The Truth of Silence:
Bad Signal of No Analyst Report

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This study introduces a novel measure of analyst silence and explores its cross-sectional asset pricing implications and impact on the capital market. Consistent with the intuition that analysts tend to choose silence over issuing adverse reports when faced with bad news, we find that analyst silence and future stock returns are negatively correlated. Stock portfolios with low analyst silence generate 0.99% more monthly returns than portfolios with high silence. Analyst silence is associated with more bad news and less good news in the future. Further evidence suggests that while analyst silence hinders information dissemination, it also serves a monitoring role. Our results indicate that analysts can keep silent in a strategic way.

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1 Introduction

In the information ecosystem of the capital market, analysts, as key information intermediaries, play a vital role in processing and disseminating information (Womack, 1996; Barber et al., 2001). Some scholars believe that research reports published by analysts help to improve the information environment and positively influence corporate decisions (To et al. al., 2018). Analysts can also serve as outsider monitors to maintain the quality of information disclosure (Yu, 2008) and corporate governance (Jensen and Meckling, 1976; Chen et al., 2015). Despite the bright side of financial analysts, a large body of literature shows that analyst recommendations are overly optimistic, resulting in analyst reports that often lack useful information (Loh and Stulz Stulz, 2011; Kumar and Rantala Rantala，2022). Scholars have made a lot of active exploration on how to improve the information intermediary function of analysts (Crane and Crotty, 2020; Dechow and Sloan, 2000; Brown et al., 2015). However, neither ability nor motivation is sufficient to fully cover the formation sources of analysts' collective optimism bias. In fact, even among high-ability analysts or analysts with weak self-interest motivation, optimism bias is not absent (Wu et al., 2013).

At the same time, the existing literature also points out that compared with the positive information, the negative news reported by analysts tends to have higher information content (Barber et al., 2006). However, unless there is sufficient information and motivation, analysts are generally unwilling to release negative information and hope to establish a good relationship with the management (Hsieh et al., 2023). This also results in a very small number of negative reports, less than 10% of all reports. Therefore, this paper attempts to find a scientific method that can perfectly remove the interference of optimism bias and has sufficient quantity to accurately capture the intermediary value of analyst information, and analyst silence just provides an appropriate research perspective.

The optimism bias can be "strategic" or "nonstrategic" (Malmendier and Shanthikumar, 2014). Non-strategic distortion may come from the genuine overoptimism of analysts, e.g., credulity (Teoh and Wong, 2002). Strategic distortion reflects the incentive to maintain good relationships with company management to get valuable and timely information (Lim, 2001), generate corporate finance business (Kolasinski and Kothari, 2008), and stimulate trading to generate brokerage commissions (Cowen et al., 2006; Brown et al., 2015). Similar to optimism bias, analysts' motives for silence can also be divided into strategic and non-strategic types. On the one hand, if analysts have some negative information or evaluation on the covered firms, they can either issue a downgrading report or keep silent. To maintain stable relationships with listed firms, they probably mute rather than voice the bad news (McNichols and O'Brien, 1997; Scherbina, 2008). This is consistent with the strategic motive hypothesis. In spirit of Malmendier and Shanthikumar (2014), we refer to it as *strategic silence*. On the other hand, analysts can drop the firms simply due to limited attention or busyness. We refer to this as a *nonstrategic silence* motive. Although the literature on signals expressed in analyst reports is extensive, the information generated by the analyst silence is less explored. Furthermore, we know little about the relative importance of strategic and nonstrategic silence.

In this paper, we investigate information embedded in analyst silence and examine how this silence, whether strategic or nonstrategic, affects the firms and capital market. We propose a novel measure, i.e., the time length since the last report, to identify the analyst silence. We show that the analyst silence can negatively predict future stock returns. It is noted that both *strategic silence* and *nonstrategic silence* can predict negative future returns.

For *strategic silence*, what the analyst does not tell is the company's bad news. The stock underperformance will be predictable if the market cannot immediately reflect the negative news embedded in the analyst silence. Nonstrategic silence can reduce investors' attention and the enthusiasm of their buying demand because of fewer (positive) reports, associated with a price decline. To further understand the mechanism, we utilize the unique institutional background of analyst site visit mandatory disclosure in China to examine the return predictability within the group with site visits during the silence period. We also delve into analyst silence's information and monitoring roles to further distinguish the effects of *strategic silence* and *nonstrategic silence*. Our evidence suggests that *strategic silence* may play a more critical role.

Specifically, our empirical analysis consists of four steps. First, we use the Chinese Broker and Financial Analyst System dataset from CNRDS to construct a measure for analyst silence. For each stock at the end of each month, we measure the analyst silence as the average time length since the last report of each securities company that has issued at least one report in the past year. In the portfolio analysis, we sort stocks into ten deciles according to their analyst silence. We observe that stocks in the top silence decile (silent group) exhibit significantly lower returns. For instance, the value-weighted (equal-weighted) monthly return of the silence group is -0.280% (0.108%), while the bottom silence decile (active group) generates a return of 0.710% (0.950%). An Active-minus-Silent (AMS) strategy, which buys (short sells) the value-weighted (equal-weighted) portfolio of the active (silent) group, can generate a significant out-of-sample monthly return of 0.990% (0.842%). This return remains as high as 1.103% (0.997%) and 1.214% (0.875%) when adjusted by the CH4 (Liu et al., 2019) and Fama-French factor models (Fama and French, 1992, 2015).

A natural concern is that the analyst silence can be correlated with many other characteristics contributing to the return predictability. To address this concern, we perform various double-sorting portfolio analyses by sorting stocks into correlated characteristics, e.g., size, book-to-market, and profitability, and then sorting stocks according to the analyst silence within each group to control for the characteristics' differences. We also conduct multivariate Fama-Macbeth regressions to control for a list of characteristics simultaneously. The double-sorting portfolio and the multivariate analyses confirm the power of our measure to predict stock returns. The economic magnitude of analyst silence in the Fama-Macbeth regressions is similar to the portfolio analysis result and remains unchanged after controlling for other predictive characteristics.

Second, we examine whether the analyst silence contains negative fundamental information. We first employ the Financial News Database of Chinese Listed Companies (CFND) to examine the predictability of analyst silence on the number of monthly future good news or bad news. Good and Bad news is defined according to the sentiment score of financial news. In the panel OLS regressions, we find that an increase in analyst silence from the bottom decile to the top decile is associated with a 0.3627 decrease in the number of good news and a 0.1908 increase in the number of bad news, which accounts for 6.6% and 5.7% of the mean values of positive and negative news. The Poisson regressions exhibit similar results. These findings indicate that analyst silence does contain negative information in general.

We further investigate the relationship between analyst silence and future earnings surprise. We observe that analyst silence can negatively predict earnings surprises for the next one to four quarters. For instance, an increase in analyst silence from the bottom decile to the top decile is associated with a 0.664 decline in standardized unexpected earnings (*SUE*), which accounts for 58.5% of the standard deviation of *SUE*. This result suggests that negative earnings information is embedded in the analyst silence, which is consistent with the *strategic silence* hypothesis.

Third, we delve into the roles played by analysts during the silence period. According to Bradshaw et al., (2017)[1], financial analysts can play both information and monitoring roles. For the information role, they can either serve as the information productor by providing forward-looking predictions or the information processor and interpreter by helping stock price incorporate public information. In our context, if analyst remains in silence, the influence of information role can be mitigated because investor have fewer interpretations of corporate earnings information to refer to. We follow the literature on post-earnings-announcement drift (PEAD) (see Zhang 2008; Chen et al., 2010) to examine the information role of analyst silence. We find that the coefficients of post-earnings-announcement drift on the interaction terms between *SUE* and analyst silence are positive and significant. This result suggests that the analyst silence impede the incorporation of the earnings information into prices.

Furthermore, we classify the *SUE* into positive *SUE* and negative *SUE* and conduct similar regressions. It is observed that only the coefficients of interaction terms between negative *SUE* and analyst silence remain positively significant, suggesting that the analyst silence fails to incorporate negative news immediately into the stock price, which echoes the negative information suppressed in the analyst silence and its return predictability. Our results remain highly robust after controlling for other documented factors contributing to

[1] See Givoly and Biddle (2018) for a brief book review.

the PEAD effects and the squared terms of *SUE* and analyst silence to adjust the correlations between *SUE* and analyst silence (Balli and Sørensen, 2013). These findings highlight the potential impediment of analyst silence on the information incorporation in capital markets.

We then explore the monitoring role of analyst silence. While the information role of analyst silence is fairly intuitive, the effects of the monitoring role can be driven by two contradictory factors. On the one hand, analyst silence can be associated with less analyst coverage, which is documented as weaker monitoring power in literature (e.g., Irani and Oesch, 2013; Chen et al., 2015; Ellul and Panayides, 2018). On the other hand, if keeping silent is to maintain good relationships with management for future coordination, analysts can still serve as outside monitors or financial experts to share their knowledge with the company. Companies' expertise can be more important than usual when encountering business difficulties. The examination of the monitoring role thus provides a sharp identification of *strategic silence* and *nonstrategic silence*.

We examine the effects of analyst silence on company investment efficiency (Richardson, 2006) and earnings management activities (Yu, 2008). Our results show that analyst silence is not associated with worse governance. Instead, the firms with silent analysts are observed to reduce investment inefficiency and discretionary accruals. The monitoring effects are more pronounced within firms with under-investment and positive accruals than in over-investment and negative accruals. It reconciles the observations that the predictive coefficients of analyst silence on future *SUE*s turn from negative to positive after one year. These findings suggest that although the analysts remain silent in public, they can still serve as outside monitors and provide valuable information to management in private. The results of monitoring further support the *strategic silence* hypothesis.

Fourth, we explore other potential explanations for our findings. We take advantage of the unique institutional background of the mandatory disclosure of analyst site visits in China to examine the first alternative explanation, i.e., the inattention channel. We divide the stocks into two groups according to whether any analyst visits the company during the silence. We find that in the subsample with on-site visits, the AMS strategy generates a monthly return of 1.075%, while within the no-visit sample, the AMS strategy earns a slightly lower return of 0.952%. This subsample analysis confirms that even if analysts do not publish research reports, they may still be keeping a close eye on the company's situation. Furthermore, the on-site visit can provide analysts with an informational advantage (Han et al., 2018), confirming the choice of *strategic silence*. Last, we also examine whether future on-site visits play a moderate role in monitoring activities. Our results indicate that the monitoring effect on investment efficiency is only present with future on-site visits, and the impact on earnings management is more pronounced with these visits.

Another potential reason for keeping silent is the coordination between analysts and institutional investors or insiders out of trading demand (Ellul and Panayides, 2018), namely the *coordination hypothesis*. We explore this alternative mechanism by examining the stock illiquidity and probability of informed trading (*VPIN*) following analyst silence. Our results suggest that the stock liquidity decreases with the analyst silence. At the same time, the analyst silence is also associated with a lower probability of informed trading, which rules out the *coordination hypothesis*. We also show that institutional investors gradually sell the stocks with high analyst silence, instead of immediately getting rid of them. These results help us rule out the coordination hypothesis.

We then investigate the relationships between sentiment and the return predictability of analyst silence. Stambaugh et al., (2012) find that because of short-sale impediments, a broad set of anomalies are more pronounced in the high-sentiment period, driven by the short legs rather than long legs. We find that in our setting, the long and short legs underperform during high-sentiment periods, though insignificantly. The long-short portfolio performs similarly between these two regimes, which suggests that sentiment-related overpricing may not drive our findings.

We also conduct a battery of robustness checks, including using the median value of analyst silence, different ranking periods (2 years), using only positive reports, controlling for other analyst-related predictors, and short-selling constraints. Our results remain highly robust.

Our paper contributes to the broader literature on strategic recommendations because of conflicts of interest. Previous literature has documented that analysts can strategically make recommendations out of the incentives to maintain good relationships with company management (Das et al., 1998; Lim, 2001; Lourie, 2019; Bradley et al., 2022), generate corporate finance business (Ljungqvist et al., 2007; Kolasinski and Kothari, 2008), and stimulate trading to generate brokerage commissions (Cowen et al., 2006; Agrawal and Chen, 2008; Brown et al., 2015). Another strand of this literature examines how analysts speak in "two tongues" to please their clients (Malmendier and Shanthikumar, 2014; Hirshleifer et al., 2024) or provide insider information to their clients without any public disclosure (Li et al., 2021). Our paper shows that beyond issuing overly optimistic reports, analysts can strategically keep silent when facing bad news on covered firms. In this manner, the analyst silence is associated with unobserved unfavorable information and can negatively and significantly predict future returns.

Our paper also contributes to the literature on analyst roles in information dissemination (Zhang 2008; Chen et al., 2010; Chen et al., 2022) and monitoring (Yu, 2008; Irani and Oesch, 2013; Chen et al., 2015; Ellul and Panayides, 2018; Guo et al., 2023). This paper finds that analyst silence does hurt to stock informativeness with delayed earnings information incorporation, which is also related to a classical strand of literature on PEAD effects[2]. We show that analyst strategic silence can impede negative news incorporated into the stock price, which induces an asymmetric post-earnings announcement drift.

