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Does Abstract Thinking Facilitate Information Processing? Evidence from Financial Analysts

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Abstract

We study whether abstract thinking – an essential cognitive trait established by psychological and neuroscientific studies – facilitates analysts' information processing. Exploiting analysts' questions during earnings calls, we construct an Abstract Thinking Index (*ATI*) that measures their tendency to involve abstract words, logical reasoning, broader topics, and future outlooks. We find that abstract thinking improves analysts' forecast accuracy and recommendation informativeness. Consistent with abstract thinking featuring identifying central characteristics and comprehending intangible things, *ATI* has stronger effects for firms with fundamentals co-moving more with peers and less tangible information. Additional analyses suggest that *ATI* captures analysts' cognitive traits rather than information access.

Key Words: Abstract thinking, equity analyst, information processing, forecast accuracy
JEL Classification: G12; G14; G24

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Abstract thinking singles out the rational, logical qualities of a given content from its intellectually irrelevant components.

—Carl Jung

1. Introduction

Abstract thinking is a hallmark of human intelligence. It features identifying the central characteristics of the object and comprehending things that are distant from concrete and observable physical objects and experiences (Trope and Liberman, 2010). Many scientific discoveries can be attributed to the abstract thinking of scientists. A famous example is Einstein's elevator thought experiment.[1] It was the ability to relate gravity with acceleration, two disparate concepts, that allowed him to derive the predictions of general relativity.

Despite the extensive psychological and neuroscientific evidence on how abstract thinking affects judgments, little is known about whether it facilitates information processing in the financial market. Identifying the value of abstract thinking for finance professionals has important implications for well-functioning capital markets (Bradshaw, Ertimur, and O'Brien, 2017), especially with the advent of artificial intelligence. Although artificial intelligence aims to develop algorithms that resemble human intelligence, they are particularly limited in the extrapolation and generalization of unseen situations (Chollet, 2019). By contrast, humans have a potential edge in abstract thinking which facilitates processing information in the financial market where unprecedented scenarios with limited prior data constantly emerge. Analyzing the benefits of abstract thinking for information processing can help in evaluating the advantages of humans vs. machines and making informed decisions about labor retention in the finance industry (Grennan and Michaely, 2020; Coleman, Merkley, and Pacelli, 2020; Cao, Jiang, Wang, and Yang, 2021). In this paper, we exploit the laboratory of earnings conference calls to construct a novel measure of abstract thinking propensity for individual financial analysts and examine how abstract thinking affects their research output quality.

Neuroscience has shown that abstract thinking is associated with the posterior regions of the prefrontal cortex—particularly those parts associated with vision and concrete thinking, in contrast, activates fronto-parietal regions that focus on goal-directed actions (Badre, Kayser,

[1] Einstein reasoned that an observer inside an enclosed elevator finds an equivalence between an object freely falling in a uniform gravitational field and that in uniform acceleration. See more examples of Einstein's thought experiments at https://en.wikipedia.org/wiki/Einstein%27s_thought_experiments.

and D'Esposito, 2010; Gileads, Liberman, and Maril, 2014). The psychological and organizational behavior literature has identified various ways that abstract thinking affects judgment and decision making. For example, Hadar et al. (2022) and Reyt and Wiesenfeld (2015) find that abstract thinking facilitates information aggregation and explorative learning. Förster and Friedman (2004) show that subjects primed to think more abstractly perform better in insight tasks and generating creative solutions.

As abstract thinking is particularly useful for tasks featuring complexity, uncertainty, and ambiguity, our main hypothesis is that abstract thinking improves the quality of equity analysts' research output. However, studies also show that concrete thinking improves memory for specific items (Hadar et al., 2022) and the use of concrete language benefits communication (Pan et al., 2018; Elliott, Rennekamp, and White, 2014). It is also conceivable that selective recruitment processes and career competition filter out candidates with thinking styles that are unsuitable for the job, resulting in surviving candidates having generally homogenous thinking styles. Therefore, whether abstract thinking or concrete thinking enhances the job performance of finance professionals is an empirical question.

A challenge in assessing the effects of abstract thinking on decision making is that agents' cognitive processes and decision qualities are usually unobservable. The sell-side analyst industry offers an ideal testing ground. First, the output of analysts' cognitive activities can be objectively measured. That is, we can measure the accuracy of their earnings forecasts and evaluate the profitability of their stock recommendations. Second, most importantly, we can "observe" their thinking styles through their interactions with firms' top executives during the question and answer (Q&A) portions of earnings conference calls. Linguistic and psychological studies have established a close linkage between a person's linguistic and cognitive traits (Semin and Fiedler, 1988).[2] Specifically, the development of abstract thinking is believed to be related to the development of human language.[3] The Q&A sessions of earnings conference calls are ideal for characterizing analysts' thinking styles for several reasons. First, analysts typically ask about things they deem crucial, revealing their priority in the thinking

[2] Recent economic studies such as Chen (2013) associate language features with individual behavior.
[3] Additional evidence comes from several laboratory experiments where subjects can be primed to think abstractly with linguistic cues (Trope and Liberman, 2010). Snefjella and Luperman (2015) use millions of social media texts to establish the link between abstract languages and a higher level of mental abstractness in the field.

process. Second, given the spontaneous nature of Q&As, their follow-up responses to answers from corporate executives reflect their instinctive and default thinking style when absorbing new information.[4]

We obtain a comprehensive sample of earnings conference call transcripts from FACTSET Events & Transcripts over the 2011 to 2019 period. We construct an Abstract Thinking Index (*ATI*) for analysts based on four aspects of their dialogues with corporate executives during earnings calls: 1) the frequency with which they mention the future over the past; 2) the frequency with which they discuss why over how; 3) the frequency of semantically abstract words over concrete ones; and 4) the focus on broad versus narrow topics. The first two components are motivated by the fact that abstract thinking is characterized by time and hypotheticality dimensions of psychological distance; that is, moving beyond the past (now) and the question of how, to contemplate the future and the question of why, entails a higher level of mental construal—namely, abstract thinking.[5] The third component of semantic abstractness is guided by the linguistic category model, which asserts that abstract language features adjectives, nonspecific quantifiers, and future-focused words.[6] The fourth component considers the topic scope of analysts' questions. Intuitively, a broader topic—resulting in fewer categories of factors determining firm value—indicates more abstract thinking.[7] We then combine the four components into one composite measure—*ATI*. A higher *ATI* score indicates a higher propensity for abstract thinking.

We find that analysts differ significantly in their tendency to think abstractly. Analyst fixed effects alone explain up to 70.9% of the variation in *ATI*, whereas firm, brokerage house, and time fixed effects separately account for 23.1%, 7.1%, and 2%. This evidence suggests that *ATI* likely captures a personal trait. Analysts employed by more prestigious brokerage firms think more abstractly, consistent with Smith and Trope (2006) who show that individuals'

[4] Ray Dalio writes in his book *Principals* that "smart people are the ones who ask the most thoughtful questions, as opposed to thinking they have all the answers. Great questions are a much better indicator of future success than great answers." Cen et al. (2020) exploit questions analysts raise during conference calls to construct a topic-specific skill.

[5] See, for example, Friedman and Liberman (2004) and Trope and Liberman (2010).

[6] For example, the linguistic category model suggests that adjectives are generalized descriptions and summaries of characteristics across multiple contexts, whereas verbs describe observable and verifiable actions, and hence the former are more abstract (Semin and Fiedler, 1988; Snefjella and Kuperman, 2015; Elliott, Rennekamp, and White, 2015).

[7] For example, topics such as industry competition are broader than the projected amount of capital expenditures.

elevated social status and power are associated with more abstract information processing. An analyst's *ATI* score also positively correlates with that of peer analysts covering the same stocks, consistent with a learning effect. In contrast, abstract thinking is not significantly related to other analyst characteristics such as general experience, gender, race, and educational background. Overall, these findings suggest that *ATI* is mainly determined by individuals' nature but also varies through nurture.

Our main analyses examine the impact of analysts' abstract thinking on the quality of their research output. We find that analysts with higher *ATI* scores (abstract thinking analysts hereafter) issue more accurate earnings forecasts than analysts with lower *ATI* scores (concrete thinking analysts hereafter), and the stock market responds more strongly to recommendations issued by abstract thinking analysts. Using a calendar-time portfolio approach, we find that trading strategies following upgrades (downgrades) issued by abstract thinking analysts significantly outperform (underperform) the upgrades (downgrades) issued by concrete thinking analysts. These findings are consistent with the notion that capital market participants place greater emphasis on research produced by abstract thinking analysts, and investors can earn higher returns by following such analysts' advice.

We further explore the potential channels through which the abstract thinking style affects the quality of analysts' research output. First, the psychological literature suggests that abstract thinking improves agents' ability to identify central characteristics. This channel predicts that abstract thinking is more valuable for forecasting firms whose fundamentals comove strongly with peer firms ("bellwether" firms). Second, abstract thinking helps analysts comprehend things that are disconnected from concrete, observable physical objects, and experiences. This channel implies that abstract thinking should offer analysts a more substantial competitive advantage when covering harder-to-value firms. Our results support both channels. Specifically, we find that the effect of *ATI* on the quality of analyst research is stronger for bellwether firms (Hameed et al., 2015), younger firms, and firms with higher stock return volatility, lower stock liquidity, and more intangible assets.

The evidence suggests that abstract thinking is a value-enhancing attribute for analysts. However, one alternative interpretation of our results is that *ATI* may capture better access to private information instead of a cognitive attribute of analysts. A possible narrative is that analysts who are more closely connected with the management team of the firm they cover strategically ask more abstract questions that managers can flexibly or impressively answer. In this case, analysts curry favor with managers and *ATI* captures analysts' advantages in accessing managers and private information. To test this explanation, we examine whether abstract thinking analysts more likely ask questions or ask the first question in earnings calls, which indicates superior access to private information (Mayew, Sharp, and Venkatachalam, 2012 and Cen et al., 2021). We do not detect any meaningful association between analysts' *ATI* scores and the number or sequence of questions they raise. Additionally, we investigate how the impact of *ATI* varies with the geographical distance between analysts and their covered firms. This test is motivated by Malloy (2005), who documents that geographically proximate analysts are more likely to possess an information advantage. Interestingly, we find that abstract thinking helps improve forecast accuracy more for firms located further away from the analyst. Collectively, this body of evidence lends support to the cognitive attribute interpretation of *ATI* and is inconsistent with the alternative explanation that *ATI* captures analysts' superior information access.

Since abstract thinking analysts produce higher quality research than concrete thinking analysts, a natural question is whether abstract thinking can help analysts achieve favorable career outcomes. We examine two measurable career outcomes—being voted an all-star analyst and the likelihood of working in a high-status brokerage house. The results show that abstract thinking analysts more likely work in a high-status brokerage house and concrete thinking analysts are *less* likely to be voted all-star analysts.

Our final test focuses on the real effects of analyst abstract thinking on the information environments of covered firms. Prior studies show that analyst coverage improves the information environment of covered firms and reduces information asymmetries among market participants (Roulstone, 2010; Kelly and Ljungqvist, 2012; Harford et al., 2019). If abstract thinking analysts can better uncover hidden information and the true value of a firm, we expect that a larger proportion of abstract thinking analysts covering a firm will improve its information environment. Using several proxies for a firm's information environment (return volatility, bid-ask spread, and Amihud illiquidity), we find evidence supporting this conjecture. Importantly, as we control for the number of analysts following a firm in this test, our results suggest that abstract thinking analysts are better able to mitigate information asymmetry for outside investors.

We perform extensive robustness checks. In particular, we vary the measure construction for *ATI* and conduct external validity checks. Our main findings are robust to 1) excluding the focal firm from *ATI* construction; 2) restricting our sample to analysts with at least five valid dialogues each quarter; 3) different groupings of *ATI* components; and 4) different standardization procedures for *ATI*. Importantly, we demonstrate external validity by constructing *ATI* using analysts' research reports on a subsample. We find that research-report-based *ATI* has a strong positive correlation with conference-call-based *ATI* and again reduces forecast errors. These results assure that our ATI methodology identifies abstract thinking propensities across contexts.

The paper makes two contributions. First, it provides novel evidence of an important cognitive trait—abstract thinking—that influences decision quality among finance professionals. Despite evidence from laboratory studies pointing out the various cognitive benefits of abstract thinking, there is little systematic evidence from the field on whether different thinking styles impact agents' performance in a highly competitive environment. The analyst setting allows us to evaluate the effects of abstract thinking on job performance while controlling for task difficulty. This is important, because agents with different thinking styles may self-select into different job types, which may confound interpretation. By directly characterizing and evaluating neutral cognitive attributes of finance professionals, our paper also adds to the behavioral finance literature that mostly infers and studies cognitive biases with trading data (Kahneman and Tversky, 1979).

Second, our study is related to the voluminous literature in finance and accounting that documents the determinants of high quality research. Earlier studies have documented several important characteristics that affect analyst performance, including brokerage resources, conflicts of interest, portfolio complexity, general and firm-specific forecasting experience, forecast consistency, and industry expertise (Clement, 1999; Kadan, et al., 2009; Kadan, et al., 2012; Hilary and Hsu, 2013; Bradley, Gokkaya, and Liu, 2017). Our paper is closely related to recent studies that use earnings conference calls to measure analysts' personal traits. For example, Cen, Han, and Harford (2022) construct analysts' supply-chain-specific skill and

Yezegel (2022) measures analysts' ability to elicit information. Given that equity research is a cognitively demanding job, it is surprising that few studies have looked at the impact of cognitive traits on the quality of analyst research.[8] One exception is a recent paper by Hirshleifer et al. (2019), who show that analysts' decision quality deteriorates with mental fatigue. In contrast, we contribute to this literature by identifying a value-enhancing cognitive attribute of analysts.

2. Hypotheses Development

Abstract thinking is considered as a high-order, complex form of cognition. It is activated when one analyses scenarios, looks for relationships or patterns, notices connections, forms a theory about why something happens, and thinks outside the box. Abstract thinking has several features that distinguish it from concrete thinking (Smith and Trope, 2006; Burgoon, Henderson, and Markman, 2013). It favors identifying the central characteristics of the object and extracting a gist from disparate examples. For example, categorization involves abstract thinking and giving examples is concrete thinking. Abstract thinking also allows comprehending things that are distant from concrete and observable physical objects and experiences. Humor is one example of abstract thinking, as jokes involve making unexpected connections.

The psychological and organizational behavior literature has studied the ways that abstract versus concrete thinking affects judgments, influences the way people store, retrieve, and integrate knowledge, and shifts their mental horizons (Rosch et al., 1976; Hinds, Patterson, and Pfeffer, 2001; Mandler and McDonough, 1998; Trope and Liberman, 2010). Other studies demonstrate the favorable consequences of abstract thinking for innovation, gaining power, risk taking, and handling change.[9]

As abstract thinking is particularly useful for tasks featuring complexity, uncertainty, and ambiguity, we conjecture that abstract thinking affects the quality of equity research output for two reasons. First, forecasting firm earnings, issuing target share prices, and generating

[8] Several papers show that analysts' behavioral and demographic traits are important drivers of forecast accuracy. Such personal traits include gender (Kumar, 2010), conservatism (Jiang, Kumar, and Law, 2016), cultural bias (Pursiainen, 2020), and achievement drive (He et al., 2019).
[9] Abstract thinking is also shown to affect self-control (Fujita et al., 2006), life satisfaction (Updegraff and Suh, 2007), and health outcomes (Ayduk and Kross, 2009).

stock recommendations is a complex process. To generate accurate forecasts and profitable recommendations, an analyst needs to draw connections among an array of factors that influence firm fundamentals and valuation. She needs to assimilate a great deal of qualitatively and quantitatively disparate information to articulate an investment opinion. In this case, abstract thinking helps her navigate through a complex situation, and thus identify key factors and their interactions.

Second, firm cash flows and stock performance are highly unpredictable. The concept of firm growth, an essential driver of firm value, is by and large intangible and cannot be observed directly. The information set that analysts rely on when making forecasts is usually incomplete.[10] To fill the logical gaps in the financial analysis and uncover the hidden connections, analysts need to detect the underlying patterns, make inferences, and think outside the box. Abstract thinking relaxes the constraints of limited information and experiences, and therefore enables them to generate useful and incremental insights.

