Empty Vessels Make the Most Noise: Analyst Self-Promotion Behavior and Market Outcomes

Chun Liu* Shunzhi Pang†

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Abstract

Based on analysts' LinkedIn profiles, we identify a robust negative correlation between the expressive tone conveyed in their self-presentations and forecast accuracy, particularly among male analysts, less experienced professionals, and those with fewer LinkedIn followers. We interpret this *tone-performance inverse effect* not as a behavioral bias, but as a strategic self-promotion behavior aimed at compensating for skill gaps and increasing visibility. Both investors and employers value such expressive tone. Market reactions show stronger excess returns for high-tone analysts' upward revisions and positive ratings, with no similar effect for negative signals, highlighting a *Mad Money*-like pricing distortion. Low-accuracy but high-tone analysts achieve the highest career promotion rates relative to their peers. These findings offer new insights into the unintended consequences of impression management in financial markets.

Keywords: Self-Promotion; Analyst Behavior; Impression Management; Pricing Distortion; LinkedIn Profile

* School of Economics and Management, Tsinghua University; Email: liuch@sem.tsinghua.edu.cn

† School of Economics and Management, Tsinghua University; Faculty of Economics and Business, KU Leuven; Email: psz22@mails.tsinghua.edu.cn

1 Introduction

The proverb "*Empty vessels make the most noise*" is widely recognized across cultures, often used to describe individuals who, lacking real expertise, rely on exaggerated assertions to attract attention. A comparable Chinese saying, "*Ban Guan Shui, Xiang Ding Dang*", similarly criticizes overconfidence and flamboyant self-praise, advocating instead for modesty and authenticity. However, when delving deeper into the logic behind, such behavior can also be viewed as a strategic response aimed at increasing one's visibility and influence. When enhanced exposure translates into competitive advantages or tangible benefits, such behavior aligns with the notion of "self-promotion", defined as the strategic use of positive statements about oneself to shape others' perceptions. Especially in today's Internet-driven era, where attention often translates into economic value, the deliberate creation of "noise" can yield tangible benefits.[1] Thus, the self-promotion behavior exhibits a dual nature, apparently unwise yet practically beneficial, which determines the complexity in understanding such conduct. In this study, we provide empirical evidence to disclose the self-promotion strategies employed by financial analysts, explore the driving forces behind these actions, and assess their broader implications for market dynamics.

As innately social creatures, humans consistently assess their own performance and share these evaluations with others, thus shaping perceptions across social and professional settings. Self-presentation significantly influences one's ability to land jobs, advance in their career, or secure better compensation. In this context, self-promotion serves as a proactive strategy within impression management, where individuals highlight their strengths, achievements, and aspirations to create favorable impressions, even when their actual abilities may not fully support such portrayals (Jones, 1982; Stevens and Kristof, 1995; Harris et al., 2007; Den Hartog et al., 2020; Harvey, 2024).

[1]For instance, in the short video industry or China's booming live-streaming e-commerce sector, content creators frequently employ sensational or exaggerated narratives to attract viewers, monetizing attention through ads and sponsorships. Verifying content authenticity is costly for viewers, whose emotions are easily influenced by these curated impressions, ultimately fostering trust in the creators.

While self-promotion has been extensively studied in fields such as management, organizational behavior, and psychology, its application in accounting and finance remains limited. Through experimental methods, Exley and Kessler (2022) reveal stable gender differences in self-promotion that can potentially shape economic outcomes, including gender gaps in job opportunities and compensation. Building on this line of research, we extend the inquiry to investigate the broader economic implications of self-promotion within financial markets. Specifically, we focus on sell-side financial analysts, a professional group that plays a pivotal role in mitigating information asymmetries and shaping investor expectations. The motivation behind this group's self-promotion and the rationale for selecting them as the research object will be discussed in Section 2.

We examine the personalized self-descriptions that analysts curate on their LinkedIn profiles. These narratives serve dual functions: they reflect analysts' self-perceived competencies and market value, while simultaneously acting as critical signaling mechanisms that influence initial impressions formed by investors and potential employers. Unlike standardized resume components that document objective qualifications, self-descriptions are intrinsically subjective, providing nuanced insights into individuals' personalities and self-presentation strategies. To systematically analyze these texts, we employ TextBlob, a Python-based natural language processing (NLP) toolkit, to quantify emotional tone through polarity scores (ranging from -1 to 1, where higher values denote greater positivity). Our data comprises 727 analysts whose LinkedIn profiles were manually collected, all containing self-descriptions of 20 words or more.

Based on annual earnings forecasts for 3,336 U.S.-listed firms between 2021 and 2023, we find that analysts with a more positive tone in their self-presentations demonstrate systematically lower forecast accuracy. This counterintuitive finding, which challenges the conventional wisdom linking self-assurance with competence, is termed the *tone-performance inverse effect*. The results remain consistent across alternative forecast accuracy metrics, time horizons, large language models, and model specifications, suggesting that it is pri-

marily driven by analysts' individual characteristics. The heterogeneity analysis shows that this paradox is more pronounced among: (1) male analysts, (2) individuals without formal training in economics or management, (3) professionals with limited LinkedIn social capital (measured by follower count), (4) junior analysts with less work experience, and (5) those affiliated with smaller brokerage firms. As these demographic subgroups are subject to heightened career insecurity and competitive pressures within the sell-side research industry, they appear to strategically employ inflated positive self-presentation as a compensatory impression management tactic, a behavioral pattern that directly corroborates the *compensation for skill gaps* mechanism.

Through rigorous empirical testing, we decisively rule out two competing psychological bias explanations for this observed phenomenon. First, we examine optimism bias, a well-established cognitive tendency in financial research (Butler and Lang, 1991; Das et al., 1998; Cowen et al., 2006). Although analysts with more positive self-presentation tones demonstrate greater forecast optimism, controlling for this bias leaves both the economic magnitude and statistical significance of the *tone-performance inverse effect* virtually unchanged. This empirical evidence decisively rules out *optimism bias* as the dominant driver. Rather, we observe that high-tone analysts systematically produce excessively optimistic forecasts for small-cap firms and those with low market-to-book (MB) ratios, can be interpreted as a strategic effort to cater to investor preferences and enhance personal visibility.

Second, we test for herding behavior among analysts and document that those high-tone analysts exhibit significantly stronger conformity to consensus forecasts, while being less likely to issue bold, independent predictions. This finding directly contradicts the *overconfidence bias* hypothesis, which posits that overconfident analysts should overweight their private information relative to consensus. Instead, it supports the *compensation for skill gaps* mechanism, where less-skilled analysts strategically herd to mitigate reputation risk (Scharfstein and Stein, 1990; Trueman, 1994; Clement and Tse, 2005). Moreover, controlling for herding behavior does not weaken the *tone-performance inverse effect*.

To further uncover the underlying motivation behind analysts' self-promotion behavior, we examine how analyst characteristics relate to the intensity of self-promotion, measured by the ranking gap between an analyst's self-presentation tone and their actual performance. Among all characteristics considered, the number of LinkedIn followers emerges as the only variable that significantly affects the promotion intensity. It highlights that the desire to increase visibility serves as a fundamental driver of analysts' self-promotion behavior.

We next investigate what tangible benefits such visibility may bring to analysts. First, building on existing research showing investors' general preference for analysts with greater forecast accuracy (Malloy, 2005; Du et al., 2017; Bradley et al., 2017), we examine how markets respond to analysts' self-presentation tone on LinkedIn. Our findings reveal a striking asymmetry: while upward revisions from high-tone analysts produce significantly stronger excess returns, negative signals show no comparable effect. This pattern holds consistently for stock recommendations: high-tone analysts' buy recommendations generate more pronounced market reactions, but no similar effect among their sell or hold recommendations. These asymmetric responses align perfectly with the established *Mad Money effect* (Engelberg et al., 2012), where less sophisticated investors emotionally overreact to positive signals. Two key observations reinforce this interpretation. First, the enhanced market response to high-tone analysts fades progressively, vanishing completely after 90 days, indicating temporary attention-driven distortions rather than fundamental reevaluations. Second, the effect proves particularly strong among smaller firms and those with lower MB ratios, stocks that typically face greater liquidity constraints and arbitrage difficulties.

Second, we examine whether self-promotion enhances analysts' career prospects. Using the I/B/E/S database, we calculate the number of career transitions for each analyst, as well as the number of upward transitions. We find analysts with low forecast accuracy but high self-presentation tone consistently experience the highest rates of upward career transitions, both in terms of brokerage size and forecast quality. Thus, self-promotion can indeed help underperforming analysts obtain more favorable job opportunities.

Our study makes several important contributions to the literature. First, while the concept of strategic self-promotion has been extensively studied in the fields of management and psychology (Schlenker, 1980; Leary and Kowalski, 1990; Bolino et al., 2008, 2016), its implications in accounting and finance remain relatively underexplored. In fact, impression management is particularly prevalent in the finance industry, especially in high-stakes settings such as interviews for high-paying positions. However, little is known about its real impact on financial outcomes. Chen and Hwang (2022) provide early evidence that investors' online information-sharing behavior can be shaped by impression management motives. We build on this emerging literature by analyzing LinkedIn self-presentation as a form of impression management, and linking it to the well-established literature on analysts' characteristics and forecast accuracy (Clement, 1999; Brown et al., 2015; Brauer and Wiersema, 2018). Our findings bear a strong resemblance to those of Chen and Hwang (2022), who show that investors tend to share articles that are more favorable for impression management, even though such articles are less accurate in predicting returns. Additionally, both studies highlight how impression management incentives, whether originating from investors or analysts, can inadvertently contribute to asset mispricing. Our conclusions carry direct practical implications: the principle *actions speak louder than words* is still applicable in the finance industry. Accordingly, investors are advised to focus more on professionals' actual performance rather than their narratives.

Second, alongside identifying self-promotion as a novel form of analyst behavior, we also contribute by studying how it interacts with other well-known behaviors such as intentional optimism bias, herding, and reputation management (Cowen et al., 2006; Clement and Tse, 2005; Fang and Yasuda, 2009; Ertimur et al., 2011), thereby offering a deeper understanding of the motivations behind these behaviors. For instance, the desire for greater visibility simultaneously drive analysts to engage in self-promotion and to exhibit optimism bias toward certain firms. While impression management shares similarities with reputation management in that both aim to enhance career prospects, it differs in a critical way: analysts do not

necessarily need high performance or strong qualities to benefit. As long as their voice is loud enough, even "noise" can generate attention and yield tangible rewards.

Last, by uncovering the *Mad Money*-like pricing distortion induced by analysts' self-promotion behavior, we contribute to the growing literature on sentiment and asset pricing. While prior studies primarily focus on aggregate market or firm-specific investor sentiment (Baker and Wurgler, 2007; Tetlock, 2007; Loughran and McDonald, 2011; Stambaugh et al., 2012; Da et al., 2015), we highlight a distinct yet related dimension: the tone conveyed in analysts' self-presentations. Unlike existing research that examines sentiment embedded in analysts' professional outputs, such as equity reports or earnings forecasts (Huang et al., 2014; Cuculiza et al., 2021), this tone functions more as soft information, reflecting how analysts personally frame themselves in nonstandardized communications. Investors, particularly individuals, may fail to interpret such cues rationally, leading to short-term mispricing in asset prices. Such findings also closely relate to Hu and Ma (2021), who show that start-up founders can influence investment decisions through the delivery of positive emotional cues during pitch presentations. While they emphasize how investors are susceptible to emotional persuasion under high uncertainty, we reveal that even when hard information (e.g., analysts' track records) is observable, investors can still be misled by emotionally charged self-presentation. This contrast highlights the broader relevance of soft information in shaping investor behavior, regardless of information environments.

The remainder of this paper is organized as follows. Section 2 outlines the research motivation. Section 3 describes the data and methodology. Section 4 presents evidence for the existence of the *tone-performance inverse effect* and discusses its underlying mechanisms. Section 5 examines which analysts are most likely to engage in self-promotion and explores its underlying motivation. Sections 6 and 7 investigate how investors and employers interpret analyst self-promotion. Finally, Section 8 concludes the paper.

2 Motivation and Research Background

As critical intermediaries in capital markets, sell-side analysts serve an essential function in reducing information asymmetries between companies and investors. Through their production of earnings forecasts, equity research reports, and sector analyses, these financial professionals significantly influence market expectations and inform capital allocation decisions (Kothari et al., 2016; Brauer and Wiersema, 2018). Their compensation, typically tied to brokerage commissions and investment banking fees, incentivizes them to produce influential and market-relevant analyses.

Though the analyst profession is highly rewarding, it remains one of the most fiercely competitive fields in finance. Achieving success demands not only exceptional technical competencies but, more crucially, the capacity to differentiate oneself within an overcrowded marketplace.[2] In this competitive landscape, an analysis based on the I/B/E/S shows that over 3,000 U.S.-listed companies were covered by an average of more than 10 analysts from different brokerage firms in 2023. Faced with this overwhelming number of opinions, a key question arises for investors: whose insights should they trust?