Furthermore, despite the unfavorable information role during the silence, our results indicate that analysts can still play a monitoring role by disciplining investment and earnings management activities. This paper extends the previous literature on analyst coverage, which relies on the exogenous shock of analyst coverage (more like *nonstrategic silence*, such as He and Tian, 2013; Chen et al., 2015; Ellul and Panayides, 2018). We show that under *strategical silence*, the monitoring and financial expertise still work, which is in contrast to the *nonstrategic* reduced analyst coverage[3].

We conduct our analysis on the Chinese stock market due to several advantages. Firstly, the mandatory disclosure of analyst and investor site-visit in China presents a unique institutional characteristic that enables us to identify *strategic silence*. This setting has been widely used in literature (see Cheng et al., 2016; Han et al., 2018; Jiang and Yuan, 2018; Dong et al., 2021; Chen et al., 2022; Guo et al., 2023). Secondly, listed firms in emerging markets such as China operate in an opaque information environment, and retail investors dominate

[2] Ball and Brown (1968) first documented PEAD. One popular explanation is that the PEAD effect is driven by investors' underreaction to earnings surprises, which is related to the disposition effect (Frazzini, 2006) and limited attention. For example, Dellavigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), and Kottimukkalur (2019) propose inattention to firm-specific news as an explanation for PEAD.

[3] Analyst silence is associated with less earnings management, aligning with the less pressure explanation by He and Tian (2013). However, the moderating effects of on-site visits suggest that the positive aspects of analyst silence are not due to reduced pressure.

trading activities. Analysts are thus more likely to choose strategic silence to please the listed firms to maintain good relationships or get informational advantages. There is little evidence of the information embedded in analyst silence in emerging markets like China. However, information dissemination and monitoring are critical, particularly in developing emerging markets.

The rest of the paper is organized as follows. Section 2 provides a detailed description of the data source and variable construction and explores the return predictability of analyst silence. Section 3 inspects the mechanism and discusses the economic role of analyst silence. Section 4 presents additional robustness tests. Section 5 concludes the paper.

2 Data, Variable Construction, and Cross-Section Analysis

2.1 Data Source and Main Variables

The data we use, including data on returns, trading, and financial statements, are from the China Stock Market & Accounting Research (CSMAR) database. The relevant data of analyst reports are from the Chinese Research Data Services Platform (CNRDS). The period for our analysis is from January 1, 2010, through December 31, 2023. To enable reasonable precision and power and follow Liu et al. (2019), we only contain the stocks whose first two digits are 60, 30, and 00 after imposing our filters, which include eliminating stocks (i) in the bottom 30% of firm size, (ii) listed less than six months, and (iii) having less than 120 trading records in the past year or less than 15 trading records in the past month.

Analyst report recommendations are one of the major focuses of this paper. Panel A of Table 1 shows the distribution of analyst report grading in China from 2010 to 2023. Among 866,871 analyst reports, 50.90% are Strong Buy; 39.40% are Buy; 3.87% are Neutral; 0.01% are Sell; 0.12% are Strong Sell. Only 0.13% of reports present negative opinions (Sell or Strong

Sell), which implies the negative analyst reports are "not widely accepted". Regarding the report number changes, panel B of Table 1 presents the number of analyst reports in our sample. From 2010 to 2023, the proportion of positive analyst reports (Buy or Strong Buy) increased significantly, especially those rated as Strong Buy. The distribution and trend are consistent with optimism bias (Brown et al., 2015), meaning Chinese analysts only tend to issue positive recommendations. In other words, Chinese analysts restrict the extent of informativeness in their public recommendations while employing upbeat opinions to stimulate retail trading activities.

Motivated by the above facts, we propose an intuitive measure of analyst silence, defined as the average number of days between the last report date and the current date. We include all reports with gradings rather than solely focusing on earnings forecasts for two reasons: first, reports with gradings offer broader coverage, and second, analysts can communicate their perspectives to the market through general reports or in-depth special reports without necessarily providing earnings forecasts.

[Insert Table 1]

Panel C of Table 1 shows the summary statistics of the main variable in Fama-Macbeth regressions, containing 267,814 firm-month observations. The average of *Silence* is about 134 days, with a median value of 126 days. To mitigate the impact of seasoning factors, we use the cross-sectional rank of *Silence*, i.e., *Rank Silence*, to conduct empirical research. The cross-sectional rank can also provide easy-to-interpret results. We also use the logarithm of *Silence* for a robustness check.

2.2 Univariate Portfolios of Stocks Sorted by Silence

We start our analysis with univariate portfolio sorting. For each month from January

2010 to December 2023, stocks are sorted into decile portfolios based on their length of silence in analyst reports measure, *Silence*, where decile 1 (decile 10) contains the most active (silent) stocks. Next, we calculate the next-month value-weighted average portfolio returns and equal-weighted average portfolio returns, and this procedure is repeated each month until the sample is exhausted.

Table 2 reports for each decile the next-month average excess return and the risk-adjusted returns (alphas) based on the CAPM, CH4, FF3, and FF5 models. The last row in Table 2 presents the AMS (Active-minus-Silent) average return and alpha spreads for the hedge portfolio that is long in the decile of stocks with the lowest *Silence* and short in the decile of stocks with the highest *Silence*.

[Insert Table 2]

Univariate portfolio sorts indicate a significantly negative relation between the length of *Silence* in analyst reports and next-month average returns. The value-weighted portfolio of stocks with the lowest *Silence* earns an average excess return of 0.71% per month, whereas the average excess return on the value-weighted portfolio of stocks with the highest *Silence* is -0.28% per month. The return predictability of analyst silence is driven by both the long and short legs. For the value-weighted portfolios, the active group generates a monthly alpha of 0.468% (*t*=2.90), 0.553% (*t*=2.92), 0.413% (*t*=2.55), and 0.331% (*t*=1.96) adjusted by CAPM, CH4, FF3, and FF5 models, respectively.

The arbitrage portfolio with a long position in the lowest *Silence* stocks and a short position in the highest *Silence* stocks (AMS) earns on a value-weighted average of 0.99% per month with a Newey and West (1987) *t*-statistic of 3.04. The last row in Table 2 further presents the next month's risk-adjusted returns for the AMS portfolio. The CAPM, CH4, FF3, and FF5 alpha spread for the long-short portfolio are all positive, economically significant, ranging from 1.00% to 1.21% per month, and highly significant with *t*-statistics in the range of 3.07 and 5.70. The above findings also apply to the equal-weighted portfolios.

[Insert Figure 1]

The AMS Strategy outperforms the market in different time dimensions. Panel A of Figure 1 shows the cumulative returns of the monthly-rebalanced ASM Strategy. Over the entire sample period (2010 - 2023), the strategy achieved a return of 345.4%. A remarkable feature is that the AMS strategy performed relatively steadily during the Bubble-Crash episode in 2015. For the Buy-and-Hold AMS Strategy, panel B of Figure 1 shows the 12-month cumulative abnormal return is 2.49%, above 0 at the 95% confidence interval. The buy-and-hold strategy achieves highest 8 months after formation, generating a cumulative return of 3.38%. The buy-and-hold returns suggest that the bad news embedded within the analyst silence is gradually incorporated into the stock price.

2.3 Bivariate Portfolios of Stocks Sorted by Silence and Control Characteristics

One may think that the return predictability of analyst silence could be explained by documented characteristics. In this section, we conduct dependent bivariate portfolio sorts using 8 control characteristics as their mean values differ significantly across *Silence* groups (see Table A1 for details). At the end of each month, we form value-weighted decile portfolios by first sorting stocks into three groups based on one of the control characteristics. Next, we divide each group of stocks sorted by the control characteristic into deciles according to their *Silence* value to generate 3×10 portfolios for each characteristic and *Silence*. Then we average each of the *Silence*-sorted portfolios across the control characteristic groups, producing portfolios with dispersion in *Silence* that are similar in terms of the control characteristic. In addition, we form a portfolio that is long in the resulting Active portfolio and short in the resulting Silent portfolio (Low-High *Silence* portfolio).

[Insert Table 3]

Table 3 reports the next-month excess returns for each value-weighted portfolio averaged across the control groups. After controlling for 8 stock characteristics, the last 5 rows in Table 3 show that all the spread portfolios (AMS Portfolio) command significantly negative next-month returns and CAPM, CH4, FF3, and FF5 alpha spreads, with the excess returns ranging from 0.61% to 0.98% per month with *t*-statistics in the range of 2.78 and 4.74. An important point in Table 3 is that when controlling for size, book-to-market ratio, liquidity, beta, idiosyncratic volatility, asset growth, gross profitability, and earnings-to-price ratio, the negative relation between *Silence* and future returns remains highly significant.

2.4 Firm-Level Cross-Sectional Regressions

The univariate and bivariate sort analyses are conducted at the portfolio level, which may introduce aggregation effects by limiting individual stock-level information in the cross-section. To address these effects and simultaneously control for the potential influence of other stock characteristics, we perform Fama and MacBeth (1973) regressions at the individual stock level, accounting for a comprehensive set of firm characteristics:

$$R_{i,t} = \beta_{0,t} + \beta_{Silence,t} Rank\ Silence_{i,t-1} + \beta_{X,t} X_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

where $R_{i,t}$ is the excess return of stock *i* in month *t*. $Rank\ Silence_{i,t-1}$ is the cross-sectional rank of *Silence* of stock *i* in month *t*-1, which is standardized into [0, 1] uniformly. $X_{i,t-1}$ denotes the set of controls representing the characteristics of stock *i* in month *t*-1, including

Size (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio, Liu et al., 2019), *Asset growth* (growth rate of total assets), *Gross Profitability* (Novy-Marx, 2013), *IVOL* (idiosyncratic volatility, Ang et al., 2006), *Reversal* (stock returns in month *t*-1), *lnAmihud* (logarithm of Amihud illiquidity ratio, Amihud, 2002), and *Turnover* (average daily turnover ratio).

[Insert Table 4]

Table 4 presents the time series averages of the slope coefficients from monthly cross-sectional regressions of next-month excess returns on *Rank Silence* and various stock characteristics from January 2010 to December 2023. The first specification examines the cross-sectional relation between *Rank Silence* and next-month stock returns without any controls. Consistent with our findings from the univariate portfolio sorts, column (1) of Table 4 provides evidence of a negative and significant relation between *Rank Silence* and next-month returns, with an average slope of -0.913 and a *t*-statistic of -4.02.

After confirming the significantly negative relationship between *Rank Silence* and future returns at the individual stock level using univariate Fama and MacBeth (1973) regressions, we proceed to control for a range of stock characteristics. We first control for the size, book-to-market ratio, earnings-to-price ratio, asset growth, and gross profitability in the specification (2), and then idiosyncratic volatility, reversal, illiquidity, and turnover in the specification (3). For the economic magnitude, an increase from the bottom decile (average rank = 0.05) to the top decile (average rank = 0.95) is associated with a negative monthly return of 0.841% (0.935*0.9), which is consistent with the results of univariate portfolio sorting. These results suggest that the return predictability of analyst silence is not driven by the common predictors examined. Specifications (4) and (5) replicate the same set of regressions using the value-weighted method. We still document a negative and robust relation between stocks' *Rank Silence* and future returns in the market capitalization-weighted and gross return-weighted regressions. Our findings remain highly significant when using the logarithm of analyst silence, see Table A2. Overall, these results demonstrate that *Silence* provides distinct and significant information beyond established firm characteristics, serving as a strong and robust predictor of future equity returns. This confirms our main finding that *Silence* is priced in the cross-section of individual stocks.

3 Inspecting the Mechanisms

3.1 Analyst Silence and Corporate News

To investigate whether analyst silence signals negative fundamental information, we utilize the Financial News Database of Chinese Listed Companies (CFND) to assess its predictive power regarding the frequency of future monthly good or bad news. The CFND database collects relevant reports on listed companies from major Chinese financial media. Good and bad news are classified based on financial news sentiment scores. As shown in Columns (1) and (3) of Table 5, the panel OLS regressions reveal that moving from the lowest decile to the highest decile of analyst silence corresponds to a decrease of 0.3627 in the number of good news articles and an increase of 0.1908 in the number of bad news articles. These changes represent 6.6% and 5.7% of the average values for positive and negative news, respectively. Similar results are observed in the Poisson regressions reported in Columns (2) and (4) of Table 5. Overall, these findings suggest that analyst silence generally conveys negative information hidden by analysts.

[Insert Table 5]

3.2 The Information Role of Analyst Silence

In order to further explore the specific role of analyst silence, we delve into the roles played by analysts during the silence period. According to Bradshaw et al., (2017), financial analysts can play both information and monitoring roles. Firstly, we explore the relationship between analyst silence and future earnings surprises. Panel A of Table 6 reveals that increased analyst silence can serve as a negative predictor of earnings surprises over the next one to four quarters (for more intuitive results, see Figure 2). In specification (1), a shift from the lowest to the highest decile of analyst silence correlates with a 0.664 reduction in standardized unexpected earnings (*SUE*), representing 58.5% of the standard deviation of SUE. This finding supports the notion that analyst silence reflects underlying negative earnings information, aligning with the *strategic silence* hypothesis. However, an interesting result is that the coefficients become significantly positive after one year. This pattern inspires us to further explore the monitoring role of analyst silence. We will discuss this later.

