

The Two-System View of Cognition and Investor Choice: Evidence from Mutual Fund Launch Livestreams*

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Abstract

This paper examines the interplay between investors' intuition (System 1) and analytical processing (System 2) in investment decisions. Using livestream promotions for mutual fund offerings in China over 2020–2024, we study a setting without prior performance records or portfolio disclosures. Favorable impressions formed from presenters' emotional displays—vocal tone, facial expressiveness, and body movement—are positively related to fund subscriptions. This relation is weaker when livestreams convey complex information or feature fund managers, consistent with greater System 2 processing. The attenuation is less pronounced when System 2 faces capacity constraints from concurrent livestreams, extreme market returns, or longer livestreams.

Keywords: two-system view, intuition, analytical processing, livestreams, impressions, information processing, capacity constraints, mutual funds, machine learning, generative AI

JEL classifications: G11; G14; G20; D83

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Abstract

This paper examines the interplay between investors' intuition (System 1) and analytical processing (System 2) in investment decisions. Using livestream promotions for mutual fund offerings in China over 2020–2024, we study a setting without prior performance records or portfolio disclosures. Favorable impressions formed from presenters' emotional displays—vocal tone, facial expressiveness, and body movement—are positively related to fund subscriptions. This relation is weaker when livestreams convey complex information or feature fund managers, consistent with greater System 2 processing. The attenuation is less pronounced when System 2 faces capacity constraints from concurrent livestreams, extreme market returns, or longer livestreams.

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“The central characteristic of agents is not that they reason poorly but that they often act intuitively. And the behavior of these agents is not guided by what they are able to compute, but by what they happen to see at a given moment.”

– Kahneman (2003a, p. 1469) based on his Nobel Prize lecture

1. Introduction

Under the “homo economicus” assumption in economics, an agent is endowed with a single deliberative cognitive system that can process information perfectly and make rational decisions (Thaler 2000). However, a growing body of research finds that effortless intuition can significantly influence investment decisions, suggesting that economic agents are also “homo sapiens” and rely on intuition rather than analytical processing in high-stakes decision-making. For example, Blankespoor, Hendricks, and Miller (2017) show that investor perceptions of a CEO, based on 30-second content-filtered video clips from initial public offering (IPO) roadshow presentations, are positively associated with IPO pricing. Davila and Guasch (2022), Huang, Ivković, Jiang, and Wang (2023), and Hu and Ma (2025) find that entrepreneurs’ facial features and expressions, body expansiveness, and vocal tone during startup pitches are strongly associated with investors’ capital allocation decisions.

While these seminal studies highlight the role of effortless intuition (System 1) in influencing investor decisions, they leave an equally important question unanswered: How does intuitive judgment interact with analytical processing (System 2) when information is available? In Kahneman’s framework (Kahneman and Frederick 2002; Kahneman 2011), System 2 lightly monitors System 1 and is activated when the novelty, complexity, or conflict of information exceeds what System 1 can handle automatically, shifting decision-making from intuition to analytical processing. Because information is the cornerstone of financial markets, understanding this interaction is essential for explaining investor behavior and for designing effective disclosure and capital market policies.

In this paper, we conduct the first empirical analysis of how System 2 information

processing delineates the boundaries of System 1 intuition in real-world financial decision-making. Our analysis builds on the psychology literature on bounded rationality and dual-process cognition, pioneered by Kahneman (1973, 2011), Tversky and Kahneman (1974), and Stanovich and West (2000), and synthesized in Kahneman and Frederick (2002), Kahneman's Nobel lecture (2003a, 2003b), Evans (2009), and Kahneman (2011). This framework posits two modes of thinking and deciding. "The operations of System 1 are fast, automatic, effortless, associative, and often emotionally charged; they are also governed by habit, and are therefore difficult to control or modify. The operations of System 2 are slower, serial, effortful, and deliberately controlled; they are also relatively flexible and potentially rule-governed" (Kahneman 2003a, p. 1451).¹ Kahneman (2003b, p. 716) further notes that "Highly accessible impressions produced by System 1 control judgments and preferences, unless modified or overridden by the deliberate operations of System 2," and that System 2 processing is effortful and capacity-constrained, making it less effective under distraction or cognitive overload (Kahneman 2011).

Specifically, we examine livestream promotional events for mutual fund launches in China. While watching those livestreams, investors are exposed to two sources of cues: 1) livestream presenters' nonverbal cues, such as vocal tone, facial expressiveness, and body movement, which are processed by System 1; and 2) complex and technical information about a fund and/or the presence of a fund manager in a livestream, which are analyzed by System 2. We employ audio/video analytics, machine learning, and generative AI to

¹ There is substantial evidence across different fields showing that people are not accustomed to thinking hard (System 2) and often rely on intuition that comes quickly to mind (System 1) to make decisions. For example, Benartzi and Thaler (2001) uncover that investors tend to follow the "1/n strategy" when presented with a menu of funds in their 401(k) plans. Choi, Laibson, Madrian, and Metrick (2002) report that investors largely pick the default option in their 401(k) plans. Barber and Odean (2008) show that retail investors are drawn to attention-grabbing stocks when making purchase decisions. Duarte, Siegel, and Young (2012) find that perceptions of applicants' trustworthiness are positively correlated with loan funding outcomes. In political science, Todorov, Mandisodza, Goren, and Hall (2005) and Antonakis and Dalgas (2009) show that voters' impressions of candidates' faces predict electoral outcomes.

separately capture presenters' dynamic and fluid behavior that shapes investors' impressions (System 1) and the information conveyed that engages investors' analytical processing (System 2). We predict that investors' favorable impressions of presenters are positively associated with fund launch outcomes. We further investigate whether and how investors' System 2 analytical processing constrains the influence of their System 1 impressions—an inquiry that prior studies have not addressed.

We focus on fund launch livestream events for two key reasons. First, a fund launch livestream introduces a fund and/or its manager to investors for the first time, creating a direct link between investors' intuitive impressions (System 1) and their subscription decisions, as in many psychology studies and prior research in finance and accounting (see, for example, Blankespoor, Hendricks, and Miller 2017; Huang, Ivković, Jiang, and Wang 2023; Hu and Ma 2025). Second, because these events occur when investors have limited information about the fund and its manager, they provide a useful setting in which we can systematically measure the amount and complexity of information that engages investors' analytical processing (System 2). This setting allows us to study how System 1 and System 2 interact in a real-world decision context.

Our proxy for investors' System 1 intuition is grounded in two strands of social psychology. First, it is well known that an individual's expressive nonverbal behavior offers observers a valid measure of her internal states and dispositions (Jussim 1991; DePaulo 1992). Second, the "thin slice" literature shows that many impressions and judgments of others occur quickly and unconsciously, similar to System 1, and are based on a wealth of nonverbal cues (e.g., Ambady and Rosenthal 1992; Ambady, Bernieri, and Richeson 2000).²

² Prior research shows that people draw on a wide range of nonverbal cues when forming impressions, including changes in tone of voice, facial expressions, eye gaze, and overall body movement (Rosenthal et al. 1979). Consistent with the importance of nonverbal behavior, Hobson, Mayew, and Venkatachalam (2012) and Mayew and Venkatachalam (2012) find that managers' affect conveyed through vocal cues in earnings calls contains information about financial misreporting and future performance. Blankespoor, Hendricks, and Miller (2017) show that investors' impressions of CEOs based on the latter's expressive dynamic behavior (e.g., vocal

This research also shows that such impressions and judgments can accurately predict medical assessments, educational outcomes, and job performance, especially when derived from dynamic and fluid behavior rather than static images (Ambady, Hallahan, and Conner 1999; Ambady, Bernieri, and Richeson 2000). Building on both strands of this research, we use audio and computer vision models to capture presenters' dynamic nonverbal behavior: vocal tone, facial expressiveness, and body motion, as inputs to investors' rapid impression formation (System 1). In parallel, we use natural language processing (NLP) methods to analyze livestream transcripts, quantifying the amount and complexity of information conveyed that can engage System 2 processing.

Our analysis shows that investors' favorable impressions of livestream presenters are positively and significantly associated with the number and amount of fund subscriptions. However, this positive association is significantly attenuated when livestreams provide (complex) information or when a fund manager is present, making livestreams more informational than promotional. These results are consistent with greater System 2 analytical processing moderating the influence of favorable System 1 impressions on financial decisions.

Using fund livestream videos from the Tiantian Fund website, the largest mutual fund distribution platform in China, we compile a new dataset of 789 fund launch livestreams from July 1, 2020, to May 31, 2024. Like traditional e-commerce livestreams, fund livestreams feature live video feeds with hosts and guests (collectively referred to as presenters), interactive text, and shopping cart functions. We focus on fund launch livestreams because investors have limited prior information, which provides a useful setting to examine the role of System 1 intuition and the interplay between System 1 intuition and System 2 analytical processing in investment decisions.

cues, facial features, and body language) during road shows influence IPO pricing.

Guided by the two-system view of cognition, we isolate livestream presenters' nonverbal, visual, and auditory signals that shape investors' rapid, System 1 impressions. We do so by extracting multidimensional expressive features that are stripped of information content: vocal tone, facial expressiveness, and body motion.³ From each video, we first obtain the full audio stream, which we decompose into a vocal component and a textual component generated by a speech-to-text method (i.e., a transcript). We then capture the two visual dimensions using still images sampled at one frame per second (3,600 images for a one-hour livestream), following the “thin-slice” approach (Ambady and Rosenthal 1992; Ambady, Bernieri, and Richeson 2000). Using machine learning methods, we extract these features and combine them into presenters' expressive-behavior measure, *Impression Score*, which proxies for investors' System 1 processing.

To quantify the amount of information conveyed during livestreams, we use generative AI models to analyze the transcripts. Specifically, we measure a livestream's information content by comparing the amount of information in its transcript to that in the Fund Overview section on the Tiantian Fund website. The Fund Overview is a prominent feature of the platform that is easily accessible and widely consulted by investors. In addition to structured fund information (e.g., fund name and code), it provides a brief description of the fund organized into six topic categories: investment objectives, investment philosophy, investment scope, investment strategy, dividend policy, and risk-return characteristics.

We first segment each transcript and use a generative AI model (DeepSeek) to extract topics from each segment. We then assess whether a segment's content matches any of the six key topics in the Fund Overview section or any of the nine additional topics.⁴ This procedure

³ We implement this pipeline with widely available machine learning models and tools, including Speech Emotion Recognition, DeepFace, and YOLO11.

⁴ We apply DeepSeek for unrestricted topic extraction to 20 livestream transcripts representing various fund types. From the resulting list, we select the nine most frequent topics not covered by the six overview topics as our additional topics: market trend analysis, macroeconomic policy analysis, industry analysis, product features and trends, fund manager's professional background, investor education, index characteristics, stock-picking

yields the variable *Info*, which measures the amount of information content conveyed during a livestream beyond what is already contained in the Fund Overview. For the six overview topics, we compute the cosine similarity between each topic-specific segment and the corresponding overview text, and classify segments with similarity scores above a threshold as repetitive. For each topic, we define the variable *Info Ratio* as one minus the proportion of repetitive content in that topic's segments. For the nine additional topics, we set *Info Ratio* to one for the relevant segment(s), as these topics are not covered in the Fund Overview. Finally, we aggregate the topic-level *Info Ratio* measures to the livestream level to construct the variable *Info*, which captures the amount of new information shared with investors during a livestream.

We document a number of key findings. First, fund launch livestreams are positively linked to issuance performance. For funds with livestreams, investors' favorable impressions of presenters, capturing their System 1 intuition, are associated with better fund issuance outcomes.⁵ Second, we examine how investors' favorable impressions (System 1) interact with analytical processing (System 2) to shape investment decisions. We find that higher information content in livestreams, which engages investors' analytical processing, significantly reduces the positive association between their favorable impressions and fund issuance performance. When a livestream's information content ranks in the top quintile of the sample, the estimated association between *Impression Score* and fund subscription amount is not statistically different from zero. In other words, the positive association between favorable System 1 impressions and fund subscription amount is attenuated when livestreams convey more information, consistent with greater System 2 analytical processing.

Third, we examine heterogeneity in the extent to which System 2 processing attenuates

strategy, and quantitative modelling.

⁵ In Online Appendix Table IA6, we also show that more favorable investor impressions at launch are associated with poorer subsequent fund performance, consistent with the findings in Hu and Ma (2025) and deHaan et al. (2026).

the influence of favorable System 1 impressions. We employ several generative AI models to classify the information conveyed during livestreams as complex or non-complex. Complex topics are difficult for retail investors to understand and require professional interpretation, whereas non-complex topics are more readily understood by retail investors. We then measure the information content of each type. Our findings indicate that System 2 constrains the influence of System 1 only when it is engaged by complex information. Relatedly, we examine whether the presence of fund managers in a livestream matters. We first show that livestreams featuring fund managers convey more information, particularly more complex information, than those without managers. We then show that the positive association between investors' favorable impressions and fund issuance performance disappears when a fund manager appears in the livestream. We also examine how fund type moderates the interaction between System 1 and System 2. When livestreams promote active funds with complex strategies, investors face greater informational complexity and are more likely to engage in analytical processing. In this setting, System 2 scrutiny attenuates the influence of favorable System 1 impressions on investment decisions.

Finally, we examine the boundary conditions under which System 2 may be less effective in constraining the influence of favorable System 1 impressions. Specifically, we conduct subsample analyses using proxies for investor distraction and cognitive overload, including the number of concurrent livestreams on the Tiantian platform, extreme market-return days, and livestream duration. We find that the attenuation of the association between favorable System 1 impressions and fund issuance performance is significantly weaker when investors are more likely to face distraction or cognitive overload, consistent with Kahneman's characterization of System 2 as capacity-constrained and reliant on limited attentional resources.

The decision to livestream a fund launch is not random. For example, funds that believe

they have superior livestreaming skills may expect more favorable subscription outcomes, creating a positive association between hosting a launch livestream and subsequent subscriptions. Our main research question, however, is whether and how investors' System 2 analytical processing interacts with System 1 intuition during a fund-launch livestream, and it is not clear how this selection would bias our conclusions. Empirically, we find that when livestreams convey more information, which may engage System 2 processing, the positive association between favorable System 1 impressions and fund issuance performance is attenuated. This interaction pattern is difficult to reconcile with a simple selection-on-livestream-quality explanation.

Similarly, a fund manager's decision to appear in a livestream is endogenous and may be intended to improve launch outcomes. Managers who expect their presence to attract more subscriptions may be more likely to participate, which would predict a positive association between manager presence and subsequent subscription outcomes. The negative coefficient on the indicator for fund-manager presence is inconsistent with this interpretation. An alternative selection-based explanation is that managers are more likely to appear when weak subscription outcomes are anticipated, which is more consistent with the negative coefficient. Even this explanation, however, does not readily account for our main interaction result: the positive association between investors' favorable impressions and fund issuance performance is attenuated, rather than strengthened, when a fund manager is present. Together, these patterns suggest that our central findings on the interaction between System 1 and System 2 are unlikely to be driven solely by endogenous selection into livestreaming or manager participation.

Our study employs mutual fund launch data from China. A natural question is whether inferences drawn from this setting generalize outside China. At a high level, our paper examines whether and how the cognitive processes associated with Systems 1 and 2 interact,

and Kahneman (2011) presents this two-system framework as a general account of human cognition. In addition, regulations of the Chinese capital markets in general, and the asset management industry in particular, largely emulate those in the United States and are therefore broadly comparable (Duan, Li, Rogo, and Zhang 2024; deHaan, Huang, Kannan, and Qiu 2026). We thus see little reason to expect that our main findings on the interactions of the two systems would not extend to other countries.

In conclusion, our evidence is consistent with Kahneman and Frederick (2002) and Kahneman (2011), who characterize System 1 as the default mode of judgment whose influence can be constrained by System 2 when analytical processing is engaged. We further show that this constraining role of System 2 depends on the information environment and investors' available cognitive capacity. Given the growing importance of livestreaming in everyday economic activity, our findings have significant implications for disclosure choices and capital-market rulemaking.

The rest of the paper is organized as follows. Section 2 discusses our contribution to the literature. Section 3 provides institutional background and describes our sample. Section 4 explains how we construct measures of investor impressions (System 1) and information processing (System 2) from livestreams. Section 5 reports the main findings, including the relation between fund livestreams and issuance performance and how the association between investors' impressions and fund issuance performance varies with information processing, followed by robustness checks. Section 6 examines the capacity constraints of System 2 processing. Section 7 concludes. Additional technical details and supplementary materials are included in the Online Appendix.

2. Relation to Prior Literature

Our paper contributes to several strands of literature. First, it advances the emerging use

of video analysis to study how visual and auditory cues in communication affect investor behavior and asset prices (Blankespoor, Hendricks, and Miller 2017; Curti and Kazinnik 2023; Gorodnichenko, Pham, and Talavera 2023; Chang et al. 2025; Hu and Ma 2025; deHaan et al. 2026). We extend this work by applying the two-system framework of cognition (Kahneman 1973, 2011; Tversky and Kahneman 1974; Stanovich and West 2000) to mutual fund launch livestreams and, to the best of our knowledge, provide the first evidence on the interplay between investors' System 1 intuition and System 2 analytical processing in a large-scale, real-world investment setting.⁶ Leveraging advanced video analytics and generative AI, we are also among the first to analyze full-length livestream videos (approximately 60 minutes on average), rather than the brief snippets typically used to study rapid, System 1-driven judgments (e.g., Ambady and Rosenthal 1992; Blankespoor, Hendricks, and Miller 2017). This approach allows us to capture the amount and complexity of information that engages investors' System 2 processing and to delineate the conditions under which such processing becomes less effective.

Our paper is closely related to deHaan et al. (2026) but differs in several important ways. First, the conceptual framework and research questions are distinct. deHaan et al. (2026) study whether mutual fund livestreaming helps retail investors make better-informed buying decisions, drawing on the persuasion literature in marketing. In contrast, we analyze the interaction between intuition and analytical processing within the two-system cognition framework of Kahneman and Frederick (2002) and Kahneman (2011). Accordingly, we focus on initial fund offerings where livestreams occur before any performance records or portfolio

⁶ Our two-system framework is related to, but distinct from, the hard-versus-soft information distinction in finance and accounting. Hard and soft information characterize the nature of information: hard information is generally standardized, quantitative, and readily verifiable, whereas soft information is more qualitative, difficult to codify, and often embedded in interpersonal communication (e.g., Stein 2002; Petersen and Rajan 2002). By contrast, System 1 and System 2 characterize how information is processed. Thus, the two distinctions need not map one-to-one. In our setting, presenters' nonverbal cues are relatively soft and may generate favorable impressions through System 1 processing, whereas substantive fund information, whether relatively hard or soft, may engage System 2 analytical processing when it requires greater cognitive effort.

disclosures are available, allowing us to cleanly isolate the effects of the two distinct cognitive processes.

Second, the key variables of interest also differ. deHaan et al. (2026) treat nonverbal cues as measures of persuasion. We instead use audio/video analytics to quantify presenters' nonverbal cues as proxies for investors' intuition (System 1) and apply generative AI and machine learning to livestream transcripts to assess the amount and complexity of information. We then use these information measures and the presence of fund managers in livestreams as triggers for investors' analytical processing (System 2). Our primary variable of interest is the interaction between Systems 1 and 2 in regressions of fund subscription outcomes, providing the first empirical evidence on how these two systems jointly operate in a real-world investment setting.

Our paper also contributes to the literature on financial technology (fintech) platforms and investor behavior, which shows that digital channels such as online fund distribution, robo-advisors, and mobile trading apps broaden market participation and alter investment patterns (D'Acunto, Prabhala, and Rossi 2019; Barber, Huang, Odean, and Schwarz 2022; Rossi and Utkus 2024; Hong, Lu, and Pan 2025). We build on this work by examining livestreaming, a rapidly growing fund distribution channel that uniquely combines fund promotion with real-time information disclosure. We show that more favorable investor impressions at launch are associated with greater fund inflows but poorer short-term subsequent performance, suggesting that these impressions may lead retail investors to allocate capital to funds without correspondingly stronger performance. Importantly, we also find that the positive association between favorable impressions and fund subscriptions is attenuated when livestreams convey more information, particularly more complex information, consistent with greater System 2 analytical processing.