This question has been a central topic in both academic research and financial practice (Clement, 1999; Brown et al., 2015). Although an analyst's future performance does not necessarily mirror past results, literature has demonstrated that certain individual characteristics systematically influence an analyst's ability to produce valuable information, such as cultural background, educational qualifications, and professional experience (Cohen et al., 2010; Du et al., 2017; Bradley et al., 2017, 2020; Zhang, 2022). These traits are typically difficult to change in the short term, and as such, they can serve as useful indicators for predicting an analyst's future performance. Yet, the practical challenge lies in developing reliable mechanisms for market participants to observe and appraise these attributes.

The rise of digital platforms provides an answer. The development of the Internet has sig-

[2]For instance, media outlets like *Institutional Investor* annually rank analysts and publish "Star Analyst" lists, which impact their reputation and career prospects (Fang and Yasuda, 2014; Cheng et al., 2021).

nificantly lowered communication barriers and mitigated social distance among individuals. Even without face-to-face interactions, we can gain valuable insights into a person through publicly available online information. For example, we often learn about the biographies of public figures through Wikipedia. LinkedIn, in particular, serves as one of the best public resources for gathering detailed individual characteristics of financial professionals.[3]

The digital landscape presents investors with unprecedented access to analyst information. A typical search for an analyst's background on Google will frequently surface their LinkedIn profile among the top results, making it a natural focal point for due diligence.[4] Upon accessing the profile, you will find standardized elements, including a photo, location, social connections, educational background, and professional experience, which facilitate objective evaluation of qualifications. More revealing, however, is the personalized summary section prominently featured at the profile's apex, where analysts craft narrative self-presentations. By reading this content, you can gain deeper insights into the analyst and even sense their personality through the tone and style of their writing.[5]

The evaluation process demonstrates a cognitive spillover effect, wherein investors' judgments become influenced through dual information channels: both standardized professional metrics and carefully constructed personal narratives. This phenomenon highlights why analysts craft self-presentations and position them prominently at the top of their profiles as a form of impression management. It motivates us to explore the drivers behind such self-descriptive content and their influence on investors' perceptions.

[3]Several recent studies have utilized LinkedIn to analyze analysts' professional experience, social connections, cultural backgrounds and work locations, see Bradley et al. (2017, 2020), Li et al. (2023), Hao et al. (2025) and Sautner et al. (2024). In Liu and Pang (2024), an analysis of 10,043 I/B/E/S analysts from 2011 to 2022 revealed that 5,943 (over 60%) had LinkedIn profiles, indicating that the majority of analysts maintain a presence on the platform.

[4]This pattern has been consistently observed during our manual data collection process involving thousands of analyst profiles.

[5]This process is equally relevant if you are an employer. The self-description functions much like an opening self-introduction during an interview, complemented by the standardized resume that follows.

3 Data and Methodology

3.1 Sample Construction

Based on the Institutional Brokers' Estimate System (I/B/E/S) database, we manually downloaded and collected LinkedIn profiles for 2,757 out of approximately 6,000 analysts who issued at least one annual earnings forecast for U.S.-listed firms between 2021 and 2023.[6] Of these, 1,076 analysts included a summarized self-description at the beginning of their profiles. These self-descriptions typically provided an overview of their professional experience, technical expertise, and personal interests, essentially highlighting the aspects of their careers that they most wish to emphasize to external audiences. In addition, we extracted several other pieces of information from LinkedIn profiles, including each analyst's gender, the number of connections and followers, and educational background, which were used as control variables in the empirical analysis.[7]

To analyze these self-descriptions, we utilized Python for text mining and extracted the content from the profiles. To ensure the robustness of our analysis, we excluded samples where the total word count was fewer than 20 words.[8] This step was necessary to eliminate overly short or incomplete descriptions that could potentially distort the analysis. Additionally, we excluded profiles where the self-description content consisted only of brokerage-mandated disclaimers or lacked any meaningful personal or professional information.[9]

[6]Among these 6,000 analysts, the I/B/E/S Recommendation sub-database provides information on 4,381 analysts, including each analyst's surname and the initial of their first name. We matched analysts with their brokerage firms to locate their full names on LinkedIn. A similar methodology has been employed in previous studies, such as Bradley et al. (2017), Li et al. (2023), and Hao et al. (2025).

[7]While LinkedIn does not explicitly list gender, we manually identified the gender from profile photos, provided that the photo was available. The connection and follower counts are based on the numbers as of the data collection date. In cases where an analyst's LinkedIn connections exceeded 500, the platform displays "500+", and we approximated this as 500. Regarding educational background, since nearly all analysts hold at least a bachelor's degree, we identified whether they also held a master's or doctoral degree. Additionally, we assessed whether each analyst had an undergraduate degree in economics or business.

[8]The choice of this word count threshold does not affect the robustness of our results.

[9]For instance, one example of an analyst's self-description that was purely a company-required disclaimer, reads as follows: "The Raymond James & Associates' associated person is not acting in the capacity of a financial advisor and as such will not be effecting or attempting to effect retail transactions in securities or rendering personalized investment advice for compensation."

Our final sample comprises 727 analysts who issued annual earnings forecasts for 3,336 U.S.-listed firms between the calendar year 2021 and 2023. To ensure temporal alignment between LinkedIn self-descriptions (collected during Q4 2023) and forecast performance, we restricted our analysis to predictions made within the contemporaneous three-year window. This approach maintains consistency between the analysts' self-presentation and their corresponding forecast behavior during the matching period.

Analysts frequently revise earnings forecasts during a fiscal year in response to new information or peer influence. We included all forecasts in the *full sample* for the main regression analysis, totaling 87,427 forecasts.[10] We constructed two complementary subsamples: the *first forecast sample*, consisting of each analyst's initial forecast for a firm within a given year, to mitigate herding or learning effects, and the *last forecast sample*, which includes the final forecast made before the earnings announcement to capture analysts' information-gathering abilities. Both subsets contain 21,805 forecasts.

Finally, financial data for firms were sourced from Compustat, while daily stock performance data were obtained from the Center for Research in Security Prices (CRSP). We classified industries according to the 3-digit Standard Industrial Classification (SIC) codes as provided by the U.S. Securities and Exchange Commission.

3.2 Tone Intensity Measurement

Our analysis of 727 analysts' LinkedIn profiles reveals substantial variation in the length of personal statements, with an average of 77 words (median = 59, range = 20-273 words). To evaluate the tone expressed in these self-descriptions, we employed TextBlob, a Python-based natural language processing (NPL) library that offers built-in tools for text analysis. This tool generates polarity scores ranging from -1 (extremely negative) to +1 (extremely positive), with 0 representing neutral tone.[11]

[10]We excluded firms covered by only one analyst in a given year to ensure meaningful comparison of relative performance across analysts.

[11]TextBlob provides efficient sentiment analysis through its pre-trained model, evaluating texts along two dimensions: polarity (emotional direction) and subjectivity (degree of personal expression). While prior

We construct a tone intensity measure $Tone_i$ for each analyst i based on their LinkedIn profile's self-description text. Across our sample of 727 analysts, the average tone score is 0.13 (median = 0.11), ranging from -0.29 to 0.80. Approximately 90% of analysts demonstrate non-negative tone scores, consistent with professionals generally avoiding strong negative expressions in career-oriented self-presentations. We construct a dummy variable $HighTone_i$, which equals 1 if $Tone_i$ above the median (0.11) and 0 otherwise. Additionally, our analysis reveals a negative correlation ($\rho = -0.118$) between tone score and text length, potentially reflecting that longer self-descriptions tend to incorporate more neutral or balanced expressions due to their greater informational scope. However, as we demonstrate in subsequent analyses, it is the tone measure itself - rather than text length - that exhibits significant predictive power for analysts' forecast accuracy.

3.3 Accuracy Measurement

Consistent with Clement (1999), Bae et al. (2008) and Bradley et al. (2017), we use the Proportional Mean Absolute Forecast Error ($PMAFE$) to measure the accuracy of an analyst's earnings forecast. It is calculated as:

$$AFE_{ijtk} = |FE_{ijtk} - AE_{jt}|, \tag{1}$$

$$\overline{AFE}_{jt} = \frac{1}{NK} \sum_{i}^{N} \sum_{k}^{K} AFE_{ijtk}, \tag{2}$$

$$PMAFE_{ijtk} = \frac{AFE_{ijtk} - \overline{AFE}_{jt}}{\overline{AFE}_{jt}}, \tag{3}$$

where AFE_{ijtk} is the absolute forecast error of analyst i's k-th forecast of firm j's earnings in fiscal year t, measured as the difference between the forecast value FE_{ijtk} and the actual value

research often employs domain-specific dictionaries (e.g., Loughran-McDonald) for formal financial texts, TextBlob is particularly suited for analyzing the professionally framed yet subjective narratives in LinkedIn profiles. Our focus on polarity is justified by its greater relevance to analyst performance compared to subjectivity.

AE_{jt}. The term $\overline{AFE}_{jt}$ is the mean absolute forecast error across all analysts' forecasts for firm j in fiscal year t, serving as a benchmark.[12] Then, $PMAFE_{ijtk}$ is the difference between AFE_{ijtk} and $\overline{AFE}_{jt}$, scaled by $\overline{AFE}_{jt}$ to control for heteroskedasticity. $PMAFE_{ijtk} < 0$ indicates that the analyst's forecast accuracy is better than the average level for that firm and fiscal year, with larger values signifying greater relative accuracy. To mitigate the influence of extreme values, we winsorize $PMAFE_{ijtk}$ at the 1% level annually, ensuring that outliers do not disproportionately affect the results.

To ensure robustness, we alternatively use a metric that is also widely adopted in the literature, see Bae et al. (2008) and Li et al. (2023):

$$Range_{ijtk} = \frac{\max_{i,k} AFE_{ijtk} - AFE_{ijtk}}{\max_{i,k} AFE_{ijtk} - \min_{i,k} AFE_{ijtk}} \times (-1), \tag{4}$$

which measures the difference between the highest absolute forecast error for firm j in year t and analyst i's k-th absolute forecast error, divided by the total range. The measure is multiplied by -1, so that smaller values correspond to higher forecast accuracy. Similarly, it is winsorized at the 1% level annually, ensuring that outliers do not skew the results. As we will demonstrate, the choice of measurement does not affect the robustness of findings.

3.4 Regression Model

In the primary empirical analysis of this study, we aim to examine the relationship between the tone expressed in analysts' personal self-descriptions on LinkedIn profiles and their professional performance. To do so, we employ the following OLS regression model:

$$PMAFE_{ijkt} = \beta_0 + \beta_1 \times Tone_i + \mathbf{\Gamma} \times \mathbf{X}_{ijkt} + \mathbf{Y}_{ijkt} + \epsilon_{ijkt}, \tag{5}$$

[12] Consistent with Bradley et al. (2017), we use the full I/B/E/S sample to compute the mean absolute forecast error $\overline{AFE}_{jt}$.

where the accuracy measurement $PMAFE_{ijkt}$ can be replaced by $Range_{ijkt}$ to ensure the robustness, and the tone intensity measurement $Tone_i$ can be replaced by $HighTone_i$ to examine the threshold effect. The model also includes a vector of control variables $\mathbf{X}_{ijkt}$ which accounts for analyst-, firm-, and forecast-specific characteristics. $\mathbf{Y}_{ijkt}$ represents fixed effects to control for unobserved heterogeneity across analysts, firms or time periods, and the error term ϵ_{ijkt} captures random noise. Detailed definitions of control variables are listed in Table 1.

3.5 Descriptive Statistics

Table 2 presents the summary statistics for the full sample. The accuracy measure, represented by $PMAFE$, averages at -0.04 with a standard deviation of 0.75. Analysts' self-descriptions have an average length of 77.49 words, and the tone intensity $Tone$ has a mean of 0.12, consistent with the individual-level data. Only 11% of the forecasts are made by female analysts, highlighting the low participation of women in the analyst community.[13] Regarding educational background, 72% of the forecasts are issued by analysts with a degree in economics or management, while 48% are made by those with a bachelor's degree in these fields. Furthermore, 60% of the forecasts are attributed to analysts holding a master's degree, whereas only 4% are issued by analysts with a doctoral degree.