[Insert Table 6]

In their informational role, analysts can function as either information producers by offering forward-looking predictions or as processors and interpreters of information by aiding integrating public information into stock prices. An interesting and important question is how analyst silence influences information dissemination. To answer this question, we draw on the literature related to post-earnings-announcement drift (PEAD). PEAD is well documented in the literature in both the U.S and international stock markets including China (Hu et al., 2024; Li and Yang, 2024).

Specifically, we conduct following regressions:

$$CAR[2,60]_{i,t} = \alpha + \beta \times SUE_{i,t} \times Rank\ Silence_{i,t-1} + \gamma_1 \times SUE_{i,t} + \gamma_2 \times RankSilence_{i,t-1} + \gamma X_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where $CAR[2,60]_{i,t}$ denotes the cumulative abnormal returns from 2 days to 60 days after the earnings announcement, which is adjusted by the market model (subtract the market returns). The main independent variables include *SUE* (standardized unexpected earnings), *Rank Silence* (the observation at the end of the month before the earnings announcement date), and their interaction term. The coefficient of interest is β. A higher positive β means a stronger post-earnings announcement drift, suggesting that information is reflected in the stock price more slowly. We also control for other characteristics, as well as the firm and quarter fixed effects.

In Panel B of Table 6, Columns (1) and (2) demonstrate that the coefficients of PEAD on the interaction terms between *SUE* and *Analyst Silence* are positive and significant. This finding indicates that analyst silence hinders the incorporation of earnings information into stock prices. In column (2), an increase from the bottom decile to the top decile of analyst silence is associated with a 0.060% higher abnormal return from the mean value of *SUE*, which accounts for 33% of the mean value of CAR [2, 60]. The return spread of one-standard-deviation increase in *SUE* between the highest and lowest decile analyst silence is 0.76%[4]. The coefficients of *Rank Silence* are negative and significant, which is consistent with the findings that analyst silence contains bad news. The interaction term between analyst silence and *SUE* absorbs the positive relation between *SUE* and *CAR*, which is significant without including the interaction term in unreported results. This suggests that analyst silence may play an essential role in the formation of PEAD effects in China.

[4] The estimated coefficient of the interaction term is 0.007. The mean value of *SUE* is 0.09. Then an increase from the bottom decile to the top decile of analyst silence is associated with a $0.09 \times 0.0074 \times 0.9 = 0.060\%$. The mean value of CAR [2, 60] is 0.18%. The fraction is $0.060\%/0.18\% = 33\%$. The standard deviation of *SUE* is 1.134, and then the return spread of one-standard-deviation increase in *SUE* between the highest decile analyst silence and lowest decile analyst silence is $1.134 \times 0.9 \times 0.0074 = 0.76\%$.

We further divide *SUE* into positive and negative categories and conduct similar regressions. Columns (3) to (5) of Panel B reveal that only the interaction terms between negative *SUE* and analyst silence maintain positive significance. This suggests that analyst silence delays the incorporation of negative news into stock prices, reinforcing the idea that negative information is suppressed within analyst silence, contributing to its return predictability. These results remain robust even after controlling for other factors known to generate PEAD effects, as well as the squared terms of *SUE* and analyst silence to account for their correlations (Balli and Sørensen, 2013). These findings underscore the potential obstructive role of analyst silence in the timely incorporation of information in capital markets.

3.3 The Monitoring Role of Analyst Silence

We then investigate the monitoring role of analyst silence. While the informational aspect of analyst silence is relatively straightforward, the monitoring effects can stem from two opposing factors. On the one hand, analyst silence may indicate reduced analyst coverage, which has been linked to weaker monitoring capabilities in the literature (e.g., Irani and Oesch, 2013; Chen et al., 2015; Ellul and Panayides, 2018), which supports the *nonstrategic silence hypothesis*. On the other hand, if analysts remain silent to preserve good relationships with management for future collaboration, they can still function as external monitors or financial experts, providing valuable insights to the company (Guo et al., 2023), which is consistent with the *strategic silence hypothesis*. This expertise may become particularly crucial during periods of business challenges. Therefore, examining the monitoring role of analyst silence offers a clear distinction between *strategic silence* and *nonstrategic silence*.

We explore the impact of analyst silence on company investment efficiency (Richardson, 2006) and earnings management practices (Yu, 2008). As presented in Table 7, companies with silent analysts tend to show improvements in investment efficiency and reductions in discretionary accruals, which is indicated by the significantly negative coefficients of *Rank Silence*. These monitoring effects are more significant in firms experiencing under-investment and positive accruals compared to those with over-investment and negative accruals (see Table A3). This aligns with the observation that the predictive coefficients of analyst silence on future *SUE*s shift from negative to positive after one year (see Columns (5) and (6) of Panel A in Table 6 and Figure 2). These results imply that, while analysts may remain publicly silent, they can still act as external monitors and offer valuable insights to management privately, further supporting the *strategic silence* hypothesis.

[Insert Table 7]

Furthermore, on-site visits can give analysts an informational edge (Han et al., 2018) and opportunity to communicate and share knowledge with the management (Jiang and Yuan, 2018; Guo et al., 2023), supporting the idea of *strategic silence*. We investigate whether future on-site visits contribute to moderating the monitoring activities of analysts. Table A4 reveals that the positive impact on investment efficiency is observed only when future on-site visits occur, and the influence on earnings management is significantly stronger in the presence of these visits.

To sum up, analyst silence impedes the incorporation of information, especially negative news, into stock prices. However, analysts still monitor the companies in silence. Our findings highlight the informational void and persistent monitoring created by analyst silence, offering a novel perspective that enhances our understanding of the intricate relationships between analysts and companies.

3.4 Alternative Explanations

3.4.1 Inattention Channel

We take advantage of the unique institutional background of the mandatory disclosure of analyst site visits in China to examine the inattention channel. We divide the stocks into two groups according to whether any analyst visits the company during the silence. Table 8 presents that in the subsample with on-site visits, the AMS strategy generates a monthly return of 1.075%, while within the no-visit sample, the AMS strategy earns a slightly lower return of 0.952%. This subsample analysis confirms that even if analysts do not publish research reports, they may still be keeping a close eye on the company's situation. From columns (2) to (7) of Table 8, the result is consistent with the attention of retail investors (Baidu Searching Index) and the attention of institutional investors (Institutional Investor Holdings), which means the inattention channel is not an important mechanism.

[Insert Table 8]

3.4.2 Coordination Hypothesis

Another alternative explanation for the silence of analysts could be a coordinated effort with insiders based on trading demands, often referred to as the *coordination hypothesis* (Ellul and Panayides, 2018). The coordination can occur between analysts and institutional investors, as well as between analysts and insiders. For institutional investors, we show that they gradually, rather than immediately, sell their holdings of high-silent stocks, as shown in Table A5. This phenomenon suggests that institutional investors, at least, do not fully understand the truth of analyst silence. For the insiders, we investigate this potential mechanism by analyzing stock illiquidity and the Volume-Synchronized Probability of

Informed Trading (*VPIN*) after periods of analyst silence following Ellul and Panayides (2018). As shown in Table A6, stock liquidity tends to decline during periods of *Analyst Silence*. Concurrently, *Analyst Silence* correlates with a reduced likelihood of informed trading, thereby discounting the *coordination hypothesis*.

3.4.3 Investor Sentiment

We also explore the relationship between sentiment and the return predictability associated with *Analyst Silence*. Stambaugh et al. (2012) observe that due to short-sale constraints, a wide range of anomalies are more pronounced during periods of high sentiment, primarily driven by short positions rather than long ones. However, as shown in Table A7, in our analysis, both long and short positions underperform during high-sentiment periods, though the results are not statistically significant. The performance of the long-short portfolio remains consistent across different sentiment regimes, indicating that sentiment-related overpricing may not be the primary factor behind our findings.

4 Robustness Checks

4.1 Alternative Measures of Analyst Silence

In this section, we replicate the univariate portfolios of stocks sorted by *Silence* through 3 different forms. Firstly, we replace the mean with the median of silence to generate a new variable *Median-Silence* and use it as the grouping criterion. Secondly, we extend the ranking period from one year to two years to observe whether the ranking period has an impact on the results. Thirdly, we focus on the positive reports with buy and strong buy views to exclude the similar impact of negative reports with analyst silence. From Table 9, we find that the AMS strategy still generates significantly positive returns, both the value-weighted and the equal-weighted returns, confirming the robustness of return analyst silence's return predictability.

[Insert Table 9]

4.2 Controlling for Other Analyst-related Predictors

A potential threat to our findings is that our measure of analyst silence is a rediscovery of documented characteristics of analyst forecast. To further confirm the credibility of the results of Fama-Macbeth (1973) regressions, we add other analyst-related predictive control variables, including *Forecast Change*, *Forecast Revision*, *Earnings Forecast/Price*, *Dispersion*, *Analyst Coverage*, and *skew*. Table 10 shows that the coefficients of silence are still significantly negative, and the economic magnitude is slightly smaller after controlling for other analyst-related predictors. This result further supports the predictive power of silence for future returns.

[Insert Table 10]

4.3 Short Selling Constraints

Given that the development of margin trading and short selling in China has been gradual, we divide the sample into two groups based on whether short selling is permitted and then sorted by silence (each group is further divided into 5 subgroups due to the small sample size of shorting-eligible stocks). As shown in Table A8, within the short-selling eligible stocks, the value-weighted returns indeed weaken, with the raw returns being marginally significant. However, after adjusting for other factor models, the results become significant, and the equal-weighted returns remain significant. Therefore, short-selling constraints matter to some extent, but the magnitude of this impact is within a reasonable range.

5 Conclusion

Analysts typically convey information to the market through research reports, serving as key information intermediaries. Beyond issuing recommendations, analysts may also choose to remain silent. This paper introduces a novel measure of analyst silence and examines its cross-sectional asset pricing implications and impact on the capital market.

Our findings first demonstrate that analyst silence can negatively predict future stock returns. Both portfolio analyses and Fama-Macbeth regressions confirm this negative return predictability. To explore the underlying mechanism, we investigate the information embedded in analyst silence. We show that analyst silence is associated with more bad news and less good news in the future. Additionally, analyst silence can predict firms' unexpected earnings. Our results suggest that when faced with bad news, analysts are more likely to remain silent rather than issue negative reports. Consequently, the truth of silence is the potential presence of negative news.

We then delve into the informational and monitoring roles of analyst silence to further distinguish between *strategic* and *non-strategic* silence in spirit of Malmendier and Shanthikumar (2014). We find that stocks with longer periods of silence experience larger Post-Earnings Announcement Drift (PEAD) effects, indicating that analyst silence hinders information dissemination. Interestingly, despite choosing to remain silent, analysts do not abandon their monitoring role. Firms with longer periods of silence exhibit reduced investment inefficiency and earnings management. Our evidence suggests that *strategic silence* may play a more critical role.