Finally, our paper adds to the mutual fund marketing literature, which shows that

advertising can attract fund flows without improving risk-adjusted performance (Jain and Wu 2000) and that fund families strategically promote products with strong recent returns (Nanda, Wang, and Zheng 2004; Gaspar, Massa, and Matos 2006). More recent research highlights the strategic use of disclosures and marketing content to influence fund flows and competitive outcomes (deHaan, Song, Xie, and Zhu 2021; Roussanov, Ruan, and Wei 2021; Chen, Jiang, and Xiaolan 2023). We extend this literature by studying livestreaming as a new communication channel that simultaneously conveys nonverbal presentation cues and substantive fund information. This setting allows us to show that favorable investor impressions are positively related to fund subscriptions, while this relation is attenuated when livestreams convey information more likely to engage System 2 analytical processing. Our findings therefore highlight an important interaction between how fund products are presented and the information they convey in shaping investor responses to mutual fund marketing.

3. Institutional Background and Sample Formation

3.1. Institutional Background

The mutual fund industry in China began in 2001, with the launch of the first mutual fund, Hua'an Innovation Mixed Fund, in September of that year. Retail investors mainly buy mutual fund products through commercial banks and independent fund distributors. When the COVID-19 pandemic began in early 2020, access to traditional information channels, such as financial advisors at local bank branches and broker offices, was severely limited. To compensate for retail investors' lost access to financial advisors and fund information, fund companies began offering fund livestreams on social media platforms. For instance, in 2023, over 140 fund companies, representing more than 80% of all fund families in China,

organized approximately 54,000 livestreams.⁷

Livestream channels are typically overseen by a fund family. A typical session features a host and invited guests, such as fund managers, analysts, investment advisors, or industry experts, who discuss topics including industry developments, market trends, investment strategies, and risk-return characteristics. Sessions usually last about an hour. Speakers and topics are announced up to a week in advance, and viewers can submit questions beforehand or in real time.

Our main data source is East Money's Tiantian Fund platform, the largest and one of the earliest third-party mutual fund distribution platforms in China. By the end of 2023, total fund sales on the platform had surpassed 10 trillion yuan, with an average of over 1.5 million daily active users. According to Hong, Lu, and Pan (2026), the platform has a significant impact on retail investors and market trends in China.

3.2. Sample Formation

We downloaded livestream videos from the Tiantian Fund website⁸ in early June 2024. We then compiled a dataset of livestreams linked to the initial offerings of mutual funds between July 1, 2020, and May 31, 2024, as the earliest available mutual fund livestream on the platform dates back to July 2020. Because these funds are marketed before any performance history or portfolio holdings are available, investors have limited prior information, providing a useful setting to examine the role of System 1 intuition and its interplay with System 2 analytical processing. Figure IA1 in the Online Appendix provides a screenshot of the livestream interface and related details on the Tiantian Fund website.

⁷ By the end of 2024, 833 million people had watched livestreams, representing 75.2% of all internet users. Among them, 597 million had viewed e-commerce livestreams, accounting for 54.7% of all internet users. Notably, 71.2% of these viewers made purchases after watching short videos or livestreams, indicating that livestream e-commerce has become a mainstream phenomenon. For more details, see https://app-web.chnfund.com/jx/202402/t20240226_4328340.html and <https://www.vidchina.cn/outcome/46>.

⁸ See: <https://roadshow.eastmoney.com/list?type=1>.

We begin with an initial sample of 2,786 livestreams potentially related to newly launched funds during the sample period, identified through keyword searches. To ensure data relevance and accuracy, we manually review all videos. We exclude livestreams that cannot be linked to a fund launch or that occur after a fund's subscription period, the window in which investors may subscribe to the new fund. After these exclusions, our sample consists of 1,688 livestreams over the sample period. Figure IA2, Panel A lists the top 10 fund families by the number of fund launch livestreams during the sample period, and Panel B presents the distribution of livestream start times. We show that the top three fund families have over 100 livestreams linked to fund launches. Figure IA3, Panel A reports the distribution of the number of presenters per livestream. In our full sample of 1,688 livestreams, there are on average 1.88 presenters (untabulated); 72.7% feature at least two presenters. Panel B shows that 60% feature a fund manager.⁹

To maintain consistency across our analyses and avoid duplicating information already provided in a fund's initial launch livestream (if we analyze subsequent livestreams of the same fund), we retain only the first livestream for each new fund, reducing the sample to 853 livestreams. In China, mutual funds are usually marketed in two share classes (A and C), which are identical except for load and service fees.¹⁰ Consequently, each livestream may be associated with two sets of outcome variables if the fund is available in both classes. After requiring data availability for livestream, fund, and fund manager characteristics, the final sample comprises 789 livestreams associated with 1,422 launch outcome observations.¹¹

⁹ We obtain presenter names and job titles from the livestream introductions on the Tiantian Fund website, and we double-check and supplement this information by manually reviewing the videos and recording presenter names and job titles.

¹⁰ Classes A and C of a fund are virtually identical; for example, they have the same portfolio, gross performance, managers, and disclosures, and they are equally affected by external events such as industry trends. The only difference is that Class A charges front-end loads but no service fees, while Class C charges service fees but no front-end loads.

¹¹ Among 789 livestreams, 488 are the only livestreams conducted by their respective funds, while 301 are the first livestreams conducted by funds that held multiple livestreams. Following our sample selection rule, for funds with multiple livestreams, we retain only the first livestream.

Table IA1 in the Online Appendix outlines the sample construction process.

3.3. Summary Statistics

We obtain fund, fund manager, and stock market characteristics from the RESSET Database and the Wind Database. Fund manager performance is measured by the average annualized net asset growth rate of the funds they previously managed, which matches the manager performance metric displayed on the Tiantian Fund platform. We also record gift-giving during livestreams using keyword searches and manual review, and collect livestream viewership via web scraping. Table 1, Panel A reports summary statistics for fund, fund manager, and market characteristics, and Panel B reports summary statistics for livestream characteristics. Variable definitions are provided in Online Appendix A.

Table IA2, Panel A offers a comparative analysis of new funds that host livestreams (*Livestream* = 1) versus those that do not (*Livestream* = 0), suggesting that fund livestreams are positively linked to the number (amount) of subscriptions. Panel B reports the results from a linear probability model. Across all specifications, the coefficients on *Fund Fees* and *State-owned Fund Family* are positive and significant, implying that higher-fee funds and funds affiliated with state-owned families are more likely to host launch livestreams. The positive coefficient on *Number of Fund Launches* suggests that funds are more likely to host launch livestreams when facing greater competition, i.e., when many funds of the same style are launched in the same month. We include these fund characteristics as controls in our launch-outcome regressions.

4. Methodology: Constructing Impression and Information Measures in Livestreams

In this section, we construct measures that capture investors' System 1 intuition and System 2 analytical processing during livestreams. Guided by seminal work in social and cognitive psychology (Strahan and Zytowski 1976; Rosenthal et al. 1979; Krauss et al. 1981;

Ambady and Rosenthal 1992; Ambady, Hallahan, and Connor 1999; Kahneman and Frederick 2002; Kahneman 2003a, 2003b), we apply audio and computer vision models to measure livestream presenters' dynamic nonverbal behavior along three dimensions: vocal tone, facial expressiveness, and body motion, cues that can shape the intuitive impressions generated by investors' System 1.¹²

Our setting also allows us to examine how information conveyed during livestreams, which engages investors' System 2 analytical processing, interacts with presenters' nonverbal cues that shape favorable System 1 impressions. Specifically, the Fund Overview section on the Tiantian Fund website provides structured information about each new fund (for example, investment objectives and philosophy) sourced from the prospectus. Using this section as a benchmark, we apply generative AI and machine learning methods to assess the amount and complexity of the information conveyed during livestreams.

4.1. Constructing Investor Impression Measures

Figure 1 shows a flowchart of how we construct the impression measures, and Table IA3 in the Online Appendix provides implementation details for transparency and replication.

4.1.1. Vocal tone

We focus on vocal cues not captured by the textual content of a fund's livestream. Unlike images, which can independently provide rich information, splitting audio into fixed high-frequency segments, similar to a series of images, may lose information embedded in the audio's temporal dependency structure. Instead, we divide each audio stream into speaker logs (Wang et al. 2023).¹³ These logs naturally preserve the audio's temporal dependency

¹² Because livestream transcripts convey both substantive fund information and presenters' sentiment through spoken language, incorporating transcript-based sentiment cues into our baseline measure could make it difficult to separate impression formation from information processing. Our baseline measure, *Impression Score*, therefore relies on content-filtered audio and visual cues. As a robustness check, we add transcript-based verbal sentiment (*Verbal Positive*) to *Impression Score* and find that our main results remain qualitatively unchanged.

¹³ Using CAM++ and clustering techniques, Alibaba DAMO Academy has developed a speaker-logging system. When provided with an audio segment of a conversation among multiple speakers, the model can

structure and align with human cognitive processes. We then use Speech Emotion Recognition, a Python package that implements deep-learning methods for speech emotion recognition, to identify seven vocal emotions: anger, disgust, fear, happiness, neutrality, sadness, and surprise. Our variable, *Vocal Positive*, is the combined probability that the vocal emotion of presenters in a livestream is happiness or surprise. We compute this measure as the average across all speaker logs in a livestream. This aggregation also captures the intensity of vocal cues, which likely increases their salience by making them more prominent. Figure IA4 provides visualized examples of high- and low-pitched vocal features.

4.1.2. Facial expressiveness

Given that fund livestreams typically last about one hour, considerably longer than startup pitch videos (Hu and Ma 2025), we extract images at a rate of one frame per second, following Curti and Kazinnik (2023). We then apply DeepFace (Taigman, Yang, Ranzato, and Wolf 2014) to detect human faces and assess presenters' emotional expressions. The algorithm identifies the speaker, tracks facial feature points (e.g., the nose and eyes), and probabilistically classifies seven facial emotions: anger, disgust, fear, happiness, neutrality, sadness, and surprise. We define *Visual Positive* as the combined probability of happiness or surprise. We compute this measure by first averaging across presenters within a frame and then across all frames in a livestream. Figure IA5 provides examples of high- and low-positivity facial features.

4.1.3. Body motion

Following Chen, Yao, and Kotha (2009) and Davila and Guasch (2022), we measure the magnitude of presenters' movements in a livestream.¹⁴ We extract images at a rate of one

automatically determine the number of speakers and assign each sentence to its respective speaker.

¹⁴ Because our measure captures the upper-body movement of camera-facing presenters as viewed by livestream audiences, it differs from the in-person pitch setting studied by Davila and Guasch (2022), where camera-angle adjustments are relevant. We therefore measure presenter body movement using the raw, unadjusted displacement magnitude.

frame per second and use YOLO11, developed by Ultralytics, to identify skeletal key points and assemble skeletons. We then use optical flow to measure displacement magnitudes.¹⁵ Our variable, *Body Motion*, is calculated by first averaging across presenters within each frame and then across all frames in a livestream. Figure IA6 provides examples of high- and low-body motion features.

4.1.4. Summary measure and validation

Beyond the individual impression measures, we construct a summary measure of investor impressions using Principal Component Analysis (PCA). PCA extracts the eigenvector with the highest eigenvalue from the correlation matrix of livestream features, capturing the most important common component of investor impressions, which we define as *Impression Score*.

Table 1, Panel C reports summary statistics for the investor impression measures, highlighting substantial cross-sectional variation. For example, the mean of *Visual Positive* is 0.093, indicating that on average, the probability that presenters display positive visual features is 9.3 percent. The 25th and 75th percentiles are 0.030 and 0.122, respectively, suggesting notable differences in the visual dimension. Panel C also reports each impression measure's loading on *Impression Score* and its “uniqueness.” The loadings are all positive for *Vocal Positive* (0.590), *Visual Positive* (0.627), and *Body Motion* (0.510). The uniqueness measures indicate how much of each variable's variance is left unexplained by the composite factor. *Impression Score* integrates information from the vocal, facial, and body dimensions and captures the overall level of investors' impressions of the livestream.¹⁶

¹⁵ After converting each frame to grayscale, we apply the Farneback method to compute inter-frame optical flow and decompose the flow into its horizontal and vertical components to measure pixel displacement magnitudes. Specifically, we partition each image into presenter-specific regions, extract displacement magnitudes within each region, and compute their average values. We then aggregate total displacement across all frames and calculate the average displacement variation by dividing each region's total displacement by the number of frames.

¹⁶ Table IA5 reports the correlation matrix for the key variables. We note that the three components of *Impression Score* (*Vocal Positive*, *Visual Positive*, and *Body Motion*) are strongly positively correlated.

4.2. Constructing Other Livestream Measures

Using Aliyun’s speech-to-text API, we generate text transcripts from the audio data of each speaker in a livestream. We then use StructBERT (Wei et al. 2020) to classify the sentiment of these transcripts.¹⁷ Our variable, *Verbal Positive*, is the probability that a livestream transcript expresses positive sentiment. We compute this measure as the text-length-weighted average across all speaker logs in a livestream. Figure IA7 provides examples of high- and low-positivity verbal features.

Studies in computer vision show that a video’s aesthetic quality significantly influences viewer satisfaction and purchasing behavior (e.g., Yeh, Yang, Lee, and Chen 2013; Zhou, Chen, Ferreira, and Smith 2021). Following Zhou et al. (2021), we evaluate the image quality of livestream videos. We capture images at a rate of one frame per second and use *OpenCV* to assess their clarity.¹⁸ Our variable, *Image Clarity*, is the average clarity score across all frames in a livestream. Figure IA8 provides examples of high and low image clarity.

Since the seminal work by Hamermesh and Biddle (1994) on the beauty premium in labor markets, researchers have documented favorable career outcomes, job performance, and loan application results for attractive people (e.g., Duarte, Siegel, and Young 2012; Cao, Guan, Li, and Yang 2020). Our variable, *Beauty Score*, is the average beauty score from DeepFace’s emotion recognition API across all presenters in a frame and across all frames in a livestream.

4.3. Constructing Livestream Information Measures

We construct livestream information measures by comparing transcript content with structured fund information from the Fund Overview section on the Tiantian Fund website,

¹⁷ StructBERT, developed by Alibaba DAMO Academy, is a Chinese sentiment classification model for general-domain applications. It takes natural language text as input and outputs both a sentiment label (0 = negative, 1 = positive) and its associated probability.

¹⁸ We measure image clarity using the Variance of Laplacian, which captures the sharpness of image edges.

sourced from the fund prospectus. For newly launched funds without a performance history, the Fund Overview serves as an important source of information, helping investors understand the fund’s core features and investment approach. We use the Fund Overview as our primary benchmark for assessing the amount and complexity of information conveyed during livestreams. As a robustness check, we use the Important Notice section in the front matter of the prospectus as an alternative benchmark. Figure 2 shows a flowchart of how we construct the information measures, and Table IA3 in the Online Appendix provides implementation details.

4.3.1. Step 1. Text segmentation

Text segmentation is an important step in natural language processing because it divides lengthy documents into smaller, coherent units for subsequent analysis. Fund livestream transcripts are long and complex, often involving multiple speakers and shifts across topics. Traditional approaches, such as character-based or fixed-length chunking, may split related content or combine text discussing different topics. To address this issue, we segment transcripts based on semantic similarity across sentences. Specifically, sentence embeddings are used to represent the meaning of each sentence, and adjacent sentences with similar semantic content are grouped into the same segment, while a new segment begins when the content shifts sufficiently. This approach produces segments that are more internally coherent and better aligned with changes in discussion topics.

To implement text segmentation, we use sentence embeddings to capture the semantic content of each sentence. We convert each sentence in the transcript into a high-dimensional vector and apply the GTE model developed by Alibaba DAMO Academy to compute pairwise similarity scores between sentences.¹⁹ We then identify coherent segments by

¹⁹ GTE is a transformer-based, pre-trained language model designed to produce high-quality text embeddings that capture both semantic and contextual information. We selected GTE for its efficiency and accuracy in processing complex textual data and its ability to generate robust semantic representations. For further details, see <https://huggingface.co/thenlper/gte-large-zh>.

splitting the text whenever the similarity between adjacent sentence embeddings falls below 0.75.²⁰

4.3.2. Step 2. Topic classification

We use DeepSeek to identify a topic for each segment. Specifically, we evaluate whether each segment's content matches any of the six topics outlined in the Fund Overview or any of the nine additional topics.

To do this, we first run DeepSeek for unrestricted topic extraction on 20 livestream transcripts covering various fund types (e.g., index funds, equity funds, bond funds, and hybrid funds). From the resulting list, we select the nine most common topics not included in the six topics in the Fund Overview as our additional topics. These include market trend analysis, macroeconomic policy analysis, industry analysis, product features and trends, fund manager's professional background, investor education, index characteristics, stock-picking strategy, and quantitative modelling. Segments that do not provide meaningful information or analysis, or simply serve to fill gaps between more substantial discussions, are classified as "Misc."

4.3.3. Step 3. Measuring the amount of information

Kahneman and Frederick (2002) and Kahneman (2011) argue that System 2 monitors System 1 and is more likely to be engaged when intuitive processing is insufficient, such as when information is new or complex and requires greater analytical effort. To test this conjecture, we construct *Info*, a measure of the amount of new information conveyed during a livestream. Our measure is based on the idea that, because the Fund Overview is readily accessible to investors and contains standard information about the fund, we treat livestream content that closely mirrors the Fund Overview as repetitive. In contrast, content that departs

²⁰ The threshold is adjusted incrementally based on the segmentation results to ensure there are no significant fluctuations in the number or length of segments.

from the Fund Overview is classified as new information.

First, for the six topics discussed in the Fund Overview section, we determine the proportion of livestream content on each topic that is repetitive relative to the Fund Overview. Specifically, for each topic, we compare its segment with the corresponding content in the Fund Overview and calculate a similarity score using Pinecone’s internal cosine similarity method. We adopt a conservative threshold of 0.90 to determine whether the focal segment is highly similar to the content in the Fund Overview, following Liu, Pei, and Wang (2025) and Suh et al. (2025).²¹ If the similarity score exceeds this threshold, the indicator $I(\text{Repetitive})$ is set to 1 for the focal segment; otherwise, it is set to 0.

Our topic-specific measure for quantifying the amount of information in livestream i on topic k , $\text{Info Ratio}_{k,i}$, is constructed as follows:

$$\text{Info Ratio}_{k,i} = 1 - \frac{\sum_{s=1}^S \text{Segment Length}_{s,k,i} \times I(\text{Repetitive}_{s,k,i})}{\sum_{s=1}^S \text{Segment Length}_{s,k,i}}, \quad (1)$$

where $\text{Segment Length}_{s,k,i}$ represents the number of words in segment s of livestream i on topic k , and $I(\text{Repetitive}_{s,k,i})$ is an indicator that takes a value of 1 if segment s of livestream i contains information on topic k that is identified as repeating the Fund Overview content on the same topic.²² The variable S refers to the total number of segments in livestream i covering topic k .

Second, to capture the overall amount of information across all topics in a livestream, we aggregate $\text{Info Ratio}_{k,i}$ to the livestream level using the following equation:

$$\text{Info}_i = \sum_{k=1}^K \text{Topic Proportion}_{k,i} \times \text{Info Ratio}_{k,i}, \quad (2)$$

where $\text{Topic Proportion}_{k,i}$ represents the share of word counts in livestream i attributed to topic k relative to the total word count of livestream i ’s transcript. When topic k is included in the Fund Overview, $\text{Info Ratio}_{k,i}$ is calculated as in Equation (1). When topic k is not included

²¹ We also use 0.70 and 0.80 as alternative thresholds. We note that our main findings remain unchanged.