Our sample reveals several key patterns in analyst professional networks and forecasting activity. The average analyst maintains 1,370 LinkedIn followers and 470 direct connections, while possessing approximately 15 years of general work experience and 5.2 years of firm-specific expertise. Annually, each analyst generates an average of 106 earnings forecasts spanning 23 distinct firms. At the brokerage level, the average brokerage firm in our sample employs 71 analysts. Notably, the mean coverage duration for these brokerages (8.6 years) exceeds the average analyst's firm-specific tenure, suggesting that while individual analysts

[13]Due to limitations in identifying gender from profile photos, gender information is available for only 590 out of the 727 analysts. As a result, the variable $Female$ in the forecast-level data is missing for approximately 20% of the observations. However, it does not affect the robustness of our findings.

may rotate, brokerage firms maintain more stable research coverage of companies. The sample firms receive substantial analytical coverage, with an average of 76 annual forecasts per firm derived from 17 different analysts representing 16 unique brokerages.

4 Analyst Self-Promotion Behavior

4.1 Self-Presentation Tone and Forecast Accuracy

Table 3 presents the regression results based on the full sample, examining the relationship between analysts' self-presentation tone and forecast performance. Column (1) reports the results from a baseline regression that includes fixed effects at the year, quarter, and brokerage levels. In column (2), we extend the model by incorporating commonly used control variables at the analyst and brokerage levels. Column (3) further adds LinkedIn related individual characteristics, such as gender, educational background, and social network indicators. In column (4), we introduce firm-level control variables, such as firm size, MB ratio, and leverage, along with industry fixed effects to account for unobserved heterogeneity at the industry level. Column (5) further includes firm fixed effects, controlling for time-invariant firm-specific factors that could influence forecast accuracy.

Across all specifications, the coefficient for the key explanatory variable *Tone* remains consistently positive and statistically significant. It suggests that analysts with a more positive tone in their self-presentations tend to exhibit lower forecast accuracy. Notably, this effect remains robust even after incorporating the firm-level fixed effect, indicating that it is primarily driven by analysts' personal characteristics, such as strategic motivations or behavioral biases, which in turn negatively associate with their professional performance.

As discussed earlier, longer texts are more likely to include neutral or mixed expressions, which associate with lower polarity scores. In the context of LinkedIn profiles, analysts who write longer self-descriptions may appear more serious or thoughtful about their profession. Thus, the observed negative relationship between *Tone* and forecast accuracy could

potentially be driven by this subgroup. To address this concern, column (6) includes the length of the self-description as a control variable. The result indicates that text length is not significantly associated with forecast accuracy, while the *tone-performance inverse effect* remains robust. Additionally, TextBlob provides another measure quantifying the degree of text subjectivity. In column (7), *Subjectivity* is added and does not have any impact.

Finally, in column (8), we remove the control variable $Female$ and the *tone-performance inverse effect* remains. It indicates that the missing gender observations, which account for approximately 20% of the forecast-level data, have not introduced noticeable bias into the sample distribution or affected the robustness of the findings.

For the other control variables, the positive coefficient for $Horizon$ indicates that forecast accuracy improves as the earnings announcement date approaches, reflecting analysts' ability to incorporate updated information. The significant negative coefficient for $Order$, representing the sequence of forecasts for a firm within a year, suggests that more frequent revisions lead to greater accuracy. Female analysts' forecasts are significantly less accurate, highlighting the disadvantages women face in the analyst profession (Fang and Huang, 2017), which aligns with their under-representation in the sample. Lastly, analysts with greater firm-specific experience provide more accurate forecasts, likely due to accumulated knowledge and familiarity with the firm over time.

To ensure robustness, we replace the accuracy measurement with *Range* and the explanatory variable with $HighTone$ to examine the threshold effect, as shown in columns (1) and (2) of Table 4. Furthermore, we conduct two additional tests using the first and the last forecast sample and the results remain robust across all specifications. Interestingly, the effect is stronger in the first and the full sample compared to the last forecast sample. This suggests that high-tone analysts may engage in herding behaviors over time, reducing the performance gap observed in their earlier forecasts. We will explore this phenomenon further in Subsection 4.5.

4.2 Possible Explanations

The finding that analysts with more positive self-presentations tend to perform worse is intriguing, as one might intuitively expect better performance to be associated with more favorable self-evaluations. While our regression framework treats tone intensity as an explanatory variable, this does not necessarily imply that stronger self-presentation causes poorer performance. Instead, we emphasize that the observed *tone-performance inverse effect* should be interpreted as a correlation rather than a causal relationship.

Several underlying mechanisms may account for this correlation, including omitted variables that simultaneously affect both tone and performance, or reverse causality. In the following analysis, we propose and evaluate three theoretical explanations, each of which offers a plausible interpretation of the effect:

(1) *Compensation for Skill Gaps*: Positive self-presentations may serve as a compensatory strategy for analysts who are less skilled or competitive. In the job market, a financial professional's employment prospects depend not only on actual ability but also on perceived ability. For underperforming analysts, improving actual ability is often difficult and time-consuming, whereas enhancing perceived ability through self-promotion is comparatively easier and less costly. By exaggerating their strengths, these analysts may seek to increase visibility and advance their careers. This explanation aligns with the impression management literature, which highlights the strategic use of self-presentation in competitive environments. If this mechanism holds, we would expect the *tone-performance inverse effect* to be more pronounced among analysts with greater career pressure, or stronger peer competition.

(2) *Optimism Bias*: Analysts with optimistic personalities may consistently overestimate both their own abilities and the prospects of the firms they cover. This pervasive optimism not only shapes their self-descriptions but also translates into overly favorable earnings forecasts, resulting in larger forecast errors. In the literature, analyst optimism bias can be either inherent or strategic. The mechanism here focuses on optimism as an internal trait, which functions as an omitted variable that jointly drives both factors.

(3) *Overconfidence Bias*: Analysts with overconfident personalities may overrate their own abilities, leading to inflated self-descriptions. This cognitive bias can impair their judgment, making them less responsive to new information and more prone to underestimating risks or overestimating forecast precision. Overconfidence differs from optimism in that it reflects an inflated belief in one's judgment or skill, rather than a general tendency to expect favorable outcomes. Nevertheless, like optimism, overconfidence may serve as an omitted variable causing the observed *tone-performance inverse effect*.

To uncover the underlying mechanisms, Subsection 4.3 conducts a heterogeneity analysis and provides insights into potential driving factors. Subsection 4.4 examines whether the observed effect stems from analysts' innate optimism, while Subsection 4.5 investigates the role of herding behavior in explaining this phenomenon.

4.3 Heterogeneity Analysis

In this subsection, we aim to conduct a heterogeneity analysis to identify which individual factors, such as education, gender, or experience, influence the manifestation of this effect and to explore the underlying mechanisms behind it. Table 5 shows the empirical results.

Columns (1) and (2) examine gender-based heterogeneity and show that for male analysts the *tone-performance inverse effect* remains. For female analysts, while the coefficient on *Tone* is larger in magnitude, it is not statistically significant, likely due to the smaller sample size. This pattern supports the plausibility of the three proposed mechanisms. While men are more prone to optimism and overconfidence in financial decisions (Barber and Odean, 2001; Huang and Kisgen, 2013), the competitive nature of the industry may also motivate them to engage in self-promotion (Exley and Kessler, 2022).

Next, columns (3) and (4) investigate the role of analysts' academic background, distinguishing between those with and without an undergraduate degree in economics or management. The results show that the *tone-performance inverse effect* is particularly pronounced among analysts lacking such a degree. It appears to support the third proposed explana-

tion. While there is no direct evidence linking individual optimism or overconfidence to academic background, analysts without formal training in economics or management (particularly at the undergraduate level) may exhibit skill gaps that contribute to poorer forecast performance (as shown in Table 3, where the coefficient for $BSem$ is significantly negative). Consequently, these analysts may rely more heavily on self-promotion to compensate for their lack of technical expertise and to enhance perceived credibility.

Further, columns (5) and (6) focus on the number of LinkedIn followers, which serves as a proxy for analysts' social influence and market visibility. The median number of followers among the 727 analysts is 949. When dividing the sample based on whether an analyst's follower count exceeds this median, the *tone-performance inverse effect* remains significant in both subsamples but is more pronounced among analysts with fewer followers. Consistently, this pattern suggests that analysts with lower existing visibility may be more likely to adopt optimistic self-presentations as a compensatory strategy to boost their exposure to employers and investors.

Finally, we examine the impact of analysts' professional experience and the size of their affiliated brokerage firms. Generally, analysts with longer work histories or affiliations with larger financial institutions are believed to possess greater information endowment, enabling them to acquire information at lower cost. Here, an analyst is classified as more experienced if his general work experience at the time of making a forecast ($Workexp$) exceeds the median level in that calendar year, and less experienced otherwise. As shown in columns (7) and (8), the *tone-performance inverse effect* is stronger among less experienced analysts, suggesting that analysts with limited industry tenure may rely more on optimistic self-presentations to compensate for their lack of expertise or credibility. Similarly, when classifying analysts based on the size of their brokerage ($Bsize$), we find that the effect is more pronounced for analysts working at smaller brokerages. This may reflect the greater pressure faced by analysts in smaller firms to differentiate themselves and attract attention, as they often operate in a more resource-constrained and competitive environment.

Taken together, the heterogeneity analysis in this subsection reveals the *tone-performance inverse effect* is more pronounced among male analysts, those without an undergraduate academic background in economics or management, analysts with fewer LinkedIn followers, less experienced professionals, and those employed at smaller brokerage firms. These patterns collectively suggest that analysts facing greater career pressure and more intense peer competition are more likely to engage in self-promotion behavior, lending support to the third proposed explanation *compensation for skill gaps*.

4.4 Optimism Bias

In this subsection, we aim to test the first proposed explanation: *optimism bias*, to determine whether it drives the *tone-performance inverse effect*. Referring to Jackson (2005), we define analysts' optimism bias as follows:

$$Optimism_{ijkt} = \frac{FE_{ijkt} - AE_{jt}}{Price_{jt}} \times 100, \tag{6}$$

which is the difference between the forecast value and the actual value, divided by the fiscal year-end close price and multiplied by 100. Positive values of $Optimism$ indicate that the analyst's forecast exceeds the actual earnings, capturing the degree of overestimation or optimism bias in the forecast. Consistent with other continuous variables in this study, variable $Optimism$ is winsorized at the 1% level by year.

We use $Optimism$ as the dependent variable and $Tone$ as the explanatory variable to examine their correlation. Panel A of Table 6 reports the regression results. Column (1) includes the same control variables and fixed effects as in column (4) of Table 3. The coefficient for $Tone$ is significantly positive, indicating that analysts with more positive self-presentations tend to exhibit greater optimism bias. However, when firm fixed effects are included in column (2), the coefficient becomes insignificant. This change implies that the observed relationship may be driven, at least in part, by firm-specific factors.

Inspired by this, columns (3) to (6) further examine the relationship across different firm characteristics. The results show that the optimism bias of high-tone analysts is more pronounced in smaller firms and firms with lower MB ratios. This may reflect analysts' tendency to overestimate the potential of companies operating in more opaque and uncertain environments, where information asymmetry is greater. Alternatively, such firms often suffer from lower liquidity and may benefit from optimistic coverage that attracts investor attention. In these cases, high-tone analysts may issue overly favorable forecasts not due to inherent optimism, but as a strategic move to enhance their own visibility.

Lastly, we retest the relationship using the first and last forecast samples. The results in columns (7) to (10) show that the coefficient is significant only in the first forecast sample and without firm fixed effects. This suggests that the optimism bias of high-tone analysts for some firms is most evident in their initial forecasts. Over time, they may adjust their predictions through herding, gradually reducing their optimism bias as more information becomes available or as they align with market consensus.

Although we find a correlation between tone and optimism bias, it does not necessarily imply that optimism bias is the underlying cause of the *tone-performance inverse effect*. In Panel B of Table 6, we control the optimism bias indicator in the main regression model. The results show that both the magnitude and significance of the $Tone$ coefficient remain largely unchanged, suggesting that optimism bias cannot fully account for the effect.

Furthermore, we conduct a firm-level heterogeneity analysis. The *tone-performance inverse effect* remains significant for large firms and those with high MB ratios, while optimism bias cannot explain the inaccuracy. In contrast, for small firms and those with low MB ratios, the inverse effect becomes less pronounced, whereas optimism bias shows greater explanatory power. These suggest that the strategic use of optimism, potentially employed to attract attention or signal confidence, may drive the inverse effect in certain types of firms. However, such evidence is more aligned with the *compensation for skill gaps* mechanism than with the *optimism bias* mechanism, as it reflects a strategic rather than inherent bias.

4.5 Herding Behavior

As evident from the previous analysis, the *tone-performance inverse effect* is stronger in the first and full forecast samples compared to the last forecast sample. Additionally, the optimism bias of high-tone analysts is most pronounced in their initial forecasts for certain firms. These findings suggest that high-tone analysts may rely on the forecasts of others to adjust their predictions over time. While herding is a well-documented behavior in the literature (Trueman, 1994; Hong et al., 2000), it remains unclear whether high-tone analysts are more prone to herding. If this is indeed the case, we have reason to reject the *overconfidence bias* mechanism, as overconfident analysts are expected be more likely to trust their own judgments and less inclined to conform to the consensus.