Based on the above discussion, we hypothesize that *the quality of an analyst's research output increases with her propensity for abstract thinking.*

However, there are also benefits of thinking in a concrete way. Construal level theories (Trope and Liberman, 2010 and Hadar et al., 2022) suggest that concrete thinking may improve memory for specific items and the use of concrete language reduces feelings of distance, which may help agents impress the audience and convey ideas more persuasively. Pan et al. (2018) find that investors' willingness to invest increases when concrete language is highlighted in a prospectus. Elliott, Rennekamp, and White (2014) document that investors react positively to top managers' use of concrete language in communications. Accordingly, if concrete thinking analysts can disseminate their opinions more efficiently and convincingly to investors and clients, their research may elicit stronger market reactions.

It is also possible that the selective recruitment process and career competition fails candidates with thinking styles that are unsuitable for the job, and hence surviving candidates' thinking style should be rather homogenous for a given job. Thus, ex ante, it is unclear whether

[10] For example, studies show that sell-side analysts produce more informative research when they have access to corporate executives, in-house macroeconomists, and semi-public data (Green et al., 2014; Hugon, Kumar, and Lin, 2016; Klein, Li and Zhang, 2020).

thinking style differs across analysts and whether different thinking styles matter for their performance. We empirically test these competing hypotheses in the following sections.

3. Data, Variables, and Summary Statistics

3.1 Data and Sample Construction

We obtain corrected earnings conference call transcripts from FACTSET Events & Transcripts. Analyst forecast and recommendation data are from I/B/E/S Detail History Files. Firm financial data and stock price information are from COMPUSTAT and CRSP.

Table A2 shows the details of the sample construction. In total, we have 86,765 U.S. earnings conference call transcripts, covering the period from 2011 to 2019. We use text parsing tools to go through each transcript and extract the firm name, firm ticker (trading symbol), call date, participants' full names and affiliations, dialogue marks, and dialogue contents. We keep the Q&A dialogues from analysts and drop those with less than 10 words. We then match the earnings conference call data with the data from the Institutional Brokers' Estimate System (I/B/E/S) Detail Recommendation file based on analysts' last names and initials and brokerage names. Because the brokerage firm's full name is missing for some brokerages in the I/B/E/S dataset, we manually check the match between the affiliations in the scripts and brokerage abbreviations in I/B/E/S. Our final sample includes 1,032,541 sell-side analyst dialogues, and 285,669 analyst–call pairs. In Panel B, we compare analyst characteristics across three samples—analysts in our sample, those in the I/B/E/S universe but not in the dataset of earnings conference calls, and those in the dataset of earnings conference calls but excluded from our sample due to filtering criteria. The results indicate that our sample includes analysts who work for larger and higher-status brokers, and cover more firms and industries than the analysts in the I/B/E/S universe, but there is no difference in the average forecast accuracy.

3.2 Abstract Thinking Index

We measure an analyst's abstract thinking based on the Q&A sessions of earnings conference calls. These Q&A sessions are ideal for characterizing how analysts approach the task of equity valuation for two reasons. First, analysts typically ask about things they deem crucial that are not readily available elsewhere. Second, given the spontaneous nature of Q&As,

an analyst's follow-up responses to answers from corporate executives reflect her instinctive, default thinking mode when absorbing new information.

We construct an Abstract Thinking Index (*ATI*) for analysts based on their dialogues with the firm management during earnings calls. *ATI* consists of four components, selected based on the psychology, neuroscience, and linguistics literature: 1) frequency of mentioning the future over the past; 2) frequency of discussing why over how; 3) frequency of using semantically abstract words over concrete ones; and 4) focusing on broad versus narrow topics. The first and second components are based on the finding that abstract thinking is distinguished by the time and hypotheticality dimensions of psychological distance; that is, focusing on the future and why, rather than the past (now) and how, entails a higher level of mental construal—namely, abstract thinking. The third component of semantic concreteness is guided by the linguistic category model, which holds that abstract language is characterized by adjectives, nonspecific quantifiers, and future-focused words. The fourth component considers the topic scope of analysts' questions. Topic modeling allows us to characterize the topics covered in the dialogue, and we then manually classify them into different levels of abstractness. For example, the topic of industry competition is broader than the projected amount of capital expenditures. Intuitively, a broader topic—resulting in fewer categories of factors that determine firm value—is indicative of more abstract thinking.

These components of *ATI* may contribute to analysts producing higher quality research. When predicting firm performance, the intellectual pursuit of the future provides new insights and thoughts, compared to dwelling on past facts. Similarly, a general understanding of the macroeconomic condition, industry trends and competition, and corporate culture may have a more significant impact on assessing firm value than a particular financial ratio or tax rate. These broader topics can be generalizable factors crucial for determining firm value and represent the elephant in the room, easily overlooked by analysts who are excessively focused on narrow, concrete firm-specific issues.[11]

[11] There is no fixed template as to what a good firm should look like. The more relevant issue is why certain firms are more likely to succeed. If analysts are fixated on financial ratios or other quantitative indicators, they can easily miss out on unconventional firms with high growth potential and unprecedented business models. They could also be misled by easily observable facts and numbers when evaluating firms. After all, sound financial position of a firm is likely the result of being successful, rather than the reason why the firm succeeded in the first place.

We now describe in detail the construction process for *ATI*. We start with constructing its four components at the dialogue level. *Future-abstractness (past-concreteness, why-abstractness, how-concreteness)* is the number of words focusing on the future (past and now, why, how) scaled by the total word counts in a dialogue.[12] *Semantic-abstractness* is calculated as the difference between abstract- and concrete-attribute words in a dialogue, and then scaled by their sum. Abstract-attribute words include adjectives (e.g., "good"), modals ("could"), and determiners ("some"), and concrete-attribute words include verbs ("buy") and cardinal digit ("$100"). *Topic-abstractness* refers to the abstractness score of the dialogue's topic. We use structural topic modeling (STM) tools to identify 40 topics, and manually read them to rate their abstractness using a 3-point scale, where one means the topic is the least broad and three means the broadest. For example, the market trend is a broad topic scoring three and expense number is a narrow topic scoring one.[13]

Second, for each component, we aggregate the dialogue-level measures to the analyst-call level by averaging across all dialogues an analyst engaged in during a call and then standardize the measure at the analyst-call level.[14] Third, we construct the composite abstractness measure at the analyst-call-level by taking the average of four components. Fourth, we compute the quarterly composite abstractness measure as the average of analyst-call-level abstractness measures across all earnings conference calls attended by the analyst during a quarter, where a quarter is defined as 3 months before the earnings forecast or recommendation announcement date. Finally, our main independent variable *ATI* is the moving average of the quarterly analyst abstractness measure within the year before the earnings forecast or recommendation announcement date.

For illustration purposes, Table A3 shows some sample dialogues underpinning *ATI*. We select analysts with the highest and lowest propensity of abstract thinking at the analyst-year

[12] Table IA3 in the Internet Appendix lists future-focused words such as *foresee*, *soon*, and *will*, and past-focused words such as *ago*, *earlier*, and *done*.
[13] Table IA1 in the Internet Appendix lists the topics and their scores. The detailed procedure of topic modeling is discussed in Table IA2 in the Internet Appendix.
[14] In Table A7 where we examine each component of *ATI*, the dependent variables *ATI_semantic, ATI_topic, ATI_future, ATI_past, ATI_why,* and *ATI_how* are, respectively, the moving average of quarterly standardized analyst-call semantic-abstractness, topic-abstractness, future-abstractness, past-concreteness, why-abstractness, and how-concreteness on all earnings conference calls within a year before the earnings forecast or recommendation announcement date.

level and list their dialogues, names, and brokerage houses.

3.3 Other variables

Our main dependent variables of interest are analyst forecast accuracy (*Forecast Error*), and cumulative abnormal return around recommendation changes (*RECCAR*). *Forecast Error* is defined as the absolute difference between the forecasted EPS and the realized EPS, divided by either the stock price 12 months prior to the quarterly earnings announcement date or the absolute value of realized EPS. *RECCAR[i,j]* is the cumulative abnormal return (adjusted by value-weighted market index returns) from day *i* to *j* around the recommendation announcement date. For downgrade recommendations, we take the negative value of the cumulative abnormal returns so that a higher value of *RECCAR[i,j]* always indicates greater market reaction.

We control for analyst characteristics that have been documented as important factors affecting analyst performance. Specifically, we define *Broker size* as the number of analysts employed by a brokerage house. Analysts from larger brokers are shown to issue more accurate earnings forecasts and their recommendations elicit a stronger market reaction (Clement, 1999). We sort brokers into deciles by broker size each year. *High Status Broker* is a dummy variable that equals one if the broker is in the highest decile. We control for the complexity of an analyst's portfolio by the number of firms covered by the analyst (*Coverage*). Clement (1999) shows that an analyst's general experience is related to forecast accuracy. We control for analyst general working experience (*GEXP*), which is calculated as the natural logarithm of one plus the number of years since the analyst first issued any forecast in the I/B/E/S database. We also control for analyst firm-specific experience (*FEXP*), which is calculated as the natural logarithm of one plus the number of years since the analyst first issued a forecast for the firm. Previous studies show that forecasts announced closer to earnings announcement are usually more accurate, so we control for *Forecast Age*, defined as the natural logarithm of the number of days from the forecast date to the earnings announcement date. In addition, we control for several firm characteristics that have been shown to affect stock returns and firms' information environment. Definitions of all variables are given in Table A1.

3.4 Summary Statistics

Table 1 reports the summary statistics of the main variables used in our analysis. Panel A reports the summary statistics of the dependent variables, including forecast error, recommendation announcement return (*RECCAR*), all-star indicator (*Star*), promotion indicator (*Promotion*), and proxies for firm uncertainty and information environment (*Volatility, Spread,* and *Illiquidity*). The mean (median) forecast error (scaled by stock price) is 0.003 (0.001). The mean recommendation announcement return *RECCAR[0,2]* is around 250 basis points. In Panel B, we report the summary statistics for the key independent variable of interest, *ATI*. The mean (median) of *ATI* is -0.004 (-0.002), with a standard deviation of 0.128, suggesting considerable variation of *ATI* across analysts. In Panels C and D, we report the summary statistics of the analyst-level and firm-level control variables used in our analysis.

4. Abstract Thinking and Analyst Performance

We next turn to examining how abstract thinking affects the quality of analysts' research output. We begin by examining the variation of *ATI*. We then test how earnings forecast accuracy and investors' reactions to stock recommendations vary with analysts' abstract thinking style. Thirdly, we compare the investment value of stock recommendations issued by analysts with different levels of *ATI*. Finally, we examine the economic mechanisms through which *ATI* affects the quality of analysts' research. Collectively, these tests will shed light on which type of thinking style—abstract vs. concrete thinking—is associated with superior research output and why.

4.1 Variation of Abstract Thinking Index

Before testing the effect of the abstract thinking style, we explore its variation. We first compare the explanatory power of various fixed effects separately. Panel A of Table 2 reports the adjusted R-squared from different specifications. We find that across different specifications, the specification with analyst fixed effects in column (1) has the highest R-squared of 0.709, which implies that time-invariant analyst characteristics alone explain 70.9% of the variation in *ATI*. In columns (2) and (3), the specifications with firm and broker fixed effects have a modest adjusted R-squared of approximately 0.23 and 0.07, respectively. In contrast, year-quarter fixed effects in column (4) have close to zero explanatory power. Results in Panel A suggest that analyst-level factors dwarf others in driving the abstract thinking style, and *ATI* likely captures a persistent personal trait.

Next, we examine the abstract thinking style in connection with specific analyst characteristics and report results in Panel B of Table 2. Column (1) focuses on time-invariant analyst characteristics and controls for analyst gender (*Gender*) and race (*Race*).[15] Columns (2) and (3) add controls of analysts' social status and general experiences and regress *ATI* on broker reputation (*High Status Broker*), all-star analyst status (*Star*), the number of firms covered by the analyst (*Coverage*), analyst general experience (*GEXP*), analyst industry-specific experience (*INDEXP),* and the number of industries covered by the analyst (*No. of Industries*). Column (4) further includes analyst firm-specific experience (*FEXP)* and the average *ATI* of her peers with an overlapping coverage portfolio (*ATI_peers*). Columns (1) and (2) control for time fixed effects and Columns (3) and (4) further include analyst and brokerage fixed effects which absorb time-invariant analyst and brokerage attributes.

Results show that neither *Race* nor *Gender* explains the extent of abstract thinking in a statistical sense. There is no clear relationship between *ATI* and general experience proxies. However, *ATI* is positively related to *High Status Broker* across different specifications, suggesting that analysts employed by more prestigious brokerage houses engage more in abstract thinking. Since analyst and broker fixed effects partially rule out the selection effect, this result is consistent with Smith and Trope (2006) who show that individuals' elevated social status and power are positively associated with them engaging more in abstract information processing. Column (4) shows a positive and significant coefficient on *ATI_peers*, suggesting that experiences of learning from peers can reinforce analyst abstract thinking propensity.

In unreported tests, we also check the persistency of the abstract thinking style across firms and industries an analyst covers and across time. In the spirit of Hong and Kubik (2003) and Hilary and Hsu (2013), we first calculate each analyst's relative ranking of *ATI* on a 0-100 scale for a given firm-year (industry-year) pair. We then obtain the standard deviation of these rankings over firms (industries) in an analyst's coverage portfolio. This standard deviation has

[15] We also consider analyst education background as an additional characteristic by including a dummy variable *Ivy* indicating whether an analyst attended Ivy League colleges as an undergraduate (*Ivy*) for a subsample of analysts. We find *Ivy* does not explain *ATI* in a statistical sense. As only 17.4% of sample analysts have available education information, we do not report this result in Table 2. We thank Sinan Gokkaya and Xi Liu for sharing with us the analyst education data used in Bradley, Gokkaya, and Liu (2020).

a mean of 16.5 (4.2), which represents *ATI's* within-analyst persistency over firms (industries). Analysts whose *ATI* is ranked in the highest/lowest quartile show more consistency. We repeat the exercise for the time dimension and get an average standard deviation of 0.08. These results indicate that an analyst's abstract thinking style is reasonably stable (relative to peers) across circumstances.

4.2 Main Results

4.2.1. Earnings Forecast Accuracy

To test the impact of abstract thinking on analysts' earnings forecast accuracy, we regress analyst quarterly forecast error on our key explanatory variable *ATI*, along with an array of analyst and broker characteristics that previous research has identified as related to differences in forecast error (e.g., Clement, 1999; Harford, et al., 2019). The model is specified as follows:

$$oneForecast\ Error_{i,j,t} = a_0 + a_1 ATI_{i,t} + a_2 Broker\ Size_{i,t} + a_3 Coverage_{i,t} + a_4 GEXP_{i,t} + a_5 FEXP_{i,t} + a_6 No.of\ Industry_{i,t} + a_7 Forecast\ Age_{i,t} + a_8 Star_{i,t} + Fix\ Effects + \varepsilon_{i,j,t} \qquad (1)$$

where forecast error is defined as the absolute difference between the forecasted quarterly EPS and the realized EPS, scaled by the stock price 12 months prior to the quarterly earnings announcement date (PRC) or the absolute value of realized EPS (EPS). As forecast errors are affected by time-varying firm characteristics, we control for firm by year-quarter fixed effects in all specifications. The standard errors are clustered at the firm level.