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Table A. Variable Definition and Summary Statistics

Variable Name	Variable Definition
Amihud	Amihud illiquidity ratio. The daily Amihud illiquidity ratio is calculated as $\frac{\lvert Ret \rvert}{Volume}$. We use logarithm of average daily Amihud illiquidity ratio in the past six months in our empirical analysis, which is denoted by *logAmihud*.
Analyst Coverage	Logarithm of the number of analyst earnings forecasts for the current fiscal year in each month.
Asset growth	Total asset growth rate, which is calculated as $AT_T/AT_{T-1} - 1$, following (Cooper et al., 2008). The returns for May of year *T* to April of year *T*+1 are matched with accounting data for all fiscal year ends in calendar year *T*-1. This data merging process is consistent throughout the subsequent analysis.
# Bad (Good) News	The number of bad (good) news that cover the firm *i*. This dataset is from CFND (Financial News Database of Chinese Listed Companies) in CNRDS. The database covers more than 400 online media, among which the most important are news reports from 20 mainstream online financial media, such as: Hexun.com, Sina Finance, Eastmoney.com, Tencent Finance, NetEase Finance, Phoenix Finance, China Economic Net, Sohu Finance, Financial World, Huaxun Finance, FT Chinese, Panorama.com, CICC Online, China Securities Network, Securities Star, Caixin.com, The Paper, First Financial News, 21CN Financial Channel, and Caijing.com. The sentiment of each news is classified as Positive, Neutral, and Negative. We measure the number of bad (good) news as the number of news report with negative (positive) sentiment score.
BM	Book-to-market ratio. Book equity equals total shareholder equity minus the book value of preferred stocks. A stock's BM is the ratio of book equity to the product of last month-end's close price and total shares, following LSY.
Board Size	Board size, expressed as the natural logarithm of the total number of board members.
Cash Flow Ratio	Free cash flow ratio, calculated by (earnings before interest and tax + depreciation and amortization - working capital increase - capital expenditure) / total assets at the end of the period.
Control Share	Shareholding ratio of the largest shareholder.
Dispersion	Dispersion in analyst earnings forecasts, calculated by

$$\text{Dispersion} = \frac{\text{the standard deviation of earnings forecasts}}{|\text{the consensus mean forecasts}|}$$

Dual	Indicator of the integration of two jobs. When the chairman and general manager of the company are the same, the value is 1; otherwise, it takes 0.
Earnings Management	Discretionary accruals calculated by modified Jones model. To determine accruals, we first run the following cross-sectional OLS regressions by the CSRC Industry Classification Code (2012): $$\frac{TA_{i,t}}{A_{i,t-1}} = \alpha_1 \frac{1}{A_{i,t-1}} + \alpha_2 \frac{\Delta REV_{i,t}}{A_{i,t-1}} + \alpha_3 \frac{PPE_{i,t}}{A_{i,t-1}} + \varepsilon_{i,t},$$ where $TA_{i,t}$ equals Net Profit - (Extraordinary gains and losses) + Financial expenses - Net cash flow from operating activities. $\Delta REV_{i,t}$ is the changes in sales revenues, which is calculated as the difference of (Operating Income - Other business income). $PPE_{i,t}$ is the Net Fixed Assets. All the variables are scaled by total assets in t-1. Then nondiscretionary accruals can be calculated as: $NDA_{i,t} \equiv \widehat{\alpha_1} \frac{1}{A_{i,t-1}} + \widehat{\alpha_2}\left(\frac{\Delta REV_{i,t}}{A_{i,t-1}} - \frac{\Delta AR_{i,t}}{A_{i,t-1}}\right) + \widehat{\alpha_3}\frac{PPE_{i,t}}{A_{i,t-1}}$, where $\Delta AR_{i,t}$ is the change in receivables. Discretionary accruals: $DA_{i,t} = \frac{TA_{i,t}}{A_{i,t-1}} - NDA_{i,t}$
EP	Earnings-to-Price Ratio following LSY. Earnings equals the most recently reported net profit excluding nonrecurrent gains/losses. A stock's EP is the ratio of earnings to the product of last month-end's close price and total shares.
Earnings Forecast/Price	Analyst Earnings Forecast-to-Price Ratio, calculated by the consensus median forecasts for the current fiscal year divided by closing price.
Forecast Change	Changes in analyst earnings forecasts, following Hawkins, Chamberlin and Daniel (1984), as $ForecastChange = \left(f_{i,t-1} - f_{i,t-2}\right)/\left(0.5\left\lvert f_{i,t-1}\right\rvert + 0.5\left\lvert f_{i,t-2}\right\rvert\right)$, where $f_{i,t-1}$, $f_{i,t-2}$ are the consensus mean forecasts issued in month t-1 and t-2 for firm i's current fiscal year's earnings, respectively.
Forecast Revision	Revisions in analyst earnings forecasts, using the six-month moving average of past changes in analyst forecasts from Chan, Jegadeesh and Lakonishok (1996), $$Forecast\ Revision_{i,t} = \sum_{\tau=1}^{6} \frac{f_{i,t-\tau} - f_{t-\tau-1}}{P_{i,t-\tau-1}}$$ where $f_{i,t-\tau}$ is the consensus mean forecast issued in month $\mathrm{t}-\tau$ for firm i's current

	fiscal year earnings, and $P_{i,t-\tau-1}$ is the closing price in month $t-\tau-1$.
Gross Profitability	Gross profitability is calculated as (REVT-COGS)/AT, following (Novy-Marx, 2013).
Inefficient Investment	Absolute value of residual $\varepsilon_{i,t}$ of Richardson (2006) model. $Inv_{i,t} = \alpha_0 + \alpha_1 Growth_{i,t-1} + \alpha_2 Lev_{i,t-1} + \alpha_3 Cash_{i,t-1} + \alpha_4 Age_{i,t-1} + \alpha_5 Size_{i,t-1} + \alpha_6 Ret_{i,t-1} + \alpha_7 Inv_{i,t-1} + \sum Industry + \sum Year + \varepsilon_{i,t}$ In the model: $Inv_{i,t}$: Actual new investment expenditure of the firm i in year t = total investment - maintenance investment = cash paid for the purchase and construction of fixed assets, intangible assets and other long-term assets + net cash paid by subsidiaries and other business units -- net cash recovered from the disposal of fixed assets, intangible assets and other long-term assets -- net cash received from the disposal of subsidiaries and other business units -- (fixed assets discounted Old + amortization of intangible assets + amortization of long-term deferred expenses)/total assets at the beginning of the year; $Growth_{i,t-1}$: represents the growth opportunity of the firm i in year t −1, denoted by Tobin's Q; $Age_{i,t-1}$: the years since IPO for the firm *i* in *t* −1. $Lev_{i,t-1}$: the financial leverage ratio of the firm i in year *t* −1, calculated as asset-liability ratio; $Cash_{i,t-1}$: the cash flow status of the firm *i* in year *t* −1, using the net cash flow generated by operating activities/total assets at the beginning of the year; $Size_{i,t-1}$: the asset size of the firm i in year *t* −1, calculated as the logarithm of total assets; $Ret_{i,t-1}$: the stock return rate of the firm *i* in year *t* −1; $Inv_{i,t-1}$: the new investment expenditure of firm *i* in year *t* −1; $\varepsilon_{i,t}$: the residual of the model estimate, that is, the inefficient investment.
IVOL	Idiosyncratic volatility, which is measured as the standard deviation of daily returns' residuals in the CAPM model in the past 252 days with at least 120 non-missing observations.
Management Share	Management shareholding, represented by the shareholding ratio of directors, supervisors and senior executives.

Reversal	Lagged monthly stock returns.
Salary	Executive incentives, expressed by Ln (total compensation of top three executives).
Silence	For each stock i, we get the analysts A_k that have issued reports in the past one year. The *Silence* is calculated as the average time intervals by days from the last report for each A_k to the end of month t. $Silence_{i,t} = \sum_{k=1}^{N} Days_{k,t}/N$.
Size	Logarithm of market capitalization at the end of month t, including both tradable and non-tradable shares, following LSY.
Skew	Skew is defined as the difference between the mean and the median forecast scaled by the absolute value of the mean forecast.
SUE	The standardized unexpected earnings. For each stock i in quarter t, we calculate SUE as $SUE_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-4}}{\sigma_{t-8:t-1}}$, where EPS is Earnings Per Share, and $\sigma_{t-8:t-1}$ denotes the standard deviation of EPSs during the past 8 quarters with at least six EPSs observed.
Turnover	We measure 6-month turnover as the average daily share turnover. A firm's daily turnover is calculated as its share trading volume divided by its total shares outstanding.

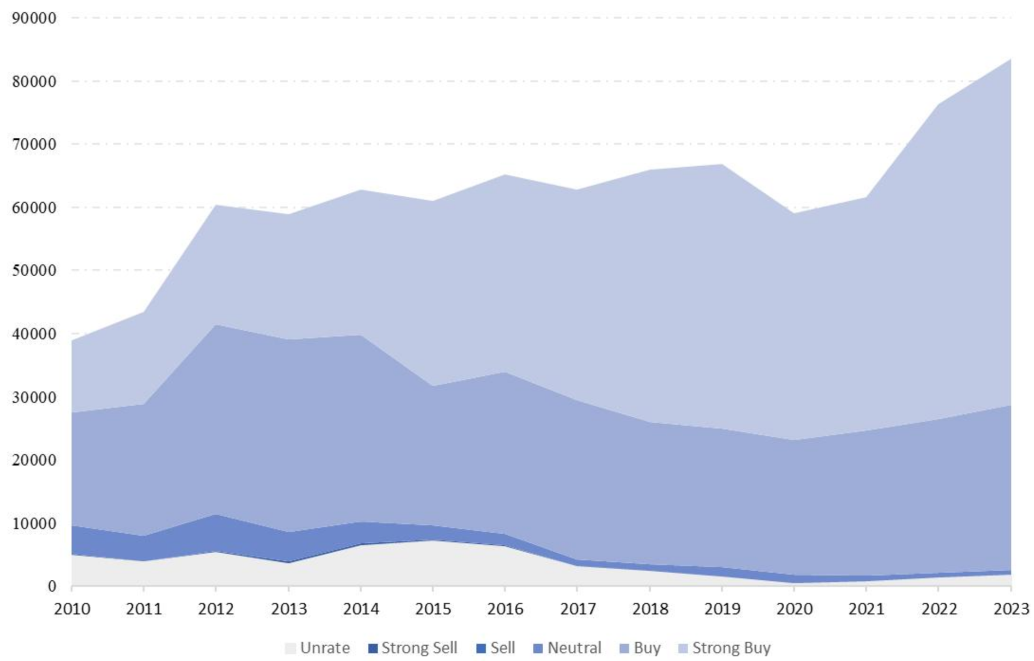
Table 1. Summary Statistics

This table provides summary statistics. Panel A presents the distribution of analyst report grading. Panel B presents the number of analyst reports in each year. Panel C shows the summary statistics of the main variable in Fama-Macbeth regressions. The variables include *Rank Silence* (the average day intervals from the last report date to the current date), *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total assets), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-2), *lnAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio).

Panel A: Distribution of Analyst Report Grading in China

All	Unrated	Strong Buy	Buy	Neutral	Sell	Strong Sell
866871	49413	441196	341544	33513	126	1079
Ratio	5.70%	50.90%	39.40%	3.87%	0.01%	0.12%

Panel B: Number of Analyst Reports in Each Year



Panel C: Summary Statistics on Main Sample

Var	Obs	Mean	Std	25th	Median	75th
Silence	267814	134.249	68.4797	87	125.645	171.737
Size	267814	16.253	0.999	15.538	16.048	16.773
BM	267687	0.498	0.902	0.232	0.375	0.602
EP	267683	0.057	1.007	0.034	0.079	0.129
Asset growth	267376	1.306	4.281	1.034	1.116	1.242
Gross Profitability	258503	0.160	0.113	0.085	0.133	0.204
IVOL	267244	0.024	0.013	0.018	0.023	0.028
Reversal	267244	0.012	0.137	-0.067	-0.002	0.073
logAmihud	267244	-6.315	1.068	-6.960	-6.252	-5.604
Turnover	267244	0.022	0.020	0.009	0.016	0.029

Table 2. Single Sorting Portfolios by Silence

This table presents the performance of portfolios single-sorted by *Silence*. At the end of each month *t*-1, stocks are sorted into ten groups according to their *Silence* levels. Each portfolio is held for one month. Panel A reports the value-weighted portfolios' performance. Panel B reports the equal-weighted performance of each group. We tabulate the excess returns, alphas adjusted by CAPM, LSY four-factor model (CH4), Fama-French three-factor model (FF 3), and Fama-French five-factor model (FF 5). At the bottom of each block, we report the performance of *AMS* (Active-minus-Silent) strategy, which longs stocks within the lowest *Silence* decile and shorts stocks within the highest *Silence* decile. *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Value-weighted Portfolios					Panel B: Equal-weighted Portfolios				
	Excess return	CAPM	CH4	FF3	FF5	Excess return	CAPM	CH4	FF3	FF5
1 (Active)	0.710	0.468	0.553	0.413	0.331	0.950	0.698	0.676	0.255	0.209
	(1.34)	(2.90)	(2.92)	(2.55)	(1.96)	(1.66)	(2.79)	(4.31)	(1.69)	(1.30)
2	0.342	0.130	0.243	0.266	0.270	0.942	0.703	0.754	0.420	0.380
	(0.72)	(0.59)	(1.30)	(1.37)	(1.43)	(1.74)	(3.43)	(4.72)	(3.01)	(2.68)
3	0.703	0.505	0.672	0.730	0.757	0.993	0.760	0.799	0.533	0.512
	(1.44)	(2.66)	(4.84)	(4.61)	(4.67)	(1.90)	(3.94)	(5.32)	(4.35)	(3.79)
4	0.260	0.060	0.310	0.243	0.266	0.744	0.509	0.552	0.270	0.234
	(0.60)	(0.40)	(2.22)	(1.88)	(2.16)	(1.42)	(2.54)	(3.88)	(2.55)	(2.12)
5	0.267	0.051	0.073	0.165	0.162	0.549	0.312	0.306	0.043	0.008
	(0.51)	(0.30)	(0.51)	(1.06)	(1.04)	(1.01)	(1.61)	(2.50)	(0.43)	(0.08)
6	0.436	0.219	0.229	0.229	0.221	0.682	0.441	0.348	0.141	0.104
	(0.91)	(2.01)	(1.57)	(1.91)	(1.73)	(1.26)	(2.24)	(3.37)	(1.54)	(1.13)
7	0.266	0.043	-0.142	-0.045	-0.076	0.507	0.262	0.124	-0.095	-0.125
	(0.48)	(0.27)	(-1.01)	(-0.30)	(-0.51)	(0.90)	(1.14)	(1.41)	(-1.13)	(-1.37)
8	-0.010	-0.242	-0.235	-0.394	-0.364	0.409	0.163	0.064	-0.218	-0.221
	(-0.02)	(-1.48)	(-1.55)	(-2.91)	(-2.96)	(0.74)	(0.75)	(0.67)	(-2.08)	(-2.17)
9	0.048	-0.192	-0.266	-0.525	-0.495	0.384	0.133	0.000	-0.345	-0.344
	(0.09)	(-0.85)	(-1.86)	(-4.21)	(-4.52)	(0.66)	(0.47)	(-0.00)	(-3.25)	(-3.42)
10 (Silent)	-0.280	-0.536	-0.550	-0.947	-0.883	0.108	-0.150	-0.321	-0.673	-0.666
	(-0.45)	(-1.70)	(-2.80)	(-4.96)	(-6.44)	(0.17)	(-0.50)	(-2.52)	(-5.32)	(-6.40)
AMS	0.990***	1.004***	1.103***	1.361***	1.214***	0.842***	0.848***	0.997***	0.928***	0.875***
	(3.04)	(3.07)	(4.74)	(5.63)	(5.70)	(4.25)	(4.29)	(4.67)	(4.79)	(4.92)