Aligning with Clement and Tse (2005), we define an indicator variable $Bold_{ijkt}$ for each forecast. This variable equals 1 if analysts i's k-th forecast of firm j in fiscal year t is either above both the analyst's prior forecast and the consensus forecast immediately before the revision (calculated as the mean of forecasts issued in the previous 90 days) or below both. Otherwise, it equals 0 and is classified as a herding forecast.[14]

First, we use $Bold$ as the dependent variable and $Tone$ as the explanatory variable to examine their correlation. Results in Table 7 show that forecasts are less likely to be bold (and more likely to align with herding behavior) when issued by analysts with higher tone in their self-descriptions and the relationship holds when just focusing on the last forecast sample. These findings suggest that high-tone analysts are more inclined to follow the consensus rather than making bold, independent forecasts, providing evidence against the overconfidence hypothesis.

Clement and Tse (2005) show that herding forecasts are usually associated with lower accuracy. This raises the question of whether herding behavior itself drives the negative relationship between self-presentation tone and forecast accuracy. To test this, we include

[14] An analyst's initial forecast is not regarded as a bold forecast. However, as observed in our analysis of the last forecast sample, this restriction does not affect the conclusions.

the *Bold* indicator as a control variable in the main regression model, as shown in columns (3) to (6). While the results confirm that herding forecasts are indeed less accurate, the *Tone* coefficient remains unchanged in both size and significance after controlling for herding behavior. This indicates that while herding is linked to lower accuracy, it does not explain the negative relationship between tone intensity and performance.

Through the heterogeneity analysis of the *tone-performance inverse effect*, along with examinations of analysts' optimism bias and herding behavior, our findings do not support the *optimism bias* or *overconfidence bias* mechanisms. Instead, they align with the *compensation for skill gaps* mechanism as the primary explanation for why analysts with more positive self-presentations tend to perform worse. Analysts who are at a competitive disadvantage are more inclined to embellish themselves to boost visibility and perceived competence.

While high-tone analysts exhibit overly optimistic forecasts for small and low MB firms, this behavior is likely driven by self-promotion motives to attract market attention rather than genuine optimism. Additionally, high-tone analysts are more prone to herding behavior, likely due to a lack of information but a strong concern for reputation. This aligns with the theoretical framework proposed by Scharfstein and Stein (1990) and Trueman (1994), which suggests that analysts with weaker informational advantages are more inclined to herd to safeguard their reputation. Together, we conclude that the *tone-performance inverse effect* stems from strategic self-promotion rather than psychological biases.

4.6 Robustness on Extended Forecast Window

Given that analysts' LinkedIn self-descriptions may carry some degree of temporal specificity, our main analysis focuses on the most recent three years (2021-2023), as discussed in Subsection 3.1. This ensures closer alignment between forecast timing and profile information, reducing concerns about explaining past behavior with present-day characteristics. In this subsection, we extend the analysis to a longer forecast window (2010-2024) to test the robustness of our results.

First, we consider the forecast sample from 2010 to 2024 based on the same group of analysts. While this extended window allows us to test the robustness, it enables us to examine potential variation in the *tone-performance inverse effect* over a longer horizon. As shown in columns (1) and (2) of Table 8, we re-estimate the regressions from Subsection 4.1, and find that the effect remains consistent across the extended sample period.

Further, Figure 1 illustrates the dynamics of forecast accuracy over time and two key observations can be drawn. First, analysts with higher tone intensity consistently exhibit lower accuracy throughout the extended period, with the only exception of 2017, further validating the robustness. Second, the gap in accuracy between two groups appears to be larger in earlier years compared to the more recent period. This trend does suggest that high tone intensity in 2023 LinkedIn profiles likely reflects a compensatory strategy for historically poor forecast accuracy. The narrowing gap and downward trend of the blue curve indicate that high-tone analysts may have improved their accuracy over time.

Next, we enlarge the sample of analysts. Among those who issued at least one annual earnings forecast for U.S.-listed firms during 2010-2024, we were able to obtain LinkedIn self-descriptions for 1,802 analysts.[15] Columns (3) and (4) re-estimate the regressions using this larger analyst set, and the results remain qualitatively consistent. However, the coefficients are relatively smaller than those in columns (1) and (2), suggesting that temporal misalignment between current resume information and historical forecast behavior may lead to an attenuation bias when identifying the *tone-performance inverse effect*.

4.7 Identification Based on Large Language Model

In recent years, Large Language Models (LLMs) such as ChatGPT and Deepseek, have demonstrated strong capabilities in processing and understanding natural language. In the financial domain, LLMs have been applied to analyze various types of text data, such as financial news, corporate disclosures, and analyst reports, enabling more efficient and scal-

[15]This includes approximately 1,000 analysts not covered in our baseline sample of 727, who had no forecast record in 2021-2023 but were still retrievable from LinkedIn in 2023.

able textual analysis (Jha et al., 2024; Chen et al., 2025; Ke, 2024). Motivated by these advancements, we leverage ChatGPT in this subsection to evaluate analysts' LinkedIn self-descriptions and test the robustness of our main findings. We input the text of each analyst's LinkedIn self-description and instruct the GPT-4o model to evaluate its emotional polarity. The prompt used is as follows:

"*Forget all previous instructions. You are now a psycholinguist. I will give you a LinkedIn self-description of a financial profession. Determine the emotional polarity of the text. Choose one of the following options: Very Negative, Somewhat Negative, Neutral, Somewhat Positive, Very Positive. Do not provide any additional responses.*"

Among the 727 analysts in our sample, 59 are classified as *Very Positive*, 342 as *Somewhat Positive*, 325 as *Neutral*, and only 1 as *Very Negative*, based on GPT's evaluation. Correspondingly, we define a variable $GPTTone$ assigning values of 1, 0.5, 0, -0.5, and -1 to the five possible categories. The correlation between $GPTTone$ and $Tone$ is 0.37, indicating a moderate degree of consistency.

In column (5) of Table 8, we replace the original measure $Tone$ with the GPT-generated one. The negative relationship between analysts' self-presentation tone and forecast performance persists, suggesting that LLMs possess a meaningful degree of interpretive capacity when evaluating the linguistic features of analysts' self-presentations. In column (6), we include both sentiment indicators as explanatory variables. While both coefficients are positive, only the coefficient on $Tone$ is statistically significant, suggesting that the lexicon-based indicator has stronger explanatory power. This is likely because the lexicon-based indicator is a continuous variable with greater variation, whereas the LLM-based indicator is derived from a limited set of discrete categories. In columns (7) and (8), we define $HighGPTTone$ as a binary variable equal to 1 if $GPTTone > 0$, and 0 otherwise. The results remain consistent with previous findings. Taken together, these results confirm that LLM-based identification offers a viable and robust alternative for identifying the *tone-performance inverse effect*.

5 Who Engages in Self-Promotion?

In the preceding analysis, we have documented a significant and robust negative correlation between analysts' self-presentation tone and their actual performance. The most plausible explanation for this phenomenon is that analysts at a competitive disadvantage are more inclined to embellish themselves to boost visibility and perceived competence.

However, it is important to note that high tone intensity alone does not necessarily indicate self-promotion. Rather, such behavior is more clearly revealed when an analyst exhibits high tone intensity but low actual forecasting performance. In this subsection, we compare analysts' actual performance with their self-presentation tone intensity to identify those who "talk big but deliver little," and examine their characteristics to gain deeper insight into the underlying motivations for self-promotion behavior.

Based on the forecast sample between 2021-2023, we compute each analyst's average forecast accuracy ($PMAFE$), and rank all analysts from 1 to 727 based on this metric. The rankings are then normalized to fall within the interval $[0, 1]$, where a value of $AccuracyRank = 1$ corresponds to the analyst with the highest accuracy, and $AccuracyRank = 0$ to the lowest. Similarly, we rank all analysts based on the intensity of their self-presentation tone, assigning $ToneRank = 1$ to the analyst with the most positive tone and $ToneRank = 0$ to the least positive one. Again, there is a significant negative correlation between $AccuracyRank$ and $ToneRank$, verifying the existence of *tone-performance inverse effect*. Next, we construct $Mismatch = ToneRank - AccuracyRank$, where $Mismatch > 0$ indicates that an analyst's self-presentation tone exceeds what would be expected given their actual performance, thus serving as a proxy for the extent of self-promotion behavior.

366 out of the 727 analysts are identified as exhibiting self-promotion behavior. We next examine which common characteristics are associated with greater incentives to engage in such behavior. In the regressions reported in Table 9, we use $Mismatch$ as the dependent variable. In addition to basic analyst characteristics retrieved from LinkedIn, we include: $MaxWorkexp$, the analyst's maximum years of work; $MaxBsize$, the maximum brokerage

size affiliated with the analyst; and $MeanOptimism$, the average value of the analyst's forecast optimism bias ($Optimism$), capturing their general tendency toward optimism.

As shown in columns (1) and (2), when analyzing the full sample of analysts, we find no individual characteristic that significantly predicts the extent of self-promotion behavior.[16] However, when restricting the sample to analysts identified as engaging in self-promotion, the results in columns (3) and (4) reveal that the variable $Follower$, which captures the number of LinkedIn followers (measured in thousands), is negatively and significantly associated with the extent of self-promotion behavior. This finding is consistent with the interpretation that self-promotion serves as a compensatory strategy: analysts with limited online exposure are more inclined to adopt a more promotional tone to close the gap in perceived competence and increase their visibility.

On the other hand, when focusing on analysts not identified as engaging in self-promotion behavior, the results in columns (5) and (6) show that the coefficient on $Follower$ becomes positive, although the significance is not robust. The reversal in sign may be explained by the interpretation of $Mismatch$ in this subgroup: for analysts with $Mismatch \leq 0$, the tone rank is lower than the accuracy rank, and a $Mismatch$ closer to zero indicates better alignment between perceived and actual ability. In this case, highly skilled analysts who also present themselves with stronger tone intensity may attract more followers, thereby generating a positive correlation between $Mismatch$ and $Follower$ in the absence of overstatement.

6 Investor Interpretation of Analyst Self-Promotion

6.1 Short Run Market Reaction

The previous analysis highlights that the desire to increase visibility serves as a fundamental driver of analysts' self-promotion behavior. A natural next question is: what kinds of ben-

[16] Again, we report results for the variable $Female$ separately, as gender information is not available for all analysts.

efits can this visibility actually bring to analysts? As discussed in Section 2, investors and employers are the two primary audiences of an analyst's LinkedIn profile. It is reasonable to conjecture that self-promotion is aimed at shaping perceptions among these two groups, either to attract investor attention or to improve career prospects.

In this section, we focus on the investor side and investigate whether and how market participants respond to analysts' self-presentations. Specifically, we examine whether the tone conveyed influences the market reaction to analysts' forecast revisions and stock recommendations. To test this, we employ the regression model outlined below:

$$\begin{aligned} CAR_{ijtk}^{s_1 s_2} = \beta_0 + \beta_1 \times HighTone_i + \beta_2 \times Revision_{ijkt} \\ + \beta_3 \times HighTone_i \times Revision_{ijkt} + \mathbf{\Gamma} \times \mathbf{X}_{ijtk} + \mathbf{Y}_{ijtk} + \epsilon_{ijtk}. \end{aligned} \tag{7}$$

Here, $CAR_{ijtk}^{s_1 s_2}$ represents the cumulative Carhart's four-factor adjusted abnormal return within the $[s_1, s_2]$-day window surrounding analyst i's k-th recommendation for firm j's stock in year t, sourced from the WRDS Event Study database. $Revision_{ijkt}$ is calculated as the difference between the analyst's k-th forecast and the $(k-1)$-th forecast, scaled by the $(k-1)$-th forecast. Observations exclude the first forecast of each firm in a fiscal year and are classified as upward revisions when $Revision_{ijtk} > 0$ and downward revisions otherwise (including unchanged forecasts).

Panel A of Table 10 reports the regression results on market reactions to forecast revisions, conditional on analysts' self-presentation tone. Columns (1) to (4) focus on the subsample of upward revisions, while columns (5) to (8) analyze downward revisions. As shown, the coefficient for the interaction term is positive and significant for upward revisions across all time windows. This suggests that among analysts with more positive self-presentations, the larger the magnitude of their upward forecast revisions, the stronger the market responses. In contrast, the interaction term is insignificant for downward revisions, suggesting that market reactions are not significantly associated with analysts' self-presentation tone when

forecasts are adjusted downward.