²² Despite the recent advances in the capability of generative AI methods, it is known that these methods are deficient in algebra. We compute these ratios manually.

in the Fund Overview, $Info\ Ratio_{k,i}$ is set to 1, since information on that topic is considered entirely new to investors. The variable K refers to the total number of topics in livestream i .

4.3.4. Step 4. Measuring the complexity of information

To further align our empirical measures of new information with the two-system framework, we construct new information measures that capture the complexity of the information conveyed during a livestream. Figure 3 shows a flowchart for constructing these information complexity measures. Specifically, we use DeepSeek to classify the 15 topics extracted from livestream transcripts into two groups: those that are readily understandable to retail investors and those that require professional interpretation. The classification prompt is reported in Panel E of Table IA3. Using Claude as an alternative model yields identical classifications, confirming the robustness of the categorization. The complex topics are macroeconomic policy analysis, industry analysis, stock-picking strategy, quantitative modelling, investment philosophy, market trend analysis, investment strategy, and risk-return characteristics, and the non-complex topics are product features and trends, fund manager's professional background, investor education, index characteristics, investment objectives, investment scope, and dividend policy.

We further validate our information complexity measure using the *Fog Index*, a readability metric computed from livestream transcripts following the Gunning Fog Index methodology (Gunning 1952; Xu, Yao, and Chen 2019). Table IA4 confirms that our topic-based classification reliably captures the textual complexity of livestream content. Figure IA9 provides examples of complex and non-complex topics.

We measure the information content of different types of topics in livestream i as follows:

$$Info\ Complex_i = \sum_{k=1}^M Topic\ Proportion_{k,i} \times Info\ Ratio_{k,i}, \quad (3)$$

$$Info\ NonComplex_i = \sum_{k=1}^N Topic\ Proportion_{k,i} \times Info\ Ratio_{k,i}, \quad (4)$$

where M is the number of complex topics, and N is the number of non-complex topics.

Table 1, Panel D presents summary statistics for our information measures. The mean of *Info* is 0.685, indicating that 68.5 percent of livestream content is new relative to the Fund Overview. Of this new information, complex topics account for 68.5 percent (0.469/0.685), while non-complex topics account for 31.5 percent (0.217/0.685).²³

5. Main Results

This section reports our main empirical results. We first examine the relation between fund livestreams and issuance performance, focusing on the role of investors' System 1 intuition in purchase decisions. We then investigate whether and how the association between favorable System 1 impressions and fund purchase decisions varies with information conveyed during livestreams, as greater information content is more likely to engage System 2 analytical processing.

5.1. Fund Launch Livestreams and Issuance Performance

To examine whether a fund's launch livestream is significantly associated with its issuance performance, we estimate the following specification using the sample of fund launches over our sample period:

$$Y_{i,t} = \beta_0 + \beta_1 \text{LiveStream}_{i,t} + \gamma \text{Controls}_{i,t} + \text{StyleFE} + \text{YearFE} + \varepsilon_{i,t}, \quad (5)$$

where Y_i represents fund i 's issuance performance, and we use the number of subscriptions (*LnSubscriptions*) and the amount of subscriptions (*LnAmount*) as the performance measures. Our primary variables of interest are *Livestream Indicator* and *Number of Livestreams*. The former denotes whether fund i has at least one launch livestream before or during the

²³ Table IA5 reports the correlation matrix for fund issuance performance, investor impressions, and livestream information measures. We note that both measures of fund issuance performance are positively associated with investors' favorable impressions of livestream presenters (with the exception of *Body Motion*), whereas the fund issuance amount is negatively correlated with two of the three information measures.

subscription period, and the latter indicates the number of launch livestreams. To control for potential confounding factors, we include fund, fund manager, and market characteristics, collectively denoted as *Controls*. Furthermore, we control for style fixed effects and year fixed effects.²⁴ Standard errors are clustered at the fund family level.

Table 2, Panel A reports the regression results for Equation (5). Whether we use the livestream indicator or the number of livestreams, the coefficients on *Livestream Indicator* and *Number of Livestreams* are significantly positive at the 1% level across all specifications. These results indicate that fund launch livestreams are associated with better issuance performance. To provide supplemental evidence on the role of launch livestreams in fund issuance outcomes, Panel B examines the relation between livestream viewership and the issuance performance of a new fund, using the sample of funds hosting launch livestreams. The coefficient on *LnViewers* in column (1) is significantly positive, indicating that higher livestream viewership is associated with better issuance performance. However, when the dependent variable is the subscription amount, there is no significant association between livestream viewership and the subscription amount, suggesting that livestream viewers are primarily small retail investors who are swayed by the livestream to participate with relatively small investments.²⁵

5.2. System 1 Intuition and Fund Issuance Performance

Under the two-system framework, agents “often act intuitively,” with their behavior guided by “what they happen to see at a given moment” (Kahneman 2003a, p. 1469). In our setting, the positive nonverbal cues conveyed by fund launch livestreams may generate

²⁴ RESSET includes 44 fund styles, e.g., Large-Cap Balanced Stock Fund, Large-Cap Value Stock Fund, Mid-Cap Growth Stock Fund, Mid-Cap Balanced Stock Fund, Standard Hybrid Fund, Active Allocation Fund (Closed), and Pure Bond Fund.

²⁵ Funds disclose the number of subscriptions if they issue only one class or, if they issue both Classes A and C, the number for Classes A and C combined. We lose six observations (= 789 – 783) because these funds did not disclose this information.

favorable impressions through System 1 processing and thereby influence investors' subscription decisions.

In this section, we examine how investors' favorable impressions formed during livestreams, our proxy for System 1 intuition, are associated with stronger fund issuance performance.²⁶ We run the following cross-sectional regression using 1,422 fund issuance observations:

$$Y_{i,t} = \beta_0 + \beta_1 \text{Impression Measures}_{i,t} + \gamma \text{Controls}_{i,t} + \text{StyleFE} + \text{YearFE} + \text{TimeofDayFE} + \varepsilon_{i,t}, \quad (6)$$

where Y_i represents fund i 's issuance performance, and we use the number of subscriptions (LnSubscriptions) and the amount of subscriptions (LnAmount) as the outcome variables. Our variables of interest are the individual impression measures (*Vocal Positive*, *Visual Positive*, and *Body Motion*) and the summary impression measure (*Impression Score*). All of these features are standardized to have a mean of zero and a unit standard deviation for ease of interpretation. We also include livestream, fund, fund manager, and market characteristics as control variables.²⁷ Furthermore, we control for style fixed effects, year fixed effects, and time-of-day fixed effects.²⁸ Standard errors are clustered at the fund family level when the dependent variable is the number of subscriptions and at both the fund family and livestream levels when the dependent variable is the subscription amount.

Table 3 reports the regression results for Equation (6). Columns (1) to (4) use the number

²⁶ This insight underpins the extensive advertising literature, which shows that sellers' communications can create perceived product differentiation even in the absence of substantive differences, an effect that is especially pronounced among less-informed or less-sophisticated consumers (e.g., Braithwaite 1928; Hurwitz and Caves 1988; Bagwell 2007).

²⁷ We include the following livestream characteristics as control variables: positive verbal measure (*Verbal Positive*), video image quality (*Image Clarity*), beauty score of presenters (*Beauty Score*), the number of presenters (*Number of Presenters*), the share of female presenters (*Share of Female Presenters*), an indicator for promotional giveaways (e.g., gift or red packet) (*Gift*), the viewership (*LnViewers*), the length of a launch livestream (*LnLength*), and the period from a fund's launch livestream to the end of its subscription period (*LnLivetoClose*).

²⁸ We partition livestreams into three time-of-day bins—morning (9:00 a.m.–12:00 p.m.), afternoon (12:00–3:00 p.m.), and non-trading hours—and include time-of-day fixed effects.

of subscriptions (*LnSubscriptions*) as the dependent variable. Columns (1) to (3) report the results for the individual impression measures. Column (4) uses *Impression Score* instead. All individual impression measures have positive loadings; the coefficients on *Vocal Positive*, *Visual Positive*, and *Impression Score* are statistically significant. Columns (5) to (8) use the subscription amount (*LnAmount*) as the performance measure and find similar results. All individual impression measures have positive loadings, and the coefficients on *Vocal Positive* and *Impression Score* are statistically significant.

Social perceptions are formed from nonverbal and paralinguistic cues, including tone of voice, facial expressions, and body language (Rosenthal et al. 1979; Ambady et al. 1999), which can engage System 1 (intuitive, automatic) processing. We show that investors' favorable impressions of livestream presenters, our proxy for System 1 intuition, are positively associated with the issuance performance of newly launched funds. These findings underscore the importance of delivery features in mutual fund livestreams and are consistent with evidence that favorable impressions influence investor decision-making (Blankespoor, Hendricks, and Miller 2017; Huang, Ivković, Jiang, and Wang 2023; Hu and Ma 2025).²⁹

However, fund livestreams also convey substantial and complex information that may engage System 2 (deliberate, analytical processing) (Kahneman and Frederick, 2002; Kahneman, 2011). In the next section, we examine whether and how System 2 analytical processing modifies the influence of favorable System 1 impressions on investors' fund purchase decisions.

²⁹ In Table IA6, we also investigate whether a fund's ability to generate favorable investor impressions during livestreams is associated with its subsequent return performance. Consistent with Hu and Ma (2025) and deHaan et al. (2026), we find that more favorable investor impressions at launch are associated with poorer short-term fund performance, a relation that weakens over longer horizons. These findings suggest that favorable System 1 impressions may lead retail investors to allocate capital to funds without correspondingly stronger subsequent performance.

5.3. The Role of System 2 Analytical Processing

To our knowledge, this is the first study to examine how System 1 and System 2 interact in a real-world investment setting. Specifically, we test whether information conveyed during fund launch livestreams, which may engage investors' System 2 analytical processing, attenuates the influence of favorable System 1 impressions on their investment decisions.

5.3.1. System 2 analytical processing, System 1 intuition, and fund issuance performance

During fund livestreams, presenters such as fund managers discuss macroeconomic conditions, market trends, industry developments, and fund-specific information. For retail investors, such content may be new or complex and therefore more likely to engage System 2 analytical processing (Kahneman and Frederick 2002; Kahneman 2011).

This setting raises a central question about the interplay between the two systems: does information that engages System 2 weaken or reinforce the influence of favorable System 1 impressions on fund issuance performance? We measure the amount of new information conveyed during livestreams using two proxies: (1) *Info*, the share of livestream content that differs from the Fund Overview available on the platform; and (2) *High Info*, an indicator variable that equals one if *Info* is in the top quintile, and zero otherwise.

To set the stage, we first estimate the following regression:

$$Y_{i,t} = \beta_0 + \beta_1 \text{Impression Score}_{i,t} + \beta_2 \text{Info}_{i,t} + \gamma \text{Controls}_{i,t} + \text{StyleFE} + \text{YearFE} + \text{TimeofDayFE} + \varepsilon_{i,t}, \quad (7)$$

where Y_i represents fund i 's issuance performance, and we use the number of subscriptions (LnSubscriptions) and the amount of subscriptions (LnAmount) as the outcome variables. We employ two standalone proxies for information shared in livestreams (*Info* and *High Info*).

Info is standardized to have a mean of zero and a unit standard deviation for ease of interpretation. The coefficients on *Impression Score* and the information measures capture the separate associations of favorable System 1 impressions and information that may engage

System 2 analytical processing with investors' choices. Because our information measures are sentiment-neutral, we do not predict a directional effect of System 2 analytical processing on investors' choices.

Table 4, Panel A reports the regression results for Equation (7). Across all specifications, the coefficient on *Impression Score* is positive and statistically significant at the 5% level or lower, indicating that investors' favorable impressions are positively associated with fund issuance outcomes. By contrast, the coefficients on our two information measures are small and statistically insignificant.

To explore the interaction between System 1 and System 2, we estimate the following regression:

$$Y_{i,t} = \beta_0 + \beta_1 \text{Impression Score} \times \text{Info}_{i,t} + \beta_2 \text{Impression Score}_{i,t} + \beta_3 \text{Info}_{i,t} + \gamma \text{Controls}_{i,t} + \text{StyleFE} + \text{YearFE} + \text{TimeofDayFE} + \varepsilon_{i,t}, \quad (8)$$

where the coefficient on the interaction term captures whether information that may engage System 2 moderates the positive association between favorable System 1 impressions and fund issuance performance.

Table 4, Panel B reports the regression results for Equation (8). Columns (1) and (3) use the interaction *Impression Score* $\times$ *Info*; columns (2) and (4) use *Impression Score* $\times$ *High Info*. Across all specifications, the interaction coefficient is negative and statistically significant at the 5% level or lower, indicating that issuance outcomes become less responsive to *Impression Score* when a livestream conveys more information. For example, in column (4), when *High Info* takes a value of 1, the estimated association between *Impression Score* and *LnAmount* is $-0.086 (= 0.191 - 0.277 \times 1)$, and is not statistically different from zero, indicating that the positive association between *Impression Score* and fund issuance performance is no longer statistically significant when information content during a livestream is high.

Our findings provide new evidence consistent with Kahneman's two-system framework of cognition. Nonverbal cues such as gestures and dynamic facial expressions are more likely to engage System 1, which is intuitive and affect-driven; when livestreams provide limited decision-relevant information, investors may therefore rely more on favorable impressions formed from these cues (e.g., positive affect). By contrast, decision-relevant information may engage System 2, which is more analytical and effortful. Accordingly, when livestreams convey little new information, the positive association between favorable impressions and fund issuance performance is stronger. When livestreams are more information-rich, this association is attenuated, consistent with greater System 2 analytical processing moderating the influence of favorable System 1 impressions.

Although the decision to livestream a fund launch is unlikely to be random, this selection does not obviously threaten our main inference. For example, funds that believe they have superior livestreaming ability may anticipate stronger subscription outcomes, creating a positive association between holding a launch livestream and subsequent subscriptions. Our central question, however, is not whether livestreaming per se improves outcomes, but whether and how investors' System 2 analytical processing interacts with System 1 intuition during a fund-launch livestream. It is not clear how selection into livestreaming would bias this mechanism-based inference. Empirically, we find that when livestreams convey more information, which may engage System 2, the positive association between favorable System 1 impressions and fund issuance performance is attenuated. This interaction pattern is difficult to reconcile with a simple selection-on-livestream-quality story.

In the next three subsections, we provide additional supporting evidence by examining heterogeneity in the extent to which System 2 processing attenuates the influence of favorable System 1 impressions.

5.3.2. The role of System 2 analytical processing: Information type

We first examine how different types of information influence the role of System 1 in fund issuance performance. We focus on information complexity, a factor that may be more likely to engage System 2 (Kahneman and Frederick 2002; Kahneman 2011). We interact *Impression Score* with the two types of information conveyed during livestreams (*Info Complex* and *Info NonComplex*). The coefficients on the interaction terms indicate whether the association between investors' favorable impressions and fund issuance performance varies with the amount of complex or non-complex information conveyed during livestreams. Table 5 reports the results.

In columns (3) and (6), the coefficient on *Impression Score* $\times$ *Info Complex* is negative and statistically significant at the 1% level, whereas the coefficient on *Impression Score* $\times$ *Info NonComplex* is not statistically significant. These results indicate that the positive association between investors' favorable impressions and fund issuance performance is attenuated when livestreams convey more complex information, whereas it does not vary significantly with non-complex information. For example, in column (6), when *Info Complex* takes a value of 0.710 (the top quartile (standardized)), the estimated association between *Impression Score* and *LnAmount* is 0.019 ($= -0.210 \times 0.710 - 0.067 \times (-0.741) + 0.118$) (-0.741 is the bottom quartile (standardized) of *Info NonComplex*). At this level of complex information, the association between *Impression Score* and *LnAmount* is statistically indistinguishable from zero, consistent with greater System 2 processing moderating the influence of favorable System 1 impressions on investors' decisions.

Complex information requires greater cognitive effort and may be more likely to engage System 2, leading investors to place greater weight on content relative to delivery. Consistent with this interpretation, the positive association between favorable impressions and fund issuance performance is attenuated when livestreams convey more complex information. By

contrast, non-complex information may be processed with less analytical effort and therefore need not substantially shift attention away from heuristic impressions formed from nonverbal cues. Accordingly, the association between favorable impressions and fund issuance performance varies little with non-complex information. Taken together, our findings are consistent with the two-system framework.

5.3.3. The role of System 2 analytical processing: Fund manager presence

We next examine fund managers' presence in livestreams for three reasons. First, their presence may affect how viewers perceive and process the event: host-only sessions may be more promotional and may rely more heavily on presentation cues associated with System 1, whereas sessions featuring a fund manager may involve more substantive discussion and therefore be more likely to engage System 2 (Kahneman and Frederick 2002; Kahneman 2011). Second, manager presence may be associated with richer and more complex content, which could require greater analytical processing. Third, fund managers are expected to maintain professionalism and comply with disclosure requirements during livestreaming activities, potentially making these sessions less promotional and more focused on fund-related information than those led by hosts or other guests.³⁰ Taken together, these considerations suggest that manager presence may provide a useful setting for examining whether greater System 2 engagement attenuates the influence of favorable System 1 impressions.

Table 6, Panel A compares investor impressions, the amount and complexity of information conveyed during livestreams, and livestream, fund, fund manager, and market characteristics across sessions with and without a fund manager present. *Impression Score* does not differ significantly between the two groups, whereas sessions featuring a fund

³⁰ In May 2021, the Asset Management Association of China (AMAC) issued the Meeting Minutes of the Special Seminar on Mutual Fund Livestreaming, which provided guidance on compliance in mutual fund livestreaming activities and emphasized professionalism and appropriate internal controls. For more details, see <https://www.amac.org.cn/xwfb/hydt/202105/P020231126370015877033.pdf>.

manager contain significantly more information and more complex information. This pattern suggests that fund manager presence is associated with richer information content, while favorable impressions do not differ meaningfully from those of other presenters. Fund managers are also more likely to participate in livestreams before the subscription period, suggesting that their participation is not primarily associated with difficulty in selling the fund. In addition, managers from state-owned fund families are more likely to appear in livestreams promoting new funds, while presenting and non-presenting managers do not differ systematically in demographic characteristics. Finally, fund managers are less likely to participate when market volatility is high or when competition from other new launches of the same style is more intense. We include all these characteristics in the subsequent regression analysis.

We estimate Equation (8) by replacing *Info* with *Manager Present*, an indicator variable equal to one if at least one manager participates in a livestream. In Table 6, Panel B, column (1), the negative coefficient on *Impression Score* $\times$ *Manager Present* indicates that the positive association between investors' impressions and fund issuance performance is attenuated when a fund manager is present. In column (2), when *Manager Present* takes a value of one, the estimated association between *Impression Score* and fund issuance performance is 0.024 ($= 0.309 - 0.285$), which is not statistically different from zero. These results are consistent with fund manager presence being associated with greater System 2 analytical processing, which may moderate the influence of favorable System 1 impressions on investment decisions. The coefficient on the standalone variable *Manager Present* is negative and significant at the 5% level. This pattern is consistent with livestreams featuring managers conveying more substantive and potentially complex information, which may be viewed less favorably than more promotional content.

A fund manager's decision to participate in a livestream is endogenous and may be

intended to improve launch performance. If managers who expect their presence to attract more subscriptions are more likely to participate, selection would predict a positive association between manager participation and subsequent subscriptions, which is inconsistent with the negative coefficient on the indicator for manager presence. An alternative selection-based explanation is that managers participate more often when weaker subscription demand is anticipated, which is more consistent with the negative coefficient. This explanation, however, does not readily account for the interaction result central to our argument: the positive association between investors' favorable impressions and issuance performance is attenuated, rather than strengthened, when a fund manager is present. Accordingly, our evidence on the interaction between System 1 and System 2 is unlikely to be driven solely by endogenous selection into manager participation. Figure IA10 further shows that manager participation declines over time, suggesting that participation decisions may have evolved as fund families and managers gained experience with livestreaming.