Table 3. Double Sorting Portfolios by Other Characteristics and Silence

This table presents the performance of portfolios dependently double-sorted by other characteristics X_t and *Silence*. At the end of each month *t*-1, stocks are first sorted into three groups according to their X_t levels. Within each group, we further divide the stocks into ten groups according to their *Silence* value. Each portfolio is value-weighted and held for one month. We tabulate the excess returns, alphas adjusted by CAPM, LSY four-factor model (CH4), Fama-French three-factor model (FF 3), and Fama-French five-factor model (FF 5) of the average performance of X_t sorted portfolios within each *Silence* decile. At the bottom of each block, we report the performance of *AMS* strategy, which longs stocks within the lowest *Silence* decile and shorts stocks within the highest *Silence* decile. *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Group	Size	BM	Amihud	Beta	IVOL	Asset Growth	Gross Profitability	EP
1 (Active)	0.793	0.597	0.749	0.571	0.595	0.607	0.704	0.560
	(1.50)	(1.12)	(1.41)	(1.01)	(1.11)	(1.10)	(1.18)	(1.00)
2	0.877*	0.528	0.762	0.543	0.502	0.371	0.519	0.152
	(1.68)	(1.08)	(1.58)	(1.06)	(0.99)	(0.74)	(0.95)	(0.30)
3	1.021**	0.712	0.833*	0.599	0.702	0.519	0.626	0.354
	(2.03)	(1.51)	(1.76)	(1.20)	(1.40)	(1.14)	(1.22)	(0.72)
4	0.751	0.414	0.662	0.306	0.261	0.417	0.366	0.153
	(1.48)	(0.89)	(1.33)	(0.62)	(0.54)	(0.82)	(0.68)	(0.30)
5	0.648	0.311	0.558	0.206	0.409	0.293	0.231	0.128
	(1.26)	(0.63)	(1.07)	(0.41)	(0.77)	(0.60)	(0.45)	(0.25)
6	0.672	0.310	0.541	0.239	0.376	0.410	0.166	0.115
	(1.26)	(0.61)	(1.08)	(0.47)	(0.73)	(0.78)	(0.32)	(0.23)
7	0.515	0.278	0.378	0.213	0.100	0.258	0.089	0.177
	(0.98)	(0.52)	(0.73)	(0.41)	(0.19)	(0.50)	(0.17)	(0.33)
8	0.493	0.018	0.303	0.188	0.008	0.108	0.216	0.195
	(0.89)	(0.03)	(0.58)	(0.35)	(0.02)	(0.20)	(0.41)	(0.37)
9	0.194	-0.099	0.225	0.119	0.019	0.023	0.190	0.051
	(0.35)	(-0.17)	(0.42)	(0.22)	(0.03)	(0.04)	(0.34)	(0.10)
10 (Silent)	-0.095	-0.381	-0.126	-0.224	-0.316	-0.130	-0.199	-0.053
	(-0.17)	(-0.61)	(-0.21)	(-0.37)	(-0.54)	(-0.21)	(-0.33)	(-0.09)
AMS								
Excess Return	0.888***	0.978***	0.875***	0.795***	0.911***	0.736***	0.902***	0.614***
	(4.74)	(3.73)	(3.88)	(3.12)	(3.44)	(2.79)	(3.37)	(2.78)
CAPM Alpha	0.892***	0.994***	0.887***	0.798***	0.926***	0.750***	0.907***	0.614***
	(4.78)	(3.87)	(3.97)	(3.15)	(3.50)	(2.85)	(3.46)	(2.84)
CH4 Alpha	1.015***	0.996***	1.067***	1.016***	1.076***	0.806***	1.055***	0.762***
	(4.60)	(4.27)	(4.52)	(3.79)	(4.12)	(3.11)	(4.07)	(3.07)
FF3 Alpha	1.016***	1.265***	1.081***	1.073***	1.170***	1.016***	1.234***	0.850***
	(5.86)	(5.91)	(5.48)	(5.30)	(4.88)	(4.76)	(5.63)	(4.75)
FF5 Alpha	0.932***	1.181***	0.996***	0.995***	1.075***	0.917***	1.133***	0.764***
	(6.07)	(6.12)	(5.76)	(5.45)	(4.93)	(4.50)	(5.52)	(4.28)

Table 4. Fama-Macbeth Regressions

This table presents the results of predictive Fama-Macbeth (1973) regressions. The dependent variable is the monthly return in month *t*. *Rank Silence* is the cross-sectional rank of *Silence*, which is uniformly standardized into [0, 1]. The control variables include *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total asset), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-2), *lnAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio). The independent variables are collected at the end of month *t*-1. We further conduct two value-weighted (gross return weighted and market capitalization weighted) Fama-Macbeth regressions for robustness check in columns (4) and (5). *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep. Var =	Return				
Rank Silence	-0.913***	-0.892***	-0.935***	-0.903***	-0.991***
	(-4.02)	(-6.24)	(-7.07)	(-6.85)	(-5.60)
Size		-0.513***	-0.542***	-0.463***	-0.225*
		(-3.46)	(-3.74)	(-3.02)	(-1.94)
BM		1.371***	0.966**	-0.002***	-0.002***
		(2.96)	(2.44)	(-4.81)	(-3.31)
EP		1.055***	1.051***	1.122***	1.205***
		(4.45)	(4.46)	(4.65)	(3.47)
Asset growth		0.245**	0.260***	0.224***	0.269***
		(2.52)	(2.97)	(2.81)	(3.05)
Gross Profitability		3.534***	3.027***	0.403	0.546
		(4.26)	(3.72)	(0.46)	(0.58)
IVOL			4.758	-44.642***	-56.335***
			(0.38)	(-3.27)	(-3.32)
Reversal			-2.897***	-3.657***	-3.288***
			(-3.61)	(-4.53)	(-3.68)
logAmihud			0.028	0.029	0.087
			(0.25)	(0.24)	(0.72)
Turnover			-18.753***	-21.036***	-15.776***
			(-4.72)	(-5.23)	(-2.89)
Weight	Baseline: Equal			Gross return	Market capitalization
Adj-Rsquare	0.006	0.064	0.100	0.006	0.100
Start	201001	201001	201001	201001	201001
End	202312	202312	202312	202312	202312
Observations	267814	257962	257403	255765	255765

Table 5. Analyst Silence and Corporate News

This table investigates the predictability of analyst silence on future news. The dependent variables are the number of good and bad news in month *t*. *Rank Silence* is the cross-sectional rank of *Silence*, which is uniformly standardized into [0, 1]. The control variables include *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total asset), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-2), *lnAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio). The independent variables are collected at the end of month *t*-1. We further add the firm and year-month fixed effects. We use OLS panel regressions in columns (1) and (3) and Poisson pseudo-maximum likelihood regressions. Adjusted R-squared or Pseudo R-squared are reported. *T*-statistics based on standard errors clustered by the stock level are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var =	# Good News		# Bad News	
Rank Silence	-0.403***	-0.108***	0.212***	0.071***
	(-6.10)	(-8.41)	(4.03)	(4.29)
Size	1.682***	0.321***	1.163***	0.361***
	(8.45)	(12.40)	(8.78)	(12.45)
BM	-0.406*	0.018	-0.449**	-0.003
	(-1.69)	(0.55)	(-2.03)	(-0.09)
EP	-0.007	-0.005	-0.050*	-0.027***
	(-0.51)	(-0.74)	(-1.69)	(-2.61)
Asset growth	-0.009**	-0.004**	-0.009***	-0.009***
	(-2.15)	(-2.51)	(-3.45)	(-4.14)
Gross Profitability	1.494**	0.426***	-1.781***	-0.607***
	(2.52)	(4.00)	(-3.89)	(-4.35)
IVOL	2.869	0.691*	0.948	0.586
	(1.06)	(1.72)	(0.87)	(1.62)
Reversal	1.652***	0.306***	0.664***	0.234***
	(10.45)	(11.11)	(5.22)	(6.35)
logAmihud	-0.047	0.005	0.011	-0.001
	(-0.57)	(0.39)	(0.19)	(-0.05)
Turnover	4.333**	1.236***	1.514	1.104**
	(2.14)	(3.20)	(1.11)	(2.27)
Model	OLS	Poisson	OLS	Poisson
Adj (Pseudo) R-square	0.689	0.510	0.632	0.482
Observations	231,091	231,075	231,091	231,060
Year-Month FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Table 6. The Information Role of Analyst Silence

This table investigates the information role of analyst silence. Panel A presents the predictive regressions of SUEs on analyst silence. The first two columns report the coefficients of *SUE* on its nearest *Rank Silence* before the announcement date. The following columns repeat the regressions of the *SUE*s of the next 2, 4, 6, and 8 horizons. Panel B explores how analyst silence affects the PEAD effects. We split SUE into positive SUE (*Pos SUE*, max (SUE, 0)) and negative SUE (*Neg SUE*, min (SUE, 0)) in columns (3) to (5). We control for *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total asset), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-2), *lnAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio). We further control for the interactions between control variables and *SUE*, and also the squared terms of *SUE* and *Rank Silence* in column (5) Panel B. Firm and quarter fixed effects are added. *T*-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Predictability of Analyst Silence on Future SUEs						
	(1)	(2)	(3)	(4)	(5)	(6)
	SUE	SUE	SUE2	SUE4	SUE6	SUE8
Rank Silence	-0.738***	-0.567***	-0.414***	-0.113***	0.055***	0.066***
	(-37.63)	(-30.11)	(-20.58)	(-5.91)	(2.60)	(3.24)
Controls	NO	YES	YES	YES	YES	YES
Adj R-square	0.103	0.170	0.114	0.107	0.105	0.088
Observations	82,715	79,795	80,349	77,284	72,586	68,784
Quarter FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Panel B: PEAD and Analyst Silence					
	(1)	(2)	(3)	(4)	(5)
Dep var =			CAR [2, 60]		
SUE	-0.001	-0.000			
	(-1.08)	(-0.39)			
Rank Silence	-0.012***	-0.025***	-0.020***	-0.019***	-0.019*
	(-5.01)	(-9.71)	(-6.40)	(-6.03)	(-1.91)
$SUE \times Rank\ Silence$	0.005***	0.007***			
	(2.81)	(3.85)			
$Pos\ SUE \times Rank\ Silence$			0.001	-0.001	-0.002
			(0.29)	(-0.30)	(-0.65)
$Neg\ SUE \times Rank\ Silence$			0.013***	0.014***	0.015***
			(4.00)	(4.06)	(4.52)
Controls	NO	YES	YES	YES	YES
$Controls \times SUE$	NO	NO	NO	YES	YES
SUE and Silence Square	NO	NO	NO	NO	YES
Adj R-squared	0.098	0.136	0.136	0.137	0.137
Observations	80,730	77,842	77,842	77,842	77,842
Quarter FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES

Table 7. The Monitoring Role of Analyst Silence

This table investigates the monitoring role of analyst silence. *Investment Inefficiency* is constructed following Richardson (2006). *Earnings management* is a firm's modified Jones (1991) discretionary accruals. The independent variable is the cross-sectional standardized rank of *Silence* (*Rank Silence*). We control for *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total asset), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-1), *lnAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio). Firm and year fixed effects are added. *T*-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep Var =	Investment Inefficiency		Earnings Management	
Rank Silence	-0.006***	-0.003**	-0.013***	-0.007***
	(-5.00)	(-1.97)	(-5.50)	(-3.21)
Size		0.006***		0.017***
		(4.76)		(7.06)
BM		-0.010**		-0.010
		(-2.13)		(-1.26)
EP		0.001		0.005***
		(0.34)		(2.63)
Asset growth		0.000		0.001**
		(1.21)		(2.46)
Gross Profitability		0.014**		0.072***
		(2.28)		(6.33)
IVOL		0.704***		-0.175
		(7.42)		(-1.07)
Reversal		-0.001		-0.001
		(-0.15)		(-0.15)
logAmihud		0.006***		0.005***
		(5.62)		(3.25)
Turnover		0.086**		0.019
		(2.22)		(0.31)
Adjusted R-squared	0.213	0.227	0.206	0.218
Observations	16,346	16,346	15,890	15,890
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Table 8. Alternative Explanations: Silence and Attention