This asymmetry in investor reactions highlights the market's stronger response to positive signals from high-tone analysts and its weaker reaction to their negative outlooks. Similarly, we examine market reactions to analysts' stock recommendations, another channel through which analysts express views on stocks. Results in Panel B of Table 10 further validate this pattern. In these regressions, *Revision* is replaced by *Recommendation*, which is coded as follows: for positive recommendations, it equals 0 for *Buy* and 1 for *Strong Buy*; for negative recommendations, it equals 0 for *Hold*, -1 for *Underperform*, and -2 for *Sell*.

6.2 Possible Explanations

It is intriguing to consider why this phenomenon exists. The literature has well established that revisions or recommendations by analysts with higher forecast accuracy, such as geographically or culturally proximate analysts, typically elicit stronger market reactions (Malloy, 2005; Du et al., 2017; Hao et al., 2025). However, our findings reveal a seemingly paradoxical pattern: high-tone analysts, despite their lower forecast accuracy, generate stronger market reactions to the positive signals they issue. This divergence suggests the presence of two underlying behavioral biases.

First, high-tone analysts with poorer forecast accuracy elicit stronger market reactions. This can be attributed to the strategic self-promotion conveyed through the positive tone of their self-descriptions, which effectively enhances their visibility and captures investors' attention. Despite their lower reliability, investors constrained by limited attention may still follow them and struggle to recognize their inaccuracies in the short term.

Second, the market responds strongly to positive signals from high-tone analysts but largely disregards negative signals. A plausible explanation is that the investors drawn to high-tone analysts are often unsophisticated and exhibit behavioral biases, such as confirmation bias and optimism preference. These biases not only make them more likely to trust high-tone analysts but also amplify their sensitivity to favorable signals.

We aim to provide further empirical evidence to support these two explanations. First, we analyze the long-term impact of analysts' self-presentation tone on market reactions. If these biases are driven by short-term attention distortions, we would expect the effect to diminish or disappear as investors' attention normalizes over time. Consistent with this, in Table 11 we find that the stronger market reactions caused by high-tone analysts issuing positive signals, whether upward earnings revisions or buy recommendations, gradually weaken in the long run and completely disappear after 90 days. This pattern suggests that the observed investor biases are likely driven by temporary attention distortions rather than fundamental reassessments of firm value.

Second, the heterogeneity analysis in Table 12 demonstrates that the effect is more pronounced among firms with smaller size or lower MB ratios (classified using the annual median values of the sample). On the one hand, smaller size and lower MB ratio firms often attract more unsophisticated investors, who usually has optimism preference and attention is more likely be distorted by high-tone analysts (Barber and Odean, 2008; Kumar, 2009).[17] On the other hand, these firms are typically characterized by lower liquidity and are more difficult to arbitrage, which limits the ability of sophisticated investors to correct mispricing in a timely manner. Consequently, positive signals from high-tone analysts not only cater to investors' optimism preference and confirmation bias, but also interacts with market frictions to lead to disproportionate and irrational market reactions.

Collectively, we argue that the key driver of this phenomenon is the positive tone of signals issued by high-tone analysts, which effectively captures investor attention. Behavioral biases, such as confirmation bias and optimism preference, further amplify this effect and create an asymmetry in market reactions. This pattern is consistent with the so-called *Mad Money effect* previously observed in the U.S. market, where stock recommendations by television host Jim Cramer generate large overnight returns that gradually reverse over sub-

[17]Barber and Odean (2008) propose that individual investors are net buyers of attention-grabbing stocks. Their attention is more easily influenced when searching for stocks to buy, whereas they do not face the same search problem when deciding to sell. This aligns with our findings that positive signals from high-tone analysts disproportionately attract investor attention and drive stronger market reactions.

sequent months, while sell recommendations exhibit relatively weak price effects (Engelberg et al., 2012).[18] In this sense, our findings also validate the notion that investors, especially individual investors, pay attention to analysts' LinkedIn profiles (see our discussions in Section 2). We conclude that analysts' self-promotion behavior distorts market in the short term and constitutes another form of media-induced mispricing.

6.3 Impression-Based vs. Information-Based Sentiment

It is interesting to note that in the literature, Huang et al. (2014) find that investors react more strongly to negative than to positive text in analyst reports. While this pattern appears to contrast sharply with our findings, we believe this discrepancy highlights the fundamental differences between the two contents and the ways investors interpret them. As discussed in Huang et al. (2014), analyst report text is directly tied to the fundamentals of stocks and is often viewed by the market as a critical source of information. Negative signals in analyst reports are particularly scarce and tend to be interpreted as important warning signs, therefore resulting in abnormal market reactions.[19] Moreover, the primary audience for analyst reports consists of institutional investors, who are generally more sophisticated and more attuned to downside risks. Their heightened sensitivity to negative information may further amplify market reactions to pessimistic tones in formal reports.

In contrast, the tone expressed in analysts' self-descriptions on LinkedIn does not directly influence market through assessments of stock fundamentals. Rather, it functions as a form of impression management and shapes investors' perceptions of the analysts themselves. Positive tone in such self-presentations primarily serves to attract investor attention and foster short-term trust in the analysts' viewpoints, as discussed. Individual investors, rather

[18] Jim Cramer is a former hedge fund manager who began hosting CNBC's financial television show *Mad Money* in 2005. In each episode, he highlights several stocks as attractive buys, often with highly enthusiastic commentary. The show draws significant attention from individual investors, and his recommendations tend to trigger short-term speculative buying, although the resulting price increases are typically not sustained. Engelberg et al. (2012) conduct a detailed analysis and offer behavioral explanations.

[19] Analysts often adopt more conservative opinions or remain silent during periods of pessimism (Trueman, 1994; Hong et al., 2000), due to concerns about career and reputation. This tendency makes negative signals in analyst reports relatively rare, which enhances their perceived importance in identifying potential risks.

than institutional investors, are more susceptible to these impression-based tone and are more likely to exhibit behavioral biases in response to positive signals. As shown, the influence of impression-based tone is short-lived, whereas the impact of information-based sentiment conveyed through analyst reports may persist for several years (Huang et al., 2014).[20]

7 Employer Interpretation of Analyst Self-Promotion

While we have shown that investors respond positively to analysts' self-presentation tone intensity, how do potential employers, another key audience on the LinkedIn platform, interpret such self-promotion? According to Smith and Kidder (2010), many employers use social media in their hiring decisions. Even among recruiters who do not directly employ LinkedIn-based screening, we can reasonably infer that analysts' self-presentation in other personal websites or application materials (e.g., cover letters) would similarly exhibit high-tone characteristics. Compared to market reactions, employment outcomes arguably have a more direct and lasting impact on analysts' personal career returns.

Theoretically, if employers are rational and base their hiring decisions on analysts' actual skill, we would expect those with stronger past performance to enjoy better career opportunities. However, if we find that high-tone analysts, usually associated with lower accuracy, are more likely to transition to better jobs, it would suggest that employers, like investors, are not fully rational and also influenced by analysts' impression management.

In this subsection, we study whether and how the tone of analysts' self-presentations on LinkedIn profiles are associated with their career trajectories. First, based on LinkedIn profiles, we calculate the total number of career experiences for each analyst. We find a significant positive correlation between the number of career experiences and the tone intensity of self-descriptions. This relationship remains robust after controlling for analysts'

[20] As noted in studies such as Huang et al. (2014) and Ke (2024), the textual content of analyst reports can be obtained through the Investext database. Future research with access to this resource could incorporate the sentiment extracted from analyst reports as a control variable to further test the robustness of the *tone-performance inverse effect* documented in this paper.

common characteristics. For high-tone analysts, the average number of career experiences is 6, compared to 4.7 for low-tone analysts. A t-test confirms that this difference is statistically significant at the 1% level (t-value = 4.87).

This finding may be interpreted as evidence that impression management through positive self-presentations do help analysts attract employers and secure more career opportunities. Alternatively, since high-tone analysts tend to have lower forecast accuracy, frequent job transitions may reflect involuntary turnover due to underperformance rather than upward mobility. The distinction depends on whether these transitions are driven primarily by promotions or terminations.

Although LinkedIn profiles offer comprehensive records of analysts' career histories, it is difficult to standardize and quantify the seniority level of each role, making it challenging to determine whether a given job transition represents a promotion or a demotion. To address this issue, we turn to the I/B/E/S database and use two proxies to capture the size and quality of a brokerage in a given year: the total number of analysts employed ($Bsize$) and the average forecast accuracy of the firm ($Baccuracy$). For each analyst i in year t, we define a job transition as occurring when the brokerage firm in year t differs from that in year $t-1$, i.e., $Moved_{it} = 1$, and 0 otherwise. Conditional on a job change, we define $BsizeUp_{it} = 1$ if the analyst moves to a brokerage with a larger analyst team, and $BaccuracyUp_{it} = 1$ if the analyst moves to a brokerage with higher average forecast accuracy.

For each analyst, we then compute the total number of job transitions ($TotalMoved$), the number of upward transitions in size ($TotalBsizeUp$), and in quality ($TotalBaccuracyUp$). Finally, we define two measures:

$$RatioBsizeUp = \frac{TotalBsizeUp}{TotalMoved}, \quad RatioBaccuracyUp = \frac{TotalBaccuracyUp}{TotalMoved}, \tag{8}$$

which represent the proportion of job transitions that are upward in terms of brokerage size and quality, respectively.

Among the 727 analysts in our sample, 432 experienced at least one job transition, allowing the two upward mobility ratios to be defined.[21] We classify analysts into high- and low-tone groups based on the median tone score, and into high- and low-accuracy groups based on mean forecast accuracy. Table 13 reports the average values of the two ratios across these groups. Interestingly, analysts with low accuracy but high self-presentation tone consistently exhibit the highest rates of upward career transitions, both in terms of brokerage size and forecast quality. This suggests that self-promotion can indeed help underperforming analysts secure more favorable job opportunities.

However, for high-accuracy analysts, a strong self-presentation tone does not appear to provide additional benefits and may even be associated with worse outcomes. Surprisingly, analysts with both high forecast accuracy and high self-presentation tone consistently exhibit the lowest promotion rates. This counterintuitive pattern warrants future investigation. One possible explanation is that supervisors may be less inclined to promote highly competent individuals who are also overtly self-promotional, as such individuals may be perceived as threatening to the leadership. Another potential explanation is adverse selection: these analysts, despite their strong track records, might face hidden barriers to promotion and thus resort to elevated self-presentation tone as a compensatory job-seeking strategy. Overall, this asymmetric role of self-presentation tone suggests that self-promotion may function more effectively as a compensatory mechanism rather than an amplifying signal. For analysts with objectively strong performance, their ability may speak for itself, rendering impression management unnecessary or even counterproductive.

8 Conclusion

To summarize, this study uncovers a robust negative correlation between analysts' self-presentation tone on LinkedIn profiles and their forecast accuracy, a phenomenon we term

[21] Here the analysis is based on the full historical records from I/B/E/S. If we restrict the sample to job transitions between 2021 and 2023, the conclusion remains robust: analysts with high tone and low accuracy are consistently the most likely to experience upward transitions.

the *tone-performance inverse effect*. We reveal that this effect is driven not by behavioral biases, such as optimism or overconfidence, but by deliberate impression management aimed at enhancing visibility and perceived competence in a competitive labor market.

Furthermore, we show that analysts' optimistic self-presentation not only correlates with weak performance but also contributes to market mispricing, resembling the *Mad Money effect*. Market reactions show stronger excess returns for high-tone analysts' upward revisions and positive ratings, with no similar effect for negative signals, highlighting the role of sentiment-driven heuristics in short-term pricing distortions.

Surprisingly, we find that analysts with low forecast accuracy but high self-presentation tone experience the highest rates of upward career transitions. This indicates that self-promotion can indeed help underperforming analysts secure more favorable job opportunities. For employers, we stress the importance of evaluating professions based on their verifiable professional track records rather than on self-framed impressions.

While we shed light on the unintended consequences of impression management in financial markets, this study has a key limitation: while the documented *tone-performance inverse effect* suggests a plausible interpretation rooted in strategic self-promotion, it does not establish any causal relationship. Since our analysis is based on a single time point of LinkedIn profile data, we are unable to capture how analysts' self-descriptions evolve over time. Additionally, unlike Exley and Kessler (2022), we cannot replicate a controlled experimental setting. Future research should aim to identify causal mechanisms and explore the dynamic evolution of self-promotion behaviors.

Moreover, future research could also investigate the impression management behavior among other professionals, such as fund managers. Prior studies reveal a mismatch between skill and scale in actively managed mutual funds (Song, 2020), and show that investors often rely on simple signals rather than learning about managers' true ability (Ben-David et al., 2022). Another promising direction is to develop more precise and systematic methods for identifying impression management behaviors. Although we present some preliminary

evidence, further progress in NLP and LLMs may help uncover subtle patterns in professional communications, deepening our understanding of their broader implications for financial markets and organizational behavior.