Table 3 reports the baseline regression results. The coefficients on *ATI* are negative and statistically significant for both measures of forecast errors, indicating that a higher propensity for abstract thinking is associated with more accurate earnings forecasts. The economic effects are also meaningful. For example, using the coefficient estimated from column (1), the difference in forecast errors between analysts with the 75th percentile *ATI* and the 25th percentile *ATI* is approximately 2.6% (= (0.083+0.089) *0.015/ (0.001*100)) of the median level of forecast errors. As a benchmark, the difference in forecast errors between analysts with the 75th percentile *GEXP* and the 25th percentile *GEXP* is around 1.1% of the median forecast error. The economic effect of *ATI* on forecast accuracy is thus comparable to other important analyst characteristics. The coefficients on the control variables are mostly consistent with previous studies. For example, analysts with more general experience have lower forecast errors, while the number of covered industries and forecast age are positively related to forecast errors (Mikhail, Walther, and Willis, 1997; Clement, 1999). Note that our results show a negative relation between forecast error and the number of covered firms, which differs from the results in Clement (1999). One potential explanation is the difference in sample selection. Cen, Han, and Harford (2020) use a similar sample to that used in our paper—analysts who ask questions during the conference calls from 2006 through 2018—and finds a similar negative correlation.

In addition to forecast accuracy, we also examine if the style of abstract thinking is associated with other forecasting behaviors. For example, if abstract thinking analysts are more likely to follow others, and fabricate patterns, themes, and relationships that do not actually exist, then we may observe an association between the propensity for abstract thinking and analyst herding and forecast biases. However, we find that analysts with higher *ATI* are less likely to herd with the consensus forecast, and do not issue significantly more biased forecasts, as shown in Table A4.

4.2.2 Stock Price Reactions to Stock Recommendations

We next investigate the stock market reactions to recommendation changes. The literature has considered such price reactions as an indicator of investors' confidence in analyst research and the amount of new information it conveys (Stickel, 1991; Womack, 1996; Michaely and Womack, 1999; Gleason and Lee, 2003; Kadan, et al., 2009). If an analyst produces more accurate earnings forecasts by piggybacking on the information produced by firms or other analysts, her research output would carry little new information content and its stock price impact would be muted. However, if the analyst's research output indeed carries significant information content, its release should generate strong stock market reactions. We expect stronger market reactions to recommendations issued by analysts with higher *ATI* if abstract thinking indeed improves analyst research quality. We estimate the following regression model to test our prediction.

$$
\begin{aligned}
RECCAR_{i,j,t} = {} & a_0 + a_1 ATI_{i,t} + a_2 Broker\ Size_{i,t} + +a_3 Coverage_{i,t} + a_4 GExp_{i,t} \\
& + a_5 FExp_{i,t} + a_6 No.of\ Industry_{i,t} + a_7 Star_{i,t} + a_8 Mktcap_{j,t} + a_9 BM_{j,t} \\
& + a_{10} Profit_{j,t} + a_{11} Growth_{j,t} + a_{12} MOM_{j,t} + a_{13} RET_{j,t} \\
& + a_{14} Lag(Recommendation)_{i,t} + Fix\ Effects + \varepsilon_{i,j,t} \qquad (2)
\end{aligned}
$$

We measure price reactions to stock recommendation changes (*RECCAR*) as the cumulative raw/market-adjusted/characteristics-adjusted returns within 2 (or 4) days since the issuance of the stock recommendation. Following the literature (e.g., Loh and Stulz, 2011; Kadan et al., 2020), to avoid potential confounding effects, we remove recommendations issued within a 3-day window of earnings announcements, and on days on which multiple analysts issue recommendations for the firm. We focus on changes instead of levels of recommendations because prior research finds that recommendation changes are more informative than levels (Boni and Womack, 2006; Jegadeesh and Kim, 2010). Upgrades are defined as upgrades to buy recommendations, and downgrades are defined as downgrades to hold or sell recommendations. As we pool all upgrades and downgrades together when running regressions, we take the negative value of *RECCAR* for downgrades.[16]

Table 4 presents the results. We find that the coefficients on *ATI* are significantly positive across all specifications. This suggests that investors react more strongly to recommendation changes issued by abstract thinking analysts. In terms of economic significance, the coefficient in column (2) suggests that market reactions to recommendation changes for analysts with the 75th percentile *ATI* are 26.7 (= (0.083+0.089) *1.555*100) basis points higher than those for analysts with the 25th percentile *ATI*. The impact of *ATI* on recommendation announcement return (*RECCAR[0,2]*) is economically meaningful, as the average 3-day market-adjusted *RECCAR[0,2]* is 250 basis points. In addition to *ATI*, firm-specific experience, the number of covered industries, firm size, and previous recommendations also have significant impacts on recommendation announcement return.

4.2.3 Investment Value of Stock Recommendations

We next study whether the investment value of recommendations is associated with

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16 We also run separate analyses for upgrades and downgrades. Results are stronger for downgrades, which is consistent with the literature that downgrades have more information content than upgrades.

analysts' propensity for abstract thinking. We hypothesize that recommendation changes issued by analysts with higher *ATI* outperform those issued by analysts with lower *ATI*. To assess the relative performance of analyst recommendations, we use a standard calendar-time portfolio approach, following the methodology used by Barber, Lehavy, and Trueman (2005) and Cohen, Frazzini, and Malloy (2010).

We first identify stocks that have been upgraded to buy/strong buy and stocks that have been downgraded to hold/sell/strong sell during our sample period. To evaluate how the performance of recommendations varies with the propensity of abstract thinking, we construct an analyst-year level Abstract Thinking Index (*ATI_AY*). *ATI_AY* is defined as the average of analyst-call abstractness at the analyst-year level. Analysts are then sorted into quartiles each year according to their *ATI_AY* in the previous year among the upgraded (downgraded) stocks. Quartile 1 (4) contains analysts with the lowest (highest) propensity of abstract thinking. Overall we have four upgrade portfolios and four downgrade portfolios. To illustrate how portfolio returns are calculated, we take as an example the upgrade portfolio of the Quartile 1 analysts. For each stock within this quartile, it is added to the upgrade portfolio by the end of the day when it is being upgraded. If more than one analyst upgrades the stock during a day, then that stock will appear in the corresponding portfolio multiple times. A stock is dropped from the upgrade portfolio when a downgrade is announced, or when the recommendation turns 365 days old. We assume an equal dollar investment in each stock within the portfolio. The portfolio is updated daily when necessary. This calculation generates a time series of daily returns to the upgrade portfolio of Quartile 1. The daily returns for other portfolios are calculated in a similar way.

We calculate abnormal return (alpha) for each of our portfolios using various factor models. The abnormal return is defined as the intercept from regressing daily portfolio excess returns on the market factor, the three Fama-French (1993) factors, the four Carhart (1997) factors, the five Fama-French (2014) factors, and the Hou-Xue-Zhang (2015) q factors. Panel A of Table 5 reports the results of the upgrade portfolios. First, regardless of how we measure a portfolio's abnormal return, the upgrade portfolio of analysts with the highest abstract thinking propensity has positive and statistically significant daily alphas of approximately 2 to 2.6 bps. In contrast, the abnormal returns of the other upgrade portfolios have mixed signs and are mostly insignificant. Second, we construct a long-short portfolio that holds the stocks upgraded by analysts in the highest quartile of abstract thinking propensity and shorts the stocks upgraded by analysts in the lowest quartile. For the long-short portfolio, the abnormal returns are always significant at the 5% level or better. The economic magnitudes are also non-trivial. Using the Fama-French three-factor alpha as an example, a daily alpha of 2.6 bps is equivalent to an annual alpha of 6.60% (assuming 252 trading days per year). Results using other factor models are similar. They indicate that upgrades issued by analysts with a more salient abstract thinking style have greater investment value.

Panel B of Table 5 reports the results of the downgrade portfolios. Except for the Quartile 1 portfolio, the daily abnormal returns of all other portfolios are mainly negative and significant, consistent with the literature showing that downgrades on average contain more information than upgrades. Based on the Fama-French (1993) three-factor alpha, the average daily alpha is -3.4 bps for analysts in the highest quartile and -0.58 bps for analysts in the lowest quartile. The average daily abnormal return of the long-short portfolio is always statistically significant, and the economic magnitude is around -2.7 bps, equivalent to an annual alpha of -6.8% (assuming 252 trading days per year). These results are consistent with results of the upgrade portfolios and show that downgrades have more information content when issued by analysts with the strongest abstract thinking style.

Overall, the results in this section are consistent with previous results on forecast accuracy and market reaction to recommendation changes and support our hypothesis that the investment value of an analyst's stock recommendations increases with her propensity for abstract thinking.

4.3 Channel Tests

The preceding results show that abstract thinking analysts generate higher quality research output than concrete thinking analysts. In this section, we explore the potential channels through which abstract thinking affects the quality of analysts' research output. First, the psychological literature suggests that a critical feature of abstract thinking is to help identify central characteristics. This feature can assist analysts in discovering fundamental connections among firms and identifying information relevant to many firms. Thus, we expect that abstract thinking is more valuable in analyzing firms whose fundamentals comove more strongly with peer firms ("bellwether" firms). We use the approach in Hameed et al. (2015) to measure a firm's fundamental correlation with all other firms in its industry (*LPCORR_ROA*). We then sort firms into two groups based on the median value of *LPCORR_ROA* and separately examine the impact of *ATI* on forecast accuracy in the subsamples. For brevity, we only report results for forecast error scaled by stock price. Consistent with our prediction, columns (1) and (2) in Panel A of Table 6 show that *ATI* only significantly affects analyst forecast accuracy for bellwether firms.

Second, abstract thinking helps analysts comprehend things that are disconnected from concrete, observable physical objects and experiences. This channel implies that abstract thinking should offer analysts a stronger competitive advantage when covering harder-to-value firms, such as firms with more opaque information environments, higher fundamental uncertainty, and more intangible assets. We use a stock's bid-ask spread and Amihud illiquidity as proxies for a firm's information environment.[17] We use stock return volatility and firm age to proxy for fundamental uncertainty.[18] In general, firms with a higher bid-ask spread and lower liquidity have a poorer information environment, and firms with higher return volatility and younger age have greater fundamental uncertainty (Zhang, 2006). We also expect firms with more intangible assets to be harder to value (Fu et al., 2022).[19] For each measure, we divide firms into two subsamples based on the median value and estimate the baseline model separately for each subsample.

Columns (3) to (12) of Table 6, Panel A, report the results. We find stronger effects of *ATI* on forecast accuracy among the subsample of firms with higher stock illiquidity, higher bid-ask spread, higher volatility, younger age, and more intangible assets. The differences in coefficients between subsamples are mostly statistically significant at the 10% level. These findings suggest that abstract thinking offers analysts a stronger competitive advantage when

[17] We compute bid-ask spread based on daily close, low, and high stock price, following the methodology developed in Abdi and Ranaldo (2017). Abdi and Ranaldo (2017) show that compared to other low-frequency estimates, this method generally provides the highest cross-sectional and average time-series correlations with the TAQ effective spread benchmark. Moreover, it delivers the most accurate estimates for less liquid stocks. The Amihud illiquidity measure (Amihud, 2002) is computed as the average of daily Amihud illiquidity during the previous month.
[18] We measure a firm's stock return volatility as the average daily call-option implied volatility during the previous month. Firm age is defined as the number of years since the firm went public.
[19] Intangible capital (*IC*) is calculated as the value of intangible assets over the value of total assets.

covering hard-to-value firms. We find similar results in Table 6, Panel B, which shows that the impact of *ATI* on market reactions to recommendation changes is more pronounced for harder-to-value stocks.

Overall, the cross-sectional results in Table 6 further support the interpretation of *ATI* as a measure of abstract thinking. Consistent with abstract thinking as facilitating the identification of central characteristics and the comprehension of intangible things, *ATI* has stronger effects when analysts cover firms with fundamentals that are strongly correlated with peers and where there is limited tangible information.

5 Additional Analyses and Robustness Tests

5.1. Testing Alternative Explanation

One alternative interpretation of our results is that *ATI* may capture access to private information instead of a cognitive attribute of analysts. One possibility is that analysts with a closer connection to the firm may ask more abstract questions to please the management team, because abstract questions offer more room to manipulate the response. Another possibility is that analysts ask big, abstract questions because they have alternative sources of information and already have answers to concrete questions. Following the literature, we conduct two sets of tests to rule out this alternative explanation.

First, we examine whether analysts with a higher propensity of abstract thinking are more likely to ask questions or ask the first question in earnings calls. Mayew, Sharp, and Venkatachalam (2012) find that analysts who ask questions in earnings conference calls possess superior private information. Cen et al. (2021) document that analysts who ask the first question in earnings conference calls have better access to management. Therefore, we test if there is any relationship between analysts' abstract thinking styles and their participation in earnings conference calls.

We conduct tests at the analyst-year level and thus use *ATI_AY* as the main explanatory variable. For each analyst-year, we construct four variables to capture an analyst's participation in earnings conference calls. *First-Q Ratio* is the number of times an analyst asked the first question divided by the total number of questions asked in all calls attended by an analyst in a year. *First-Q (dummy)* equals one if an analyst ever asked the first question in a year. *No. of*

Calls Asking First Q is the number of calls in a year in which an analyst asked the first question. *Ratio of Calls Asking Questions* is the number of calls attended by an analyst divided by the total number of calls hosted by all firms covered by an analyst in a year. We then regress an analyst's participation variables on *ATI_AY*, and control for analyst characteristics and year, industry, and broker fixed effects. The results are presented in Panel A of Table 7. Across all columns, we find the coefficients on *ATI_AY* are insignificant, which suggests that the likelihood of an analysts asking any questions or the first question is not related to *ATI_AY*. In addition, we check the sequence of questions during earnings conference calls, and do not find any significant results. These results suggest that our abstract thinking measure is unlikely to capture analysts' connection with firm management.

Our second test investigates how the impact of abstract thinking varies with the geographical distance between an analyst and her covered firms. Malloy (2005) documents that geographically proximate analysts are more likely to possess an information advantage. Chen et al. (2022) show that analysts acquire more private information when firms become more accessible due to reduced travel costs, as analysts can visit the management, employees, and customers more frequently. Motivated by these studies, we hypothesize that if *ATI* indeed captures analysts' access to private information, its impact should be stronger on their forecasts of nearby firms. On the contrary, abstract thinking should be more important for distant firms for which analysts have less information.

Following Malloy (2005), we sort our sample into two subsamples based on whether the distance between a firm and an analyst is above or below 100 km. We then run our baseline test (Model (1) in Table 3) separately on the two subsamples. The results are reported in Panel B of Table 7. Interestingly, we find that *ATI* only improves forecast accuracy for firms located far away from the analyst. In untabulated results, we also fail to find any significant association between *ATI* and the likelihood of an analyst covering local firms. Collectively, these results lend more support to the cognitive attribute interpretation of *ATI* and are inconsistent with the alternative explanation that *ATI* simply captures analysts' superior access to private information.

5.2 Abstract Thinking and Analyst Career Outcomes

The previous sections show that analysts with a stronger abstract thinking style produce higher quality research. A question that naturally arises from our finding is whether abstract thinking impacts analysts' career outcomes. We expect analysts with a stronger abstract (concrete) thinking style to have better (poorer) career prospects. To test this conjecture, each year, we sort analysts into quartiles based on their *ATI_AY*. Analysts whose *ATI_AY* is in the highest quartile of the distribution are classified as *Abstract Analysts*, and those whose *ATI_AY* is at the lowest quartile of the distribution are classified as *Concrete Analysts*.

We then examine two measurable career outcomes—being voted an all-star analyst and working for a high-status brokerage house.[20] The data on all-star analyst status are collected from the October issue of *Institutional Investor* magazine. In our sample, 15.86% of observations have all-star status. A brokerage house is a high-status brokerage house if the number of analysts working there in a year is in the highest decile, and a low-status brokerage house otherwise.

We use a linear probability model to investigate how the propensity for abstract thinking affects the probability of an analyst being voted an all-star analyst or working for a high-status brokerage house. The dependent variable is a dummy variable that is equal to one if an analyst is named an all-star (or is at a high-status brokerage house) in a particular year, and zero otherwise. The key independent variables are two dummy variables that capture whether analysts belong to the *Abstract Analysts* or *Concrete Analysts* group. Following Hong and Kubik (2003), we also include the analyst's general forecasting experience, the number of covered firms, the average forecast frequency and accuracy for covered firms, and the average size of covered firms. An analyst's performance is measured over a 3-year period. For the determinants of *All Star*, we also control for whether the analyst was an all-star in the previous year. For all regressions, we control for year fixed effects and cluster the standard error at the analyst level.

