are based on the residuals from monthly regressions of raw star and non-star coverage, respectively, on firms' contemporaneous log market capitalization (Size), share turnover (*TO*), and momentum (*MOM*). *TO* and *MOM* are defined as trading volume scaled by shares outstanding and cumulative market-adjusted returns, respectively, over the prior 12 months ending in month *t*. The raw star (non-star) coverage is defined as the number of unique star (non-star) analyst-earnings forecast pairs summed over the prior six-month period ending at the end of month *t*. We form the decile portfolios by sorting stocks on *AStarCov* and *ANStarCov*, respectively, in ascending order. Portfolio 1 (10) is with the lowest (highest) *AStarCov* or *ANStarCov*. Panel A reports the value-weighted (VW) and equal-weighted (EW) average monthly returns and the Fama-French 4-factor adjusted alphas for the portfolio of stocks sorted by *AStarCov*. Similarly, Panel B reports the results based on *ANStarCov*. The last two columns present the differences in monthly returns and the differences in Fama-French 4-factor adjusted alphas between portfolios 10 and 1 and the corresponding *t*-statistics are reported in parentheses. The last row in each panel reports the average observations in a portfolio over the sample period from 1984-2017.

Panel A: Returns and alphas across the deciles of the abnormal coverage of star analysts (*AStarCov*)

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low	
EW return	0.987	1.028	0.981	1.061	1.063	1.08	1.211	1.278	1.508	2.444	1.456	(6.90)
EW 4-factor alpha	-0.045	-0.005	-0.036	0.055	0.079	0.129	0.306	0.443	0.671	1.607	1.653	(9.67)
VW return	0.876	1.061	0.969	1.157	1.090	1.138	1.256	1.331	1.226	1.429	0.553	(2.32)
VW 4-factor alpha	-0.095	0.116	-0.027	0.169	0.069	0.103	0.253	0.294	0.247	0.423	0.518	(4.05)
Obs.	438	439	440	438	439	440	440	439	440	440		

Panel B: Returns and alphas across the deciles of the abnormal coverage of non-star analysts (*ANStarCov*)

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low	
EW return	0.980	1.011	1.034	1.048	1.163	1.212	1.273	1.342	1.518	1.921	0.940	(4.06)
EW 4-factor alpha	-0.049	0.023	0.096	0.085	0.190	0.250	0.311	0.392	0.605	1.139	1.188	(7.56)
VW return	0.955	1.079	1.064	1.144	1.136	1.115	1.126	1.137	1.217	1.196	0.240	(0.82)
VW 4-factor alpha	-0.002	0.06	0.038	0.126	0.101	0.092	0.077	0.129	0.238	0.353	0.356	(2.60)
Obs.	439	440	440	439	438	440	440	439	440	440		

Online Appendix 2: US evidence - risk-adjusted returns on portfolios of stocks dependently sorted by the abnormal star and non-star coverage

This table reports the Fama-French 4-factor risk-adjusted returns (alphas) in percentage per month to the portfolios sorted dependently by the abnormal coverage of star analysts and that of non-star analysts on the U.S. market. In Panel A, we first sort all firms into quartiles according to the abnormal coverage of non-star analysts (*ANStarCov*), and then within each *ANStarCov* quartile we further sort the firms into quartiles to form the four portfolios based on the abnormal coverage of star analysts (*AStarCov*). *AStarCov* and *ANStarCov* are based on the residuals from monthly regressions of raw star (non-star) coverage on firms' contemporaneous log market capitalization (Size), share turnover (*TO*), and momentum (*MOM*). *TO* and *MOM* are defined as trading volume scaled by shares outstanding and cumulative market-adjusted returns, respectively, over the prior 12 months ending in month *t*. Panels A1 and A2 report the alphas for the 16 equal- and value-weighted portfolios in month *t+1*, respectively. The row of "H-L" presents the differences in alphas between the highest and lowest *AStarCov* portfolios conditional on each *ANStarCov* quartile and the corresponding *t*-statistics. The last columns labelled as "Avg" of Panel A1 and A2 report the alphas for a given *AStarCov* quartile portfolio which includes stocks across different levels of *ANStarCov*. In Panel B, we reverse the order of the two sorts. Specifically, we sort the sample firms first by *AStarCov* and then within each *AStarCov* quartile we sort the firms by *ANStarCov*. Panels B1 and B2 report the alphas for the 16 equal- and value-weighted portfolios in month *t+1*, respectively. The last columns labelled as "Avg" of Panel B1 and B2 report the alphas for a given *ANStarCov* quartile portfolio which includes stocks across different levels of *AStarCov*. The last row of each sub-panel shows *p*-values of the *GRS* statistic (Gibbons et al., 1989) for the null hypothesis that the four differences in the alphas across four *ANStarCov* or *AStarCov* portfolios are jointly equal to zero.The sample consists of 1,821,150 firm-month observations over the period 1984-2017. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Abnormal non-star coverage as the first sort and abnormal star coverage as the second sort

	Panel A1 Equal-weighted returns						Panel A2 Value-weighted returns				
	Quartiles of *ANStarCov*						Quartiles of *ANStarCov*				
AStarCov	1 (Low)	2	3	4 (High)	Avg.	*AStarCov*	1 (Low)	2	3	4 (High)	Avg.
1 (low)	-0.002	-0.024	0.050	0.081	-0.001	1 (low)	-0.061	-0.058	-0.003	0.101	-0.057
2	-0.034	0.001	0.201	0.286	0.115	2	0.050	0.020	0.156	0.196	0.062
3	0.002	0.241	0.481	0.840	0.302	3	0.060	0.160	0.071	0.172	0.095
4 (high)	0.074	0.302	0.918	1.503	0.835	4 (high)	0.150	0.325	0.290	0.735	0.217
H-L	0.076	0.325**	0.868***	1.422***	0.835***	H-L	0.211**	0.383***	0.293***	0.634***	0.274***
t-statistic	(1.05)	(2.48)	(4.21)	(9.86)	(7.92)	*t*-statistic	(2.43)	(3.01)	(2.86)	(4.40)	(3.29)
p (*GRS*):	0.00					*p* (*GRS*):	0.00				

Panel B: Abnormal star coverage as the first sort and abnormal non-star coverage as the second sort

	Panel B1 Equal-weighted returns						Panel B2 Value-weighted returns				
	Quartiles of *AStarCov*						Quartiles of *AStarCov*				
ANStarCov	1 (Low)	2	3	4 (High)	Avg.	*ANStarCov*	1 (Low)	2	3	4 (High)	Avg.
1 (low)	-0.040	-0.050	0.103	0.253	0.075	1 (low)	-0.029	0.068	0.114	0.330	-0.001
2	-0.053	0.004	0.202	0.469	0.214	2	-0.026	0.003	0.180	0.305	0.028
3	-0.035	0.010	0.291	1.104	0.314	3	-0.037	0.069	0.202	0.401	0.049
4 (high)	0.052	0.125	0.370	2.340	0.594	4 (high)	0.076	0.080	0.221	0.472	0.079
H-L	0.092	0.175	0.267**	2.087***	0.518***	H-L	0.105	0.012	0.107	0.142	0.080
t-statistic	(1.08)	(1.61)	(2.20)	(10.01)	(6.67)	*t*-statistic	(1.03)	(0.23)	(0.86)	(1.25)	(1.05)
p (*GRS*):	0.08					*p* (*GRS*):	0.28				