References

Bae, K.-H., Stulz, R. M., and Tan, H. (2008). Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. *Journal of Financial Economics*, 88(3):581–606.

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2):129–151.

Barber, B. M. and Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, 116(1):261–292.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2):785–818.

Ben-David, I., Li, J., Rossi, A., and Song, Y. (2022). What do mutual fund investors really care about? *The Review of Financial Studies*, 35(4):1723–1774.

Bolino, M., Long, D., and Turnley, W. (2016). Impression management in organizations: Critical questions, answers, and areas for future research. *Annual Review of Organizational Psychology and Organizational Behavior*, 3(1):377–406.

Bolino, M. C., Kacmar, K. M., Turnley, W. H., and Gilstrap, J. B. (2008). A multi-level review of impression management motives and behaviors. *Journal of Management*, 34(6):1080–1109.

Bradley, D., Gokkaya, S., and Liu, X. (2017). Before an analyst becomes an analyst: Does industry experience matter? *The Journal of Finance*, 72(2):751–792.

Bradley, D., Gokkaya, S., and Liu, X. (2020). Ties that bind: The value of professional connections to sell-side analysts. *Management Science*, 66(9):4118–4151.

Brauer, M. and Wiersema, M. (2018). Analyzing analyst research: A review of past coverage and recommendations for future research. *Journal of Management*, 44(1):218–248.

Brown, L. D., Call, A. C., Clement, M. B., and Sharp, N. Y. (2015). Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research*, 53(1):1–47.

Butler, K. C. and Lang, L. H. (1991). The forecast accuracy of individual analysts: Evidence of systematic optimism and pessimism. *Journal of Accounting Research*, pages 150–156.

Chen, H. and Hwang, B.-H. (2022). Listening in on investors' thoughts and conversations. *Journal of Financial Economics*, 145(2):426–444.

Chen, J., Tang, G., Zhou, G., and Zhu, W. (2025). ChatGPT and deepseek: Can they predict the stock market and macroeconomy? *arXiv preprint arXiv:2502.10008*.

Cheng, Q., Chen, X., Lin, A.-P., and Wang, K. (2021). A star is born: Star analyst voting and analyst research. *Available at SSRN 3875973: https://ssrn.com/abstract=3875973*.

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics*, 27(3):285–303.

Clement, M. B. and Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *The Journal of Finance*, 60(1):307–341.

Cohen, L., Frazzini, A., and Malloy, C. (2010). Sell-side school ties. *The Journal of Finance*, 65(4):1409–1437.

Cowen, A., Groysberg, B., and Healy, P. (2006). Which types of analyst firms are more optimistic? *Journal of Accounting and Economics*, 41(1-2):119–146.

Cuculiza, C., Antoniou, C., Kumar, A., and Maligkris, A. (2021). Terrorist attacks, analyst sentiment, and earnings forecasts. *Management Science*, 67(4):2579–2608.

Da, Z., Engelberg, J., and Gao, P. (2015). The sum of all fears investor sentiment and asset prices. *The Review of Financial Studies*, 28(1):1–32.

Das, S., Levine, C. B., and Sivaramakrishnan, K. (1998). Earnings predictability and bias in analysts' earnings forecasts. *The Accounting Review*, pages 277–294.

Den Hartog, D. N., De Hoogh, A. H., and Belschak, F. D. (2020). Toot your own horn? Leader narcissism and the effectiveness of employee self-promotion. *Journal of Management*, 46(2):261–286.

Du, Q., Yu, F., and Yu, X. (2017). Cultural proximity and the processing of financial information. *Journal of Financial and Quantitative Analysis*, 52(6):2703–2726.

Engelberg, J., Sasseville, C., and Williams, J. (2012). Market madness? The case of Mad Money. *Management Science*, 58(2):351–364.

Ertimur, Y., Mayew, W. J., and Stubben, S. R. (2011). Analyst reputation and the issuance of disaggregated earnings forecasts to I/B/E/S. *Review of Accounting Studies*, 16:29–58.

Exley, C. L. and Kessler, J. B. (2022). The gender gap in self-promotion. *The Quarterly Journal of Economics*, 137(3):1345–1381.

Fang, L. H. and Huang, S. (2017). Gender and connections among wall street analysts. *The Review of Financial Studies*, 30(9):3305–3335.

Fang, L. H. and Yasuda, A. (2009). The effectiveness of reputation as a disciplinary mechanism in sell-side research. *The Review of Financial Studies*, 22(9):3735–3777.

Fang, L. H. and Yasuda, A. (2014). Are stars' opinions worth more? The relation between analyst reputation and recommendation values. *Journal of Financial Services Research*, 46:235–269.

Hao, H., Liu, C., and Pang, S. (2025). Geographical proximity, cultural familiarity and financial information production. *Journal of Empirical Finance*, 80:101576.

Harris, K. J., Kacmar, K. M., Zivnuska, S., and Shaw, J. D. (2007). The impact of political skill on impression management effectiveness. *Journal of Applied Psychology*, 92(1):278.

Harvey, J.-F. (2024). Self-promotion in entrepreneurship: A driver for proactive adaptation. *Journal of Applied Psychology*.

Hong, H., Kubik, J. D., and Solomon, A. (2000). Security analysts' career concerns and herding of earnings forecasts. *The Rand Journal of Economics*, pages 121–144.

Hu, A. and Ma, S. (2021). Persuading investors: A video-based study. Technical report, National Bureau of Economic Research.

Huang, A. H., Zang, A. Y., and Zheng, R. (2014). Evidence on the information content of text in analyst reports. *The Accounting Review*, 89(6):2151–2180.

Huang, J. and Kisgen, D. J. (2013). Gender and corporate finance: Are male executives overconfident relative to female executives? *Journal of Financial Economics*, 108(3):822–839.

Jackson, A. R. (2005). Trade generation, reputation, and sell-side analysts. *The Journal of Finance*, 60(2):673–717.

Jha, M., Qian, J., Weber, M., and Yang, B. (2024). ChatGPT and corporate policies. Technical report, National Bureau of Economic Research.

Jones, E. (1982). Toward a general theory of strategic self presentation. *Psychological Perspectives on the Self/Erlbaum*.

Ke, S. (2024). Analysts' belief formation in their own words. *Available at SSRN 5025830*.

Kothari, S. P., So, E., and Verdi, R. (2016). Analysts' forecasts and asset pricing: A survey. *Annual Review of Financial Economics*, 8(1):197–219.

Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance*, 64(4):1889–1933.

Leary, M. R. and Kowalski, R. M. (1990). Impression management: A literature review and two-component model. *Psychological Bulletin*, 107(1):34.

Li, C., Lin, A.-P., and Lu, H. (2023). The effect of social skills on analyst performance. *Contemporary Accounting Research*, 40(2):1418–1447.

Liu, C. and Pang, S. (2024). Analyst-peer alumni tie. *Available at SSRN 5010875: https://ssrn.com/abstract=5010875*.

Loughran, T. and McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, 66(1):35–65.

Malloy, C. J. (2005). The geography of equity analysis. *The Journal of Finance*, 60(2):719–755.

Sautner, Z., van Lent, L., Vilkov, G., and Zhang, R. (2024). Climate value and values discovery. *Available at SSRN 4596668: https://ssrn.com/abstract=4596668*.

Scharfstein, D. S. and Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, pages 465–479.

Schlenker, B. R. (1980). *Impression Management*, volume 526. Monterey, CA: Brooks/Cole.

Smith, W. P. and Kidder, D. L. (2010). You've been tagged! (Then again, maybe not): Employers and Facebook. *Business Horizons*, 53(5):491–499.

Song, Y. (2020). The mismatch between mutual fund scale and skill. *The Journal of Finance*, 75(5):2555–2589.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2):288–302.

Stevens, C. K. and Kristof, A. L. (1995). Making the right impression: A field study of applicant impression management during job interviews. *Journal of Applied Psychology*, 80(5):587.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3):1139–1168.

Trueman, B. (1994). Analyst forecasts and herding behavior. *The Review of Financial Studies*, 7(1):97–124.

Zhang, R. (2022). Language commonality and sell-side information production. *Management Science*, 68(6):4435–4453.

Figure

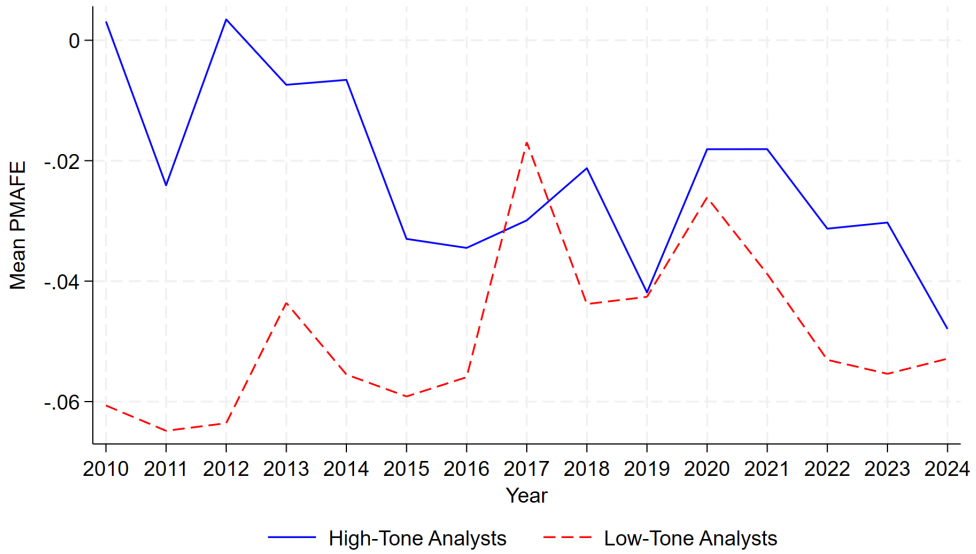

Figure 1: Analyst Self-Presentation Tone and Forecast Accuracy (2010-2024)

Tables

Table 1: List of Variables

Variable Name	Variable Definition
Panel A: Explained Variables	
$PMAFE_{ijtk}$	Relative accuracy of analyst i's k-th forecast of firm j in fiscal year t.
$Range_{ijtk}$	Deviation range of analyst i's k-th forecast of firm j in fiscal year t.
Panel B: Explanatory Variables	
$Tone_i$	The polarity score of analyst i's self-description.
$HighTone_i$	Dummy variable that equals to 1 if $Tone_i$ is over the median level, and 0 otherwise.
Panel C: Control Variables	
$Length_i$	The text length of analyst i's self-description.
$Subjectivity_i$	The subjectivity score of analyst i's self-description.
$Female_i$	Dummy variable that equals to 1 if analyst i is a female.
Sem_i	Dummy variable that equals to 1 if analyst i has a degree in economics, finance or management.
$BSem_i$	Dummy variable that equals to 1 if analyst i has a bachelor's degree in economics, finance or management.
$Master_i$	Dummy variable that equals to 1 if analyst i has a master's degree.
PhD_i	Dummy variable that equals to 1 if analyst i has a doctoral degree.
$Follower_i$	The number of analyst i's LinkedIn followers, measured in thousands.
$Connection_i$	The number of analyst i's LinkedIn connections, measured in thousands.
$Horizon_{ijtk}$	Time span in years between the announcement date of analyst i's k-th forecast and firm j's earnings disclosure date in fiscal year t.
$Order_{ijtk}$	The sequence number of the revision made by analyst i for firm j in fiscal year t, where k represents the specific revision order.
$Workexp_{ijtk}$	Time span in years between analyst i's first forecast in I/B/E/S and the current forecast.
$Firmexp_{ijtk}$	Time span in years between analyst i's first forecast for the specific firm j in I/B/E/S and the current forecast.
$Aforecast_{it}$	Number of forecasts analyst i provides in year t.
$Afirm_{it}$	Number of firms analyst i covers in year t.
$Bsize_{it}$	Number of analysts working for the brokerage in I/B/E/S that analyst i is associate with in year t.
$Bfirmexp_{ijtk}$	Time span in years between analyst i's affiliated brokerage's first forecast for the specific firm j in I/B/E/S and the current forecast.
$Fanalyst_{jt}$	Number of analysts firm j is covered by in fiscal year t.
$Fforecast_{jt}$	Number of times firm j is predicted in fiscal year t.
$Fbroker_{jt}$	Number of brokerages firm j is covered by in fiscal year t.
$Size_{jt}$	Natural logarithm of firm j's total market value in fiscal year t.
MB_{jt}	Ratio of firm j's market-to-book value of equity in fiscal year t.
$Leverage_{jt}$	Ratio of firm j's total liabilities to its total assets in fiscal year t.

Note. This table provides definitions of the explained, explanatory, and control variables. All continuous variables are winsorized at the 1% level by year.