Table 8 presents the regression results. Interestingly, we find that in column (1), the coefficient on *Concrete Analysts* is significantly negative, while in column (2), the coefficient

[20] Our results that ATI leads to more valuable investment advice also imply that abstract thinking analysts should be compensated more. The investment value of analysts' recommendations affects their ranking by institutional investors and how institutions value them. This, in turn, affects how much trading volume the investors direct toward analysts' brokerage house, which also factors into their compensation (Di Maggio et al., 2021). As we do not have data on analysts' compensation, we cannot test this prediction directly.

on *Abstract Analysts* is significantly positive. These results indicate that analysts with a higher propensity for concrete thinking are less likely to be voted all-star analysts, while analysts with a higher propensity for abstract thinking are more likely to work for a high-status brokerage house. The coefficients on other control variables are largely consistent with the literature (Bradley, Gokkaya, and Liu, 2017). For example, the significantly positive coefficients on *Broker Size* and *Average Firm Size* in column (1) suggest that analysts employed by higher status brokerage houses and those who follow larger firms are more likely to become all-star analysts.

5.3 The Real Effects of Analyst Abstract Thinking on Firm Information Environments

Analysts are among the most important information intermediaries in capital markets. Regulators and other market participants view analysts' research as enhancing the informational efficiency of stock prices (Frankel, Kothari, and Weber, 2006). Academic studies also show that analyst coverage affects the information environment of covered firms and reduces information asymmetry between insiders and outside investors (Kelly and Ljungqvist, 2012; Harford et al., 2019). Having documented the benefits of abstract thinking for individual analysts, we expect firms covered by more abstract thinking analysts to have better information environments, conditional on the amount of analyst coverage.

Different from the previous tests where the analysis is mainly at the analyst-firm-time level, the analysis in this subsection is at the firm-year level. We construct two variables to capture the average abstract thinking style of analysts covering a firm. The first variable, *ATI_firm,* is computed as the average *ATI_AY* of all analysts covering the firm in a year. The second variable, *Abstract Analyst Firm,* is the proportion of *Abstract Analysts* out of all analysts covering the firm in a year. We define analysts whose *ATI_AY* is in the top quartile of the cross-sectional distribution in a year as *Abstract Analysts*. When constructing *ATI_firm* and *Abstract Analyst Firm,* we exclude the focal firm's earnings conference calls. This is to address the reverse causality concern that a firm's information environment can affect the type of questions asked by analysts during its conference calls.

Following the literature, we use three variables to measure the degree of information asymmetry for a stock, namely return volatility, bid-ask spread, and Amihud illiquidity. The main independent variables are *ATI_firm* and *Abstract Analyst Firm.* In addition, we control for a list of variables that have been shown to affect information asymmetry, including firm size, the number of analysts issuing earnings forecasts for a firm, return-on-assets (ROA), and firm leverage. We also control for firm and year fixed effects. Standard errors are clustered at the firm level.

Table 9 presents the results. Panel A reports results when we use *ATI_firm* to measure the average abstract thinking propensity of analysts covering a firm. Consistent with our expectation, the coefficients on *ATI_firm* are significantly negative for all three measures of information asymmetry. These results indicate that when a firm is covered by analysts who on average have a stronger abstract thinking style, such firms' stocks experience lower information asymmetry. Economically, the coefficient estimate in column (3) of Panel A suggests that when a stock's *ATI_firm* increases from the 25th percentile to the 75th percentile, its Amihud illiquidity measure on average decreases by 0.0225 or 30.8% (= 0.0225/0.073) relative to the mean level of Amihud illiquidity. Panel B of Table 9 presents result of using *Abstract Analyst Firm* to measure the analysts' propensity for abstract thinking at the firm level. Consistent with the results in Panel A, the coefficients on *Abstract Analyst Firm* are all negative and highly significant.

One important caveat in interpreting the above results is that, although we document a negative association between the number of abstract thinking analysts covering a stock and its degree of information asymmetry, it is difficult to make any causal inference from the above tests. Unfortunately, as there are very few events of major brokerage house mergers and closures during our sample period, we are unable to follow the literature and use the exogenous loss of covering analysts to identify the causal impacts of abstract thinking analysts on firms' information environment.

5.4 Nature Versus Nurture

Scientists find that abstract thinking is linked to the structure of the brain, which varies across individuals. However, there are ways to induce and improve abstract thinking. Piaget (1972) shows that children develop abstract reasoning skills as part of their last stage of development. Scientific evidence is inconclusive regarding the relative weight of nature vs.

nurture in explaining individual heterogeneity in abstract thinking.[21] In Section 4.1, we provide evidence consistent with both nature and nurture, in that analyst fixed effects account for about 70% of the variation in *ATI* and analysts can increase their abstract thinking abilities by learning from peers.

To shed further light on whether the explanatory power of abstract thinking is entirely driven by nature, we repeat our analysis of forecast accuracy while including analyst fixed effects. In this case, the coefficient on *ATI* captures the impact of the change in an analyst's *ATI* on her forecast accuracy. Table A5 shows that the coefficients on *ATI* remain significantly negative, suggesting that an increase in an analyst's propensity for abstract thinking leads to improvement in her forecast accuracy. This specification also helps account for the confounding effects on forecast errors due to other unobserved and time-invariant analyst characteristics. However, the statistical power of *ATI* drops somewhat when we account for individual fixed effects, which suggests that cross-sectional variation in *ATI* across analysts (rather than time-series variation within an analyst) is the main driver of the positive association between *ATI* and forecast accuracy. Overall, the evidence suggests that abstract thinking is largely a personal trait, one shaped more by nature than nurture.

5.5 Robustness Tests

5.5.1 Components of ATI

Because our *ATI* is constructed from different components, we also explore which component drives the main effect. Specifically, we include in the regression the abstract level of language (*ATI_semantic*) and dialogue topic (*ATI_topic*), the number of words capturing future and past in a dialogue (*ATI_future* and *ATI_past*), and the number of times "why" or "how" appears in a dialogue (*ATI_why* and *ATI_how*). A larger value of *ATI_semantic, ATI_topic, ATI_future,* and *ATI_why* indicates a higher level of abstract thinking, while a larger value of *ATI_past* and *ATI_how* indicates a higher level of concrete thinking.

Table A6 reports the results. Panel A reports results on forecast errors (scaled by stock

[21] A few finance studies investigate the nature vs. nurture components of investment behavior. For example, Cronqvist and Siegel (2010) show that genetic traits account for 50% of investment biases. Grinblatt, Keloharju, and Linnainmaa (2011, 2012) document a positive relation between IQ and stock market participation and performance. More recently, Chaudhuri, Ivković, and Simonov (2021) examine the role of nurture in individuals' financial decision-making.

prices). Consistent with the results using the composite *ATI* measure, the coefficients on *ATI_semantic*, *ATI_topic*, *ATI_future*, and *ATI_why* are negative while the coefficients on *ATI_past* and *ATI_how* are positive. However, in terms of both statistical and economic significance, all component measures have a smaller impact on forecast errors than the composite *ATI* measure. Panel B reports the results for market reactions to recommendation changes. The sign of coefficients on the components of *ATI* is generally consistent with our hypothesis, although the statistical significance of each component measure is smaller than for the composite *ATI* measure. These results suggest that the composite *ATI* better captures abstract thinking as a style, probably because it combines different dimensions of abstract thinking and averages out idiosyncratic noise in each component measure.

5.5.2 Alternative Measures of Abstract Thinking

To further strengthen our results, we repeat our main analysis with several alternative measures of *ATI*. Table A7 shows that our main finding that abstract thinking style improves analysts' forecast accuracy is robust when we use these alternative measures of *ATI*.

In column (1), to ensure our key result is not driven by the mechanical correlation between a firm's earnings conference call and analyst accuracy in forecasting its stock, we construct *ATI_X* by excluding the focal firm's own conference calls. In column (2), we restrict our sample to analysts with at least five valid dialogues in each quarter in the rolling window to construct *ATI*. In column (3), we construct *ATI* using alternative values for dialogue topic abstractness, setting the topic abstractness scores of Topic 5, Topic 7, and Topic 23 equal to 2. In column (4), we remove the component *ATI_topic* when constructing the composite *ATI* measure, to address the concern that the scores for topic abstractness are subjective. In column (5), we remove the components of *ATI_future* and *ATI_past* when constructing the composite *ATI* measure, to address the concern that these components may be mechanically related to analysts' job responsibilities. In column (6), we standardize the components of *ATI* at the firm-level instead of the full sample.

For external validity checks, we also construct *ATI* using analyst reports from a subsample of analysts. Specifically, we focus on analysts from JP Morgan and sort their *ATI_AY* into quartiles. We select the top ten analysts from each quartile and collect their research reports. Then we construct a report-based *ATI* at the analyst-year level by averaging the semantic, future, past, why, and how components measured from reports.[22] We first show that the correlation between analyst report-based *ATI* and earnings call-based *ATI* is approximately 0.12 with a *p*-value of 0.0002. This significantly positive correlation assures us that our methodology for *ATI* construction indeed captures analysts' abstract thinking propensity across contexts. We then regress analysts' earnings forecast errors for next year on these report-based *ATI* values; column (7) shows that forecast errors decline with report-based *ATI*. This result provides external validity for our main finding, in that abstract thinking analysts perform better whether their *ATI* is measured by spontaneous verbal dialogues or well-prepared written reports.

5.5.3 Stock price reactions to analyst earnings forecast revisions

We also use the stock price reactions to earnings forecast revisions as an alternative measure of the informativeness of analyst research output. We measure market reactions within 2 or 4 days following the issuance of revisions with three cumulative abnormal return *(REVCAR*) measures: cumulative raw returns, cumulative market-adjusted returns, and characteristics-adjusted returns following Daniel et al. (1997). We exclude forecasts issued within a 3-day window of earnings announcements to avoid the potential confounding effects of earnings announcement returns. To increase the power of this test, in the regressions, we pool all upward and downward revisions together. To draw consistent inferences, we take the negative value of *REVCAR* for downward revisions. Therefore, a higher *REVCAR* indicates a stronger price reaction to forecast revisions. In all specifications, we control for firm and year-month fixed effects. The standard errors are clustered at the analyst and the year-month level. Table A8 shows that the stock market responds more strongly to forecast revisions issued by analysts with a higher propensity for abstract thinking, consistent with the results for forecast accuracy and recommendation announcement returns.

5.5.4 Additional robustness tests

We report the results from three additional robustness tests in Table A9. First, column

[22] When constructing the analyst report-based *ATI*, we do not include the topic component as a research report usually discusses many different topics.

(1) shows that the forecast accuracy results are robust when we examine annual earnings forecasts instead of quarterly earnings forecasts. Second, we construct an analyst-level *ATI* by taking the average of call-level *ATI*. Column (2) reports that the impact of analyst-level *ATI* on forecast accuracy is similar to that of analyst-year level *ATI*, both economically and statistically. Third, column (3) shows that the effect of *ATI* remains significant after we control for several attributes of earnings calls, including the length and tone of the latest earnings call before the issuance date of the earnings forecast.

5. Conclusion

Using dialogues between analysts and corporate executives during earnings conference calls, we construct an abstract thinking index to quantify analysts' propensity to think in an abstract way. Our findings clearly show that abstract thinking is associated with superior performance among analysts. Abstract thinking analysts produce more accurate earnings forecasts, and their forecast and recommendation revisions elicit stronger market reactions. Trading strategies following recommendation changes issued by abstract thinking analysts generate 6–7% higher annual alphas relative to those issued by concrete thinking analysts. Consistent with abstract thinking featuring identifying central characteristics and comprehending intangible things, *ATI* has stronger effects for firms with fundamentals co-moving more with peers and less tangible information. Examining whether abstract thinking is associated with more favorable career outcomes, we find that analysts with higher propensity of abstract thinking are more likely to work for a high-status brokerage house, while those who think in a more concrete way are less likely to be voted an all-star analyst. The benefits of abstract thinking spill over to financial markets, as we show that stocks covered by a greater proportion of abstract thinking analysts are associated with lower information asymmetry.

In addition to documenting the importance of abstract thinking for agents' information processing in a highly competitive profession, our paper has several further implications. Given rapid developments in information technology and the rise of robot-analysts on Wall Street, it is increasingly important for humans to possess traits that are complementary to or irreplaceable by those of machines. Our study suggests that the ability to think abstractly could be a desirable cognitive attribute that enables humans to generate insights in situations with great uncertainty and a limited amount of information. Our abstract thinking index could also be used to quantify the degree of abstract thinking performed by other decision makers such as fund and corporate managers. We leave these interesting research questions for future research.

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Table 1. Descriptive Statistics
This table repots summary statistics for the key variables used in the main regressions. The definitions of all variables are in Table A1.

	N	Mean	SD	PC25	Median	PC75
Panel A: Dependent Variables						
Forecast Error (PRC)	243215	0.003	0.004	0.000	0.001	0.003
Forecast Error (EPS)	241921	0.232	0.335	0.036	0.096	0.250
RECCAR[0,2]	9909	0.025	0.054	-0.001	0.018	0.043
Market-adjusted RECCAR[0,2]	9909	0.025	0.052	0.001	0.017	0.040
DGTW-adjusted RECCAR[0,2]	8352	0.024	0.048	0.002	0.017	0.038
Star	8598	0.101	0.301	0.000	0.000	0.000
Promotion	2839	0.007	0.082	0.000	0.000	0.000
Volatility	15166	0.024	0.012	0.016	0.021	0.030
Spread	15166	0.008	0.004	0.005	0.007	0.010
Illiquidity	15166	0.073	0.083	0.000	0.001	0.007
Panel B: Independent Variable						
ATI_AY	10923	-0.006	0.180	-0.109	-0.005	0.099
ATI	243215	-0.004	0.128	-0.089	-0.002	0.083
Panel C: Analyst Characteristics						
High-Status Broker	243215	0.119	0.324	0.000	0.000	0.000
Coverage	243215	20.762	7.209	16.000	20.000	25.000
GEXP	243215	14.154	9.816	6.000	12.000	23.000
FEXP	243215	4.319	4.821	1.000	3.000	6.000
No. of Industries	243215	3.799	2.446	2.000	3.000	5.000
Forecast Age	243215	104.416	84.908	49.000	90.000	113.000
Panel D: Firm Characteristics						
Mktcap	9909	6.039	0.960	5.481	6.105	6.663
BM	9909	0.569	0.410	0.281	0.475	0.750
Profit	9909	0.268	0.234	0.085	0.228	0.372
Growth	9909	0.125	0.312	-0.010	0.055	0.151
MOM	9909	0.117	0.353	-0.084	0.088	0.275
RET	9909	0.010	0.104	-0.047	0.010	0.063
LPCORR	211256	-1.901	0.621	-2.313	-1.926	-1.522
Firm Age	239597	25.901	18.606	11.000	21.000	36.000
IC	240127	0.214	0.220	0.022	0.137	0.360
High Distance	102128	0.849	0.358	1.000	1.000	1.000

Table 2. Variation of ATI

This table examines the variation of abstract thinking index (*ATI*). *ATI* is defined as the rolling average of quarterly-averaged analyst-call abstractness on all earnings conference calls within a year before the earnings forecast announcement date. Panel A report the regression results of *ATI* on various fixed effects (FE), including analyst FE, broker FE, and firm FE. Panel B reports the results of regressing *ATI* on analyst and analyst-firm characteristics. All control variables are lagged by one year. To define high-status brokers, we first sort brokers into deciles by the number of analysts each year. *High Status Broker* is a dummy variable that equals one if the broker is in the highest decile. *Coverage* is the natural logarithm of 1 plus the number of firms covered by an analyst. *GEXP*, *FEXP*, *INDEXP* are the analyst's general, firm, and industry working experience, calculated as the natural logarithm of 1 plus the difference between the year and the first year in which an analyst made forecasts, for a firm and an industry respectively, in the I/B/E/S database. *Star* is an indicator variable equal to one if an analyst is named to *Institutional Investor*'s all-star team. *No. of Industries* is the number of industries covered by an analyst. *Race* is a dummy variable that equals one if an analyst is white, and zero otherwise. *Gender* is a dummy variable which equals one if an analyst is male, and zero otherwise. *ATI_peers* is the average analyst-year level *ATI* of analyst peers covering the same firms as an analyst. In Panel B, we add firm by year-quarter fixed effects in columns (1) and (2). Further, we add analyst and broker fixed effects in columns (3) and (4). Standard errors are clustered at the analyst level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