In summary, using an alternative proxy for System 2 analytical processing, we continue to find that the association between favorable System 1 impressions and fund issuance performance is attenuated when System 2 processing is greater.

5.3.4. The role of System 2 analytical processing: Fund type

We next examine whether fund type moderates the interaction between System 1 and System 2 in influencing investor choices. Passive funds track well-defined benchmarks and generally hold more transparent and predictable portfolios, potentially requiring less investor scrutiny. By contrast, active funds employ more complex strategies and may impose greater informational demands, making System 2 more likely to be engaged (Kahneman and Frederick 2002; Kahneman 2011).

We estimate Equation (8) separately for active and passive fund subsamples. Table 7 reports the results. For active funds in columns (1) and (3), the coefficient on *Impression*

Score $\times$ *High Info* is negative and statistically significant, whereas the corresponding coefficient for passive funds in columns (2) and (4) is insignificant. These results indicate that the positive association between favorable impressions and fund issuance performance is attenuated by greater information content for active funds but not for passive funds. This pattern is consistent with greater informational demands for active funds being associated with more System 2 processing and a weaker influence of favorable System 1 impressions on investors' decisions.

5.4. Robustness Checks

One potential concern is the timing of the livestream relative to the subscription period. If a livestream occurs after some investors have already subscribed, the association between livestream characteristics and fund issuance performance may partly reflect subscription decisions that preceded the livestream. To address this concern, we repeat our main analysis restricting the sample to livestreams that occurred before or on the first day of the subscription period, ensuring that the livestream precedes most subscription activity. The results in Table IA7 remain qualitatively similar to those in Table 4, Panel B, alleviating concerns that our findings are driven by the timing of livestreams relative to investor subscriptions.

Another potential concern is that information disclosure and livestream style are not randomly assigned but may instead be shaped by fund families. Specifically, fund families may adopt common practices regarding the amount and type of information conveyed and the way livestreams are presented across their products, such that observed differences in information intensity or livestream style partly reflect family-level characteristics. This creates a potential confound if unobserved fund-family characteristics are associated with both livestream design and fund issuance performance. To address this concern, we re-estimate our main analysis including fund-family $\times$ year fixed effects, which absorb time-

varying fund-family characteristics shared across products issued by the same family. The results in Table IA8 remain qualitatively similar to those in Table 4, Panel B, alleviating concerns that our findings are driven by unobserved fund-family-level factors.

Our baseline measure *Impression Score* is the first principal component of three nonverbal cues: *Vocal Positive*, *Visual Positive*, and *Body Motion*, which capture core dimensions of presenters' affective and physical expressiveness that prior research identifies as important channels of rapid impression formation (e.g., Ambady and Rosenthal 1992; Blankespoor, Hendricks, and Miller 2017). We assess whether our findings are robust to incorporating an additional verbal cue, *Verbal Positive*, and two additional nonverbal cues that may also shape impressions but capture somewhat different attributes and are more susceptible to external confounds. *Beauty Score* reflects physical appearance rather than dynamic expressive behavior, while *Image Clarity* captures video production quality instead of presenters' affective expression. Specifically, we reconstruct *Impression Score* using three alternative sets of inputs: (1) the baseline three cues plus *Verbal Positive*; (2) the baseline three cues plus *Beauty Score*; and (3) the baseline three cues plus *Beauty Score* and *Image Clarity*. For each specification, we extract the first principal component via PCA. Panels A to F of Table IA9 report the factor loadings, uniqueness measures, and corresponding regression results. Our main findings remain qualitatively unchanged across all three alternative constructions.

Furthermore, our baseline *Impression Score* is constructed from the mean values of *Vocal Positive*, *Visual Positive*, and *Body Motion* over the entire livestream. The mean preserves the influence of extreme cue realizations, which may themselves be particularly salient to investors. At the same time, a potential concern is that such observations may disproportionately influence cue-level averages. To address this concern, we recompute each cue using its median value over the livestream instead of its mean and then extract the first

principal component from the three median-based measures. Because the median is less sensitive to extreme observations, this alternative construction reduces their influence. Panels G and H of Table IA9 report the results, which remain qualitatively similar to our baseline findings.

Finally, we measure livestream information content relative to the Important Notice section of the fund prospectus, rather than the Tiantian Fund Overview used in our baseline analysis. Unlike the Fund Overview, which provides a broad description of the fund's investment strategy and characteristics, the Important Notice section is a standardized, regulatorily mandated disclosure that is concise and relatively uniform across funds. It therefore provides a useful alternative benchmark for assessing how much livestream content is already reflected in formal written disclosures.³¹ We repeat the analysis in Table 4, Panel B, using this alternative information measure. Table IA10 reports results that are qualitatively similar to our baseline findings.

6. Capacity Constraints in System 2 Processing

According to Kahneman (2011), System 2 processing is effortful and capacity-constrained. When cognitive resources are limited, analytical processing may become less effective, allowing intuitive System 1 processing to play a greater role. This suggests a boundary condition for our earlier findings: the attenuation of the positive association between favorable System 1 impressions and fund issuance performance should be weaker when investors face greater distraction or cognitive overload. We examine this possibility below.

³¹ The Important Notice appears at the front of the fund prospectus. It includes the issuer's statement regarding the authenticity, accuracy, and completeness of the prospectus and provides key regulatory disclosures concerning the fund's principal features and risks.

6.1. Distraction from Concurrent Livestreams

We examine whether investor distraction constrains System 2 analytical processing. In our setting, concurrent fund livestreams on the same platform compete for investors' limited attention. Following Hirshleifer, Lim, and Teoh (2009), we proxy for investor distraction using the number of concurrent fund livestreams on Tiantian. We split the sample into high- and low-distraction subsamples based on the within-year median and re-estimate the specification in Table 4, Panel B. Table 8, Panel A reports the results. The interaction coefficient is negative and significant in the low-distraction subsample (columns (2) and (4)) but insignificant in the high-distraction subsample (columns (1) and (3)), consistent with greater competition for investor attention limiting the extent to which System 2 moderates the influence of favorable System 1 impressions.

6.2. Distraction from Extreme Market Returns

We next examine how market-induced distraction affects the boundary conditions of System 2. On days with extreme market returns, competing information events may strain investors' limited attention and reduce their capacity for analytical processing. Following Kempf, Manconi, and Spalt (2017), we proxy for market-induced distraction using extreme market returns, defined as days in the top or bottom decile of the past three-month market-return distribution over our sample period, and split the sample into high- and low-distraction subsamples. We re-estimate the specification in Table 4, Panel B for each subsample, and Table 8, Panel B reports the results. The interaction coefficient is negative and significant in the low-distraction subsample (columns (2) and (4)) but insignificant in the high-distraction subsample (columns (1) and (3)), consistent with market-wide events crowding out attentional resources and limiting the moderating role of System 2.

6.3. Cognitive Overload

Finally, we examine how cognitive overload affects System 2 analytical processing. Longer livestreams require sustained attention and may impose greater cognitive load, reducing investors' capacity for analytical processing. We proxy for cognitive overload using livestream duration, split the sample at the median into long- and short-livestream subsamples, and re-estimate the specification in Table 4, Panel B. Table 8, Panel C reports the results. The interaction coefficient is negative and significant in the short-livestream subsample (columns (2) and (4)) but insignificant in the long-livestream subsample (columns (1) and (3)), consistent with greater cognitive load limiting the extent to which System 2 moderates the influence of favorable System 1 impressions.

Taken together, these analyses paint a consistent picture: the moderating role of System 2 analytical processing is weaker when investors face greater distraction or cognitive overload. These findings are consistent with Kahneman's (2011) characterization of System 2 as capacity-constrained and help delineate the conditions under which favorable System 1 impressions are more strongly associated with investor behavior.

7. Conclusion

Guided by Kahneman's two-system framework of cognition, this paper is, to our knowledge, the first in finance to examine the interplay between the two systems and its boundary conditions in a real-world investment setting. We construct and analyze a novel dataset of livestream promotional events linked to the initial offerings of mutual funds in China and, by focusing on launches with limited prior information, provide a useful setting to examine how investors' intuitive thinking (System 1) and analytical processing (System 2) interact in investment decisions.

We find that favorable impressions associated with livestream presenters' nonverbal cues

(e.g., vocal tone and facial expressiveness), our proxy for System 1 intuition, are positively associated with fund subscription outcomes, highlighting the importance of delivery features in mutual fund livestreams. However, when livestreams convey more information, the positive association between favorable System 1 impressions and fund subscriptions is attenuated, consistent with greater System 2 analytical processing. This attenuation is particularly pronounced when information is complex, when fund managers participate, and when the promoted fund is actively managed. We further show that the moderating role of System 2 analytical processing is weaker when investors face capacity constraints, including distraction from concurrent livestreams or extreme market conditions and cognitive overload from longer livestreams. This evidence is consistent with Kahneman's (2011) characterization of System 2 as capacity-constrained. Taken together, our findings highlight the interdependence of System 1 and System 2 cognition in real-world investor decision-making and provide a foundation for a richer positive theory of investor behavior.

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Figure 1. Flowchart for Constructing the Impression Measures

This figure presents a step-by-step flowchart illustrating the process of transforming video data from livestreams and constructing different impression measures and *Impression Score*.

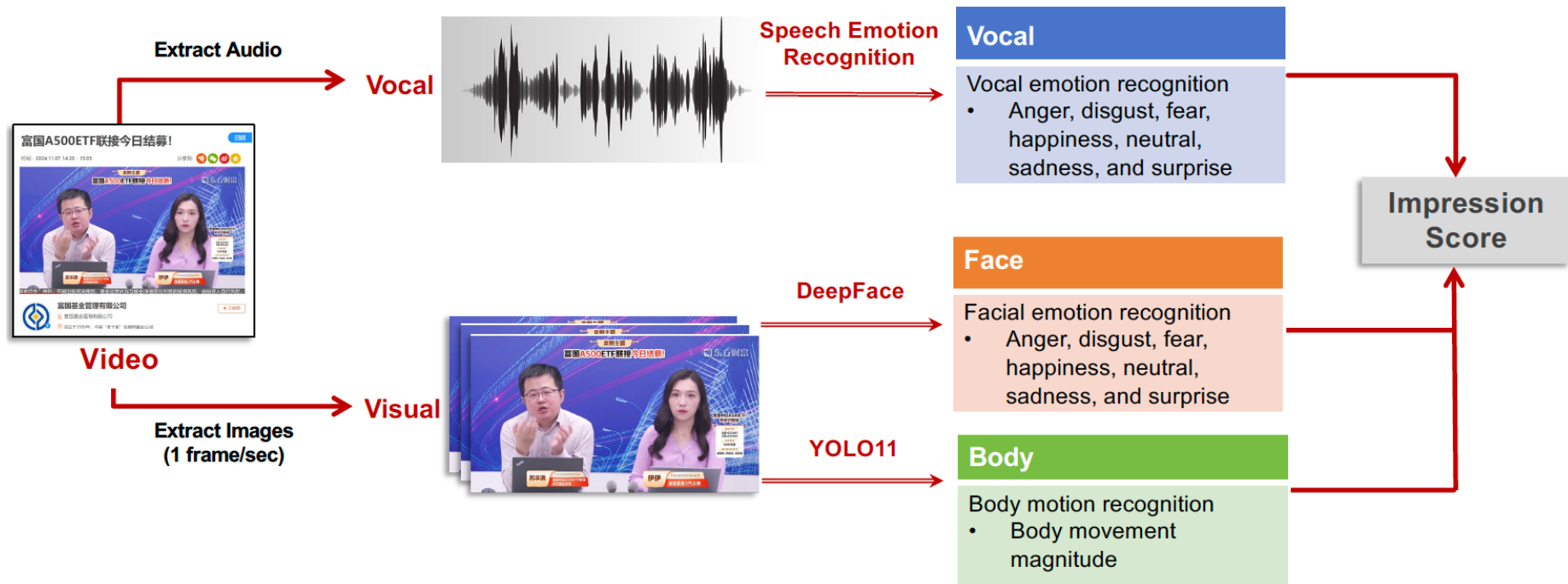


Figure 2. Flowchart for Constructing the Information Measure (*Info*)

This figure presents a step-by-step flowchart illustrating the process of constructing the information measure from livestream transcripts. Topics in blue refer to the six topics in the Tiantian Fund Overview. Topics in navy refer to the nine additional topics and the residual ‘Misc.’ category not covered by the Fund Overview.

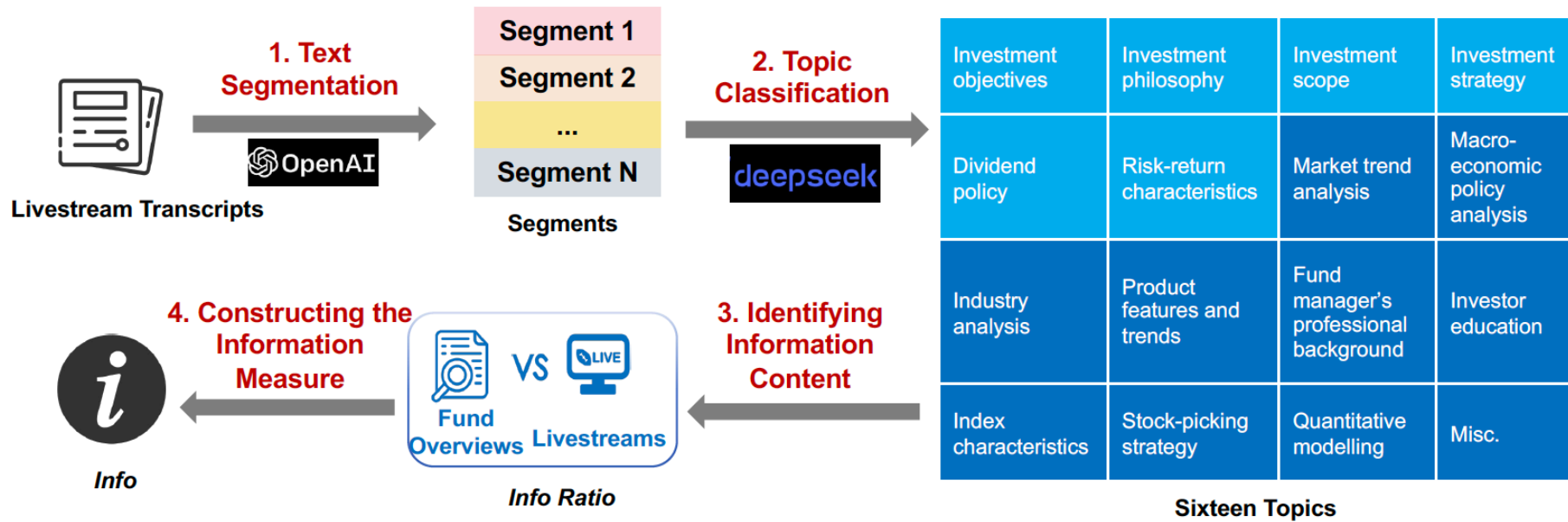


Figure 3. Flowchart for Constructing the Complex and Non-complex Information Measures (*Info Complex* and *Info NonComplex*)

This figure presents a step-by-step flowchart illustrating the process of constructing the complex and non-complex information measures. Topics in orange refer to the eight topics identified by generative AI that require interpretation by investment professionals. Topics in green refer to the remaining topics that are easily understood by retail investors.

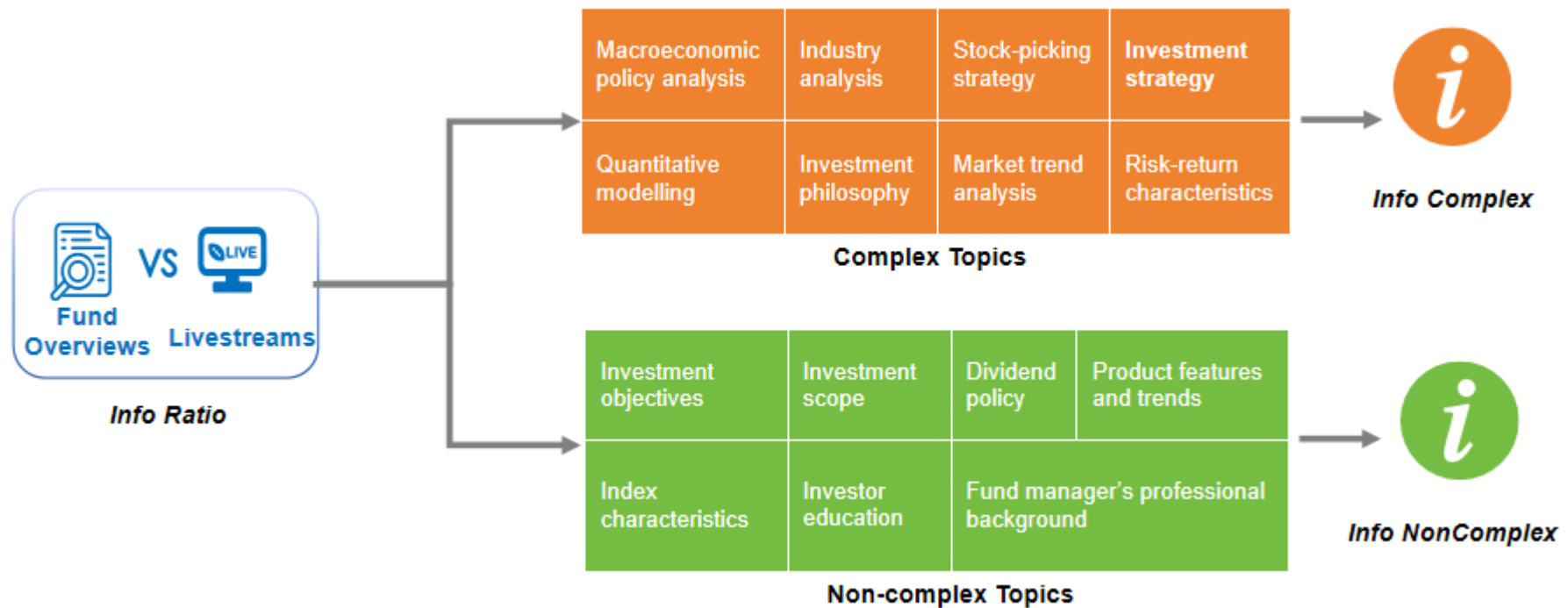


Table 1. Summary Statistics

This table reports summary statistics. Our sample period is from July 1, 2020 to May 31, 2024. Panel A reports summary statistics for fund, fund manager, and market characteristics. Panel B reports summary statistics for livestream characteristics. Panel C reports summary statistics for the impression measures; the last two columns report the factor loadings and uniqueness of each measure from the principal component analysis used to construct *Impression Score*. Panel D reports summary statistics for the information measures. Variable definitions are provided in Online Appendix A.