This table presents the performance of portfolios dependently double-sorted by proxies for attention, such as analyst on-site visits, Baidu searching index, institutional investor holdings, and *Silence*. At the end of each month *t*-1, stocks are firstly sorted into two groups according to whether there is an on-site visit during the silence period or into three groups according to the Baidu search volume and institutional holding share. Within each group, we further divide the stocks into ten groups according to their *Silence* value. Each portfolio is value-weighted and held for one month. We tabulate the excess returns, alphas adjusted by CAPM, LSY four-factor model (CH4), Fama-French three-factor model (FF 3), and Fama-French five-factor model (FF 5) of each *Silence*-sorted decile. At the bottom of each block, we report the performance of *AMS* strategy, which longs stocks within the lowest *Silence* decile and shorts stocks within the highest decile. *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	Analyst On-site Visiting		Baidu Searching Index			Institutional Investor Holdings		
Group	No-Visit	Visit	Low	Medium	High	Low	Medium	High
1 (Active)	0.707	0.880	1.203	0.544	0.551	0.657	0.321	0.767
	(1.24)	(1.46)	(1.97)	(0.92)	(0.91)	(0.97)	(0.58)	(1.38)
2	0.396	0.726	0.986	0.667	0.467	-0.218	0.352	0.527
	(0.84)	(1.43)	(1.60)	(1.24)	(0.93)	(-0.40)	(0.67)	(1.03)
3	0.620	0.586	1.203	0.681	0.775	0.784	0.57	0.709
	(1.33)	(1.03)	(1.92)	(1.27)	(1.50)	(1.37)	(1.12)	(1.45)
4	0.353	0.525	1.165	0.69	0.361	0.268	0.149	0.413
	(0.79)	(0.85)	(1.90)	(1.32)	(0.71)	(0.46)	(0.29)	(0.92)
5	0.242	0.319	0.508	0.812	0.375	-0.393	0.457	0.509
	(0.50)	(0.52)	(0.83)	(1.40)	(0.66)	(-0.70)	(0.76)	(1.04)
6	0.441	0.488	0.848	0.581	0.183	-0.275	0.613	0.526
	(0.92)	(0.80)	(1.45)	(1.03)	(0.36)	(-0.44)	(1.00)	(1.10)
7	0.166	0.449	0.563	0.425	0.341	-0.154	0.116	0.762
	(0.30)	(0.71)	(0.95)	(0.71)	(0.60)	(-0.27)	(0.21)	(1.40)
8	0.084	0.054	0.463	0.207	-0.073	-0.25	0.071	0.139
	(0.16)	(0.09)	(0.72)	(0.38)	(-0.12)	(-0.41)	(0.12)	(0.28)
9	0.074	0.141	0.581	0.012	-0.143	-0.211	0.117	0.316
	(0.14)	(0.25)	(0.97)	(0.02)	(-0.27)	(-0.34)	(0.21)	(0.62)
10 (Silent)	-0.245	-0.195	0.404	-0.068	-0.865	-0.519	-0.236	0.016
	(-0.39)	(-0.30)	(0.57)	(-0.10)	(-1.41)	(-0.77)	(-0.39)	(0.03)
AMS								
Excess Return	0.952***	1.075**	0.799**	0.612*	1.416***	1.175***	0.557*	0.751**
	(3.37)	(2.52)	(2.54)	(1.75)	(3.53)	(3.69)	(1.81)	(1.96)
CAPM Alpha	0.958***	1.093***	0.811***	0.631*	1.451***	1.171***	0.578*	0.761**
	(3.35)	(2.60)	(2.65)	(1.82)	(3.67)	(3.75)	(1.86)	(2.02)
FF5 Alpha	1.150***	1.336***	0.792***	0.665**	1.610***	1.327***	0.621**	0.980***
	(5.68)	(4.17)	(2.85)	(2.22)	(5.38)	(5.10)	(2.05)	(2.96)
CH4 Alpha	1.037***	1.055***	0.910***	0.907**	1.392***	1.331***	0.796**	0.836**
	(4.38)	(2.80)	(2.87)	(2.52)	(3.93)	(4.47)	(2.54)	(2.25)

Table 9. Robustness Check on Alternative Measures of Analyst Silence

This table presents the performance of portfolios single-sorted by different forms of *Silence*. The first form is *Median-Silence*, calculated as the median time intervals by days from the last report for each firm i to the end of month *t*. The second form is *Silence* (*Ranking period = 2 years*), which means the ranking period of the analyst reports is past 2 years. The third form is Silence (*Only positive reports*), which only keeps the analyst reports with buy and strong buy views. At the end of each month *t*-1, stocks are sorted into ten groups according to their *Silence* levels. Each portfolio is held for one month. Each form reports the value-weighted portfolios' performance and the equal-weighted performance of each group. We tabulate the excess returns, alphas adjusted by CAPM, LSY four-factor model (CH4), Fama-French three-factor model (FF 3), and Fama-French five-factor model (FF 5). At the bottom of each block, we report the performance of the *AMS* (Active-minus-Silent) strategy, which longs stocks within the lowest *Silence* decile and shorts stocks within the highest *Silence* decile. *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Group	Median silence		Ranking period = 2 years		Only positive reports	
	Value-weighted	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted	Equal-weighted
1 (Active)	0.811	1.093	0.575	0.987	0.663	1.049
	(1.50)	(1.93)	(1.14)	(1.76)	(1.28)	(1.85)
2	0.397	0.756	0.499	0.839	0.542	1.031
	(0.78)	(1.46)	(0.96)	(1.58)	(1.04)	(1.90)
3	0.41	0.865	0.236	0.648	0.580	1.016
	(0.86)	(1.62)	(0.50)	(1.27)	(1.18)	(1.84)
4	0.539	0.773	0.357	0.655	0.393	0.819
	(1.15)	(1.45)	(0.75)	(1.19)	(0.81)	(1.55)
5	0.507	0.747	0.235	0.648	0.368	0.647
	(1.07)	(1.36)	(0.55)	(1.23)	(0.75)	(1.20)
6	0.146	0.616	0.155	0.399	0.422	0.628
	(0.27)	(1.09)	(0.29)	(0.71)	(0.87)	(1.18)
7	-0.082	0.399	0.226	0.608	-0.041	0.498
	(-0.15)	(0.72)	(0.43)	(1.05)	(-0.08)	(0.88)
8	-0.002	0.455	0.094	0.431	0.104	0.399
	(-0.00)	(0.81)	(0.17)	(0.74)	(0.21)	(0.73)
9	0.043	0.322	0.357	0.564	-0.041	0.360
	(0.08)	(0.56)	(0.61)	(0.98)	(-0.08)	(0.62)
10 (Silence)	-0.147	0.205	-0.110	0.147	-0.340	0.039
	(-0.24)	(0.34)	(-0.18)	(0.24)	(-0.58)	(0.07)
AMS						
Excess Return	0.958***	0.889***	0.684*	0.840***	1.003***	1.010***
	(2.57)	(3.84)	(1.89)	(3.37)	(3.68)	(5.30)
CAPM Alpha	0.986***	0.901***	0.706**	0.847***	1.012***	1.013***
	(2.69)	(3.89)	(1.98)	(3.40)	(3.75)	(5.34)
CH4 Alpha	1.125***	1.078***	1.003***	1.078***	1.175***	1.174***
	(3.76)	(4.93)	(3.26)	(4.61)	(3.98)	(5.33)
FF3 Alpha	1.537***	1.107***	1.087***	0.960***	1.251***	1.067***
	(6.07)	(5.54)	(3.41)	(4.00)	(5.06)	(5.55)
FF5 Alpha	1.372***	1.024***	0.954***	0.855***	1.127***	1.020***
	(5.96)	(5.52)	(3.48)	(4.20)	(4.99)	(5.76)

Table 10.Fama-Macbeth Regressions Controlling for Other Analyst-related Predictors

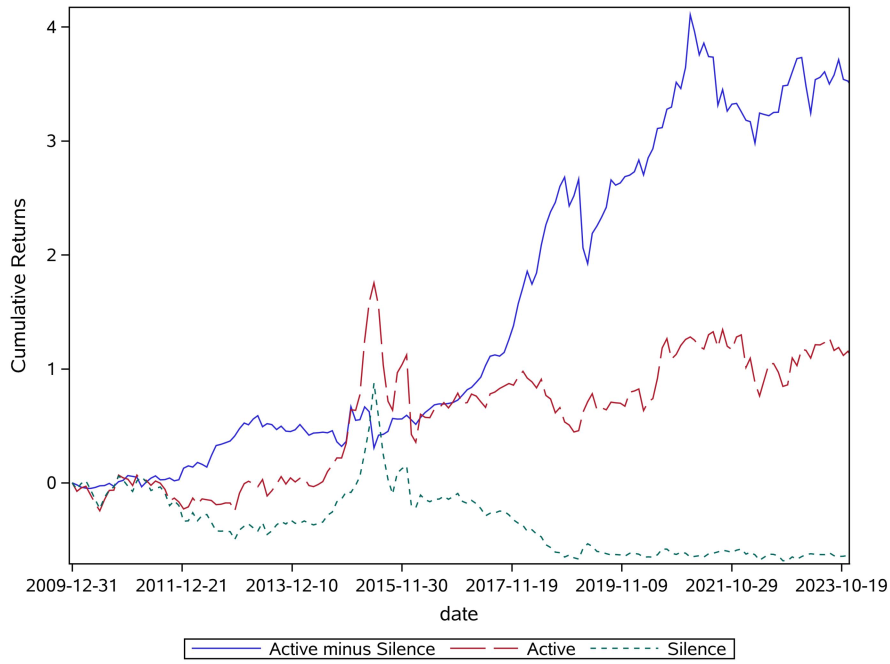
This table presents the results of predictive Fama-Macbeth (1973) regressions controlling for other analyst-related predictors. The dependent variable is the monthly return in month *t*. *Rank Silence* is the cross-sectional rank of *Silence*, which is uniformly standardized into [0, 1]. *Forecast Change* is the changes in earnings forecast in month *t*-1 from month *t*-2, normalized by their average absolute value. Forecast Revision is revisions in analyst earnings forecasts, using the six-month moving average of past changes in analyst forecasts normalized by the stock price. *Earnings Forecast/Price* is calculated by the consensus median forecasts for the current fiscal year divided by the closing price. *Dispersion* is the opinion divergence of analysts, calculated by the standard deviation of earnings forecasts divided by the absolute value of the consensus mean forecasts. *Analyst coverage* is the logarithm of one plus the number of earnings forecasts for the current fiscal year. *Skew* is the difference between the mean and the median forecast scaled by the absolute value of the mean forecast. The independent variables are collected at the end of month *t*-1. *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var =				Return			
Rank Silence	-0.816***	-0.741***	-0.809***	-0.837***	-0.712***	-0.841***	-0.772***
	(-4.38)	(-3.60)	(-4.21)	(-4.43)	(-5.82)	(-4.45)	(-3.41)
Forecast Change	0.382***						0.320**
	(2.92)						(2.27)
Forecast Revision		4.074**					3.054*
		(2.56)					(1.96)
Earnings Forecast/Price			3.440				1.664
			(1.07)				(0.50)
Dispersion				-0.019			-0.025
				(-1.00)			(-1.41)
Analyst Coverage					0.166***		-0.081
					(3.64)		(-1.06)
Skew						0.179	0.209
						(1.38)	(1.46)
Size	-0.481***	-0.497***	-0.517***	-0.490***	-0.583***	-0.494***	-0.517***
	(-3.11)	(-3.21)	(-3.34)	(-3.14)	(-3.99)	(-3.14)	(-3.44)
BM	1.020**	1.030**	0.872**	1.093**	1.004**	1.092**	0.930**
	(2.19)	(2.19)	(2.24)	(2.41)	(2.54)	(2.36)	(2.47)
EP	2.349***	2.491***	2.193***	2.585***	1.032***	2.455***	2.445***
	(3.84)	(3.95)	(3.73)	(4.30)	(4.47)	(4.15)	(3.65)
Asset growth	0.644***	0.771***	0.525***	0.549***	0.256***	0.556***	0.745***
	(3.87)	(4.53)	(3.32)	(3.37)	(2.98)	(3.40)	(4.45)
Gross Profitability	2.381**	2.271**	2.402***	2.349**	2.862***	2.369**	2.267***
	(2.59)	(2.59)	(2.71)	(2.56)	(3.66)	(2.58)	(2.74)
IVOL	3.882	5.461	5.006	3.795	5.111	4.956	7.740
	(0.25)	(0.32)	(0.32)	(0.24)	(0.41)	(0.31)	(0.44)
Reversal	-2.238**	-2.171**	-2.090**	-2.251**	-3.065***	-2.231**	-2.056**
	(-2.51)	(-2.38)	(-2.37)	(-2.54)	(-3.90)	(-2.51)	(-2.29)
logAmihud	0.090	0.062	0.081	0.084	0.041	0.088	0.052
	(0.75)	(0.50)	(0.68)	(0.69)	(0.37)	(0.72)	(0.43)
Turnover	-10.545**	-11.322**	-9.875**	-10.391**	-18.297***	-10.361**	-12.167**
	(-2.09)	(-2.11)	(-2.00)	(-2.10)	(-4.74)	(-2.09)	(-2.30)
Adj-Rsquare	0.116	0.123	0.123	0.115	0.102	0.115	0.134
Start	201001	201001	201001	201001	201001	201001	201001
End	202312	202312	202312	202312	202312	202312	202312
Observations	124997	118255	125992	125843	257634	125992	117977

Figure 1. Performance of AMS Strategy

This figure illustrates the performance of the *ASM* (Active-minus-Silence) strategy. Panel A plots the cumulative returns of the monthly-rebalanced *ASM* Strategy, which longs the stocks within the lowest decile of *Silence* and shorts the highest decile of *Silence*. Panel B presents the buy-and-hold abnormal returns relative to the market returns for varying holding periods, accompanied by 95% confidence intervals.