Panel A: fixed effects

	(1) ATI	(2) ATI	(3) ATI	(4) ATI
FE	Analyst	Firm	Broker	Year-quarter
R-sq	0.709	0.231	0.071	0.020
Adj. R-sq	0.707	0.220	0.071	0.020

Panel B: analyst characteristics

	(1) ATI	(2) ATI	(3) ATI	(4) ATI
Race	0.012	0.014		
	(0.82)	(1.02)		
Gender	-0.010	-0.008		
	(-1.23)	(-0.96)		
High-Status Broker		0.020***	0.012**	0.012**
		(3.57)	(2.11)	(2.10)
Star		0.004	0.002	0.002
		(0.57)	(0.37)	(0.35)
Coverage		-0.009	-0.008	-0.008
		(-1.13)	(-1.15)	(-1.12)
GEXP		-0.009*	0.006	0.006
		(-1.81)	(0.47)	(0.48)
INDEXP		-0.004	0.001	0.001
		(-1.06)	(0.98)	(1.00)
No. of Industries		0.011	0.008	0.007
		(1.52)	(0.80)	(0.75)
FEXP				0.000
				(0.61)
ATI_peers				0.155***
				(3.17)
Firm × Year-quarter FE	Y	Y	Y	Y
Analyst FE	N	N	Y	Y
Broker FE	N	N	Y	Y
Adj. R-sq	0.320	0.328	0.768	0.768
N	230,410	230,350	243,145	242,290

Table 3. Abstract Thinking and Analyst Forecast Accuracy

This table reports the effect of abstract thinking on analyst forecast accuracy. *ATI* is defined as the rolling average of quarterly-averaged analyst-call abstractness on all earnings conference calls within a year before the earnings forecast announcement date. *Forecast error (PRC)* and *Forecast error (EPS)* are defined as the absolute difference between the forecasted EPS and realized EPS, divided by the stock price 12 months prior to the quarterly earnings announcement date and actual EPS, respectively. We multiply the dependent variables by 100. We include the analyst-year controls *Coverage*, *GEXP*, *FXEP*, *No. of Industries* and *High-Status Broker*. In addition, we add *Forecast Age*, which is the natural logarithm of the number of days from the forecast date to the earnings announcement date, as a control. The definitions of all variables are given in Table A1. We include all quarterly EPS forecasts in the sample and omit analysts who have fewer than ten valid dialogues each quarter. We include firm by year-quarter fixed effect. Standard errors are clustered at the firm level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1) Forecast Error (PRC)	(2) Forecast Error (EPS)
ATI	-0.015**	-1.005**
	(-2.53)	(-2.24)
Coverage	-0.004*	-0.373*
	(-1.72)	(-1.88)
GEXP	-0.002**	-0.239***
	(-2.35)	(-3.44)
FEXP	-0.000	-0.004
	(-0.39)	(-0.06)
No. of Industries	0.006***	0.447***
	(2.80)	(2.76)
High-Status Broker	0.002	0.116
	(1.01)	(0.84)
Forecast Age	0.043***	2.915***
	(25.77)	(23.59)
Firm × Year-quarter FE	Y	Y
Adj. R-sq	0.680	0.616
N	243,215	241,921

Table 4. Abstract Thinking and Market Reactions to Analyst Recommendation Changes

This table reports the effect of analyst abstractness on the short-term market reaction (CAR) to analyst recommendations. We include all upgrades to buy recommendations and downgrades to hold or sell recommendations in the sample and exclude recommendations made within a 3-day window before or after an earnings announcement. *ATI* is defined as the rolling average of quarterly-averaged analyst-call abstractness on earnings conference calls within a year before the recommendation announcement date. *RECCAR[0, +i]* is the cumulative raw or abnormal returns (adjusted by market or DGTW returns) within *i* days after the recommendation announcement. For downgrade recommendations, we take the negative value of the CARs. We multiply the dependent variables by 100. We include analyst-year controls including *Coverage*, *GEXP*, *FXEP*, *No. of Industries,* and *High Status Broker*. We also add firm controls including *Mktcap*, *BM*, *Profit*, *Growth*, *MOM* and *RET*. *Mktcap* is the natural logarithm of stock market capitalization at the end of the month before the revision announcement. *BM* is the book-to-market ratio at the most recent fiscal year end. *GP* is the gross profitability defined as sales revenue minus cost of goods sold scaled by assets. *AG* is the asset growth defined as the year-over-year growth rate of total assets. *MOM* is the medium-term stock momentum, defined as the stock return of the last 12 months excluding the most recent month. *RET* is the stock return of the last month before the revision announcement. In addition, we add *lag (recommendation)* as a control. The definitions of all variables are given in Table A1. We include firm and year-month fixed effects. Standard errors are two-way clustered at the analyst and year-month level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	RECCAR[0,2]	Market-adjusted RECCAR[0,2]	DGTW-adjusted RECCAR[0,2]	RECCAR[0,4]	Market-adjusted RECCAR[0,4]	DGTW-adjusted RECCAR[0,4]
ATI	1.685***	1.555***	0.860*	2.048***	1.603***	1.182**
	(2.87)	(2.83)	(1.93)	(3.12)	(2.79)	(2.33)
Coverage	0.470**	0.435**	0.774***	0.401*	0.415*	0.694***
	(2.41)	(2.40)	(3.80)	(1.72)	(1.85)	(2.98)
GEXP	-0.147	-0.145	-0.201**	-0.208*	-0.187*	-0.167*
	(-1.51)	(-1.55)	(-2.24)	(-1.88)	(-1.78)	(-1.83)
FEXP	0.226***	0.218***	0.178**	0.323***	0.285***	0.161**
	(2.80)	(2.82)	(2.29)	(3.41)	(3.27)	(2.13)
No. of Industries	-0.396**	-0.311*	-0.310*	-0.384	-0.336	-0.394*

	(-2.04)	(-1.82)	(-1.76)	(-1.54)	(-1.52)	(-1.93)
High-Status Broker	-0.011	0.094	0.181	0.187	0.326	0.306*
	(-0.07)	(0.71)	(1.27)	(0.83)	(1.55)	(1.96)
Mktcap	-0.961***	-0.993***	-0.829***	-1.236***	-1.254***	-0.742**
	(-3.25)	(-3.61)	(-2.85)	(-3.00)	(-3.30)	(-2.09)
BM	-0.232	-0.245	-0.469	-0.504	-0.419	-0.310
	(-0.65)	(-0.68)	(-1.29)	(-1.01)	(-0.86)	(-0.75)
Profit	-2.412**	-1.958*	-1.352	-2.423*	-1.532	-1.475
	(-2.04)	(-1.75)	(-1.16)	(-1.69)	(-1.13)	(-1.14)
Growth	0.065	0.035	0.049	0.329	0.318	0.047
	(0.21)	(0.11)	(0.14)	(1.04)	(1.08)	(0.13)
MOM	0.042	0.008	0.159	0.017	-0.016	-0.068
	(0.14)	(0.03)	(0.67)	(0.05)	(-0.05)	(-0.25)
RET	-0.579	-0.407	-0.814	0.303	0.742	0.074
	(-0.61)	(-0.47)	(-0.97)	(0.29)	(0.76)	(0.07)
Lag (recommendation)	0.381***	0.217**	0.227***	0.420***	0.166*	0.241***
	(3.13)	(2.46)	(3.09)	(2.79)	(1.75)	(2.89)
Firm FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Adj. R-sq	0.165	0.178	0.202	0.126	0.138	0.170
N	9,909	9,909	8,352	9,909	9,909	8,353

Table 5. Abstract Thinking and Investment Value of Stock Recommendations

This table reports the average daily portfolio buy-and-hold returns for upgrades to buy recommendations (Panel A) and downgrades to hold or sell recommendations (Panel B) by analyst abstractness quartiles. We exclude recommendations made within a 3-day window before or after an earnings announcement. A stock enters a portfolio at the close of trading day when the recommendation is announced. If more than one broker takes the same action on a particular stock, then that stock will appear multiple times in the corresponding portfolio, once for each broker. A stock is dropped from the upgrade (downgrade) portfolio when a downgrade (upgrade) is announced, or when the stock is dropped from coverage. Each portfolio's value-weighted return is calculated each day, with the portfolio rebalanced at the end of the day, if necessary. Analyst abstractness quartiles are determined each year by ranking analysts in ascending order according to analyst-year abstractness (*ATI_AY*). L/S is the alpha of a zero-cost portfolio that holds the top quartile stocks ranked by *ATI_AY* and shorts the bottom quartile. Excess return is the raw return of the portfolio over the risk-free rate. Alpha is the intercept from a regression of daily excess return on factor returns. Factor models include: CAPM model; the Fama-French (1993) three-factor model; a four-factor model including the Fama-French three factors and Carhart's (1997) momentum factor, the Fama-French (2014) five-factor model, and the Hou-Xue-Zhang (2015) q-factor model. Returns and alphas are in daily percent; *t*-statistics are shown below the excess returns and alphas. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

Panel A: Portfolio returns of upgrade recommendations						
Quartiles	Excess returns (%)	CAPM alpha (%)	3-Factor alpha (%)	4-Factor alpha (%)	5-Factor alpha (%)	q-Factor alpha (%)
1	-0.016	-0.012	-0.005	-0.004	-0.004	0.004
(low)	(-1.60)	(-1.19)	(-0.61)	(-0.53)	(-0.52)	(0.47)
2	-0.006	-0.002	0.004	0.006	0.005	0.010
	(-0.68)	(-0.17)	(0.53)	(0.70)	(0.61)	(1.26)
3	-0.008	-0.006	0.001	0.001	0.001	0.006
	(-0.69)	(-0.48)	(0.08)	(0.14)	(0.08)	(0.56)
4	0.012	0.018*	0.022**	0.023**	0.020**	0.026***
(high)	(1.11)	(1.76)	(2.35)	(2.42)	(2.18)	(2.72)
L/S	0.015	0.029***	0.026**	0.026**	0.023**	0.021**
	(1.47)	(2.61)	(2.38)	(2.38)	(2.10)	(1.92)
Panel B: Portfolio returns of downgrade recommendations						
Quartiles	Excess returns (%)	CAPM alpha (%)	3-Factor alpha (%)	4-Factor alpha (%)	5-Factor alpha (%)	q-Factor alpha (%)
1	-0.030**	-0.012	-0.006	-0.004	-0.006	0.002
(low)	(-2.34)	(-1.17)	(-0.60)	(-0.39)	(-0.59)	(0.20)
2	-0.031***	-0.022**	-0.015*	-0.013*	-0.015*	-0.007
	(-3.02)	(-2.35)	(-1.85)	(-1.69)	(-1.84)	(-0.90)
3	-0.035***	-0.025**	-0.018*	-0.016	-0.019*	-0.013
	(-2.98)	(-2.29)	(-1.78)	(-1.60)	(-1.89)	(-1.29)
4	-0.048***	-0.040***	-0.034***	-0.032***	-0.035***	-0.029***
(high)	(-3.70)	(-3.17)	(-2.92)	(-2.74)	(-3.00)	(-2.49)
L/S	-0.018	-0.029**	-0.027*	-0.028*	-0.028*	-0.029**
	(-1.54)	(-1.98)	(-1.87)	(-1.93)	(-1.93)	(-2.01)

Table 6. Abstract Thinking and Analyst Performance: Tests of Channels

This table reports the cross-firm heterogeneity of analyst abstractness's effect on forecast accuracy. We measure a firm's fundamental correlation with all other firms in the same industry (*LPCORR*) following Hammed et al. (2015). We measure firm information environment by stock volatility, spread, and illiquidity at the monthly level. *Volatility* is calculated as the monthly averaged call-option implied volatility. *Spread* is calculated by the daily stock price following Abdi and Ranaldo (2017). *Illiquidity* is calculated as the average of daily Amihud illiquidity. We measure *Firm Age* as the number of years since the first date of the company's total assets data reported in Compustat Annual database. We measure intangible capital (*IC*) as the value of intangible assets over the value of total assets in the latest fiscal year. We then sort firms into two groups based on the median values of *LPCORR_ROA*, *Volatility*, *Spread*, *Illiquidity*, *Firm Age,* and *IC,* and examine the impact of *ATI* on forecast accuracy for each group respectively. For brevity, we only report results for forecast error scaled by stock price and market-adjusted *RECCAR[0,2]*. We report the results of F-tests on the difference between each pair of subsamples. In both panels, we add controls including *Coverage*, *GEXP*, *FXEP*, *No. of Industries*, and *High-Status Broker*. In Panel A, we also include *Forecast Age*. In Panel B, we include additional controls including *Mktcap*, *BM*, *Profit*, *Growth*, *MOM*, *RET*, and *lag (recommendation)*. The definitions of all other variables are given in Table A1. In Panel A, we include firm by year-quarter fixed effect and cluster standard errors at the firm level. In Panel B, we include firm and year-month fixed effects and two-way cluster the standard errors at the analyst and year-month level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

Panel A: Abstract Thinking and Analyst Forecast Accuracy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Low LPCORR	High LPCORR	Low Volatility	High Volatility	Low Spread	High Spread	Low Illiquidity	High Illiquidity	Younger Firm	Old Firm	Low IC	High IC
	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error
ATI	0.000	-0.024***	-0.003	-0.025**	-0.002	-0.025**	-0.004	-0.027**	-0.026***	-0.005	0.000	-0.031***
	(0.05)	(-3.13)	(-0.58)	(-2.22)	(-0.34)	(-2.24)	(-0.85)	(-2.36)	(-2.87)	(-0.68)	(0.01)	(-4.11)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm × Year-quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-statistics	4.50		3.12		3.35		3.48		3.21		6.77	

Prob > F	0.034		0.077		0.067		0.062		0.073		0.009	
Adj. R-sq	0.684	0.663	0.557	0.648	0.596	0.657	0.542	0.640	0.677	0.665	0.673	0.680
N	105,277	105,979	113,804	111,442	115,696	112,199	122,455	118,682	122,979	116,618	120,364	119,763

Panel B: Abstract Thinking and Market Reactions to Analyst Recommendation Changes

	(1) Low LPCORR	(2) High LPCORR	(3) Low Volatility	(4) High Volatility	(5) Low Spread	(6) High Spread	(7) Low Illiquidity	(8) High Illiquidity	(9) Younger Firm	(10) Old Firm	(11) Low IC	(12) High IC
	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]	RECCAR[0,2]
ATI	-0.217	2.288***	0.162	2.297**	0.119	2.173*	0.493	2.736**	1.525*	0.934*	1.521*	1.772**
	(-0.32)	(3.47)	(0.36)	(2.07)	(0.29)	(1.68)	(1.11)	(2.50)	(1.78)	(1.71)	(1.70)	(2.47)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-statistics	7.08		3.27		2.40		3.82		0.35		0.05	
Prob > F	0.009		0.072		0.123		0.052		0.558		0.827	
Adj. R-sq	0.174	0.091	0.156	0.114	0.110	0.107	0.033	0.145	0.151	0.147	0.197	0.162
N	3,234	3,224	4,891	4,292	4,399	3,720	5,271	4,378	4,671	4,816	4,761	4,830