Panel A: Fund, Fund Manager, and Market Characteristics					
	<i>Mean</i>	<i>SD</i>	<i>P25</i>	<i>Median</i>	<i>P75</i>
Active Fund	0.835	0.371	1.000	1.000	1.000
Fund Fees	1.305	0.534	0.750	1.700	1.750
Length of Subscription Period	20.902	19.270	11.000	15.000	23.000
State-owned Fund Family	0.781	0.414	1.000	1.000	1.000
Large Fund Family	0.326	0.469	0.000	0.000	1.000
Female Manager	0.235	0.424	0.000	0.000	0.000
Rookie Manager	0.063	0.242	0.000	0.000	0.000
Highest Degree	2.076	0.339	2.000	2.000	2.000
Top2 University	0.168	0.374	0.000	0.000	0.000
Manager Experience	2.537	0.708	2.510	2.701	2.851
Manager Past Performance	0.079	0.153	-0.002	0.042	0.149
Market Return	0.027	0.075	-0.026	0.044	0.073
Market Volatility	0.175	0.062	0.135	0.158	0.188
Number of Fund Launches	2.976	1.074	2.079	3.091	3.970

Panel B: Livestream Characteristics					
	<i>Mean</i>	<i>SD</i>	<i>P25</i>	<i>Median</i>	<i>P75</i>
Verbal Positive	0.793	0.109	0.730	0.811	0.877
Image Clarity	0.630	0.557	0.192	0.506	0.897
Beauty Score	2.884	0.315	2.664	2.881	3.120
Number of Presenters	1.911	0.632	2.000	2.000	2.000
Number of Female Presenters	0.502	0.362	0.333	0.500	1.000
Manager Present	0.646	0.479	0.000	1.000	1.000
Before Subscription	0.285	0.451	0.000	0.000	1.000
Gift	0.114	0.318	0.000	0.000	0.000
Number of Viewers	46,669	35,234	28,092	38,789	52,288
LnViewers	10.57	0.566	10.24	10.57	10.86
Length of Livestream	64.98	25.49	60.00	60.00	60.00
LnLength	4.140	0.263	4.111	4.111	4.111
Livestream to Close	14.39	10.46	7.000	14.00	20.00
LnLivetoClose	2.399	0.965	2.079	2.708	3.045

Panel C: Impression Measures (Unstandardized)

	<i>Mean</i>	<i>SD</i>	<i>P25</i>	<i>Median</i>	<i>P75</i>	<i>Loading</i>	<i>Uniqueness</i>
Vocal Positive	0.229	0.185	0.083	0.181	0.325	0.590	0.550
Visual Positive	0.093	0.086	0.030	0.071	0.122	0.627	0.492
Body Motion	1.328	0.874	0.694	1.065	1.734	0.510	0.664
Impression Score	0.000	0.491	-0.358	-0.067	0.276		

Panel D: Information Measures (Unstandardized)

	<i>Mean</i>	<i>SD</i>	<i>P25</i>	<i>Median</i>	<i>P75</i>
Info	0.685	0.102	0.616	0.694	0.753
Info Complex	0.469	0.137	0.373	0.474	0.566
Info NonComplex	0.217	0.106	0.138	0.202	0.276

Table 2. Fund Livestream and Issuance Performance

This table examines the association between a fund hosting a launch livestream and issuance performance. Our sample period is from July 1, 2020 to May 31, 2024. Panel A examines the association between hosting a launch livestream and fund issuance performance using the full sample. Panel B examines the association between viewership and fund issuance performance using the sample of funds that host a launch livestream. Columns (1) and (2) report the results where the dependent variable is *LnSubscriptions*, the natural logarithm of one plus the number of accounts subscribing to a fund issuance. Columns (3) and (4) report the results where the dependent variable is *LnAmount*, the natural logarithm of one plus the total subscription amount to a fund issuance. The control variables include *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*. Variable definitions are provided in Online Appendix A. Heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Whether Hosting a Launch Livestream and Fund Issuance Performance				
	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Livestream Indicator	0.820*** (0.090)		0.564*** (0.088)	
Number of Livestreams		0.252*** (0.033)		0.182*** (0.025)
Active Fund	-0.584*** (0.206)	-0.601*** (0.207)	-0.632** (0.253)	-0.640** (0.254)
Fund Fees	1.309*** (0.212)	1.351*** (0.212)	0.960*** (0.224)	0.986*** (0.225)
State-owned Fund Family	-0.017 (0.138)	-0.005 (0.135)	0.197 (0.146)	0.204 (0.143)
Large Fund Family	0.593*** (0.149)	0.607*** (0.151)	0.261* (0.141)	0.271* (0.140)
Female Manager	0.047 (0.068)	0.045 (0.069)	0.061 (0.077)	0.062 (0.078)
Rookie Manager	1.527*** (0.437)	1.597*** (0.433)	1.687*** (0.407)	1.737*** (0.406)
Highest Degree	-0.024 (0.098)	-0.020 (0.097)	-0.063 (0.088)	-0.060 (0.087)
Top2 University	-0.078 (0.103)	-0.079 (0.105)	-0.051 (0.079)	-0.050 (0.080)
Manager Experience	0.821*** (0.134)	0.838*** (0.133)	0.962*** (0.142)	0.973*** (0.141)
Manager Past Performance	0.224 (0.147)	0.223 (0.148)	0.274* (0.157)	0.273* (0.158)
Market Return	-0.167 (0.314)	-0.339 (0.312)	0.037 (0.387)	-0.112 (0.384)
Market Volatility	-0.473 (0.583)	-0.445 (0.581)	-0.336 (0.692)	-0.324 (0.688)
Number of Fund Launches	0.131*** (0.046)	0.136*** (0.046)	-0.034 (0.051)	-0.031 (0.051)
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	5,860	5,860	9,855	9,855
Adjusted R ²	0.463	0.463	0.122	0.123

Panel B: Number of Livestream Viewers and Fund Issuance Performance

	<i>LnSubscriptions</i>	<i>LnAmount</i>
	(1)	(2)
LnViewers	0.216** (0.092)	0.085 (0.090)
Active Fund	-0.502* (0.292)	-0.678** (0.327)
Fund Fees	0.386 (0.292)	0.197 (0.307)
State-owned Fund Family	0.116 (0.124)	0.264** (0.112)
Large Fund Family	0.479*** (0.110)	0.133 (0.111)
Female Manager	0.254** (0.124)	0.129 (0.119)
Rookie Manager	-0.719*** (0.257)	-0.167 (0.259)
Highest Degree	-0.245* (0.134)	-0.190 (0.128)
Top2 University	0.039 (0.127)	-0.045 (0.122)
Manager Experience	0.241 (0.229)	0.862*** (0.252)
Manager Past Performance	1.804*** (0.414)	1.714*** (0.343)
Market Return	0.500 (0.846)	0.240 (0.802)
Market Volatility	0.318 (1.194)	-1.170 (1.295)
Number of Fund Launches	0.105 (0.111)	-0.072 (0.105)
Style FE	YES	YES
Year FE	YES	YES
Observations	783	1,422
Adjusted R ²	0.359	0.233

Table 3. Investor Impressions and Fund Issuance Performance

This table examines the association between investors' impressions and fund issuance performance. Our sample period is from July 1, 2020 to May 31, 2024. Columns (1) to (4) report the results using the number of subscriptions as the dependent variable. Columns (5) to (8) report the results using the total subscription amount as the dependent variable. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>LnSubscriptions</i>				<i>LnAmount</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vocal Positive	0.168*** (0.045)				0.134*** (0.048)			
Visual Positive		0.114** (0.050)				0.078 (0.055)		
Body Motion			0.067 (0.056)				0.039 (0.057)	
Impression Score				0.184*** (0.049)				0.134** (0.055)
Verbal Positive	0.057 (0.054)	0.084 (0.053)	0.070 (0.053)	0.069 (0.054)	0.012 (0.055)	0.031 (0.054)	0.022 (0.054)	0.022 (0.054)
Image Clarity	0.030 (0.053)	0.048 (0.052)	0.056 (0.054)	0.053 (0.053)	0.134** (0.062)	0.148** (0.062)	0.152** (0.063)	0.152** (0.064)
Beauty Score	-0.028 (0.061)	-0.042 (0.063)	-0.026 (0.060)	-0.048 (0.061)	-0.053 (0.058)	-0.061 (0.061)	-0.050 (0.058)	-0.068 (0.061)
Number of Presenters	-0.113 (0.108)	-0.110 (0.109)	-0.105 (0.113)	-0.138 (0.110)	-0.053 (0.095)	-0.045 (0.095)	-0.040 (0.100)	-0.069 (0.098)
Share of Female Presenters	0.133 (0.125)	0.107 (0.129)	0.156 (0.131)	0.116 (0.126)	0.070 (0.128)	0.054 (0.131)	0.085 (0.130)	0.058 (0.128)
Gift	-0.126 (0.168)	-0.126 (0.168)	-0.119 (0.165)	-0.127 (0.165)	-0.063 (0.177)	-0.060 (0.179)	-0.055 (0.176)	-0.061 (0.176)
LnViewers	0.194* (0.105)	0.222** (0.105)	0.217** (0.104)	0.207* (0.107)	0.127 (0.124)	0.151 (0.124)	0.147 (0.122)	0.142 (0.125)
LnLength	0.126	0.092	0.122	0.117	0.127	0.096	0.115	0.117

	(0.237)	(0.239)	(0.237)	(0.236)	(0.231)	(0.239)	(0.235)	(0.236)
LnLivetoClose	-0.012	-0.014	-0.008	-0.017	-0.051	-0.052	-0.048	-0.054
	(0.079)	(0.080)	(0.079)	(0.079)	(0.084)	(0.085)	(0.085)	(0.085)
Active Fund	-0.620**	-0.578**	-0.580**	-0.592**	-0.729*	-0.696*	-0.703*	-0.716*
	(0.261)	(0.261)	(0.260)	(0.261)	(0.402)	(0.404)	(0.407)	(0.404)
Fund Fees	0.385	0.385	0.384	0.378	0.155	0.153	0.156	0.153
	(0.357)	(0.368)	(0.362)	(0.362)	(0.430)	(0.435)	(0.436)	(0.432)
State-owned Fund Family	0.159	0.112	0.119	0.113	0.290*	0.257	0.262	0.257
	(0.153)	(0.156)	(0.153)	(0.151)	(0.170)	(0.169)	(0.168)	(0.167)
Large Fund Family	0.421***	0.473***	0.469***	0.400***	0.049	0.089	0.086	0.038
	(0.139)	(0.147)	(0.155)	(0.140)	(0.126)	(0.129)	(0.133)	(0.126)
Female Manager	0.179	0.218*	0.201	0.189	0.069	0.101	0.089	0.079
	(0.136)	(0.130)	(0.132)	(0.133)	(0.143)	(0.139)	(0.140)	(0.142)
Rookie Manager	0.532	0.375	0.477	0.469	0.650	0.519	0.592	0.592
	(0.538)	(0.513)	(0.531)	(0.515)	(0.644)	(0.631)	(0.632)	(0.622)
Highest Degree	-0.249*	-0.269*	-0.261*	-0.271*	-0.191	-0.204	-0.197	-0.205
	(0.139)	(0.138)	(0.138)	(0.137)	(0.144)	(0.144)	(0.145)	(0.144)
Top2 University	0.044	0.058	0.068	0.036	-0.022	-0.008	-0.002	-0.024
	(0.185)	(0.192)	(0.195)	(0.191)	(0.151)	(0.161)	(0.160)	(0.158)
Manager Experience	0.468**	0.412**	0.449**	0.435**	0.622***	0.577**	0.605***	0.595***
	(0.181)	(0.173)	(0.178)	(0.172)	(0.223)	(0.223)	(0.222)	(0.218)
Manager Past Performance	1.851***	1.867***	1.920***	1.861***	1.771***	1.793***	1.825***	1.791***
	(0.452)	(0.469)	(0.476)	(0.450)	(0.386)	(0.398)	(0.401)	(0.389)
Market Return	0.261	0.332	0.355	0.256	-0.021	0.050	0.065	-0.019
	(0.911)	(0.874)	(0.891)	(0.902)	(0.961)	(0.950)	(0.957)	(0.960)
Market Volatility	0.086	0.137	0.111	-0.061	-1.168	-1.145	-1.156	-1.270
	(1.211)	(1.188)	(1.242)	(1.190)	(1.527)	(1.530)	(1.572)	(1.523)
Number of Fund Launches	0.081	0.094	0.101	0.086	-0.076	-0.066	-0.062	-0.072
	(0.110)	(0.110)	(0.112)	(0.109)	(0.123)	(0.119)	(0.123)	(0.120)
Style FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	783	783	783	783	1,422	1,422	1,422	1,422
Adjusted R ²	0.358	0.353	0.350	0.360	0.243	0.240	0.239	0.243

Table 4. Investor Impressions, Information, and Fund Issuance Performance

This table examines the association between investors' impressions, information processing, and fund issuance performance. Our sample period is from July 1, 2020 to May 31, 2024. Panel A examines the separate associations of investors' impressions and information processing with fund issuance performance. Panel B examines whether the association between investors' impressions and fund issuance outcomes varies with the amount of information conveyed during the livestream. Columns (1) and (2) report the results using the number of subscriptions as the dependent variable. Columns (3) and (4) report the results using the total subscription amount as the dependent variable. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Investor Impressions, Information, and Fund Issuance Performance				
	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Impression Score	0.177*** (0.048)	0.183*** (0.049)	0.129** (0.054)	0.134** (0.055)
Info	-0.071 (0.060)		-0.067 (0.073)	
High Info		-0.187 (0.148)		-0.115 (0.169)
Verbal Positive	0.069 (0.054)	0.071 (0.054)	0.022 (0.054)	0.023 (0.054)
Image Clarity	0.057 (0.053)	0.060 (0.053)	0.155** (0.064)	0.156** (0.064)
Beauty Score	-0.050 (0.061)	-0.053 (0.061)	-0.069 (0.061)	-0.070 (0.061)
Number of Presenters	-0.125 (0.108)	-0.140 (0.109)	-0.057 (0.094)	-0.069 (0.099)
Share of Female Presenters	0.114 (0.125)	0.123 (0.125)	0.055 (0.128)	0.063 (0.129)
Gift	-0.130 (0.165)	-0.132 (0.164)	-0.062 (0.176)	-0.062 (0.176)
LnViewers	0.204* (0.106)	0.209* (0.105)	0.139 (0.124)	0.144 (0.124)
LnLength	0.128 (0.230)	0.117 (0.237)	0.129 (0.232)	0.117 (0.236)
LnLivetoClose	-0.018 (0.078)	-0.022 (0.078)	-0.055 (0.084)	-0.057 (0.085)
Active Fund	-0.619** (0.273)	-0.622** (0.274)	-0.744* (0.411)	-0.738* (0.408)
Fund Fees	0.374 (0.366)	0.373 (0.363)	0.153 (0.437)	0.153 (0.435)
State-owned Fund Family	0.109 (0.149)	0.116 (0.151)	0.251 (0.166)	0.257 (0.167)
Large Fund Family	0.397*** (0.141)	0.391*** (0.144)	0.036 (0.127)	0.034 (0.127)
Female Manager	0.190 (0.134)	0.197 (0.134)	0.080 (0.142)	0.083 (0.143)
Rookie Manager	0.505 (0.520)	0.472 (0.512)	0.622 (0.626)	0.592 (0.622)

Highest Degree	-0.279** (0.137)	-0.286** (0.137)	-0.214 (0.143)	-0.216 (0.142)
Top2 University	0.037 (0.188)	0.032 (0.185)	-0.023 (0.155)	-0.025 (0.155)
Manager Experience	0.449** (0.173)	0.436** (0.170)	0.606*** (0.219)	0.594*** (0.217)
Manager Past Performance	1.836*** (0.452)	1.814*** (0.447)	1.768*** (0.388)	1.761*** (0.387)
Market Return	0.251 (0.888)	0.250 (0.885)	-0.032 (0.957)	-0.022 (0.954)
Market Volatility	-0.020 (1.182)	-0.115 (1.178)	-1.243 (1.509)	-1.298 (1.524)
Number of Fund Launches	0.076 (0.110)	0.077 (0.109)	-0.081 (0.124)	-0.076 (0.121)
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	783	783	1,422	1,422
Adjusted R ²	0.360	0.361	0.243	0.243

Panel B: Interaction Between Investor Impressions and Information and Fund Issuance Performance

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.127*** (0.037)		-0.144*** (0.038)	
Impression Score × High Info		-0.307*** (0.096)		-0.277** (0.110)
Impression Score	0.174*** (0.048)	0.251*** (0.051)	0.121** (0.054)	0.191*** (0.055)
Info	-0.077 (0.058)		-0.069 (0.067)	
High Info		-0.212 (0.133)		-0.129 (0.155)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	783	783	1,422	1,422
Adjusted R ²	0.365	0.366	0.248	0.245

Table 5. Investor Impressions, Information, and Fund Issuance Performance: By Information Type

This table examines whether the attenuation of the association between favorable investor impressions and fund issuance performance differs between complex and non-complex information. Our sample period is from July 1, 2020 to May 31, 2024. We distinguish between complex information—topics requiring interpretation by professionals like fund managers and analysts—and non-complex information, which can be readily understood by retail investors. Columns (1) to (3) report the results using the number of subscriptions as the dependent variable. Columns (4) to (6) report the results using the total subscription amount as the dependent variable. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>LnSubscriptions</i>			<i>LnAmount</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
Impression Score × Info Complex	-0.147*** (0.040)		-0.187*** (0.047)	-0.166*** (0.044)		-0.210*** (0.049)
Impression Score × Info NonComplex		0.064 (0.053)	-0.062 (0.060)		0.078 (0.059)	-0.067 (0.067)
Impression Score	0.165*** (0.047)	0.178*** (0.049)	0.165*** (0.048)	0.120** (0.053)	0.133** (0.055)	0.118** (0.054)
Info Complex	-0.178*** (0.065)		-0.134* (0.078)	-0.158** (0.062)		-0.118 (0.083)
Info NonComplex		0.147** (0.057)	0.068 (0.070)		0.131** (0.059)	0.062 (0.082)
Controls	YES	YES	YES	YES	YES	YES
Style FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES	YES	YES
Observations	783	783	783	1,422	1,422	1,422
Adjusted R ²	0.373	0.365	0.373	0.252	0.246	0.252

Table 6. Investor Impressions, Information, and Fund Issuance Performance: Fund Manager Presence in Livestreams

This table examines whether the attenuation of the association between favorable investor impressions and fund issuance performance varies with fund manager presence in a livestream. Our sample period is from July 1, 2020 to May 31, 2024. Panel A reports two-sample t-tests and Wilcoxon tests comparing investor impressions, the amount and complexity of information content in a livestream, livestream, fund, fund manager, and market characteristics between livestreams with and without a fund manager present. Panel B reports regression results on the role of fund manager participation during the fund launch livestream. The dependent variable in column (1) is the number of subscriptions, and the dependent variable in column (2) is the total subscription amount. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*, and are omitted for brevity. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Comparison Between Livestreams With and Without A Fund Manager Present (Unstandardized)						
	<i>Manager Present = 1</i>		<i>Manager Present = 0</i>		<i>Test of Difference</i>	
	<i>Mean</i>	<i>Median</i>	<i>Mean</i>	<i>Median</i>	<i>t-test</i>	<i>Wilcoxon test</i>
	(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
Impression Score	0.016	-0.057	-0.043	-0.097	0.059	0.040
Info	0.698	0.708	0.670	0.678	0.028***	0.030***
High Info	0.246	0.000	0.169	0.000	0.077**	0.000**
Info Complex	0.494	0.499	0.415	0.404	0.079***	0.095***
Verbal Positive	0.817	0.827	0.750	0.774	0.067***	0.053***
Image Clarity	0.696	0.561	0.515	0.402	0.181***	0.159***
Beauty Score	2.908	2.920	2.849	2.821	0.058**	0.099**
Number of Presenters	2.191	2.000	1.441	1.000	0.750***	1.000***
Share of Female Presenters	0.425	0.500	0.639	1.000	-0.214***	-0.500***
Before Subscription	0.309	0.000	0.243	0.000	0.067**	0.000**
Gift	0.087	0.000	0.162	0.000	-0.075***	0.000***
Number of Viewers	48,114	40,835	43,751	35,557	4,363*	5,278***
Length of Livestream	66.52	60.00	61.85	60.00	4.679**	0.000***
Livestream to Close	13.47	13.00	14.14	14.00	-0.675	-1.000
Active Fund	0.772	1.000	0.875	1.000	-0.103***	0.000
Fund Fees	1.235	1.400	1.327	1.750	-0.092**	-0.350*
Length of Subscription Period	20.11	13.00	20.95	17.00	-0.837	-4.000***
State-owned Fund Family	0.828	1.000	0.721	1.000	0.107***	0.000
Large Fund Family	0.385	0.000	0.217	0.000	0.168***	0.000***
Female Manager	0.228	0.000	0.257	0.000	-0.029	0.000
Rookie Manager	0.070	0.000	0.066	0.000	0.003	0.000
Highest Degree	2.070	2.000	2.075	2.000	-0.005	0.000
Top2 University	0.164	0.000	0.162	0.000	0.003	0.000
Manager Experience	2.518	2.708	2.534	2.693	-0.016	0.015
Manager Past Performance	0.086	0.0450	0.066	0.0390	0.020*	0.006
Market Return	0.030	0.0500	0.021	0.0440	0.009	0.006
Market Volatility	0.170	0.155	0.184	0.180	-0.014***	-0.025**
Number of Fund Launches	2.856	2.890	3.047	3.296	-0.190**	-0.406**