Table 2: Summary Statistics

	N	Mean	S.D.	Min	Median	Max
$PMAFE$	87,427	-0.04	0.75	-1	-0.17	3.03
$Range$	87,427	0.69	0.29	0	0.78	1
$Tone$	87,427	0.12	0.14	-0.29	0.10	0.80
$HighTone$	87,427	0.48	0.50	0	0	1
$Length$	87,427	77.49	49.47	20	59	273
$Subjectivity$	87,427	0.32	0.17	0	0.33	1
$Female$	70,615	0.11	0.31	0	0	1
$Master$	87,427	0.60	0.49	0	1	1
PhD	87,427	0.04	0.19	0	0	1
Sem	87,427	0.72	0.45	0	1	1
$BSem$	87,427	0.48	0.50	0	0	1
$Follower$	87,427	1.37	1.38	0.03	1.08	42.45
$Connection$	87,427	0.47	0.09	0.03	0.50	0.50
$Horizon$	87,427	0.50	0.26	0	0.45	0.99
$Order$	87,427	3.08	2.02	1	3	22
$Workexp$	87,427	15.12	10.44	0	13.31	40.74
$Firmexp$	87,427	5.21	5.62	0	3.20	40.62
$Aforecast$	87,427	106.48	53.35	1	99	332
$Afirm$	87,427	23.27	9.83	1	22	72
$Bsize$	87,427	71.45	60.73	1	58	242
$Bfirmexp$	87,427	8.57	9.32	0	5.18	41.01
$Fanalyst$	87,427	16.76	10.70	2	15	65
$Fforecast$	87,427	76.26	53.76	2	63	295
$Fbroker$	87,427	15.89	10.07	1	14	59
$Size$	81,915	8.74	2.00	3.78	8.77	15.02
MB	81,915	1.95	2.19	0.06	1.20	14.49
$Leverage$	87,240	0.63	0.27	0.07	0.63	1.56

Note. This table provides summary statistics of the explained, explanatory, and control variables. All continuous variables are winsorized at the 1% level by year.

Table 3: Self-Presentation Tone and Forecast Accuracy

	$PMAFE$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tone	0.1398***	0.1405***	0.1645***	0.1570***	0.2174***	0.2186***	0.2198***	0.1791***
	(0.0424)	(0.0431)	(0.0546)	(0.0564)	(0.0658)	(0.0666)	(0.0783)	(0.0640)
Length						-0.0002	-0.0002	-0.0001
						(0.0002)	(0.0002)	(0.0002)
Subjectivity							-0.0020	0.0101
							(0.0509)	(0.0441)
Female			0.0500***	0.0621***	0.0630***	0.0619***	0.0620***	
			(0.0185)	(0.0199)	(0.0238)	(0.0237)	(0.0238)	
Master			0.0038	0.0136	0.0136	0.0117	0.0118	0.0183
			(0.0137)	(0.0131)	(0.0166)	(0.0166)	(0.0166)	(0.0136)
PhD			-0.0231	0.0040	0.0338	0.0371	0.0371	0.0017
			(0.0266)	(0.0249)	(0.0407)	(0.0410)	(0.0410)	(0.0392)
Sem			0.0233	0.0251	0.0261	0.0271	0.0270	0.0237
			(0.0207)	(0.0238)	(0.0295)	(0.0301)	(0.0296)	(0.0230)
BSem			-0.0349	-0.0443*	-0.0503*	-0.0513*	-0.0511*	-0.0450**
			(0.0218)	(0.0237)	(0.0289)	(0.0294)	(0.0286)	(0.0201)
Follower			0.0023	0.0086*	0.0089	0.0102	0.0102	0.0061
			(0.0054)	(0.0047)	(0.0068)	(0.0065)	(0.0065)	(0.0054)
Connection			0.1360*	0.1204*	0.1705*	0.1622*	0.1619*	0.1321**
			(0.0721)	(0.0708)	(0.0924)	(0.0894)	(0.0890)	(0.0641)
Horizon	1.2552***	1.2423***	1.2268***	1.2469***	1.2493***	1.2492***	1.2491***	1.2614***
	(0.0304)	(0.0304)	(0.0328)	(0.0334)	(0.0366)	(0.0366)	(0.0367)	(0.0333)
Order	-0.0199***	-0.0227***	-0.0230***	-0.0262***	-0.0269***	-0.0270***	-0.0270***	-0.0262***
	(0.0037)	(0.0038)	(0.0042)	(0.0046)	(0.0053)	(0.0053)	(0.0053)	(0.0046)
Workexp		0.0000	0.0005	0.0007	0.0008	0.0010	0.0010	0.0008
		(0.0006)	(0.0007)	(0.0006)	(0.0008)	(0.0009)	(0.0009)	(0.0007)
Firmexp		-0.0026***	-0.0033***	-0.0027**	-0.0028**	-0.0027**	-0.0027**	-0.0023**
		(0.0010)	(0.0011)	(0.0011)	(0.0014)	(0.0013)	(0.0013)	(0.0011)
Aforecast		0.0006***	0.0007***	0.0006**	0.0007**	0.0007**	0.0007**	0.0004*
		(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Afirm		-0.0015	-0.0025**	-0.0023**	-0.0024**	-0.0023**	-0.0023**	-0.0010
		(0.0009)	(0.0010)	(0.0010)	(0.0012)	(0.0012)	(0.0011)	(0.0008)
Bsize		-0.0000	0.0000	-0.0000	0.0003	0.0003	0.0003	-0.0000
		(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Bfirmexp		-0.0014***	-0.0012**	-0.0005	-0.0002	-0.0001	-0.0001	-0.0003
		(0.0005)	(0.0006)	(0.0007)	(0.0010)	(0.0010)	(0.0010)	(0.0008)
Fanalyst				-0.0036	-0.0055	-0.0054	-0.0054	-0.0029
				(0.0034)	(0.0040)	(0.0040)	(0.0040)	(0.0036)
Fforecast				0.0014***	0.0010*	0.0010*	0.0010*	0.0010**
				(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
Fbroker				-0.0035	0.0016	0.0015	0.0015	-0.0020
				(0.0042)	(0.0052)	(0.0052)	(0.0052)	(0.0046)
Size				-0.0187***	-0.0013	-0.0010	-0.0010	-0.0042
				(0.0044)	(0.0138)	(0.0138)	(0.0138)	(0.0122)
MB				0.0079***	0.0048	0.0049	0.0049	0.0058
				(0.0024)	(0.0053)	(0.0053)	(0.0053)	(0.0045)
Leverage				-0.0045	0.0166	0.0156	0.0156	-0.0151
				(0.0193)	(0.0603)	(0.0604)	(0.0604)	(0.0511)
Constant	-0.6167***	-0.6010***	-0.6669***	-0.5168***	-0.7554***	-0.7404***	-0.7399***	-0.6614***
	(0.0223)	(0.0473)	(0.0584)	(0.0693)	(0.1584)	(0.1532)	(0.1513)	(0.1358)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Brokerage FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	Y	Y	Y	Y	Y
Firm FE	N	N	N	N	Y	Y	Y	Y
Observations	87,424	87,424	70,611	66,014	65,906	65,906	65,906	81,624
Adjusted R^2	0.225	0.226	0.221	0.229	0.256	0.256	0.256	0.257

Note. This table presents the regression results based on model (5), which examines the impact of analysts' self-presentation tone on their forecast performance. The dependent variable is the performance indicator $PMAFE$, and the key explanatory variable is the sentiment score *Tone* derived from analysts' LinkedIn profile self-descriptions. Control variables are specified in Table 1, and fixed effects are applied at the year, quarter, brokerage, industry, and firm levels. Standard errors are double-clustered at the analyst and firm levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Self-Presentation Tone and Forecast Accuracy (Continued)

	Full Sample		First Forecast Sample			Last Forecast Sample		
	PMAFE	*Range*	*PMAFE*		*Range*	*PMAFE*		*Range*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tone		0.0616***	0.2174***			0.1541**		
		(0.0183)	(0.0644)			(0.0685)		
HighTone	0.0393***			0.0465***	0.0133**		0.0348**	0.0120**
	(0.0148)			(0.0169)	(0.0054)		(0.0174)	(0.0055)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	65,906	65,906	16,201	16,201	16,201	16,199	16,199	16,199
Adjusted R^2	0.255	0.329	0.187	0.186	0.295	0.228	0.228	0.282

Notes. This table examines the robustness of the relationship between analysts' self-presentation tone and their forecast performance. The dependent variables are the performance indicators *PMAFE* and *Range*, while the key explanatory variables are *Tone* and *HighTone*. Control variables are detailed in Table 1, and fixed effects are included at the year, quarter, brokerage, industry, and firm levels to account for unobserved heterogeneity. For brevity, coefficient estimates for control variables are omitted. Standard errors are double-clustered at the analyst and firm levels and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Heterogeneity Analysis of Self-Presentation Tone and Forecast Accuracy

	$PMAFE$									
	Male	Female	Bachelor SEM	Non Bachelor SEM	More Followers	Fewer Followers	More Experienced	Less Experienced	Larger Brokerage	Smaller Brokerage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tone	0.2294***	0.3578	0.0744	0.4450***	0.2567***	0.4763***	0.1756*	0.2129**	0.1678	0.2173***
	(0.0715)	(0.5397)	(0.0732)	(0.1035)	(0.0756)	(0.1288)	(0.1061)	(0.0876)	(0.1046)	(0.0597)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	58,913	6,953	32,255	33,508	38,768	27,015	33,165	32,575	30,582	35,204
Adjusted R^2	0.258	0.282	0.297	0.270	0.268	0.296	0.290	0.278	0.274	0.267

Notes. This table presents the regression results for the heterogeneity analysis of the impact of analysts' self-presentation tone on forecast performance. The dependent variable is the performance indicator $PMAFE$, and the key explanatory variable is the sentiment score $Tone$. Control variables are specified in Table 1, and fixed effects are applied at the year, quarter, brokerage, industry, and firm levels. Standard errors are double-clustered at the analyst and firm levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Self-Presentation Tone and Optimism Bias

Panel A	*Optimism*									
	Full Sample		Larger Size	Smaller Size	Higher MB	Lower MB	First Forecast Sample		Last Forecast Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tone	0.0113***	0.0006	-0.0007	0.0135**	0.0022	0.0196***	0.0135**	-0.0012	0.0019	-0.0020
	(0.0042)	(0.0028)	(0.0019)	(0.0067)	(0.0024)	(0.0070)	(0.0062)	(0.0036)	(0.0038)	(0.0039)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	N	N	N	N	Y	N	Y
Other FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	66,014	65,906	32,359	33,649	32,646	33,361	16,590	16,201	16,590	16,199
Adjusted R^2	0.114	0.437	0.115	0.145	0.0417	0.188	0.122	0.421	0.0684	0.339
Panel B	*PMAFE*									
	Full Sample		Larger Size		Smaller Size		Higher MB		Lower MB	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tone	0.2174***	0.2171***	0.2980***	0.2974***	0.0964	0.0963	0.2653***	0.2652***	0.1162*	0.1149*
	(0.0658)	(0.0659)	(0.0994)	(0.0990)	(0.0626)	(0.0622)	(0.0964)	(0.0962)	(0.0636)	(0.0635)
Optimism		0.5219***		-0.5577		0.6856***		-0.0155		0.6453***
		(0.1467)		(0.9447)		(0.1361)		(0.6576)		(0.1503)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	65,906	65,906	32,348	32,348	33,548	33,548	32,579	32,579	33,288	33,288
Adjusted R^2	0.256	0.257	0.290	0.290	0.227	0.231	0.265	0.265	0.252	0.255

Notes. Panel A of this table presents the regression results for the relationship between analysts' self-presentation tone and optimism biases in forecasts. The dependent variable is the optimism indicator *Optimism*, and the key explanatory variable is the sentiment score *Tone*. Panel B incorporates *Optimism* as a control variable to reassess the impact of analysts' self-presentation tone on forecast performance. In both panels, control variables are specified in Table 1, and fixed effects are applied at the year, quarter, brokerage, industry, and firm levels. Standard errors are double-clustered at the analyst and firm levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Self-Presentation Tone and Herding Behavior

	Bold		*PMAFE*			
	Full Sample	Last Forecast Sample	Full Sample		Last Forecast Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Tone	-0.0370*	-0.0723*	0.2174***	0.2157***	0.1541**	0.1517**
	(0.0213)	(0.0387)	(0.0658)	(0.0657)	(0.0685)	(0.0683)
Bold				-0.0458***		-0.0330**
				(0.0086)		(0.0134)
Controls	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	65,906	16,199	65,906	65,906	16,199	16,199
Adjusted R^2	0.259	0.222	0.256	0.256	0.228	0.229