Table 7. Testing Alternative Explanations

This table tests alternative explanations of the effect of *ATI* on analyst performance. Panel A reports the results of whether analysts with higher *ATI* are more likely to ask questions or ask the first question in earnings calls. We conduct tests at the analyst-year level. For each analyst-year, we construct four variables to capture an analyst's participation in earnings conference calls. *First-Q Ratio* is the number of times an analyst asked the first question divided by the total number of questions asked in all calls attended by the analyst in a year. *First-Q (dummy)* equals one if an analyst ever asked the first question in a year, and zero otherwise. *No. of Calls Asking First-Q* is the number of calls in which an analyst asked the first question in a year. *Ratio of Calls Asking Questions* is the number of calls where an analyst asked questions divided by the total number of calls hosted by her covered firms in a year. We add year, industry, and broker fixed effects and standard errors are clustered at the analyst level. Panel B reports the results for how the impact of *ATI* varies with the geographical distance between an analyst and her covered firms. We measure the distance between analysts and firms by the distance between the geographic coordinates of the city where the analyst's brokerage is located and the city where the firm is headquartered. We divide our sample into two groups, *High Distance* and *Low Distance*, based on whether the distance between a firm and an analyst is above or below 100 km. We then run Model (1) separately on the two subsamples. Control variables include *Coverage*, *GEXP*, *FXEP*, *No. of Industries,* and *High-Status Broker*. In Panel B, we also include *Forecast Age* as an additional control. The definitions of all other variables are given in Table A1. We include firm by year-quarter fixed effects. Standard errors are clustered at the firm level. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

Panel A: ATI and Analysts Asking First Questions

	(1)	(2)	(3)	(4)
	First-Q Ratio	First-Q (dummy)	No. of Calls Asking First-Q	Ratio of Calls Asking Questions
ATI_AY	-0.001	0.055	-0.088	0.161
	(-0.04)	(1.41)	(-0.13)	(0.96)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Broker FE	Y	Y	Y	Y
Adj. R-sq	0.247	0.096	0.277	0.273
N	5,240	5,240	5,240	5,240

Panel B: The Effect of ATI on Forecast Accuracy in High and Low Distance Groups

	(1) Low Distance		(2) High Distance
	Forecast Error		Forecast Error
ATI	0.038		-0.025**
	(1.39)		(-2.36)
Controls	Y		Y
Firm × Year-quarter FE	Y		Y
F-statistics		4.59	
Prob > F		0.032	
Adj. R-sq	0.667		0.677
N	12,685		84,826

Table 8. Abstract Thinking and Analyst Career Outcomes

This table reports the effect of abstract thinking on analysts' career outcomes, as proxied by being voted an all-star analyst and being in a high-status brokerage firm. To classify abstract and concrete analysts, we first sort analysts by their *ATI_AY* into quartiles each year. *Abstract Analyst* is a dummy variable that equals one if an analyst is in the highest quartile, and zero otherwise. *Concrete Analyst* is a dummy variable that equals one if an analyst is in the lowest quartile, and zero otherwise. *Star* is an indicator variable equal to one if an analyst is named to *Institutional Investor*'s all-star team, and zero otherwise. All independent variables are lagged by one year. *Average Firm Size* is the average size of all firms covered by an analyst in a year. *DFREQ* is the number of earnings forecast revisions issued by analyst *i* for firm *j* in the year, minus the average number of earnings forecast revisions issued by all analysts for firm *j* in the year. *Average DFREQ* is the average of *DFREQ* for an analyst across all covered firms. *PMAFE* is the proportional mean absolute forecast error calculated as the difference between the absolute forecast error of analyst *i* on firm *j* in the year and the mean absolute forecast error for firm *j* in the year scaled by the mean absolute forecast error for firm *j* in the year. *Average PMAFE* is the average of *PMAFE* for an analyst across all covered firms in a year. The definitions of all other variables are given in Table A1. We include year fixed effects. Standard errors are clustered at the analyst level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1) All Star	(2) High-Status Broker
Abstract Analyst	-0.003	0.024***
	(-0.61)	(2.61)
Concrete Analyst	-0.008*	-0.005
	(-1.80)	(-0.53)
Coverage	0.019***	0.058***
	(3.82)	(4.41)
GEXP	0.003	-0.018**
	(1.11)	(-2.12)
No. of Industries	0.001	0.023*
	(0.21)	(1.68)
Broker Size	0.017***	0.434***
	(7.06)	(65.97)
Average Firm Size	0.012***	-0.009
	(4.33)	(-1.21)
Average DFREQ	0.0001	-0.0001
	(1.13)	(-0.42)
Average PMAFE	-2.531*	3.340
	(-1.79)	(1.50)
Lag (Star)	0.689***	-0.099***
	(48.92)	(-6.35)
Year FE	Y	Y
Adj. R-sq	0.607	0.638
N	8,598	9,333

Table 9. Abstract Thinking Analysts and Firm Information Environment

This table reports the effect of analyst abstract thinking on covered firms' information environment. In Panel A, we measure analyst abstract thinking at firm level using *ATI_firm*, defined as the average *ATI_AY* of all analysts covering the firm in a year. We exclude the focal firm's earnings calls when constructing analyst *ATI_AY*. In Panel B, we use *Abstract Analyst Firm*, defined as the proportion of *Abstract Analyst* of all analysts covering the firm in a year. *Volatility*, *Spread*, and *Illiquidity* are also calculated at the firm-year level. We also include the controls *NUMEST*, *Size*, *ROA*, and *LEV*. *NUMEST* is the number of analysts issuing earnings forecasts for the firm. *Size* is the natural log of a firm's market capitalization. *ROA* is the firm's income before extraordinary items divided by total assets. *LEV* is the firm leverage calculated as the total long-term debt scaled by total assets. We include firm and year fixed effects. Standard errors are clustered at the firm level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

Panel A: Firm Abstractness and Firm Information Environment

	(1) Volatility	(2) Spread	(3) Illiquidity
ATI_firm	-0.036**	-0.0008**	-0.191*
	(-2.53)	(-2.56)	(-1.67)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Adj. R-sq.	0.826	0.838	0.344
N	13,957	15,169	15,169

Panel B: Fraction of Abstract Analysts and Firm Information Environment

	(1) Volatility	(2) Spread	(3) Illiquidity
Abstract Analyst Firm	-0.011**	-0.0004***	-0.033***
	(-2.33)	(-3.87)	(-3.28)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Adj. R-sq.	0.823	0.837	0.556
N	13,956	15,166	15,166

Appendix Tables

Table A1. Variable Definitions

Dependent Variables	
Forecast Error (PRC)	The absolute difference between the forecasted EPS and the realized EPS, scaled by the stock price 12 months prior to the quarterly earnings announcement date.
Forecast Error (EPS)	The absolute difference between the forecasted EPS and the realized EPS, scaled by the actual EPS.
REVCAR[i,j] (Market-adjusted REVCAR[i,j] or DGTW-adjusted REVCAR[i,j])	The cumulative raw or abnormal returns (adjusted by market or DGTW returns) from *i* to *j* days before and after the forecast revision announcement date.
RECCAR[i,j] (Market-adjusted RECCAR[i,j] or DGTW-adjusted RECCAR[i,j])	The cumulative raw or abnormal returns (adjusted by market or DGTW returns) from *i* to *j* days before and after the recommendation announcement date.
Star	An indicator variable equal to one if an analyst is named to *Institutional Investor*'s all-star team.
Promotion	An indicator variable equal to one if an analyst is promoted from a non-high-status broker to a high-status broker. We sort brokers into deciles by the number of analysts each year. A broker is classified as a high-status broker if it is in the highest decile.
Volatility	The average call-option-based implied volatility. It is calculated at the monthly level in Table 8, and at the yearly level in Table 11.
Spread	In Table 8, the monthly spread is calculated by the daily close, low and high price following Abdi and Ranaldo (2017). Spread = $2\sqrt{E(c_t - n_t)(c_t - n_{t+1})}$, in which *c* is the daily log-price and *n* is the daily mid-range, which is the average of daily high and low log-prices. The yearly spread is calculated as the average of monthly spread in a calendar year.
Illiquidity	Illiquidity is calculated as the average of daily Amihud illiquidity. It is calculated at the monthly level in Table 8, and at the yearly level in Table 11.
Optimism	The difference between a forecast and the existing consensus, scaled by the stock price 12 months prior to the quarterly earnings announcement date.
Herding	A binary variable with a value of 1 if an analyst's forecast of a company at time t is between the consensus forecast at time t and her own previous forecast, and 0 otherwise.
First-Q Ratio	The number of times an analyst asked the first question divided by the total number of questions asked in all calls attended by an analyst in a year.
First-Q (dummy)	A dummy variable that equals 1 if an analyst ever asked the first question in a year.
NO. of Calls Asking First-Q	The number of calls in which an analyst asked the first question in a year.

Ratio of Calls Asking Questions	The number of calls attended by an analyst divided by the total number of calls hosted by the covered firms by an analyst in a year.
Independent Variables	
ATI	The rolling average of quarterly-averaged analyst-call abstractness on all earnings conference calls within a year before the earnings forecast, forecast revision, or recommendation announcement date. Analyst-call abstractness is calculated as the average of standardized analyst-call semantic-abstractness, topic-abstractness, future-abstractness, negative value of past-concreteness, why-abstractness, and negative value of how-concreteness.
ATI_AY	The analyst-year abstractness is calculated as the average of quarterly-averaged analyst-call abstractness on all earnings conference calls in a year.
ATI-X	The rolling average of quarterly-averaged analyst-call abstractness on all earnings conference calls excluding the focal firm's own calls within a year before the earnings forecast, forecast revision, or recommendation announcement date.
ATI_semantic	The dialogue semantic-abstractness, calculated as the difference between abstract-attribute words and concrete-attribute words, then scaled by the total number of abstract-attribute and concrete-attribute words in a dialogue. Abstract-attribute words include adjective, modal, and determiner, while concrete-attribute words include verb and cardinal digit. We construct analyst-call semantic-abstractness as the average of dialogue semantic-abstractness across all dialogues with at least 10 words from an analyst in each call. *ATI_semantic* is the rolling average of quarterly-averaged standardized analyst-call semantic-abstractness on all earnings conference calls within a year before the earnings forecast or forecast revision announcement date.
ATI_topic	The dialogue topic-abstractness is defined as the abstractness score of the topic of a dialogue. The topic of a dialogue is identified by Structed Topic modeling (STM) tools. The abstractness score of each topic is manually assigned. The detail topics and scores are listed in Internet Appendix Table IA1. Analyst-call topic-abstractness and *ATI_topic* are calculated similarly as above.
ATI_future	The dialogue future-abstractness is defined as the number of words focusing on the future in a dialogue. The detailed list of future-focused words is in Internet Appendix Table IA3. Analyst-call future-abstractness and *ATI_future* are calculated similarly as above.

ATI_past	The dialogue past-concreteness is defined as the number of words focusing on the past in a dialogue. The detailed list of past-focused words is in Internet Appendix Table IA3. Analyst-call past-concreteness and *ATI_past* are calculated similarly as above.
ATI_why	The dialogue why-abstractness is defined as the number of instances of the word “why” in a dialogue. Analyst-call why-abstractness and *ATI_why* are calculated similarly as above.
ATI_how	The dialogue how-concreteness is defined as the number of instances of the word “how” in a dialogue. Analyst-call how-concreteness and *ATI_how* are calculated similarly as above.
Abstract Analyst	We first sort analysts by their *ATI_AY* into quartiles each year. *Abstract Analyst* is a dummy variable that equals one if an analyst is in the highest quartile, and zero otherwise.
Concrete Analyst	We first sort analysts by their *ATI_AY* into quartiles each year. *Concrete Analyst* is a dummy variable which equals one if an analyst is in the lowest quartile, and zero otherwise.
ATI_peers	The average *ATI_AY* of the analyst peers covering the same firms as an analyst.
ATI_firm	The firm-year abstractness is defined as the average of *ATI_AY* of all analysts covering the firm. We exclude the focal firm’s earnings calls when constructing analysts’ *ATI_AY*.
Abstract Analyst Firm	The proportion of *Abstract Analysts* among all analysts covering the firm.
Analyst Controls	
High Status Broker	We sort brokers into deciles by the number of analysts each year. *High Status Broker* is a dummy variable that equals one if the broker is in the highest decile.
Coverage	The natural logarithm of 1 plus the number of firms covered by an analyst.
GEXP	The analyst general working experience, calculated as the natural logarithm of 1 plus the difference between the year and the first year that an analyst made a forecast in I/B/E/S database.
INDEXP	The analyst industry working experience, calculated as the natural logarithm of 1 plus the difference between the year and the first year that an analyst made a forecast for an industry in I/B/E/S database.
FEXP	The analyst firm working experience, calculated as the natural logarithm of 1 plus the difference between the year and the first year that an analyst made a forecast for a firm in I/B/E/S database.
Forecast Age	The natural logarithm of the number of days from the forecast date to the earnings announcement date.
No. of Industries	The natural logarithm of the number of industries covered by an analyst.
Race	A dummy variable that equals one if an analyst is white, and zero otherwise. We identify an analyst’s race by their full name.
Gender	A dummy variable that equals one if an analyst is male, and zero otherwise. We identify an analyst’s gender by their first name.

Average Firm Size	The average size of all firms covered by an analyst.
DFREQ	The number of earnings forecast revisions issued by analyst *i* for firm *j* in the year, minus the average number of earnings forecast revisions issued by all analysts for firm *j* in the year. *Average DFREQ* is the average of *DFREQ* by an analyst across all covered firms in the year.
PMAFE	The proportional mean absolute forecast error calculated as the difference between the absolute forecast error of analyst *i* on firm *j* in the year and the mean absolute forecast error for firm *j* in the year scaled by the mean absolute forecast error for firm *j* in the year. *Average PMAFE* is the average of *PMAFE* by an analyst across all covered firms in the year.
Firm Controls	
Mktcap	The natural logarithm of stock market capitalization at the end of the month before the earnings forecast, forecast revision, or recommendation announcements.
BM	The book-to-market ratio, defined as book equity scaled by market capitalization.
Profit	The gross profitability, defined as sales revenue minus cost of goods sold scaled by assets.
Growth	The asset growth, defined as the year-over-year growth rate of total assets.
MOM	The medium-term stock momentum, defined as the stock return of the last 12 months excluding the most recent month.
RET	The stock return of the last month before the recommendation announcement.
NUMEST	The number of analysts issuing earnings forecasts for the firm.
ROA	Income before extraordinary items divided by total assets.
LEV	Leverage, calculated as total long-term debt scaled by total assets.
Firm Heterogeneity	
LPCORR	A firm's fundamental correlation with all other firms in the same industry (*LPCORR*), measured following Hammed et al. (2015).
Firm Age	The age of a firm, defined as the number of years since the first date of the company's total assets data reported in the Compustat Annual database.
IC	Intangible capital (*IC*), defined as the value of intangible assets over the value of total assets.
High Distance	A dummy variable that equals 1 if the distance between the analyst and firm is above 100 km, and otherwise 0. We measure the distance between analysts and firms by the distance between the geographic coordinates of the city where the analyst's brokerage is located and the city where the company's headquarters is located.

Table A2. Sample Construction and Comparison

This table shows the construction process of the sample, with the number of documents or observations at each step (Panel A) and compares the characteristics of analysts included in this paper with the I/B/E/S universe (Panel B). We collect earnings conference call transcripts from 2011 to 2019. We identify question dialogues in the scripts and keep question dialogues with at least 10 words. We match the analysts in the earnings conference calls with analysts in the I/B/E/S dataset and eventually identify the dialogues that are from sell-side analysts. Then we construct analyst-call abstractness based on valid dialogues in each conference call. In Panel B, we report the average mean and standard errors (in parentheses) of the analyst-level characteristics of analysts in our sample, those in the I/B/E/S universe but lacking dialogue in earnings conference calls, and those with at least one dialogue but which are not included in our sample due to filtering criteria. The differences between each pair within the three groups are statistically significant at 1% (t-test results are not included for brevity).