Panel B: Interaction Between Investor Impressions and Fund Manager Presence and Fund Issuance Performance

	<i>LnSubscriptions</i>	<i>LnAmount</i>
	(1)	(2)
Impression Score $\times$ Manager Present	-0.205** (0.085)	-0.285*** (0.107)
Impression Score	0.309*** (0.075)	0.309*** (0.091)
Manager Present	-0.402** (0.159)	-0.408** (0.166)
Controls	YES	YES
Style FE	YES	YES
Year FE	YES	YES
Time-of-Day FE	YES	YES
Observations	783	1,422
Adjusted R ²	0.370	0.252

Table 7. Investor Impressions, Information, and Fund Issuance Performance: By Fund Type

This table examines the attenuation of the association between favorable investor impressions and fund issuance performance separately for active and passive funds. Our sample period is from July 1, 2020 to May 31, 2024. The dependent variable in columns (1)-(2) is the number of subscriptions, and the dependent variable in columns (3)-(4) is the total subscription amount. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*, and are omitted for brevity. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	Active (1)	Passive (2)	Active (3)	Passive (4)
Impression Score × High Info	-0.228** (0.114)	-0.275 (0.224)	-0.237* (0.131)	-0.237 (0.337)
Impression Score	0.209*** (0.064)	0.242 (0.153)	0.147*** (0.055)	0.300 (0.235)
High Info	-0.209 (0.160)	-0.141 (0.250)	-0.188 (0.164)	-0.079 (0.251)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	628	152	1,188	232
Adjusted R-squared	0.415	0.250	0.240	0.444

Table 8. Capacity Constraints on System 2 Processing

This table examines whether the attenuation of the association between favorable investor impressions and fund issuance performance varies with capacity constraints on System 2 analytical processing. Panel A splits the sample into high- and low-distraction groups based on the number of concurrent fund livestreams on the Tiantian platform. Panel B splits the sample into high- and low-distraction groups based on extreme market returns, defined as returns in the top or bottom decile of the past three-month market-return distribution. Panel C splits the sample into long- and short-livestream groups based on livestream duration, which serves as a proxy for cognitive overload. In each panel, we replicate the analysis in Panel B of Table 4. The dependent variable in columns (1)-(2) is the number of subscriptions, and the dependent variable in columns (3)-(4) is the total subscription amount. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Distraction Induced by Concurrent Livestreams

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	High Distraction	Low Distraction	High Distraction	Low Distraction
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.020 (0.055)	-0.158*** (0.059)	-0.056 (0.060)	-0.156*** (0.058)
Impression Score	0.220*** (0.077)	0.116 (0.073)	0.135 (0.086)	0.099 (0.081)
Info	-0.116 (0.098)	-0.016 (0.079)	-0.127 (0.087)	-0.008 (0.085)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	345	433	620	800
Adjusted R-squared	0.343	0.413	0.264	0.279

Panel B: Distraction Induced by Extreme Market Returns

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	High Distraction	Low Distraction	High Distraction	Low Distraction
	(1)	(2)	(3)	(4)
Impression Score × Info	0.108 (0.121)	-0.111*** (0.042)	0.126 (0.129)	-0.140*** (0.049)
Impression Score	0.107 (0.118)	0.167*** (0.052)	0.212* (0.125)	0.079 (0.055)
Info	0.064 (0.168)	-0.062 (0.060)	0.125 (0.180)	-0.066 (0.070)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	120	655	220	1,197
Adjusted R-squared	0.553	0.349	0.451	0.258

Panel C: Cognitive Overload

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	Long Livestream (1)	Short Livestream (2)	Long Livestream (3)	Short Livestream (4)
Impression Score $\times$ Info	-0.118 (0.078)	-0.142*** (0.049)	-0.060 (0.091)	-0.177*** (0.048)
Impression Score	-0.026 (0.092)	0.220*** (0.057)	0.056 (0.100)	0.145** (0.062)
Info	-0.077 (0.131)	-0.140** (0.063)	-0.121 (0.188)	-0.112* (0.064)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	181	594	339	1,080
Adjusted R-squared	0.170	0.408	0.243	0.272

Online Appendix for “The Two-System View of Cognition and Investor Choice: Evidence from Mutual Fund Launch Livestreams”

Online Appendix A. Variable Definitions

Variable	Definition and Construction
<i>Issuance Performance</i>	
LnSubscriptions	Natural logarithm of one plus the number of accounts subscribing to a fund issuance.
LnAmount	Natural logarithm of one plus the total subscription amount to a fund issuance.
<i>Livestream Characteristics</i>	
Vocal Positive	Probability that the vocal emotion of presenters in a livestream is happiness or surprise, as identified by <i>Speech Emotion Recognition</i> . The unit of analysis is a speaker log. The algorithm assigns probabilities of anger, disgust, fear, happiness, neutrality, sadness, and surprise to each speaker log. We average these probabilities across all speaker logs in a livestream.
Visual Positive	Probability that the facial emotion of presenters in a livestream is happiness or surprise, as identified by DeepFace’s emotion recognition Application Programming Interface (API). The algorithm assigns probabilities of anger, disgust, fear, happiness, neutrality, sadness, and surprise to each presenter at one frame/sec. We average these probabilities across presenters in a frame, and then average across frames in a livestream.
Body Motion	Movement magnitude of presenters in a livestream. We use skeletal key points identified by YOLO11 to construct each presenter’s skeleton and apply the optical flow method to calculate displacement magnitudes at one frame per second. We first average the measure across presenters within each frame and then across frames in a livestream.
Impression Score	First principal component of <i>Vocal Positive</i> , <i>Visual Positive</i> , and <i>Body Motion</i> .
Info	Share of information content in a livestream relative to the Tiantian Fund Overview. See detailed variable construction in Section 4.3.
High Info	Indicator variable that takes a value of one if the value of <i>Info</i> is in the top quintile, and zero otherwise.
Info Complex	Share of information content in a livestream related to the complex topics, including macroeconomic policy analysis, industry analysis, stock-picking strategy, quantitative modelling, investment philosophy, market trend analysis, investment strategy, and risk-return characteristics, relative to the Tiantian Fund Overview.
Info NonComplex	Share of information in a livestream related to topics outside complex topics, including product features and trends, fund manager’s professional background, investor education, index characteristics, investment objectives, investment scope, and dividend policy, relative to the Tiantian Fund Overview.
Verbal Positive	Probability that the sentiment of a livestream is positive, as identified by StructBERT. The unit of analysis is a speaker log. The algorithm assigns a probability of positive sentiment to each speaker log. We compute the text-length-weighted average across all speaker logs in a livestream.
Image Clarity	Clarity score of a livestream, as measured by <i>OpenCV</i> . The algorithm computes the measure at one frame/sec. We average the measure across all frames in a livestream.
Beauty Score	Beauty score assigned by DeepFace’s facial analysis API. The algorithm assigns each presenter a score between 0 and 5, with higher values indicating greater attractiveness, at one frame/sec. We first average across presenters within each frame and then average across all frames in a livestream.
Number of Presenters	Number of presenters in a livestream.
Share of Female Presenters	Share of female presenters in a livestream.

Manager Present	Indicator variable that takes a value of one if at least one fund manager is present during a livestream, and zero otherwise.
Before Subscription	Indicator variable that takes a value of one if a fund's (first) launch livestream takes place before the start of its subscription period, and zero otherwise.
Gift	Indicator variable that takes a value of one if a livestream mentions any of the following: coupons, points, gifts, presents, prizes, red envelopes, lotteries, or gift packs, and zero otherwise.
Number of Viewers	Number of viewers of a livestream.
LnViewers	Natural logarithm of one plus the number of viewers of a livestream.
Length of Livestream	Number of minutes that a livestream lasts.
LnLength	Natural logarithm of one plus the number of minutes that a livestream lasts.
Livestream to Close	Number of days from a fund's (first) launch livestream to the end of its subscription period.
LnLivetoClose	Natural logarithm of one plus the number of days from a fund's (first) launch livestream to the end of its subscription period.
Fog Index	A Chinese-adapted readability index, defined as the arithmetic mean of (i) the average number of words per clause and (ii) the proportion of adverbs and conjunctions in each sentence.
<i>Fund Characteristics</i>	
Livestream Indicator	Indicator variable that takes a value of one if a fund has at least one launch livestream before or during its subscription period, and zero otherwise.
Number of Livestreams	Number of launch livestreams before or during a fund's subscription period.
Active Fund	Indicator variable that takes a value of one if a fund is actively managed by a manager or a team of managers, and zero otherwise. Active funds include non-index funds and enhanced-index funds.
Fund Fees	Sum of the annual fund management and custodian fees, expressed in percentage points (there is no load when purchasing new funds on the Tiantian Fund platform).
Length of Subscription Period	Number of days between the start and end dates of a fund's subscription period.
State-owned Fund Family	Indicator variable that takes a value of one if a fund is from a fund family controlled by the state, and zero otherwise.
Large Fund Family	Indicator variable that takes a value of one if a fund is from one of the top 10 fund families based on AUM in a year, and zero otherwise.
<i>Fund Manager Characteristics</i>	
Female Manager	Indicator variable that takes a value of one if at least one fund manager is female, and zero otherwise.
Rookie Manager	Indicator variable that takes a value of one if all fund managers are rookies (with no prior experience as a fund manager), and zero otherwise.
Highest Degree	The highest academic degree obtained by a fund manager: 3 for a Ph.D., 2 for a master's degree, and 1 for a bachelor's degree or lower. For funds with multiple managers, we take the average across managers.
Top2 University	Indicator variable that takes a value of one if at least one fund manager has a degree from Peking University or Tsinghua University, and zero otherwise.
Manager Experience	The natural logarithm of one plus the average years of fund management experience across managers of a fund.
Manager Past Performance	Average annualized net asset growth rate of funds previously managed by a fund manager. For a fund manager, we first compute the annualized net asset growth rate for a fund under her management, and then take the average across funds under her management. For funds with multiple managers, we take the average across managers.
<i>Market Characteristics</i>	
Market Return	Cumulative daily market return over the three-month window from month $t-3$ to month $t-1$, where month t is the month of a livestream.
Market Volatility	Volatility of daily market returns over the three-month window from month $t-3$ to month $t-1$, where month t is the month of a livestream.

Number of Fund Launches	Natural logarithm of one plus the number of new fund launches in the same style and month t as the focal livestream.
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Figure IA1. A Screenshot of the Fund Livestream Interface on the Tiantian Fund Platform

This figure presents a screenshot of the fund livestream interface and additional details from the Tiantian Fund website. It is a recent example used solely for illustrative purposes.

Livestream title

Date and time

**Fund name
& fund code**

**Participant name
& job title**

Fund family

**Brief
introduction**

**Participant name
& job title**

富国A500ETF联接今日结募!

时间: 2024.11.07 14:20 - 15:05

本期主题: 富国A500ETF联接今日结募!

东方财富

富国中证A500ETF联接基金

富国A500ETF联接基金

富国基金管理有限公司

富国基金管理有限公司

成立于1999年, 中国“老十家”全牌照基金公司

介绍

简介: 富国A500ETF联接今日结募!

活动嘉宾

苏华清 | 伊伊

富国中证A500ETF联接基金经理

富国中证A500ETF联接基金经理

Here is the translation of text in the screenshot:

Livestream title:

The Fullgoal A500 ETF connect fund is going to end its subscription period today!

Date and time:

November 7, 2024, 14:20 – 15:05

Fund name and fund code:

- Fund name: Fullgoal A500 ETF Connect
- Fund code: 022463 (Class A), 022464 (Class C)
- Risk level: R3, medium risk
- Suitable for investor types: Balanced, growth or aggressive investors.

Participant name & job title:

Huaqing Su (fund manager) || Yi Yi (host)

Fund family:

- Fullgoal Fund Management Co. Ltd.
- Established in 1999, one of China’s “Old Ten” fund companies with a full suite of licenses.

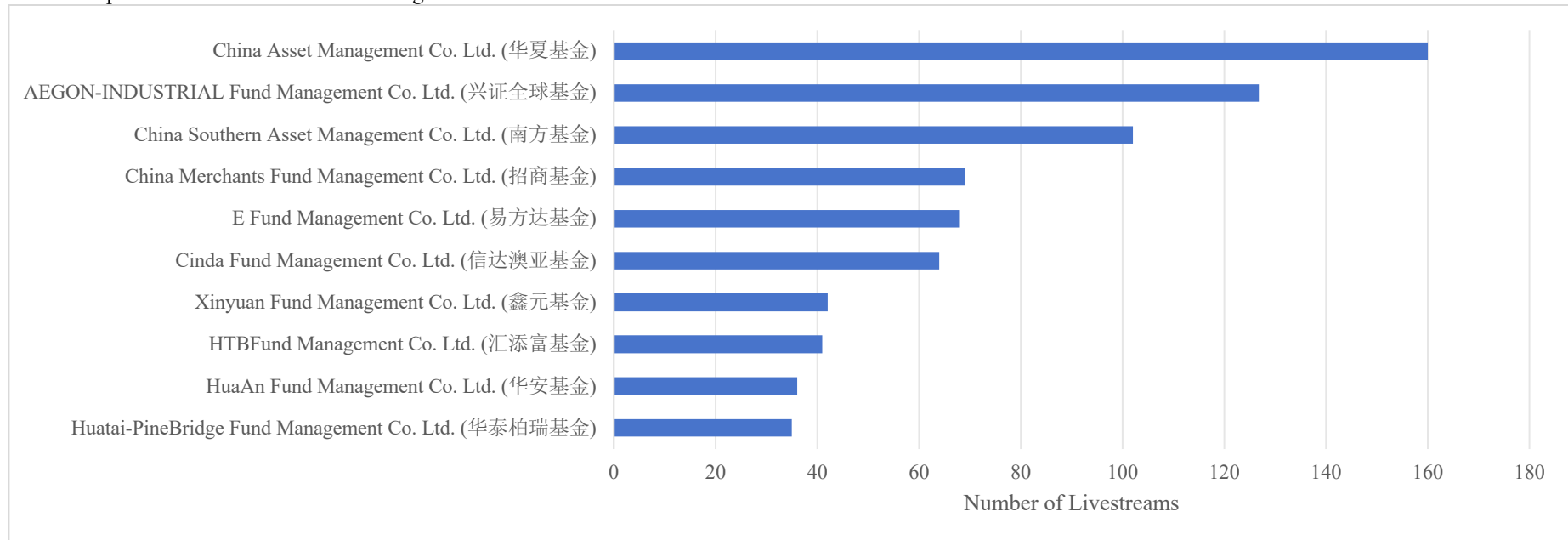
Brief introduction:

The Fullgoal A500 ETF connect fund is going to end its subscription period today!

Figure IA2. Fund Livestream Overview: Top Fund Families and Start Time Distribution

Panel A lists the top ten fund families that hosted the largest number of fund launch livestreams over the period from July 1, 2020—when the first mutual fund livestream on the Tiantian Fund platform took place—to May 31, 2024. The blue bars indicate the number of livestreams for each fund family. The x-axis measures the number of livestreams. Panel B reports the distribution of livestream start times.

Panel A: Top Ten Fund Families With the Largest Number of Fund Launch Livestreams



Panel B: Distribution of Livestream Start Times

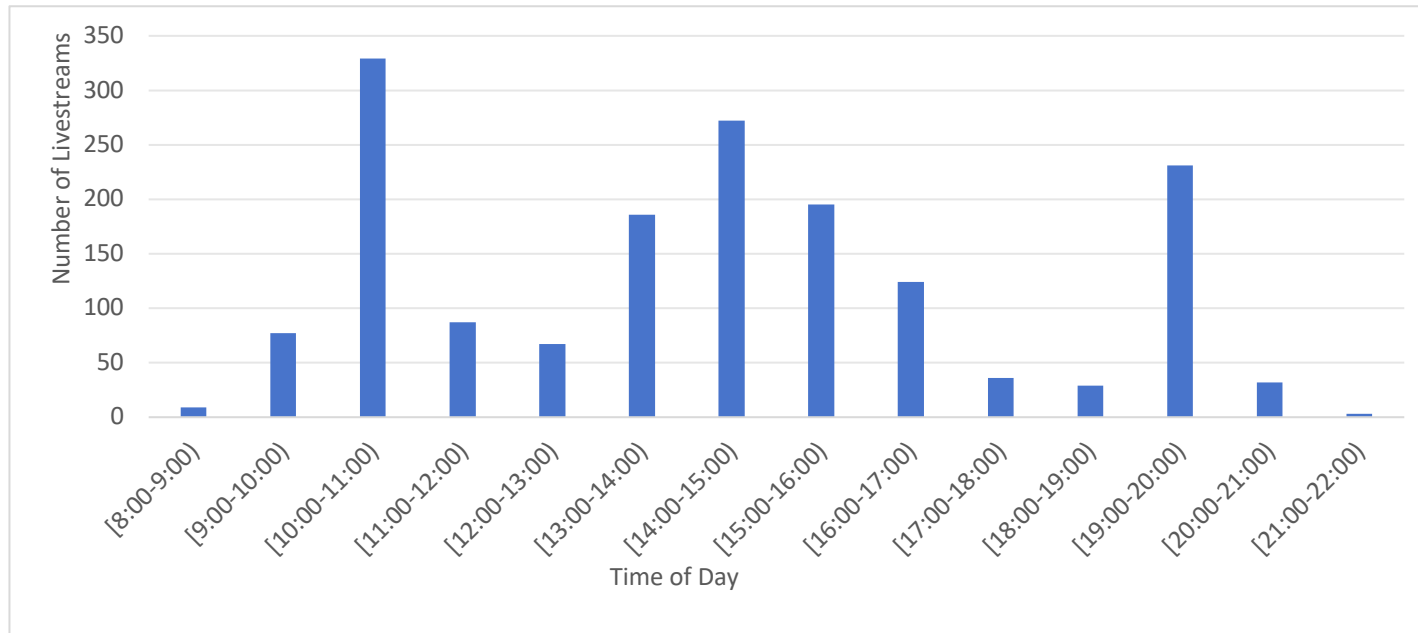
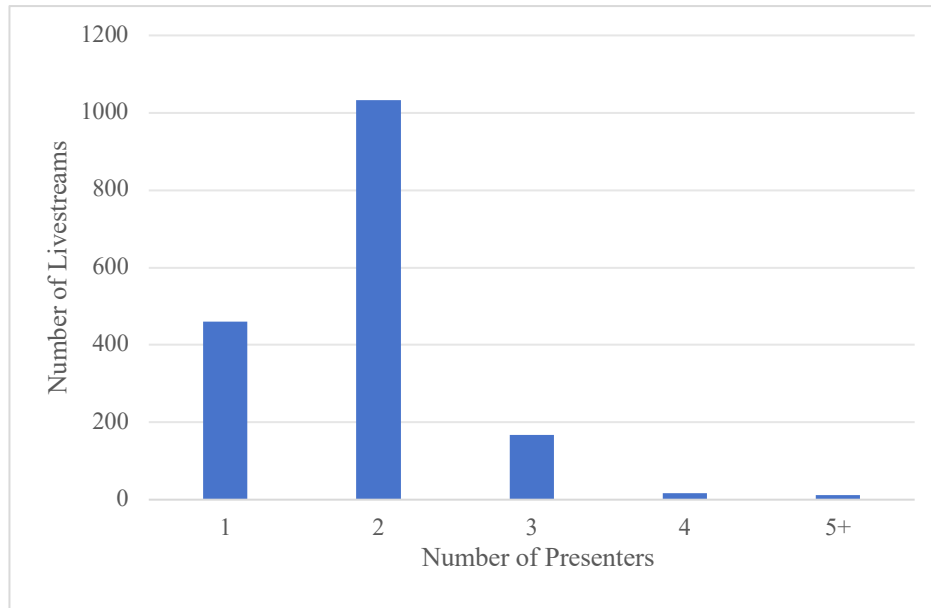


Figure IA3. Fund Livestream Presenters

Panel A reports the distribution of the number of presenters in a fund launch livestream. Panel B reports the proportion of fund launch livestreams that feature at least one fund manager.