Panel A: *The Cumulative Returns of ASM Strategy*



Panel B: *The Buy-and-Hold Cumulative Abnormal Returns*

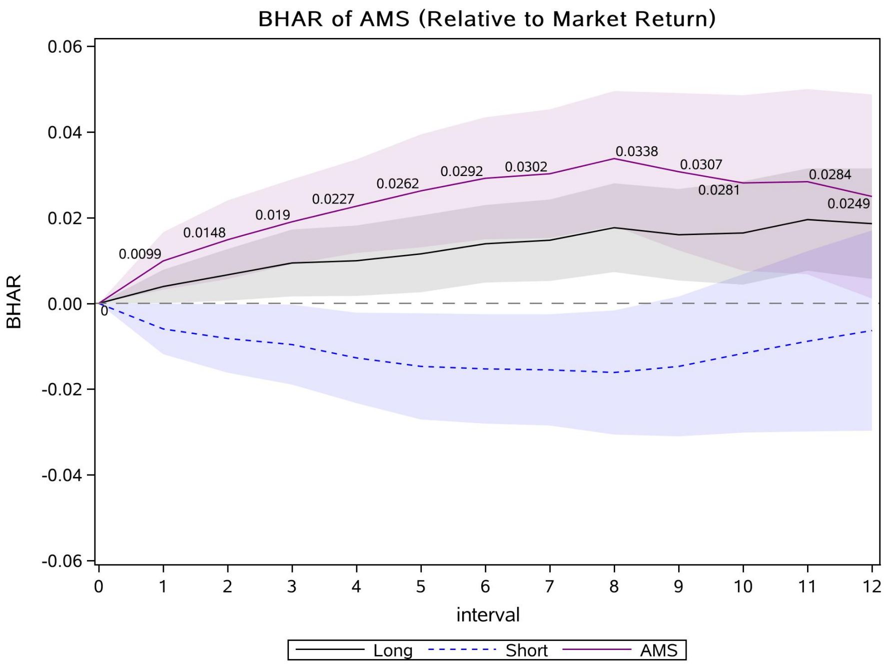
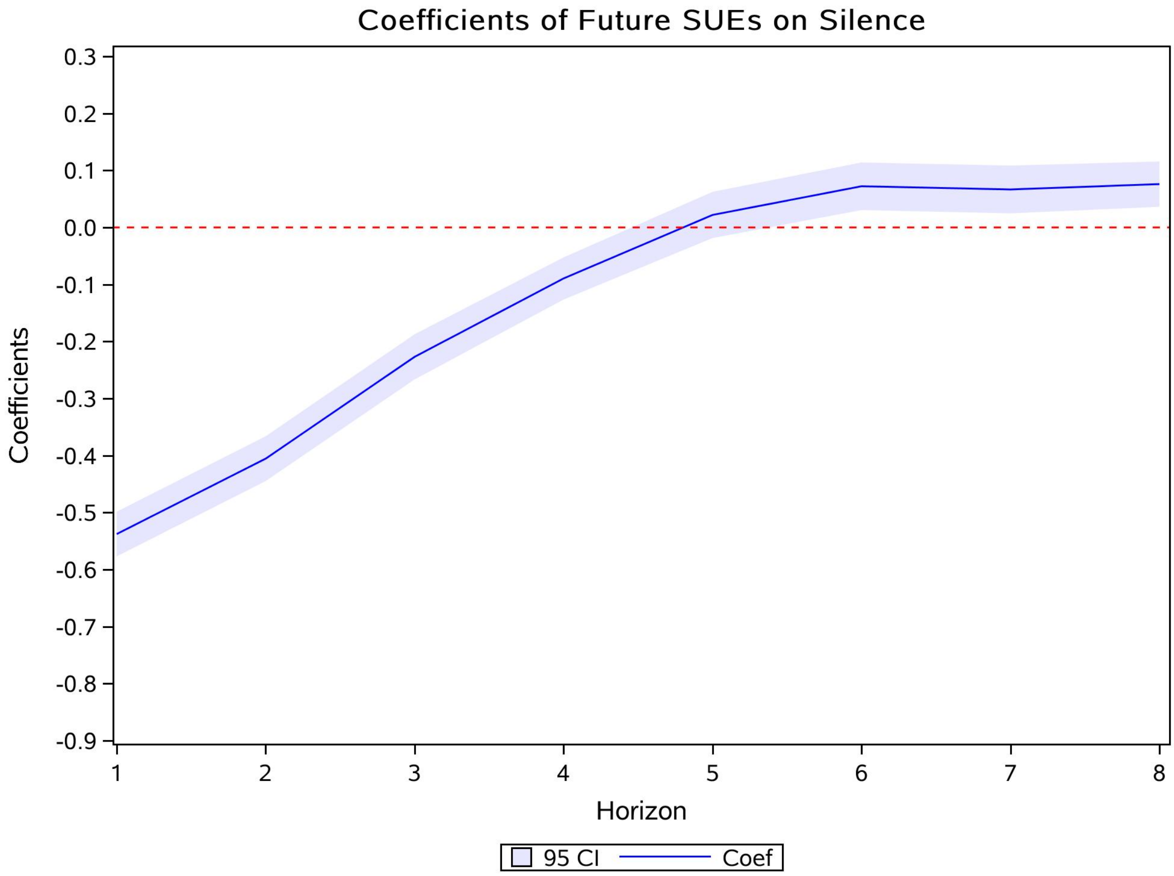


Figure 2. Different Coefficients of Future SUEs on Silence

This figure illustrates the coefficients of future SUEs on *Rank Silence*, accompanied by 95% confidence intervals.



Internet Appendix

The Truth of Silence:
Bad Signal of No Analyst Report

A. Institutional Background of Staggered Reductions of Leverage Trading in China

On March 31, 2010, the CSRC introduced a pilot program, which allows an initial list of 90 stocks to be qualified for both margin buying and short selling. In the following years, CSRC progressively reduced the trading restrictions in the Chinese stock market. Subsequent expansions occurred in November 2011 (278 stocks), January 2013 (500 stocks), September 2013 (700 stocks), September 2014 (900 stocks), March 2017 (950 stocks), August 2019 (1600 stocks), and October 2022 (2200 stocks). According to the Shanghai Stock Exchange and Shenzhen Stock Exchange, a security must meet several criteria to be eligible as a margin trading and short-selling stock[5]:

(i) The company has been listed and traded on the Exchange for more than 3 months;

(ii) The circulating share capital of the target stock purchased through margin trading is not less than 100 million shares or the circulating market value is not less than RMB 500 million, and the circulating share capital of the target stock sold through margin trading is not less than 200 million shares or the circulating market value is not less than RMB 800 million;

(iii) The number of shareholders is not less than 4,000;

(iv) None of the following circumstances has occurred in the past 3 months:

1. The average daily turnover rate is lower than 15% of the average daily turnover rate of the benchmark index, and the average daily transaction amount is less than RMB 50 million;

2. The deviation between the average daily increase and decrease and the average increase and decrease of the benchmark index exceeds 4%;

3. The fluctuation range is more than 5 times the fluctuation range of the benchmark index.

[5] See https://www.szse.cn/lawrules/rule/stock/trade/t20230217_598777.html and https://www.sse.com.cn/lawandrules/sselawsrules/trade/specific/margin/c/c_20230827_5725660.shtml

(v) The stock issuing company has completed the equity split reform;

(vi) The stock transaction has not been subject to risk warning by the Exchange;

(vii) Other conditions specified by the Exchange.

Typically, the eligible stocks are large and liquid stocks. In a ranking rule disclosure by Shanghai Stock Exchange, the stocks that are not already on the list are ranked according to: $X_i = 2 \times \frac{Cap_i}{AveCap} + \frac{Volume_i}{AveVolume}$. Then the top-ranked stocks are selected with some discretions from the exchanges.

Before 2015, the bubble-crash episode in China, the leverage trading business kept increasing. However, after the dramatic crash in mid-June that wiped out around 30% of the market value by the end of July 2015, in august 2015, several major brokerages announced the suspension of short-selling trading business[6]. They gradually resumed security lending business after March 2016[7].

[6] See https://m.yicai.com/news/4664778.html.

[7] See http://www.xinhuanet.com/politics/2016-03/25/c_128831449.htm.

Table A1. Summary Statistics of Silence-sorted Portfolios

This table tabulates the summary statistics of the main variables. Each month, we first divide the stocks into ten groups according to the silence cross-sectionally. Within each group, we calculate the mean values of the characteristics and report the time-series mean values of each group. The variables include Silence (the average day intervals from the last report date to current date), *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total asset), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-2), *lnAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio).

Silence Group	Silence	Reversal	Size	BM	logAmihud	Turnover	Beta	IVOL	Asset growth	Gross Profitability	EP
1 (Active)	42.27	3.77%	16.02	0.43	-6.00	0.03	1.12	0.02	1.64	0.16	0.06
2	75.66	2.02%	16.42	0.44	-6.37	0.02	1.11	0.02	1.36	0.18	0.10
3	92.71	1.65%	16.51	0.47	-6.46	0.02	1.12	0.02	1.36	0.19	0.11
4	106.45	1.08%	16.49	0.49	-6.46	0.02	1.12	0.02	1.30	0.18	0.10
5	119.52	0.96%	16.43	0.50	-6.44	0.02	1.13	0.02	1.30	0.17	0.09
6	133.33	0.62%	16.32	0.51	-6.36	0.02	1.14	0.02	1.31	0.17	0.08
7	149.26	0.59%	16.21	0.50	-6.28	0.02	1.15	0.02	1.28	0.16	0.07
8	169.40	0.34%	16.08	0.51	-6.19	0.02	1.16	0.02	1.27	0.14	0.05
9	199.88	0.41%	15.93	0.50	-6.08	0.02	1.17	0.02	1.26	0.13	0.02
10 (Silence)	269.89	0.59%	15.73	0.48	-5.91	0.03	1.16	0.02	1.20	0.12	-0.08
10 minus 1	227.62	-3.18%	-0.29	0.05	0.09	0.00	0.04	0.00	-0.43	-0.04	-0.14
T-stat	122.87	-13.86	-20.67	8.04	4.45	-1.27	9.13	-4.09	-6.37	-22.67	-7.78

Table A2. Robustness Check on Fama-Macbeth Regressions Using Logarithm of Silence

This table presents the results of predictive Fama-Macbeth (1973) regressions. The dependent variable is the monthly return in month *t*. *logSilence* is the logarithm of *Silence*. The control variables include *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total asset), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-2), *lnAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio). The independent variables are collected at the end of month *t*-1. We further conduct two value-weighted (gross return weighted and market capitalization weighted) Fama-Macbeth regressions for robustness check in columns (4) and (5). *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep. Var =	`Return				
logSilence	-0.456***	-0.409***	-0.437***	-0.431***	-0.506***
	(-5.14)	(-6.77)	(-8.35)	(-7.81)	(-6.27)
Size		-0.485***	-0.520***	-0.442***	-0.216*
		(-3.24)	(-3.55)	(-2.85)	(-1.85)
BM		1.363***	0.957**	-0.002***	-0.002***
		(2.93)	(2.40)	(-4.83)	(-3.32)
EP		1.087***	1.081***	1.152***	1.239***
		(4.45)	(4.48)	(4.67)	(3.54)
Asset growth		0.249**	0.263***	0.227***	0.275***
		(2.55)	(2.98)	(2.82)	(3.08)
Gross Profitability		3.653***	3.137***	0.502	0.604
		(4.33)	(3.80)	(0.56)	(0.64)
IVOL			5.107	-44.344***	-55.601***
			(0.41)	(-3.25)	(-3.30)
Reversal			-2.916***	-3.679***	-3.308***
			(-3.63)	(-4.55)	(-3.67)
logAmihud			0.022	0.023	0.077
			(0.20)	(0.19)	(0.63)
Turnover			-18.934***	-21.179***	-16.317***
			(-4.78)	(-5.28)	(-2.98)
Weight	Baseline: Equal			Gross return	Market capitalization
Adj-Rsquare	0.003	0.064	0.100	0.064	0.003
Start	201001	201001	201001	201001	201001
End	202312	202312	202312	202312	202312
Observations	267814	257962	257403	255765	255765