Panel A: Sample Construction

	No.
Earnings conference call transcripts	86,765
Total dialogues	6,616,558
Question dialogues	2,410,422
Question dialogues with wordcount >= 10	1,624,435
Sell-side analyst dialogues	1,032,541
Analyst-call abstractness	285,669

Panel B: Sample Comparison

	Analyst in our sample	Analyst in I/B/E/S but not in earnings conference calls	Analyst not in our sample but in earnings conference calls
Forecast Error	0.003	0.003	0.003
	(.005)	(.005)	(.005)
Broker Size	74.395	47.819	72.219
	(57.024)	(50.442)	(59.668)
Coverage	20.450	18.999	18.002
	(6.151)	(6.916)	(6.977)
No. of Industries	3.602	3.366	2.985
	(2.052)	(2.018)	(1.902)
High-Status Broker	*0.702*	*0.456*	*0.623*
	(.458)	(.498)	(.485)
No. of Analysts in a Year	*1,139*	*956*	*463*

Table A3. Sample dialogues underpinning ATI

This table shows sample dialogues of analysts with the highest and lowest propensity of abstract thinking at the analyst-year level. *ATI_AY* is the analyst-year abstractness, calculated as the average of quarterly-averaged analyst-call abstractness during all earnings conference calls in a year. We list the names of analysts and their brokerage houses.

Analyst	Brokerage	Year	ATI_AY	Questions during Earnings Conference Calls
Cooley May	Macquarie Capital (USA)	2015	2.331	Continuing a downward trend And so I'm looking—I'm trying to figure out, is this an industry-wide issue? And where spreads are likely to settle out toward the end of the year? And if you're a buyer of wood pulp in Asia, why would you buy here—why wouldn't you destock inventory, press price lower as much as you can?
James D. Parker	Raymond James & Associates	2014	2.217	How can you say with confidence that you will be able to repatriate some or all of that cash that you have there, just what are the political, economic reasons why you're optimistic about those funds eventually being repatriated? Pedro, why not take some or all of your capacity out and redeploy it in other markets where you'll actually get paid?
Andy Hargreaves	Pacific Crest Securities	2017	-1.237	Hi, thanks. Just, I have a couple of clarifications. I wondered, one, if you could just give us a sort of comment on what ad volume was in the quarter, how much it grew in the quarter? And then wanted to go through the sales employee stuff a little bit more. So if I heard you right you ended at 529. Does that include the people that were let go or does that happen all in Q1?
Drew Borst	Goldman Sachs	2012	-1.276	Great, thanks. Guys, when I look at your JV revenue sharing revenue that was in the quarter, when you do that as a percent of the global box office it looked like it was a little bit lower in the quarter. So, I think by my numbers it was about 75% in the third quarter and it was closer to 9%, 95%. Could you give us the breakdown of the box office between domestic and international?

Table A4. Abstract Thinking and Analyst Forecasting Behaviors

This table reports the effect of abstract thinking on analysts' other forecasting behaviors. *Herding* is a binary variable that equals one if an analyst's forecast of a company at time t is between the consensus forecast at time t and his own previous forecast, and zero otherwise. *Optimism* is the difference between a forecast and the existing consensus, scaled by the stock price 12 months prior to the quarterly earnings announcement date. We include the controls *Coverage*, *GEXP*, *FXEP*, *No. of Industries*, *High-Status Broker*, and *Forecast Age*. We use OLS and Logit regression methodologies, respectively. The definitions of all other variables are given in Table A1. We include firm by year-quarter fixed effects. Standard errors are clustered at the firm level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1) Herding	(2) Herding	(3) Optimism	(4) Optimism
ATI	-0.014*	-0.285***	-0.003	-0.092
	(-1.66)	(-3.00)	(-0.36)	(-1.10)
Coverage	-0.002	-0.003	0.003	0.099**
	(-0.42)	(-0.07)	(0.86)	(2.55)
GEXP	-0.001	-0.035**	-0.002**	-0.045***
	(-0.37)	(-2.12)	(-2.06)	(-3.09)
FEXP	-0.003*	-0.003	-0.002**	0.047***
	(-1.95)	(-0.19)	(-2.00)	(3.46)
No. of Industries	0.005	0.067**	-0.007***	0.020
	(1.64)	(2.01)	(-3.03)	(0.65)
High-Status Broker	-0.002	0.020	0.005**	0.047*
	(-0.68)	(0.65)	(2.21)	(1.66)
Forecast Age	0.005***	0.080***	-0.012***	0.173***
	(4.29)	(5.94)	(-10.42)	(14.47)
Firm × Year-quarter FE	Y	Y	Y	Y
Methodology	OLS	Logit	OLS	Logit
Adj. R-sq	0.054	0.044	0.538	0.076
N	179,432	179,584	179,432	178,722

Table A5. Abstract Thinking and Analyst Forecast Accuracy: Nature Versus Nurture

This table reports the effects of *ATI* on analyst forecast accuracy by adding an analyst fixed effect in Model (1). Controls are *Coverage*, *GEXP*, *FXEP*, *No. of Industries*, *High Status Broker*, and *Forecast Age*. The definitions of all other variables are given in Table A1. We also include firm by year-quarter fixed effects. Standard errors are clustered at the firm level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1) Forecast Error (PRC)	(2) Forecast Error (EPS)
ATI	-0.044**	-2.793*
	(-2.21)	(-1.79)
Controls	Y	Y
Analyst FE	Y	Y
Firm × Year-quarter FE	Y	Y
Adj. R-sq	0.714	0.513
N	243,208	241,914

Table A6. Individual Components of Abstract Thinking Index and Analyst Performance

This table reports the effect of analyst abstractness on analyst's quarterly forecast errors (Panel A) and market adjusted recommendation *CAR* (Panel B) with respect to component abstractness. All component abstractness is constructed as the rolling average of quarterly-averaged standardized analyst-call component abstractness in earnings conference calls within a year before the earnings forecast announcement date. *ATI_semantic* is constructed by the dialogue semantic-abstractness, calculated as the difference between abstract-attribute words and concrete-attribute words, then scaled by the total number of abstract-attribute and concrete-attribute words. *ATI_topic* is constructed by the abstractness score of the dialogue topic. The topic of a dialogue is identified by Structed Topic modeling (STM) tools. The detailed topics and scores are listed in Internet Appendix Table IA1. *ATI_future* and *ATI_past* are constructed by the numbers of words focusing on the future and past respectively in a dialogue. Detailed lists of future-focused and past-focused words are given in Internet Appendix Table IA3. *ATI_why* and *ATI_how* are constructed by the numbers of the words "why" and "how" included in a dialogue. We construct analyst-call component abstractness as the average of dialogue component abstractness across all dialogues with at least ten words and then perform standardization. In all panels, we include the controls *Coverage*, *GEXP*, *FXEP*, *No. of Industries*, and *High Status Broker*. In Panel A, we add *Forecast Age*. In Panel B, we add the controls *Mktcap*, *BM*, *Profit*, *Growth*, *MOM*, *RET,* and *lag (recommendation)*. The definitions of all other variables are given in Table A1. In Panel A, we include firm by year-quarter fixed effects and cluster standard errors at the firm level. In Panel B, we include firm and year-month fixed effects and two-way cluster the standard errors at the analyst and year-month level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

Panel A: ATI and Forecast Error: Components

	(1) Forecast Error	(2) Forecast Error	(3) Forecast Error	(4) Forecast Error	(5) Forecast Error	(6) Forecast Error	(7) Forecast Error
ATI_semantic	-0.004**	-0.005**					
	(-2.13)	(-2.46)					
ATI_topic	-0.002		-0.002				
	(-0.82)		(-0.69)				
ATI_future	-0.001			-0.001			
	(-0.31)			(-0.26)			
ATI_past	0.002				0.002		
	(1.04)				(1.03)		
ATI_why	-0.000					0.001	
	(-0.15)					(0.30)	
ATI_how	0.008***						0.007***
	(3.12)						(3.01)
Controls	Y	Y	Y	Y	Y	Y	Y

Firm × Year-quarter FE	Y	Y	Y	Y	Y	Y	Y
Adj. R-sq	0.680	0.680	0.680	0.680	0.680	0.680	0.680
N	243,215	243,238	243,215	243,238	243,238	243,238	243,238

Panel B: ATI and CAR to Analyst Recommendation: Components

	(1) RECCAR[0,2]	(2) RECCAR[0,2]	(3) RECCAR[0,2]	(4) RECCAR[0,2]	(5) RECCAR[0,2]	(6) RECCAR[0,2]	(7) RECCAR[0,2]
ATI_semantic	0.121	0.188					
	(0.57)	(0.92)					
ATI_topic	0.116		0.109				
	(0.50)		(0.48)				
ATI_future	0.411**			0.406*			
	(2.03)			(1.98)			
ATI_past	-0.404*				-0.390*		
	(-1.88)				(-1.83)		
ATI_why	0.086					-0.016	
	(0.46)					(-0.08)	
ATI_how	-0.256						-0.184
	(-1.58)						(-1.09)
Controls	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y
Adj. R-sq	0.177	0.177	0.177	0.177	0.177	0.177	0.177
N	9,909	9,909	9,909	9,909	9,909	9,909	9,909

Table A7. Abstract Thinking and Analyst Forecast Accuracy: Alternative Constructions of ATI

This table reports the results of examining abstract thinking on analyst forecast accuracy using alternative constructions of *ATI*. In column (1), we construct *ATI* excluding the focal firm's own conference calls. In column (2), we restrict the sample to analysts with at least five valid dialogues each quarter in the rolling-average window to construct *ATI*. In column (3), we use *ATI* constructed by an alternative measure of dialogue topic abstractness: Topic 5, Topic 7, or Topic 23 with a topic abstractness score equal to 2. In columns (4) and (5), we construct *ATI* by excluding topic or future and past components, respectively. In column (6), we construct *ATI* by standardizing call-abstractness at the firm level instead of full sample. In column (7), we construct *ATI* using analyst reports for a subsample of analysts, match the report-based *ATI* with analysts' earnings forecasts in the next year and run Model (1). In all columns, we include the controls *Coverage*, *GEXP*, *FXEP*, *No. of Industries*, *High-Status Broker*, and *Forecast Age*. The definitions of all other variables are given in Table A1. We include firm by year-quarter fixed effects in columns (1) to (6), and the year-quarter fixed effect in column (7). Standard errors are clustered at the firm level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ATI constructed by excluding the focal firm	Restricting sample to analysts with at least 5 valid dialogues each quarter	*ATI* constructed with alternative *ATI_topic*	*ATI* constructed by excluding *ATI_topic* component	*ATI* constructed by excluding *ATI_future* and *ATI_past* components	*ATI* constructed by standardizing components at firm level	*ATI* constructed using analyst report
	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error
ATI	-0.013**	-0.010**	-0.015**	-0.019***	-0.021***	-0.012**	-0.031***
	(-2.21)	(-2.08)	(-2.52)	(-2.94)	(-2.90)	(-2.06)	(-4.45)
Controls	Y	Y	Y	Y	Y	Y	Y
Firm × Year-quarter FE	Y	Y	Y	Y	Y	Y	N
Year-quarter FE	N	N	N	N	N	N	Y
Adj. R-sq	0.680	0.689	0.680	0.680	0.680	0.680	0.077
N	243,200	314,397	243,215	243,238	243,215	243,199	1,150

Table A8. Abstract Thinking and Market Reactions to Analyst Forecast Revisions

This table reports the effect of analyst abstractness on the short-term market reaction (*REVCAR*) to analyst forecast revision. We include all upward and downward revisions in the sample and exclude the revisions made within the 3-day window before or after an earnings announcement. *ATI* is defined as the rolling average of quarterly-averaged analyst-call abstractness on earnings conference calls within a year before the revision announcement date. *REVCAR[0, +i]* is the cumulative raw or abnormal returns (adjusted by market or DGTW returns) within *i* days after the revision announcements. For downward revisions, we take the negative value of the *CAR*s. We multiply dependent variables by 100. We also include analyst-year controls, namely, *Coverage*, *GEXP*, *FXEP*, *No. of Industries* and *High Status Broker*. Also, we add firm controls including *Mktcap*, *BM*, *Profit*, *Growth*, *MOM* and *RET*. In addition, we add the absolute value of forecast revision (*Abs(FREV)*) as a control. The definitions of all variables are given in Table A1. We include firm and year-month fixed effects. Standard errors are two-way clustered at the analyst and year-month level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	REVCAR[0,2]	Market-adjusted REVCAR[0,2]	DGTW-adjusted REVCAR[0,2]	REVCAR[0,4]	Market-adjusted REVCAR[0,4]	DGTW-adjusted REVCAR[0,4]
ATI	0.883***	0.727***	0.551***	0.931**	0.791**	0.694***
	(3.28)	(2.88)	(2.83)	(2.52)	(2.45)	(2.67)
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Adj. R-sq	0.059	0.063	0.066	0.056	0.062	0.060
N	18,107	18,107	17,966	18,107	18,107	17,975

Table A9. Abstract Thinking and Analyst Forecast Accuracy: Additional Robustness Tests

This table reports the results of additional robustness tests on the effect of analyst abstract thinking on forecast accuracy. In column (1), we examine annual forecast errors instead of quarterly forecast errors. In column (2), we construct an analyst-level ATI by averaging across the conference-level ATIs of each analyst. In column (3), we control for other characteristics of earnings conference calls, including the length and the tone of the latest earnings calls before the date of earnings forecast. Controls include *Coverage*, *GEXP*, *FXEP*, *No. of Industries, High Status Broker*, and *Forecast Age*. The definitions of all other variables are given in Table A1. We include firm by year-quarter fixed effects. Standard errors are clustered at the firm level. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

	(1) Annual Forecast Error	(2) *ATI* constructed at analyst level	(3) Control for the length and tone of the latest earnings calls
	Forecast Error	Forecast Error	Forecast Error
ATI	-0.129***	-0.019**	-0.016**
	(-2.87)	(-2.56)	(-2.37)
Controls	Y	Y	Y
Firm × Year-quarter FE	Y	Y	Y
Adj. R-sq	0.762	0.680	0.667
N	58,819	243,238	180,697

Internet Appendix to "It Pays to See the Forest: Abstract Thinking and Analyst Performance"

Table IA1. Topics and Abstractness Score

This table reports the label, frequent terms, and abstractness score of each topic identified by sell-side question dialogues from 2011 to 2019. The topics are identified by STM topic modeling tools. The detailed procedure for topic modeling is in Internet Appendix Table IA2. For each topic, we report the first 10 terms with the highest FREX index values. The labels and abstractness scores are manually assigned based on representatives of each topic.