Notes. This table presents the regression results for the relationship between analysts' self-presentation tone and herding behavior. The dependent variables are *Bold* and *PMAFE*, and the explanatory variables are *Tone* and *Bold*. Control variables are specified in Table 1, and fixed effects are applied at the year, quarter, brokerage, industry, and firm levels. Standard errors are double-clustered at the analyst and firm levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Robustness Analysis of Self-Presentation Tone and Forecast Accuracy

	Extended Forecast Period (2010-2024)				GPT Based Identification			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tone	0.1272***		0.0655**			0.2026***		
	(0.0414)		(0.0287)			(0.0727)		
HighTone		0.0258***		0.0153*				0.0325**
		(0.0094)		(0.0083)				(0.0153)
GPTTone					0.0486***	0.0172		
					(0.0185)	(0.0214)		
HighGPTTone							0.0314**	0.0195
							(0.0132)	(0.0135)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	228,049	228,049	351,043	351,043	65,906	65,906	65,906	65,906
Adjusted R^2	0.232	0.232	0.220	0.220	0.255	0.256	0.255	0.255

Notes. This table examines the robustness of the relationship between analysts' self-presentation tone and their forecast performance. In columns (1) to (4), we include analyst all forecasts during the extended period from 2010 to 2024. The dependent variable is the performance indicator $PMAFE$, while the key explanatory variables are $Tone$ and $HighTone$. In columns (5) to (8), the explanatory variables are replaced by the GPT-generated tone intensity indicators $GPTTone$ and $HighGPTTone$. Control variables are detailed in Table 1, and fixed effects are included at the year, quarter, brokerage, industry, and firm levels to account for unobserved heterogeneity. For brevity, coefficient estimates for control variables are omitted. Standard errors are double-clustered at the analyst and firm levels and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Analyst Characteristics and Self-Promotion Behavior

	$Mismatch$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Female$		0.0189		-0.0277		0.0456
		(0.0523)		(0.0442)		(0.0450)
$Master$	-0.0102	-0.0029	-0.0222	-0.0093	-0.0017	-0.0097
	(0.0365)	(0.0404)	(0.0291)	(0.0328)	(0.0305)	(0.0336)
PhD	-0.0437	-0.0485	-0.0443	-0.0458	0.0005	0.0065
	(0.0725)	(0.0806)	(0.0548)	(0.0590)	(0.0618)	(0.0644)
Sem	-0.0299	-0.0501	-0.0625	-0.0471	-0.0026	-0.0150
	(0.0486)	(0.0553)	(0.0416)	(0.0463)	(0.0407)	(0.0443)
$BSem$	0.0420	0.0672	0.0105	0.0121	-0.0096	0.0231
	(0.0437)	(0.0500)	(0.0371)	(0.0421)	(0.0361)	(0.0413)
$Follower$	-0.0014	-0.0045	-0.0201**	-0.0222**	0.0041**	0.0025
	(0.0044)	(0.0038)	(0.0079)	(0.0093)	(0.0019)	(0.0056)
$Connection$	0.0844	-0.0553	-0.1038	-0.1819	-0.0547	0.0240
	(0.1655)	(0.2067)	(0.1587)	(0.1823)	(0.1170)	(0.1504)
$MaxWorkexp$	0.0023	0.0020	-0.0004	0.0005	0.0002	0.0000
	(0.0015)	(0.0017)	(0.0012)	(0.0014)	(0.0012)	(0.0013)
$MaxBsize$	-0.0003	-0.0004	-0.0000	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$MeanOptimism$	-0.0510	-0.1719	-0.1054	-0.1584	-0.6726	-0.6618
	(0.5452)	(0.5631)	(0.3405)	(0.3621)	(0.4302)	(0.4774)
Constant	-0.0268	0.0629	0.4869***	0.5000***	-0.3034***	-0.3359***
	(0.0888)	(0.1079)	(0.0797)	(0.0900)	(0.0631)	(0.0818)
Observations	727	590	366	307	361	283
R^2	0.008	0.012	0.033	0.034	0.009	0.014

Notes. This table reports regression results examining the relationship between analysts' observable characteristics and the intensity of their self-promotion behavior. Columns (1) and (2) include all analysts. Columns (3) and (4) restrict the sample to analysts with $Mismatch > 0$, indicating the presence of self-promotion behavior. Columns (5) and (6) include those with $Mismatch \leq 0$. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Self-Presentation Tone and Market Reaction

Panel A	Upward Revision				Downward Revision			
	$[-1,1]$	$[-1,0]$	$[-1,2]$	$[-1,3]$	$[-1,1]$	$[-1,0]$	$[-1,2]$	$[-1,3]$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HighTone	0.0009	0.0005	0.0009	0.0006	0.0024	0.0019	0.0020	0.0019
	(0.0012)	(0.0012)	(0.0013)	(0.0014)	(0.0018)	(0.0016)	(0.0018)	(0.0019)
Revision	-0.0009*	-0.0010	-0.0007	-0.0007*	-0.0003	-0.0003	-0.0004	-0.0003
	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
HighTone	0.0016***	0.0014**	0.0013**	0.0017***	0.0011	0.0002	0.0007	0.0008
$\times$*Revision*	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0009)	(0.0004)	(0.0006)	(0.0006)
PMAFE	-0.0023**	-0.0021**	-0.0030***	-0.0031**	0.0042***	0.0040***	0.0040***	0.0038***
	(0.0012)	(0.0009)	(0.0011)	(0.0012)	(0.0014)	(0.0012)	(0.0014)	(0.0015)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	23,771	23,774	23,771	23,770	19,364	19,365	19,363	19,362
Adjusted R^2	0.122	0.106	0.115	0.112	0.110	0.0957	0.107	0.0967
Panel B	Buy Recommendation				Sell Recommendation			
	$[-1,1]$	$[-1,0]$	$[-1,2]$	$[-1,3]$	$[-1,1]$	$[-1,0]$	$[-1,2]$	$[-1,3]$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HighTone	-0.0051	-0.0064*	-0.0044	-0.0083	-0.0076	-0.0069	-0.0100	-0.0095
	(0.0044)	(0.0036)	(0.0047)	(0.0053)	(0.0067)	(0.0059)	(0.0067)	(0.0072)
Recommendation	0.0039	0.0067	0.0075	0.0130	0.0005	0.0080	-0.0010	0.0007
	(0.0104)	(0.0090)	(0.0115)	(0.0120)	(0.0063)	(0.0058)	(0.0065)	(0.0067)
HighTone	0.0303***	0.0202***	0.0300***	0.0317***	0.0029	-0.0036	0.0021	0.0011
$\times$*Recommendation*	(0.0085)	(0.0075)	(0.0092)	(0.0095)	(0.0118)	(0.0106)	(0.0106)	(0.0103)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,338	2,338	2,338	2,338	2,128	2,128	2,128	2,128
Adjusted R^2	0.0312	0.0364	0.0239	0.0203	0.125	0.109	0.112	0.108

Notes. This table presents the impact of analysts' self-presentation tone on market reactions. Panel A reports the relationship between EPS forecast adjustments and market reactions, while Panel B focuses on stock recommendations. The dependent variable is the cumulative abnormal return (CAR) over various periods $[s_1, s_2]$, including $[-1,1]$, $[-1,0]$, $[-1,2]$, and $[-1,3]$. In Panel A, the key explanatory variables are *HighTone*, *Revision* and the interaction term $HighTone \times Revision$. Control variables are defined in Table 1, and fixed effects are applied at the year, quarter, brokerage, industry and firm levels. In Panel B, the key explanatory variables are *HighTone*, *Recommendation* and the interaction term $HighTone \times Recommendation$, and fixed effects are applied at the year, quarter, brokerage and industry levels. Standard errors are double-clustered at the analyst and firm levels, and are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Self-Presentation Tone and Long Run Market Reaction

	CAR							
	Upward Revision				Buy Recommendation			
	$[-1,30]$	$[-1,60]$	$[-1,90]$	$[-1,180]$	$[-1,30]$	$[-1,60]$	$[-1,90]$	$[-1,180]$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HighTone	0.0008	0.0026	0.0054	0.0129	-0.0080	-0.0153	-0.0202	-0.0750
	(0.0024)	(0.0037)	(0.0053)	(0.0095)	(0.0120)	(0.0212)	(0.0309)	(0.0609)
Revision	-0.0003	-0.0001	-0.0003	0.0011				
	(0.0004)	(0.0006)	(0.0010)	(0.0021)				
HighTone	0.0022***	0.0018*	0.0023	0.0011				
×*Revision*	(0.0008)	(0.0011)	(0.0015)	(0.0031)				
PMAFE	-0.0022	-0.0047	-0.0045	0.0074				
	(0.0024)	(0.0037)	(0.0050)	(0.0097)				
Recommendation					-0.0117	-0.0125	-0.0113	0.0589
					(0.0283)	(0.0366)	(0.0515)	(0.1157)
HighTone					0.0481*	0.0332	0.0394	0.0797
×*Recommendation*					(0.0246)	(0.0337)	(0.0499)	(0.0982)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	23,608	22,178	21,950	18,547	2,272	2,119	2,035	1,783
Adjusted R^2	0.0932	0.102	0.136	0.262	-0.00456	0.0111	0.0172	0.0701

Notes. This table examines the long-term impact of analysts' self-presentation tone on market reactions, focusing specifically on positive signals. The dependent variable is the cumulative abnormal return (CAR) over various time periods $[s_1, s_2]$, including $[-1, 30]$, $[-1, 60]$, $[-1, 90]$, and $[-1, 180]$. In columns (1) to (4), the key explanatory variables are *HighTone*, *Revision*, and their interaction term *HighTone* × *Revision*. Control variables are defined in Table 1, and fixed effects are applied at the year, quarter, brokerage, industry, and firm levels. In columns (5) to (8), the key explanatory variables are *HighTone*, *Recommendation*, and their interaction term *HighTone* × *Recommendation*. Fixed effects are applied at the year, quarter, brokerage, and industry levels. Standard errors are double-clustered at the analyst and firm levels, with values shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Heterogeneity Analysis of Self-Presentation Tone and Market Reaction

	CAR							
	Upward Revision				Buy Recommendation			
	Larger Size	Smaller Size	Higher MB	Lower MB	Larger Size	Smaller Size	Higher MB	Lower MB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HighTone	0.0006	0.0025	0.0015	-0.0014	-0.0003	-0.0061	-0.0017	-0.0078
	(0.0014)	(0.0024)	(0.0018)	(0.0017)	(0.0043)	(0.0078)	(0.0062)	(0.0078)
Revision	-0.0002	-0.0013*	0.0001	-0.0014**				
	(0.0004)	(0.0008)	(0.0004)	(0.0006)				
HighTone	0.0013**	0.0018**	0.0012**	0.0014**				
×*Revision*	(0.0006)	(0.0008)	(0.0005)	(0.0007)				
PMAFE	-0.0035**	-0.0008	-0.0053***	0.0006				
	(0.0014)	(0.0020)	(0.0018)	(0.0015)				
Recommendation					0.0094	0.0082	0.0191	-0.0166
					(0.0123)	(0.0195)	(0.0158)	(0.0123)
HighTone					0.0214*	0.0352**	0.0257	0.0352***
×*Recommendation*					(0.0120)	(0.0151)	(0.0162)	(0.0129)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	12,582	11,153	12,283	11,392	1,056	1,229	1,142	1,146
Adjusted R^2	0.0840	0.109	0.133	0.131	0.00387	0.0217	0.0207	0.0222

Notes. This table analyzes the heterogeneous impact of analysts' self-presentation tone on market reactions, focusing on positive signals. The dependent variable is the cumulative abnormal return (CAR) over the period $[-1, 1]$. In columns (1) to (4), the key explanatory variables are *HighTone*, *Revision*, and their interaction term *HighTone* × *Revision*. Control variables are defined in Table 1, and fixed effects are applied at the year, quarter, brokerage, industry, and firm levels. In columns (5) to (8), the key explanatory variables are *HighTone*, *Recommendation*, and their interaction term *HighTone* × *Recommendation*. Fixed effects are applied at the year, quarter, brokerage, and industry levels. Standard errors are double-clustered at the analyst and firm levels, with values shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Analyst Self-Presentation Tone and Career Transition

Panel A: *RatioBsizeUp*	High-Tone	Low-Tone	Diff = High-Tone - Low-Tone	t-value
High-Accuracy	0.4404	0.5364	-0.0960	-2.1600
Low-Accuracy	0.5411	0.4569	0.0842	1.8655
Panel B: *RatioBaccuracyUp*	High-Tone	Low-Tone	Diff = High-Tone - Low-Tone	t-value
High-Accuracy	0.4083	0.4632	-0.0548	-1.2682
Low-Accuracy	0.4755	0.4186	0.0569	1.2173

Notes. This table reports summary statistics on analysts' career transitions and examines their associations with analysts' self-presentation tone and forecast performance.