Panel A: Number of Presenters



Panel B: Fund Manager Participation

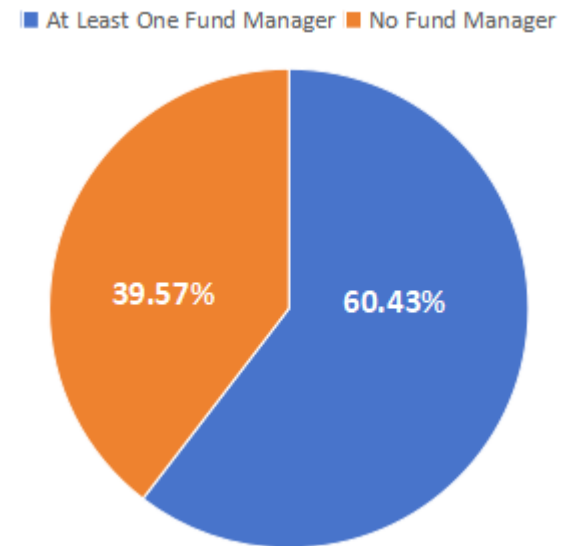
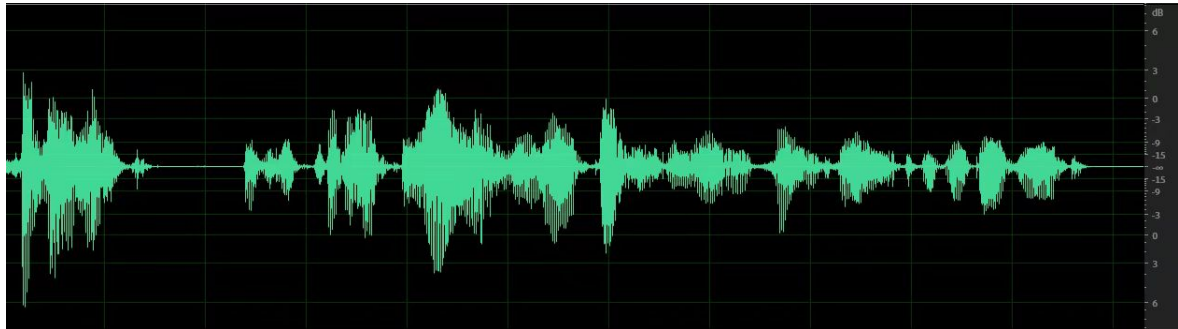


Figure IA4. High- and Low-Pitched Vocal Features

Panel A presents a visualized example of high-pitched vocal features. Panel B presents a visualized example of low-pitched vocal features.

Panel A: Visualized Example of High-Pitched Audio Clip



Panel B: Visualized Example of Low-Pitched Audio Clip



Figure IA5. High- and Low-Positivity Facial Features

Panel A presents an example of high-positivity facial features. Panel B presents an example of low-positivity facial features.

Panel A: Example of High-Positivity Facial Features



Panel B: Example of Low-Positivity Facial Features



Figure IA6. High and Low Body Motion Features

Panel A presents an example of high-body motion features. Panel B presents an example of low-body motion features.

Panel A: Example of High Displacement Magnitude



Panel B: Example of Low Displacement Magnitude



Figure IA7. High- and Low-Positivity Verbal Features

Panel A presents an example of high-positivity verbal features. Panel B presents an example of low-positivity verbal features.

Panel A: Example of High-Positivity Transcript

现在是一个权益布局的好时间，因为整个国内经济趋稳，复苏政策持续积极发力，全年经济的预计增长都非常的乐观。当前 A 股的整体盈利增速和估值都是具有比较强的吸引力的，股票资产的配置价值也在不断凸显。目前我们重点关注大消费、地产和基建相关的产业链的投资机遇，长期也比较看好高端制造和医药板块。

Now is a good time to increase exposure to equities, as the domestic economy is stabilizing, supportive recovery policies continue to take effect, and the outlook for full-year economic growth remains very optimistic. At present, both earnings growth and valuations in the A-share market are relatively attractive, making the case for allocating to equities increasingly compelling. We are focusing on investment opportunities in the consumer, real estate, and infrastructure-related sectors, while remaining optimistic over the longer term about high-end manufacturing and healthcare.

Panel B: Example of Low-Positivity Transcript

现在我们看到的央企的估值，确实是一个长期低估的一个状态。其实如果各位投资者朋友啊去关注一下相关的这个研报也好，或者是银华的公众号也好，会有关材料，大家可以去参考，里面会有一些阐述。其实央企在过去很长一段时间里头，它的估值都处于低估的一个状态。央企的估值可能长期被低估，它可能低于地方国企。

The valuations of central state-owned enterprises (SOEs) that we see today have indeed remained depressed for a long time. Investors who are interested can refer to relevant research reports or materials published on Yinhua Fund's official WeChat account, where this issue is discussed in more detail. In fact, central SOEs have traded at relatively low valuations for an extended period. Their valuations may have been persistently underestimated and may even be lower than those of local state-owned enterprises.

Figure IA8. High and Low Image Clarity

Panel A presents an example of high image clarity. Panel B presents an example of low image clarity.

Panel A: High Image Clarity



Panel B: Low Image Clarity



Figure IA9. Complex and Non-complex Topics

Panel A presents an example of complex topics in livestreams. Panel B presents an example of non-complex topics in livestreams.

Panel A: Example of Complex Topics (Industry Analysis)

新能源板块，我主要看好的是创新和应用两个方面。在创新方面，比如锂电池领域，我关注四六八零电池的进展，今年可能是其发展的拐点。这是特斯拉主导的电池技术路线。去年，其产能规划已达到约 4 GWh，规模已经不小。今年产能是否有望向 30 GWh 级别迈进，明年是否可能进一步迈向 100 GWh，这是值得期待的。3 月 1 日，马斯克在得州工厂的投资日活动上应该会有发言。此前有新闻报道提到特斯拉的“第三篇章”，大家都在猜测其内容。我个人的大胆预测是：可能会围绕四六八零电池加储能展开，并有可能推出十几万元的低价位车型。我认为这会产生“乘法效应”——一旦电池成本降低，储能应用也将得到更大发展。

Panel B: Example of Non-complex Topics (Index Characteristics)

中小风格的指数，我们目前有几套描述市场风格的指数体系。第一套是宽基指数体系。比如上证 50，代表上海证券交易所规模最大的 50 只股票；接着是沪深 300，涵盖沪深两市规模最大的 300 只股票。这些通常被定义为大盘风格指数。在宽基指数中，再往下走就是中证 500 和中证 1000。中证 500 涵盖的是除去沪深 300 成分股之后，规模排名前 500 的股票；而中证 1000 则进一步覆盖除去沪深 300 和中证 500 之后，接下来规模最大的 1000 只股票。

In the new-energy sector, I am primarily optimistic about two areas: innovation and application. On the innovation front, in the lithium-battery segment, I am closely watching the progress of 4680 batteries, as this year could mark an inflection point in their development. This battery technology path is led by Tesla. Last year, planned production capacity had already reached approximately 4 GWh, which is a meaningful scale. The key questions are whether capacity can move toward 30 GWh this year and potentially reach 100 GWh next year. On March 1, Musk is expected to speak at Tesla's Investor Day at its Texas factory. Previous news reports have mentioned Tesla's "Master Plan Part 3," and there has been considerable speculation about its contents. My bold prediction is that it could focus on 4680 batteries and energy storage, possibly accompanied by the launch of a lower-priced vehicle in the RMB 100,000-plus range. I believe this could generate a "multiplicative effect": once battery costs decline, energy-storage applications could also expand substantially.

For small- and mid-cap style indices, we currently have several index systems that capture different market styles. The first is the broad-based index system. For example, the SSE 50 represents the 50 largest stocks listed on the Shanghai Stock Exchange, while the CSI 300 covers the 300 largest stocks listed on the Shanghai and Shenzhen stock exchanges. These are generally classified as large-cap style indices. Further down the broad-based index spectrum are the CSI 500 and CSI 1000. The CSI 500 includes the 500 largest stocks after excluding constituents of the CSI 300, while the CSI 1000 covers the next 1,000 largest stocks after excluding constituents of both the CSI 300 and CSI 500.

Figure IA10. Fund Manager Participation in Livestreaming Over Time

This figure reports the proportion of fund launch livestreams that feature at least one fund manager over the sample period from July 1, 2020 to May 31, 2024.

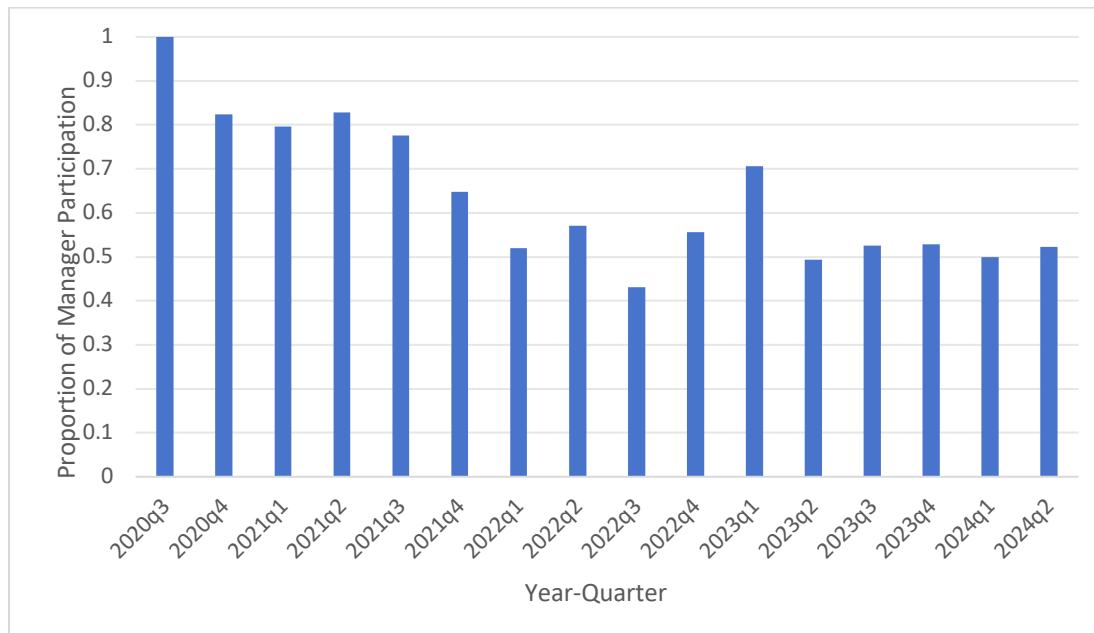


Table IA1. Sample Formation

This table lists the steps taken to create the livestream sample for newly launched funds in China, along with the corresponding fund issuance sample. Our sample period is from July 1, 2020 to May 31, 2024.

		<i>Remaining</i>
Possible livestreams featuring new funds over the period from July 1, 2020 to May 31, 2024.		2,786
We use keywords including “new fund,” “launch,” “set sail,” “on sale,” “get on board,” “new issuance,” and “first launch” in the introduction of a fund livestream to filter livestreams.		
Less: observations failing the following criteria:		
The livestream is verified to promote a new fund.	– 117	2,669
The livestream takes place before or during a fund’s subscription period.	– 981	1,688
The livestream sample		1,688
Keep the first livestream of each fund.	– 835	853
Split a fund into different share classes (A and C).	+ 671	1,524
Drop observations with missing data on livestream, fund, or fund manager characteristics.	– 102	1,422
The fund issuance sample (with corresponding livestreams)		1,422 (789)

Table IA2. Determinants of Funds Having a Launch Livestream

This table examines the determinants of whether a fund hosts a launch livestream. Our sample period is from July 1, 2020 to May 31, 2024. Panel A conducts two-sample t-tests and Wilcoxon tests comparing funds with a launch livestream (Livestream = 1) to those without (Livestream = 0). In this comparison, we do not require livestreamed funds to have full video features. Panel B reports linear probability regression estimates examining the association between fund, fund manager, and market characteristics and the likelihood of hosting a launch livestream. Variable definitions are provided in Online Appendix A. Heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Comparing Funds With a Launch Livestream to Those Without						
	<i>Livestream = 1</i>		<i>Livestream = 0</i>		<i>Test of Difference</i>	
	<i>Mean</i>	<i>Median</i>	<i>Mean</i>	<i>Median</i>	<i>t-test</i>	<i>Wilcoxon test</i>
	(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
Number of Subscriptions	25,688.52	7,597	12,360.87	2,263	13,327.65***	5,334***
LnSubscriptions	9.008	8.936	7.405	7.725	1.604***	1.211***
Amount of Subscriptions	839.50	217.70	707.92	191.46	131.57***	26.23***
LnAmount	18.99	19.21	18.40	19.07	0.585***	0.140***
Active Fund	0.840	1.000	0.801	1.000	0.039***	0.000***
Fund Fees	1.311	1.700	0.930	0.750	0.380***	0.950***
State-owned Fund Family	0.781	1.000	0.703	1.000	0.077***	0.000***
Large Fund Family	0.323	0.000	0.299	0.000	0.024*	0.000*
Female Manager	0.235	0.000	0.269	0.000	-0.034***	0.000***
Rookie Manager	0.044	0.000	0.062	0.000	-0.018***	-0.000***
Highest Degree	2.080	2.000	2.072	2.000	0.008	0.000
Top2 University	0.176	0.000	0.138	0.000	0.038***	0.000***
Manager Experience	2.539	2.701	2.560	2.688	-0.021	0.013*
Manager Past Performance	0.084	0.044	0.073	0.025	0.012	0.019***
Market Return	0.026	0.044	0.026	0.040	0.000	0.004
Market Volatility	0.175	0.158	0.179	0.155	-0.004**	0.003
Number of Fund Launches	2.963	3.045	2.699	2.708	0.264***	0.337***

Panel B: Explaining Whether a Fund Hosts a Launch Livestream			
	<i>Livestream Indicator</i>		
	(1)	(2)	(3)
Active Fund	-0.073*** (0.017)	-0.068*** (0.018)	-0.039 (0.024)
Fund Fees	0.165*** (0.014)	0.168*** (0.014)	0.122*** (0.024)
State-owned Fund Family	0.053** (0.026)	0.051* (0.026)	0.050* (0.026)
Large Fund Family	0.016 (0.035)	0.017 (0.034)	0.015 (0.034)
Female Manager	0.012 (0.012)	0.010 (0.012)	0.010 (0.013)
Rookie Manager	0.050 (0.058)	0.056 (0.055)	0.009 (0.051)
Highest Degree	-0.007 (0.015)	-0.008 (0.015)	-0.005 (0.015)
Top2 University	0.021	0.026	0.024

	(0.017)	(0.017)	(0.018)
Manager Experience	-0.009	-0.003	-0.004
	(0.018)	(0.018)	(0.018)
Manager Past Performance	-0.010**	0.002	0.002
	(0.005)	(0.007)	(0.007)
Market Return	-0.131**	-0.004	0.023
	(0.053)	(0.055)	(0.054)
Market Volatility	-0.016	0.022	0.075
	(0.083)	(0.092)	(0.083)
Number of Fund Launches	0.022***	0.016***	0.015**
	(0.005)	(0.005)	(0.007)
Style FE	NO	NO	YES
Year FE	NO	YES	YES
Observations	5,860	5,860	5,860
Adjusted R ²	0.071	0.091	0.106

Table IA3. Implementation Details

We provide more details on the steps to perform video and textual analysis used in our paper.

Panel A: Code for video processing and impression/information measure construction

```
def perform_speaker_diarization(output_dir, diarization_model_path):
    """Perform speaker diarization and save results to CSV."""
    for filename in os.listdir(output_dir):
        if filename.endswith(".wav"):
            input_wav = os.path.join(output_dir, filename)
            try:
                sd_pipeline = pipeline(
                    # ...
                )
                result = sd_pipeline(input_wav) # "Use speaker diarization model"
                # Save results to a CSV file at the output_csv path

            def extract_mood(input_file):
                """Extract mood information from audio."""
                res = model.generate(input_file, output_dir=xxx, granularity=xxx, extract_embedding=xxx)
                mood_json = res[0]
                mood_pairs = {label: score for label, score in zip(mood_json['labels'], mood_json['scores'])}
                mood_str = ', '.join([f'{label}:{score}' for label, score in mood_pairs.items()])
                return mood_str

            def extract_text(input_file):
                """Use a speech recognition model to extract text content from audio."""
                result = asr_model.generate(input_file, batch_size=xxx)
                return result[0]['text'] if result else "null"

            def extract_text_meaning(text_content):
                """Extract semantic sentiment classification information from text."""
                meaning_res = semantic_cls(input=text_content)
                meaning_pairs = {label: score for label, score in zip(meaning_res['labels'],
                    meaning_res['scores'])}
                meaning_str = ', '.join([f'{label}:{score}' for label, score in meaning_pairs.items()])
                return meaning_str

            def calculate_image_clarity(self, image):
                """Calculate image clarity."""
                gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
                laplacian_var = cv2.Laplacian(gray, cv2.CV_64F).var()
                return laplacian_var

            def deepface_extract_faces(self, img_path):
```

```

        """Perform face detection."""
        return DeepFace.extract_faces(img_path=img_path, expand_percentage=xxx, detector_backend=xxx,
...)

def deepface_analyze(self, face_img_path):
    """Perform face analysis."""
    return DeepFace.analyze(img_path=face_img_path, actions=xxx, detector_backend=xxx, ...)

def calculate_displacement_and_angle_change(xxxxxx):
    # Open video file and extract frames
    # Convert frames to grayscale
    # Get video frame width and divide into regions based on input number of people
    # Used to store displacement of each region
    # Used to count frames for each region
    while True:
        # Skip frames that don't need processing
        if frame_count % frame_interval == 0:
            frame = cv2.resize(frame, frame_size)

if prev_gray is not None:
    # Convert current frame to grayscale
    curr_gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

    # Calculate optical flow
    flow = cv2.calcOpticalFlowFarneback(prev_gray, curr_gray, None, ..... )

    # Decompose optical flow into x and y components
    flow_x = xxx
    flow_y = xxx

    # Calculate displacement magnitude of each pixel (i.e., vector norm)
    magnitude = cv2.cartToPolar(flow_x, flow_y)
    # Partition optical flow by regions and calculate displacement changes
    for i in range(num_zones):
        zone_start = xxx
        zone_end = xxx

        # Extract optical flow within the region
        zone_magnitude = magnitude[.....]

        # Calculate average displacement change for the region
        mean_displacement = np.mean(zone_magnitude)