Topic	Topic Label	Terms that are frequent within a topic or exclusive to the topic	Abstractness Score
1	market trend	see, market, trend, particular, demand, competitor, activity, environment, recent, pick	3
2	(expense) numbers	number, assume, rate, high, low, forward, run, model, level, range	1
3	updates on compliance / litigation risk	give, wonder, sense, update, provide, regard, potential, far, final, pipeline	2
4	pricing and margins	price, margin, volume, mix, gross margin, decline, sequential, improve, improvement, pressure	2
5	cash	acquisition, cash, use, investment, return, rate, plan, pay, consider, capital	2
6	clinical trial	try, different, figure, datum, find, system, technology, strategy, patient, important	1
7	expectation of an accounting item	expect, come, next, ramp, fiscal, level, anticipate, incremental, capex, expense	1
8	business strategy	store, brand, many, category, retail, lease, online, perform, center, traffic	3
9	product segmentation	segment, grow, side, opportunity, market, focu, product, large, part, fast	3
10	deals timeline	point, sound, start, end, close, target, deal, probab, hit, push	1
11	customer	customer, product, exist, service, base, client, order, account, relationship, contract	3
12	factors affecting guidance	impact, guidance, factor, outlook, assumption, quantify, range, weather, upside, topline	2
13	credit (risks) in the energy industry	sale, risk, markete, spend, loan, credit, portfolio, energy, agreement, book	2
14	accounting items quantification	cost, benefit, relat, relate, basispoint, finance, pressrelease, manage, corporate, expense	1
15	asset purchase and share repurchase	interest, remain, sell, buy, ill, share, aggressive, stock, order, buyback	2

16	project progress	add, start, result, progress, congratulation, performance, success, team, key, sales force	\
17	capacity	fair, capacity, shift, facility, ability, build, switch, supp, manufacture, enough	2
18	current investment opportunity	month, today, ago, current, percent, many, announce, acquisition, backlog, week	\
19	growth driver	growth, drive, accelerate, total, break, slow, operation, growth rate, driver, grow	3
20	divesture	business, part, profitability, piece, core, portion, longer term, side, exit, nature	3
21	working capital	work, keep, pace, capital, project, put, mind, inventory, bre, short	2
22	oil and insurance industry	open, side, service, fee, license, specialty, access, card, book, software	\
23	term/contract	term, change, mean, way, sale, issue, put, tell, point, place	\
24	settlement	long, positive, show, turn, period, negative, cycle, decision, typical, around	2
25	confirmation of info	want, hear, correct, hithank, prepared remark, mis, clarify, read, indicate, evene	1
26	outlook	half, balance, rest, future, expectation, outlook, visibility, confidence, luck, season	2
27	comparison with past	last, compare, remind, relative, prior, booke, sale, comp, mortgage, gain	2
28	thank you note	line, appreciate, enough, late, mis, queue, chief financial officer, apologize, jump, income	\
29	revenue (recognition)	increase, revenue, percentage, cost, contract, unit, account, fix, relate, recognize	2
30	medical industry	area, focus, specific, different, platform, broad, opportunity, example, group, measure	\
31	inventory	bank, major, inventory, win, tier, retail, oil, project, distributor, top	2
32	small talk/clarification	right, time, help, additional, exact, clarification, commentary, intereste, guys thank, clarity	\
33	market share	share, large, position, investment, small, gain, experience, lose, size, market share	3
34	asset composition	sort, thinke, asset, magnitude, looke, idea, disposition, context, utilization, frame	2
35	spread (real estate/interest)	relative, historical, spread, difference, benefit, high, economic, gap, volatility, conversion	1
36	industry and macro environment	overall, industry, challenge, whole, peer, picture, broad, perspective, organic, entire	3
37	scenario analysis	type, happen, potential, different, play, case, walk, away, situation, occur	3
38	Miscellaneous1	follow, ear, addres, later, leave, rather, limit, topic, world, previou	\
39	Miscellaneous2	get, people, step, ahead, pull, dont want, problem, bunch, feedback, drop	\
40	Miscellaneous3	couple, move, forward, least, last, past, les, perspective, ear, fact	\

Table IA2. Topic Modeling Procedure

1. We process the texts and construct the Document-Term Matrix based on dialogues, using the following steps:

1) Remove all non-alphabetical characters.
2) Use Named Entity Recognition to identify and remove named entities including person names, company names, and words about time (such as February, summer, date).
3) Use a part-of-speech tagger to tag every word in each sentence.
4) Identify and adjust bigrams and trigrams that have a specific meaning. Specifically, combine words with bigram (trigram) with frequency above 100 (50) having patterns as follows: adjective-noun; noun-noun; adjective-adjective-noun; adjective-noun-noun; noun-adjective-noun; noun-noun-noun; and noun-preposition-noun.
5) Remove the following common stop words.

   {‘a’, ‘able’, ‘about’, ‘above’, ‘after’, ‘afternoon’, ‘again’, ‘against’, ‘ain’, ‘albeit’, ‘all’,’also’, ‘always’,’am’, ‘an’, ‘and’, ‘answer’, ‘any’, ‘are’, ‘aren’, “aren’t”, ‘as’, ‘at’, ‘back’, ‘be’, ‘because’, ‘been’, ‘before’, ‘being’, ‘believe’, ‘below’, ‘between’, ‘bit’, ‘both’, ‘but’, ‘by’, ‘bye’, ‘callstreet’, ‘can’, ‘ccn’, ‘company’, ‘conferencecall’, ‘continue’, ‘copyright’, ‘corp’, ‘corrected transcript’, ‘could’, ‘couldn’, “couldn’t”, ‘d’, ‘did’, ‘didn’, “didn’t”, ‘do’, ‘does’, ‘doesn’, “doesn’t”, ‘doing’, ‘don’, “don’t”, ‘down’, ‘during’, ‘each’, ‘earningsconferencecall’, ‘event’, ‘every’, ‘everyone’, ‘feel’, ‘few’, ‘for’, ‘from’, ‘further’, ‘guess’, ‘guy’, ‘had’, ‘hadn’, “hadn’t”, ‘has’, ‘hasn’, “hasn’t”, ‘have’, ‘haven’, “haven’t”, ‘having’, ‘he’, ‘her’, ‘here’, ‘hers’, ‘herself’, ‘him’, ‘himself’, ‘his’, ‘how’, ‘however’, ‘i’, ‘if’, ‘in’, ‘inc’, ‘inc.’, ‘indiscernible’, ‘into’, ‘is’, ‘isn’, “isn’t”, ‘it’, “it’s”, ‘its’, ‘itself’, ‘just’,’lady’,’listen’,’little’,’ll’,’llc’,’llp’,’lot’, ‘lp’, ‘ltd’, ‘m’, ‘ma’, ‘march’, ‘may’, ‘me’, ‘might’, ‘mightn’, “mightn’t”, ‘more’, ‘morning’, ‘most’, ‘must’, ‘mustn’, “mustn’t”, ‘my’, ‘myself’, ‘need’, ‘needn’, “needn’t”, ‘no’, ‘nor’, ‘not’, ‘now’, ‘o’, ‘of’, ‘off’’, ‘okay’, ‘on’, ‘once’, ‘only’, ‘operator’, ‘or’, ‘other’, ‘our’, ‘ours’, ‘ourselves’, ‘out’, ‘over’, ‘own’, ‘page’, ‘per’, ‘please’, ‘presentation’, ‘quarter’, ‘question’, ‘raw’, ‘re’, ‘s’, ‘same’, ‘shall’, ‘shan’, “shan’t”, ‘she’, “she’s”, ‘should’, “should’ve”, ‘shouldn’, “shouldn’t”, ‘slide’, ‘so’, ‘some’, ‘still’, ‘such’, ‘t’, ‘than’, ‘thank’, ‘that’, “that’ll”, ‘the’, ‘their’, ‘theirs’, ‘them’, ‘themselves’, ‘then’, ‘there’, ‘these’, ‘they’, ‘theyre’, ‘theyve’, ‘think’, ‘this’, ‘those’, ‘thought’, ‘through’, ‘ticker’, ‘to’, ‘too’, ‘transcript’, ‘under’, ‘until’, ‘up’, ‘ve’, ‘versus’, ‘very’, ‘was’, ‘wasn’, “wasn’t”, ‘we’, ‘welcome’, ‘well’, ‘were’, ‘weren’, “weren’t”, ‘what’, ‘when’, ‘where’, ‘which’, ‘while’, ‘who’, ‘whom’, ‘why’, ‘will’, ‘with’, ‘won’, “won’t”, ‘would’, ‘wouldn’, “wouldn’t”, ‘y’, ‘year’, ‘yes’, ‘you’, “you’d”, “you’ll”, “you’re”, “you’ve”, ‘your’, ‘yours’, ‘yourself’, ‘yourselves’}
6) Lemmatization. We employ the Python Spacy package to lemmatize a word tagged as NOUN, ADJ, VERB, or ADV. Then we do further adjustment following Bybee, Kelly, Manela, and Xiu (2020) in the following order: (a) replace trailing “\sses” with “\ss”; (b) replace trailing “\ies” with “\y”; (c) remove trailing “\s”; (d) remove trailing “\ly”; (e) remove trailing “\ed” and replace remaining trailing “\ed” with \e”; and (f) replace trailing “\ing” with “\e” and remove remaining trailing “\ing”.
7) Remove words with less than three letters and double check no words in the stop words list.
8) Make vocabulary dictionary. We filter out words that appear in less than 20 dialogues and more than 70% of the dialogues.
9) Make the Document-Term Matrix, with each row representing a dialogue’s loadings on each term of the vocabulary dictionary and documents as vertical vectors.

2. After building the Document-Term Matrix, we estimate the STM model from a range of 20 to 60 topics.

3. After manually checking the outputs, we determine the number of topics to be 40.

Table IA3. Lists of Past-focused and Future-focused Words

This table lists the past-focused and future-focused words following the dictionary from the Linguistic Inquiry and Word Count (LIWC) 2015 software (Pan et al., 2018).

Past-focused words							***Future-focused words***		
accepted	died	hadn't	mothered	seen	thanked	worn	ahead	prayed	project
added	differed	hadnt	moved	sensed	they've	worsen	anticipate	prayer	seek
affected	dined	happened	must've	sent	thinned	would've	anticipation	praying	target
ago	disappeared	hamed	mustve	shared	threw	wouldve	approaching	predict	anticipating
already	disliked	hated	named	shook	thrown	written	attainable	prepar	believing
appeared	donated	healed	narrowed	should've	told	wrote	coming	promising	committed
arrived	done	heard	neared	shouldve	took	yelled	destin	prospect	committing
asked	drank	heeded	needed	shoved	traveled	yester	eventual	shall	estimating
ate	drove	held	noticed	showed	tricked	you've	eventually	shan't	forecasting
attended	e-mailed	helped	obeyed	signed	tried		fate	shant	are foreseen
attracted	earlier	hired	obtained	skied	tripped		fated	she'll	are hoped
became	earned	hoped	od'ed	slain	trotted		fates	someday	hoping
been	eaten	howd	okayed	slept	trusted		feasible	sometime	are intended
began	emailed	I'd've	organized	slid	tumbled		finna	soon	are planed
begged	ended	idve	overcame	slowed	turned		fixed	sooner	are projected
believed	entered	ignored	overdosed	smsed	twitched		forbod	soonest	are sought
bom	excelled	included	overeat	sobbed	typed		foresee	that'll	are targeted
bought	expired	informed	owed	sold	unfriended		foreshadow	thatll	willing
bounced	explained	invaded	paid	solved	used		foresight	then	
broke	fallen	joined	passed	sought	viewed		foreseeable	thereafter	
brought	fed	jumped	past	spat	visited		forthcoming	they'll	
called	fell	kept	perfected	sped	voted		futur	they'll	
came	felt	kicked	picked	spent	wagered		going	tomorrow	
cared	finished	knew	pitied	spoke	wagged		gon	tonight	
carried	fled	known	placed	spun	waited		gonna	up-and-coming	
caught	flew	lacked	played	started	walked		gotta	upcoming	
cced	filtered	laid	posted	stayed	wanted		gunna	wanna	

cc’d	flowed	lapsed	practiced	stirred	warmed	he’ll	wants
cc’ed	flown	learned	pressed	stocked	warred	headin	want
changed	followed	learnt	previous	stole	was	henceforth	we’ll
clapped	fooled	led	prior	stood	washed	hope	what’ll
cleaned	forgot	left	protested	stopped	wasn’t	hopeful	whatll
completed	former	lied	provided	stuck	watched	hopefully	who’ll
compiled	formerly	liked	questioned	studied	we’ve	hoping	wholl
confided	forwarded	listened	ran	stumbled	weakened	I’ll	will
contacted	fought	lit	ranked	stunk	weighed	I’mma	wish
costed	found	lived	realized	sucked	weirded	ima	wishes
could’ve	founded	looked	recollect	suffered	went	imma	wishing
couldve	frequented	loosed	remember	sung	wept	imminent	won’t
craved	fucked	lost	remembered	sunk	were	impending	wont
created	funded	lowered	remembering	supported	weren’t	it’ll	you’ll
cried	gave	lucked	remembers	supposed	werent	itll	youll
danced	given	made	remembrance	surfed	weve	looming	aim
dared	glided	mailed	revolved	swam	what’d	may	anticipate
decided	gone	managed	rode	swerved	whatd	might	assume
deleted	googled	mastered	roomed	swung	where’d	obtainable	believe
delegated	got	mated	rubbed	taken	wished	oncoming	commit
denied	gotten	meant	said	talked	wobbled	onward	estimate
departed	graced	messaged	sang	tasted	woke	plan	expect
depended	grew	met	sank	taught	woken	planner	forecast
descended	grossed	might’ve	sat	taxed	won	planning	foresee
destructed	grown	mightve	saw	tended	wondered	plans	hope
did	guessed	missed	searched	tested	wore	potential	intend
didn’t	had	mocked	seemed	texted	worked	pray	plan

Table IA4. Descriptive Statistics of Other Variables

This table reports summary statistics for other variables used in regressions. The definitions of all variables are given in Table A1.

	N	Mean	SD.	PC25	Median	PC75
Panel A: Dependent Variables						
RECCAR[0,4]	9909	0.025	0.063	-0.005	0.019	0.049
Market-adjusted RECCAR[0,4]	9909	0.025	0.059	-0.002	0.018	0.045
DGTW-adjusted RECCAR[0,4]	8353	0.024	0.053	0.0001	0.017	0.041
Annual Forecast Error	58819	0.960	2.356	0.053	0.167	0.567
First Q Ratio	5240	0.289	0.201	0.143	0.261	0.406
First Q	5240	0.914	0.280	1.000	1.000	1.000
No. of Calls Asking First Q	5240	6.285	5.355	2.000	5.000	9.000
Ratio of Calls Asking Questions	5240	1.283	1.134	0.800	1.174	1.571
Panel B: Independent Variables						
ATI_peers	242290	0.003	0.056	-0.037	-0.003	0.041
ATI_semantic	243215	-0.001	0.341	-0.244	-0.011	0.230
ATI_topic	243215	-0.010	0.365	-0.232	0.021	0.237
ATI_future	243215	-0.018	0.345	-0.267	-0.042	0.199
ATI_past	243215	0.014	0.310	-0.199	0.004	0.214
ATI_why	243215	-0.007	0.222	-0.179	-0.074	0.091
ATI_how	243215	-0.023	0.294	-0.239	-0.063	0.152
Abstract Analyst	9476	0.250	0.433	0.000	0.000	0.000
Concrete Analyst	9476	0.249	0.433	0.000	0.000	0.000
ATI_firm	15166	-0.004	0.085	-0.062	-0.001	0.056
Abstract Analyst Firm	15162	0.116	0.150	0.000	0.077	0.177
Panel C: Analyst Characteristics						
Race	230410	0.950	0.218	1.000	1.000	1.000
Gender	230410	0.910	0.286	1.000	1.000	1.000
INDEXP	243145	1.967	0.784	1.609	2.197	2.565

Table IA5. Abstract Thinking and Market Reactions to Recommendation Changes: Robustness Tests

This table reports the results of robustness tests of analyst abstractness's effect on recommendation *CAR*. Columns (1), (4), and (7) report results for raw *CAR*. In columns (2), (5), and (8), *CAR* is defined as the cumulative abnormal return adjusted by market return. In columns (3), (6), and (9), *CAR* is defined as the cumulative DGTW-adjusted abnormal return. The controls are *Coverage*, *GEXP*, *FXEP*, *No. of Industries*, *High-Status Broker*, *Mktcap*, *BM*, *Profit*, *Growth*, *MOM*, *RET*, and *lag (recommendation)*. The definitions of all other variables are given in Table A1. We include firm and year-month fixed effects. Standard errors are two-way clustered at the analyst and year-month level. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1) RECCAR [0, 1]	(2) Market-adjusted RECCAR[0,1]	(3) DGTW-adjusted RECCAR[0,1]	(4) RECCAR [0, 3]	(5) Market-adjusted RECCAR[0,3]	(6) DGTW-adjusted RECCAR[0,3]	(7) RECCAR [0, 5]	(8) Market-adjusted RECCAR[0,5]	(9) DGTW-adjusted RECCAR[0,5]
ATI	1.266**	1.199**	0.889**	1.987***	1.698***	0.910**	2.120***	1.811***	1.287**
	(2.54)	(2.52)	(2.09)	(3.06)	(2.97)	(2.03)	(2.97)	(2.90)	(2.43)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R-sq	0.192	0.205	0.218	0.146	0.157	0.190	0.119	0.126	0.156
N	9,909	9,909	8,343	9,909	9,909	8,353	9,909	9,909	8,353

Internet Appendix Figure IA1. Average Topic Distributions in Dialogues

This figure plots the average weights of each dialogue topic. In total, we identify 40 topics in sell-side analyst dialogues (with at least 10 words) in earnings conference calls from 2011 to 2019. The list of topics is in Internet Appendix Table IA1.