Table A3. Robustness Check and Heterogenous Effects on the Monitoring Role of Analyst Silence

This table investigates the monitoring role of analyst silence. *Investment efficiency* is constructed following Richardson (2006). *Earnings management* is firm's modified Jones (1991) discretionary accruals. Panel A presents the results of the robustness check on controlling more characteristics and alternative silence measures. The independent variables are the cross-sectional standardized rank of *Silence* (*Rank Silence*) and an indicator for the highest decile (*High Silence*). We control for *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total asset), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-1), *lnAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio). We further control for the *Control Share* (controlling shareholder's shareholding), Salary (logarithm of total compensation of the top three management team members), *Dual* (whether CEO and Chairman are the same person), *Management Share* (management shareholding), *Board Size* (logarithm of board size), and Cash Flow ratio (operating cash flow-asset ratio). Panel B divides the whole sample into subsamples of firms with over (under) investment and positive (negative) accruals. Firm and year fixed effects are added. *T*-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Controlling for More Characteristics				
	(1)	(2)	(3)	(4)
Dep Var =	Investment Efficiency		Earnings Management	
Rank Silence	-0.002*		-0.007***	
	(-1.90)		(-3.09)	
High Silence		-0.003**		-0.004*
		(-2.33)		(-1.81)
Control Share	0.008	0.008	0.026**	0.026**
	(1.10)	(1.08)	(2.14)	(2.14)
Salary	-0.005***	-0.005***	0.000	0.000
	(-3.85)	(-3.87)	(0.07)	(0.06)
Dual	-0.000	-0.000	0.002	0.002
	(-0.14)	(-0.16)	(0.62)	(0.63)
Management Share	0.000**	0.000**	0.000***	0.000***
	(2.13)	(2.11)	(3.16)	(3.16)
Board Size	-0.005	-0.005	-0.008	-0.008
	(-1.27)	(-1.29)	(-1.13)	(-1.17)
Cash Flow Ratio	0.003	0.003	-0.009	-0.009
	(0.68)	(0.66)	(-0.91)	(-0.90)
Other Controls	YES	YES	YES	YES
Adj R-square	0.229	0.229	0.220	0.219
Observations	16,329	16,329	15,873	15,873
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Panel B: Heterogeneous Effects of Analyst Silence on Investment Efficiency and Earnings Management				
	(1)	(2)	(3)	(4)
Dep Var =	Investment Inefficiency		Earnings Management	
Rank Silence	0.000	-0.003*	-0.008***	-0.001
	(0.03)	(-1.65)	(-3.28)	(-0.55)
Sample	Over-investment	Under-investment	Positive Accruals	Negative Accruals
Control Variables	YES	YES	YES	YES
Adjusted R-squared	0.216	0.257	0.196	0.216
Observations	6,587	8,743	7,361	7,572
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Table A4. Monitoring Role of Analyst Silence and On-site Visit

This table investigates the joint effects of monitoring the role of analyst silence and on-site visits. *Investment efficiency* is constructed following Richardson (2006). *Earnings management* is a firm's modified Jones (1991) discretionary accruals. Panel A presents the results of the robustness check on controlling more characteristics and alternative silence measures. *On-site Visit* is an indicator variable equal to one if the analyst visits the firm on-site in the following year. We control for *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total asset), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-1), *lnAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio). Firm and year fixed effects are added. *T*-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep Var =	Investment Efficiency		Earnings Management	
Rank Silence	-0.005***	-0.002	-0.010***	-0.005*
	(-3.35)	(-1.10)	(-3.67)	(-1.96)
On-site Visit	0.004**	0.003	0.011***	0.008**
	(2.44)	(1.59)	(3.13)	(2.14)
Rank Silence × On-site Visit	-0.004	-0.003	-0.018***	-0.015**
	(-1.42)	(-1.01)	(-2.91)	(-2.46)
Size		0.006***		0.017***
		(4.61)		(5.69)
BM		-0.010**		-0.012
		(-2.11)		(-1.13)
EP		0.001		0.006***
		(0.33)		(2.58)
Asset growth		0.000		0.001**
		(1.25)		(2.28)
Gross Profitability		0.014**		0.079***
		(2.23)		(5.37)
IVOL		0.703***		-0.192
		(7.40)		(-0.99)
Reversal		-0.001		0.001
		(-0.17)		(0.18)
logAmihud		0.006***		0.007***
		(5.63)		(3.53)
Turnover		0.086**		0.052
		(2.21)		(0.69)
F-Value (Rank Silence + Rank Silence × On-site Visit <0)	12.46***	3.09*	26.44***	13.92***
Adj R-square	0.214	0.227	0.191	0.202
Observations	16,346	16,346	15,890	15,890
Year FE	YES	YES	YES	YES

Firm FE	YES	YES	YES	YES

Table A5. Analyst Silence and Institutional Holdings Change

This table investigates the response of institutional investors' holdings changes to analyst silence. The columns report the regressions of the Institutional Holdings Percentage (*Institution Holdpercts*) of the next 1, 2, 4, 6, and 8 quarters on analyst silence. The control variables are consistent with the previous tables. Firm and quarter fixed effects are added. *T*-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) *Institution Holdpercts1*	(2) *Institution Holdpercts2*	(3) *Institution Holdpercts4*	(4) *Institution Holdpercts6*	(5) *Institution Holdpercts8*
Rank Silence	-1.494***	-1.082***	-0.862***	-0.720***	-0.450***
	(-23.02)	(-18.45)	(-13.38)	(-10.78)	(-6.51)
Size	2.511***	1.309***	0.672***	0.138	-0.264**
	(16.88)	(10.58)	(5.83)	(1.26)	(-2.44)
BM	-1.537**	-1.247***	-1.365***	-1.357***	-1.324***
	(-6.59)	(-6.64)	(-7.65)	(-7.86)	(-7.57)
EP	-0.005	-0.003	-0.028	-0.122	-0.121
	(-0.05)	(-0.03)	(-0.36)	(-1.16)	(-1.11)
Asset growth	-0.002*	-0.001	-0.001	-0.001	-0.000
	(-1.70)	(-0.92)	(-1.30)	(-1.51)	(0.133)
Gross Profitability	3.580***	2.877***	2.775***	2.645***	2.262***
	(4.34)	(3.92)	(3.72)	(3.45)	(3.06)
IVOL	24.496*	18.976*	12.997*	9.010*	6.321*
	(1.76)	(1.83)	(1.77)	(1.75)	(1.69)
Reversal	1.329***	0.546***	0.418***	0.426***	0.606***
	(9.47)	(3.56)	(2.88)	(2.82)	(4.00)
logAmihud	0.484***	0.538***	0.471***	0.415***	0.305***
	(7.39)	(9.30)	(8.44)	(7.44)	(5.70)
Turnover	-32.645	-21.422***	-15.825***	-10.042***	-6.241***
	(-10.90)	(-8.97)	(-7.42)	(-5.02)	(-3.22)
Adj R-square	0.450	0.392	0.307	0.283	0.271
Observations	84,907	84,869	82,353	78,229	74,117
Quarter FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES

Table A6. Analyst Silence, Insider Transaction, and Stock Illiquidity

This table presents the results of predictive Fama-Macbeth (1973) regressions. The dependent variables are the monthly average of daily VPIN (volume-synchronized probability of informed trading) and the logarithm of the daily average Amihud illiquidity ratio in month *t*. *Rank Silence* is the cross-sectional rank of *Silence*, which is uniformly standardized into [0, 1]. The control variables include *Size* (logarithmic market capitalization), *BM* (book-to-market ratio), *EP* (Earnings-to-price ratio), *Asset growth* (growth rate of total asset), *Gross Profitability*, *IVOL* (idiosyncratic volatility), *Reversal* (stock returns in month *t*-2), *logAmihud* (logarithm of Amihud illiquidity ratio), and *Turnover* (average daily turnover ratio). The independent variables are collected at the end of month *t*-1. *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var =	VPIN		logAmihud	
Rank Silence	-0.015***	-0.007***	0.428***	0.050***
	(-9.84)	(-9.22)	(10.13)	(6.21)
Size		-0.004***		-0.231***
		(-6.13)		(-9.71)
BM		-0.047***		0.022
		(-17.81)		(1.26)
EP		0.012***		0.005
		(6.28)		(0.48)
Asset growth		0.003***		0.002
		(5.56)		(0.84)
Gross Profitability		0.030***		0.145***
		(9.99)		(4.61)
IVOL		0.957***		-0.889
		(8.68)		(-1.07)
Reversal		0.024***		-1.212***
		(6.54)		(-16.91)
logAmihud		-0.002**		0.708***
		(-2.52)		(24.32)
Turnover		0.135***		-4.463***
		(4.51)		(-10.96)
Adj R-square	0.015	0.372	0.021	0.792
Observations	267813	257633	267813	257633

Table A7. Portfolios Sorted by Analyst Silence and Market Sentiment

This table investigates the relationships between portfolio performance sorted by *Analyst Silence* and market sentiment. First, we divide the sample period into the high-sentiment and low-sentiment periods at the end of month *t*-1 according to the median level of sentiment index (CICSI). We then sort stocks into quintiles according to the analyst silence within each period. We present the value-weighted performance of the long (Active) and short (Silent) legs of the AMS strategy, the performance of the AMS strategy within each period, and the differences of those between high-sentiment and low-sentiment periods. *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Silence	Active			Silent			AMS		
Sentiment	High Sentiment	Low Sentiment	High-Low	High Sentiment	Low Sentiment	High-Low	High Sentiment	Low Sentiment	High-Low
Excess Return	0.267	1.292	-1.025	-0.857	0.359	-1.216	1.124**	0.933**	-0.191
	[0.39]	[2.11]	[-0.92]	[-1.11]	[0.55]	[-0.98]	[2.15]	[2.46]	[-0.32]
CAPM Alpha	0.257	0.661	-0.408	-0.868	-0.288	-0.556	1.125**	0.949**	-0.148
	[1.45]	[2.95]	[-1.39]	[-1.82]	[-0.79]	[-1.03]	[2.09]	[2.53]	[-0.25]
FF 5 Alpha	0.188	0.36	-0.35	-0.955	-0.848	-0.086	1.143***	1.207***	0.265
	[0.96]	[1.58]	[-1.16]	[-7.85]	[-3.89]	[-0.31]	[4.32]	[3.91]	[0.63]
CH4 Alpha	0.318	0.808	-0.404	-0.591	-0.309	-0.093	0.910***	1.117***	0.311
	[1.52]	[3.01]	[-1.35]	[-2.98]	[-1.02]	[-0.29]	[3.05]	[2.83]	[0.71]

Table A8. Portfolios Sorted by Analyst Silence and Short-selling Constraints

This table investigates the relationships between portfolio performance sorted by *Analyst Silence* and short-selling constraints. First, we divide the stocks into shorting-eligible stocks and non-shorting-eligible stocks according to the list of margin-trading-eligible stocks at the end of month *t*-1. Within each group, we further sort stocks into quintiles according to the analyst silence. We present the value-weighted performance of each double-sorted portfolios, the AMS strategy performance, and the difference-in-difference of *Analyst Silence* sorted portfolio spreads between shorting-eligible and non-shorting-eligible groups in Panel A, and equal-weighted results in Panel B. The sample starts from January 2012 to December 2023, excluding the period from August 2015 to March 2016. *T*-statistics based on standard errors adjusted Newey-West HAC with 4 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Value-weighted Portfolio Performance			Panel B: Equal-weighted Portfolio Performance		
Group	Non-Shorting-Eligible	Shorting-Eligible	DID	Non-Shorting-Eligible	Shorting-Eligible	DID
1 (Active)	1.011	1.006		1.284	1.266	
	(1.58)	(1.91)		(1.97)	(2.28)	
2	1.183	0.872		1.324	1.096	
	(1.80)	(1.77)		(2.00)	(2.15)	
3	0.742	0.729		0.910	0.938	
	(1.12)	(1.39)		(1.38)	(1.72)	
4	0.462	0.609		0.750	0.886	
	(0.70)	(1.11)		(1.12)	(1.60)	
5 (Silent)	0.151	0.447		0.450	0.732	
	(0.21)	(0.78)		(0.63)	(1.16)	
AMS						
Excess Return	0.859***	0.559	0.300	0.834***	0.534**	0.301
	(2.63)	(1.56)	(0.75)	(3.34)	(2.51)	(1.45)
CAPM Alpha	0.936***	0.685**	0.251	0.884***	0.608***	0.276
	(2.89)	(2.04)	(0.63)	(3.53)	(3.09)	(1.33)
FF5 Alpha	0.954***	0.877***	0.052	0.873***	0.708***	0.196
	(3.38)	(3.72)	(0.14)	(3.78)	(4.21)	(0.94)
CH4 Alpha	1.174***	0.710***	0.465	1.075***	0.705***	0.371*
	(3.70)	(2.64)	(1.31)	(4.13)	(3.66)	(1.72)