```

```

        # Accumulate total displacement change for each region
        total_displacements[i] += mean_displacement
        num_frames_per_zone[i] += 1

# Update previous frame
prev_gray = curr_gray

# Calculate average displacement change for each region
avg_displacements = [total_displacements[i] / num_frames_per_zone[i] .....]

def process_deepface_analysis(self, audio_folder, csv_file):
    """Process DeepFace analysis results within a single audio folder, generate statistics, and
    save."""
    audio_folder_path = os.path.join(self.output_root_dir, audio_folder)
    csv_file_path = os.path.join(audio_folder_path, audio_folder + '_deepface_analysis_results1.csv')

    if not os.path.exists(csv_file_path):
        print(f"CSV file not found: {csv_file_path}")
        return

    # Read the CSV file containing DeepFace analysis results
    df = pd.read_csv(csv_file_path)

    # Generate speaker IDs in string format
    df['Speaker_ID'] = df['Face Image'].apply(lambda x: f"{float(str(x).split('_')[-
1].split('.')[0]):.1f}")

    # Count the total number of emotions for each speaker ID
    emotion_counts = df.groupby('Speaker_ID')['Emotion'].value_counts().unstack(fill_value=0)

    # Format emotion counts into a dictionary and store in the 'emotion' column
    result['Emotion Counts'] = result['Speaker_ID'].apply(lambda speaker_id: {
        emotion: emotion_counts.loc[speaker_id].get(emotion, 0)
        for emotion in emotion_counts.columns
    })

    # Convert dictionary columns to string representation
    result['Emotion Counts'] = result['Emotion Counts'].apply(lambda x: ',
'.join([f"{emotion}:{count}" for emotion, count in x.items()]))

```

Panel B: Code for text segmentation

```

def auto_semantic_split(text, threshold=xxx):
    sentences = split_sentences(text)
    if len(sentences) <= 1:

```

```

        return [text]

    embeddings = get_embeddings(sentences) # Normalize sentence vectors using a GTE model
    boundaries = [0]

    # Calculate similarity and compare with the threshold; segments that meet the criteria are grouped
    together

```

Panel C: Prompt for topic classification

```

def chat(model, content):
    messages = [{"role": "system", "content": "
As an expert in mutual funds and topic analysis, please identify in Chinese the topics of each segment
of the text:
Investment Objectives, Investment Philosophy, Investment Scope, Investment Strategy, Dividend Policy,
Risk and Return Characteristics.
If a segment does not cover any of the six topics above, please classify it into one of the following
topics:
Market Trend Analysis, Macroeconomic Policy Analysis, Industry Analysis, Product Features and Trends,
Fund Manager's Professional Background, Investor Education, Index Characteristics, Stock-picking
Strategy, Quantitative Modelling.
If the content is non-substantive and/or only serves to fill gaps between substantive discussions,
categorize it as "Others."
Only output all relevant topics as mentioned above for each segment. Do not repeat topics. Do not
include the reasoning process."},
        {"role": "user", "content": content}]
    res = model.chat(
        messages,
        generate_config={
            "temperature": 0
        }
    )
    result = res['choices'][0]['message']['content']
    result = re.sub(r"<think>.*?</think>", "", result, flags=re.DOTALL)
    return result.strip()

```

Panel D: Code for similarity calculation and constructing information measures

```

def main():
    args = parse_args()
    categories = ['Investment Objectives', 'Investment Philosophy', 'Investment Scope', 'Investment
Strategy', 'Dividend Policy', 'Risk and Return Characteristics'] # Target content categories

    # Load model
    tokenizer = AutoTokenizer.from_pretrained(args.model_path)
    model = AutoModel.from_pretrained(args.model_path).to(device)
    model.eval()

```

```

# Traverse directories
...
if not os.path.exists(txt_path):
    print(f"[Warning Missing] File does not exist: {txt_path}")
    for cat in categories:
        result_row[cat + "_match"] = None
    result_dict[video_id] = result_row
    continue

try:
    df_txt = pd.read_csv(txt_path)

    # Concatenate matched paragraph content
    ...

for cat in categories:
    # Paragraph judgment
    ...

    # Original is empty or no data available
    ...

    # New paragraph is missing
    ...

    # Normal matching
    try:
        # Calculate similarity
        emb1 = get_embeddings(model, tokenizer, [ref_text], device)[0] # Normalize text vector
        emb2 = get_embeddings(model, tokenizer, [para_text], device)[0] # Normalize text
vector
        sim = abs(F.cosine_similarity(emb1.unsqueeze(0), emb2.unsqueeze(0)).item())

        # Threshold judgment and subsequent calculations
        ...
    except Exception as e:
        print(f"[Warning Matching Exception] {video_id} - {cat}: {e}")
        result_row[cat + "_match"] = None

    result_dict[video_id] = result_row
# Matching complete, results written to the target column
...

```

Panel E: Prompt for topic classification

[Role]

You are an expert in behavioral finance and investor cognition, proficient in Kahneman's dual-process theory of cognition and familiar with the behavioral patterns of retail investors in China's A-share market.

[Task Objective]

From the investment topics provided below, identify those that impose cognitive complexity on retail investors and can effectively activate System 2—the slow, analytical, deliberative, and rational system—and rank them in descending order of System 2 activation intensity.

[Definition of Retail Investors]

Retail investors are non-institutional individuals who invest with limited capital. They have relatively constrained access to information and professional expertise, and exhibit systematic cognitive biases (loss aversion, anchoring, confirmation bias, etc.).

[Criteria for System 2 Activation Intensity]

The more of the following features a topic satisfies, and the more deeply it satisfies them, the higher its System 2 activation intensity:

Counterintuitiveness: The core conclusion or logic conflicts markedly with retail investors' everyday intuition and common sense, requiring deliberate suppression of the System 1 intuitive answer to arrive at a correct understanding.

Long logical chains: Complete understanding requires three or more steps of causal inference or multivariate transmission analysis; the conclusion cannot be grasped intuitively at a glance.

Active computational demand: Requires deliberate mental operations such as probability estimation, compound-return projection, indicator decomposition, or cost-benefit calculation; judgment cannot be made by intuition alone.

Bias-mitigation requirement: Requires active suppression of common retail cognitive biases—loss aversion, anchoring, confirmation bias, representativeness bias, gambler's fallacy, etc.—to reach a rational judgment.

Tradeoff nature: No single definitive answer exists; decisions require weighing multiple constraints such as risk, return, liquidity, and time horizon.

[Output Requirements]

Begin with an overview: state how many of the total topics fall into the high versus low System 2 activation tiers.

Present two categories: "High System 2 Activation Topics" and "Low System 2 Activation Topics", each ranked internally in descending order of activation intensity.

After each topic, provide an 80-100 word justification grounded in dual-process theory, explicitly identifying the cognitive mechanism through which the topic activates System 2 and the core cognitive difficulty it poses for retail investors.

[Topics]

Macroeconomic policy analysis, Industry analysis, Stock-picking strategy, Quantitative modelling, Investment philosophy, Market trend analysis, Investment strategy, Risk-return characteristics, Investment objectives, Investment scope, Dividend policy, Product features and trends, Index characteristics, Investor education, Fund manager's professional background.

Concise Definitions of the 15 Topics (for reference)

Macroeconomic policy analysis: Analyzing the direction of adjustments in central bank monetary policy (interest rates, reserve requirement ratios) and fiscal policy (taxation, infrastructure spending), and tracing their transmission through credit channels to systemic market liquidity and corporate earnings expectations.

Industry analysis: Assessing the boom cycle, upstream-downstream supply-demand dynamics, and policy support for specific industries (e.g., new energy, baijiu, semiconductors), and evaluating their position in the industry life cycle and competitive landscape.

Stock-picking strategy: A systematic framework for screening and confirming the investment value of individual stocks, encompassing fundamental assessment, valuation judgment, earnings catalyst identification, and margin-of-safety estimation—addressing the decision basis of "what to buy" and "why to buy."

Quantitative modelling: Rule-based systems for programmatic trading or risk assessment constructed from historical statistical regularities, employing multi-factor scoring, momentum/reversal strategies, or machine learning methods, with emphasis on backtestability and discipline.

Investment philosophy: The core philosophical belief guiding overall investment behavior (e.g., value investing, growth investing, contrarian investing), defining the fundamental logical path and value orientation for earning excess returns.

Market trend analysis: A comprehensive judgment of the future directional movement of broad-market or sector indices, integrating price momentum, trading volume changes, capital flows, and sentiment indicators—focusing on answering "what phase the market is currently in."

Investment strategy: The specific tactical execution rules that operationalize investment philosophy, encompassing asset-class allocation proportions, sector rotation timing, dynamic position adjustment, and the operational discipline framework for position-building, take-profit, and stop-loss.

Risk-return characteristics: The risk profile of an investment portfolio characterized by quantitative metrics such as volatility (standard deviation), maximum drawdown, Sharpe ratio, and downside risk, matched against expected returns.

Investment objectives: The overall financial vision an asset management product aims to achieve (e.g., "outperform the performance benchmark," "pursue absolute returns"), typically expressed in

qualitative, general terms without operational detail.

Investment scope: The legally permissible asset classes (equity/bond/derivative proportion ranges) and geographic boundaries (A-shares / Hong Kong stocks / U.S. stocks) stipulated in the fund contract or legal documents.

Dividend policy: The specific rules governing profit distribution by funds or stocks, including distribution conditions, frequency, method (cash dividend or dividend reinvestment), and the accounting mechanics of ex-dividend and ex-rights treatment.

Product features and trends: The operational mechanics, subscription/redemption rules, management fee structure, latest holdings changes, and interim information disclosures of a specific asset management product (fund / wealth management product).

Index characteristics: The construction and calculation methodology, constituent inclusion/exclusion criteria, market-cap weighting scheme, and style exposure labels (large-cap/small-cap, value/growth) of a specific price index (e.g., CSI 300, STAR 50).

Investor education: Outreach content aimed at disseminating basic financial knowledge, exposing common cognitive biases (e.g., excessive trading, chasing gains while cutting losses), and promoting rational investment principles.

Fund manager's professional background: A biographical profile of the fund manager, including educational credentials, years of experience, historical performance track record across managed products, and investment style preferences (e.g., turnover rate, industry concentration).

Table IA4. Validating the Information Measure

This table examines the association between our information measure and livestream transcript readability. Our sample period is from July 1, 2020 to May 31, 2024. *Fog Index* is a Chinese-adapted readability measure, defined as the arithmetic mean of (i) the average number of words per clause and (ii) the proportion of adverbs and conjunctions in each sentence. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*, and are omitted for brevity. Variable definitions are provided in Online Appendix A. Heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>Fog Index</i>	
	(1)	(2)
Info Complex	5.205*** (0.871)	
Info NonComplex		-3.550*** (1.303)
Controls	YES	YES
Style FE	YES	YES
Year FE	YES	YES
Time-of-Day FE	YES	YES
Observations	1,422	1,422
Adjusted R ²	0.556	0.542

Table IA5. Correlation Matrix

This table reports Pearson correlations for the key variables in our analysis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) LnSubscriptions	1								
(2) LnAmount	0.768***	1							
(3) Impression Score	0.132***	0.066**	1						
(4) Vocal Positive	0.065*	0.034	0.705***	1					
(5) Visual Positive	0.186***	0.110***	0.670***	0.191***	1				
(6) Body Motion	-0.001	-0.021	0.585***	0.146***	0.106***	1			
(7) Info	-0.005	-0.069***	-0.067**	-0.115***	-0.030	0.020	1		
(8) Info Complex	-0.048	-0.080***	-0.044*	-0.081***	-0.016	0.008	0.637***	1	
(9) Info NonComplex	0.063*	0.039	-0.007	-0.005	-0.010	0.012	0.126***	-0.676***	1

Table IA6. Investor Impressions and Subsequent Fund Performance

This table examines the association between investors' impressions and subsequent fund performance. Our sample period is from July 1, 2020 to May 31, 2024. We measure cumulative fund returns over the next three months (*Return 3m*), six months (*Return 6m*), or one year (*Return 12m*) after a fund's lock-up period. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*, and are omitted for brevity. Variable definitions are provided in Online Appendix A. Heteroskedasticity-robust standard errors clustered at the fund family and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>Return 3m</i>	<i>Return 6m</i>	<i>Return 12m</i>
	(1)	(2)	(3)
Impression Score	-0.007** (0.003)	-0.005* (0.003)	0.000 (0.004)
Controls	YES	YES	YES
Style FE	YES	YES	YES
Year FE	YES	YES	YES
Time-of-Day FE	YES	YES	YES
Observations	1,416	1,367	1,240
Adjusted R ²	0.159	0.199	0.504

Table IA7. Investor Impressions, Information, and Fund Issuance Performance: Using Livestreams Before Subscription Period

This table replicates the analysis in Table 4, Panel B, using a sample of launch livestreams that occurred before or on the day the subscription period began. Our sample period is from July 1, 2020 to May 31, 2024. Columns (1) and (2) report the results using the number of subscriptions as the dependent variable. Columns (3) and (4) report the results using the total subscription amount as the dependent variable. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*, and are omitted for brevity. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Impression Score $\times$ Info	-0.110** (0.046)		-0.153*** (0.049)	
Impression Score $\times$ High Info		-0.277* (0.140)		-0.270* (0.154)
Impression Score	0.157** (0.069)	0.219*** (0.072)	0.071 (0.082)	0.132 (0.089)
Info	-0.047 (0.083)		-0.049 (0.096)	
High Info		-0.041 (0.166)		-0.040 (0.217)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	434	434	790	790
Adjusted R ²	0.433	0.432	0.306	0.303

Table IA8. Investor Impressions, Information, and Fund Issuance Performance: Including Fund Family $\times$ Year Fixed Effects

This table replicates the analysis in Table 4, Panel B, including fund family $\times$ year fixed effects. Our sample period is from July 1, 2020 to May 31, 2024. Columns (1) and (2) report the results using the number of subscriptions as the dependent variable. Columns (3) and (4) report the results using the total subscription amount as the dependent variable. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*, and are omitted for brevity. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Impression Score $\times$ Info	-0.109*** (0.037)		-0.124*** (0.041)	
Impression Score $\times$ High Info		-0.244** (0.102)		-0.271** (0.122)
Impression Score	0.141** (0.061)	0.199*** (0.060)	0.064 (0.066)	0.129** (0.063)
Info	-0.063 (0.063)		-0.094 (0.079)	
High Info		-0.196 (0.168)		-0.112 (0.192)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Fund Family $\times$ Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	674	674	1,372	1,372
Adjusted R ²	0.409	0.410	0.331	0.330

Table IA9. Investor Impressions, Information, and Fund Issuance Performance: Using Alternative Impression Measures

This table replicates the analysis in Table 4, Panel B, using alternative impression measures. Our sample period is from July 1, 2020 to May 31, 2024. We reconstruct the summary measure, *Impression Score*, using four alternative approaches: (1) *Vocal Positive*, *Visual Positive*, *Body Motion*, and *Verbal Positive*; (2) *Vocal Positive*, *Visual Positive*, *Body Motion*, and *Beauty Score*; (3) *Vocal Positive*, *Visual Positive*, *Body Motion*, *Beauty Score*, and *Image Clarity*; and (4) the median values of *Vocal Positive*, *Visual Positive*, and *Body Motion* over the livestream. Panels A-B, C-D, E-F, and G-H report results for approaches (1)-(4), respectively. Within each pair, the first panel reports the factor loadings and uniqueness of the input measures from the principal component analysis used to construct *Impression Score*, while the second panel examines whether the association between investors' impressions and fund issuance performance varies with the amount of information conveyed during livestreams. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLivetoClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*, and are omitted for brevity. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Impression Measures (Unstandardized)							
	<i>Mean</i>	<i>SD</i>	<i>P25</i>	<i>Median</i>	<i>P75</i>	<i>Loading</i>	<i>Uniqueness</i>
Vocal Positive	0.229	0.185	0.083	0.181	0.325	0.678	0.540
Visual Positive	0.093	0.086	0.030	0.071	0.122	0.570	0.245
Body Motion	1.328	0.874	0.694	1.065	1.734	0.595	0.645
Verbal Positive	0.793	0.109	0.730	0.811	0.877	0.475	0.189
Impression Score	0.000	0.398	-0.281	-0.011	0.229		

Panel B: Interaction Between Investor Impressions and Information and Fund Issuance Performance (<i>Impression Score</i> is based on <i>Vocal Positive</i> , <i>Visual Positive</i> , <i>Body Motion</i> , and <i>Verbal Positive</i>)				
	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.146*** (0.038)		-0.143*** (0.039)	
Impression Score × High Info		-0.339*** (0.103)		-0.270** (0.110)
Impression Score	0.204*** (0.051)	0.290*** (0.056)	0.135** (0.056)	0.202*** (0.057)
Info	-0.074 (0.057)		-0.067 (0.066)	
High Info		-0.202 (0.130)		-0.121 (0.155)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	783	783	1,422	1,422
Adjusted R ²	0.369	0.369	0.248	0.246

Panel C: Impression Measures (Unstandardized)

	<i>Mean</i>	<i>SD</i>	<i>P25</i>	<i>Median</i>	<i>P75</i>	<i>Loading</i>	<i>Uniqueness</i>
Vocal Positive	0.229	0.185	0.083	0.181	0.325	0.594	0.647
Visual Positive	0.093	0.086	0.030	0.071	0.122	0.699	0.511
Body Motion	1.328	0.874	0.694	1.065	1.734	0.523	0.727
Beauty Score	2.884	0.315	2.664	2.881	3.120	0.530	0.719
Impression Score	0.000	0.413	-0.304	-0.032	0.243		

Panel D: Interaction Between Investor Impressions and Information and Fund Issuance Performance
(*Impression Score* is based on *Vocal Positive*, *Visual Positive*, *Body Motion*, and *Beauty Score*)

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.170*** (0.041)		-0.159*** (0.041)	
Impression Score × High Info		-0.380*** (0.097)		-0.291** (0.112)
Impression Score	0.141*** (0.048)	0.228*** (0.049)	0.082* (0.043)	0.148*** (0.046)
Info	-0.083 (0.057)		-0.074 (0.067)	
High Info		-0.210 (0.131)		-0.123 (0.155)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	783	783	1,422	1,422
Adjusted R ²	0.367	0.366	0.247	0.244

Panel E: Impression Measures (Unstandardized)

	<i>Mean</i>	<i>SD</i>	<i>P25</i>	<i>Median</i>	<i>P75</i>	<i>Loading</i>	<i>Uniqueness</i>
Vocal Positive	0.229	0.185	0.083	0.181	0.325	0.607	0.539
Visual Positive	0.093	0.086	0.030	0.071	0.122	0.695	0.512
Body Motion	1.328	0.874	0.694	1.065	1.734	0.507	0.539
Beauty Score	2.884	0.315	2.664	2.881	3.120	0.531	0.717
Image Clarity	0.630	0.557	0.192	0.506	0.898	0.098	0.229
Impression Score	0.000	0.331	-0.242	-0.025	0.198		

Panel F: Interaction Between Investor Impressions and Information and Fund Issuance Performance
(*Impression Score* is based on *Vocal Positive*, *Visual Positive*, *Body Motion*, *Beauty Score*, and *Image Clarity*)

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.172*** (0.041)		-0.165*** (0.043)	
Impression Score × High Info		-0.386*** (0.099)		-0.305*** (0.110)
Impression Score	0.143*** (0.048)	0.231*** (0.050)	0.089** (0.043)	0.157*** (0.047)

Info	-0.080 (0.057)		-0.065 (0.066)	
High Info		-0.198 (0.130)		-0.090 (0.153)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	783	783	1,422	1,422
Adjusted R ²	0.368	0.366	0.243	0.240

Panel G: Impression Measures (Unstandardized)

	<i>Mean</i>	<i>SD</i>	<i>P25</i>	<i>Median</i>	<i>P75</i>	<i>Loading</i>	<i>Uniqueness</i>
Vocal Positive Med	0.076	0.230	0.000	0.000	0.001	0.699	0.512
Visual Positive Med	0.050	0.092	0.000	0.008	0.067	0.680	0.537
Body Motion Med	1.014	0.612	0.605	0.890	1.253	0.472	0.777
Impression Score	0.000	0.424	-0.266	-0.131	0.105		

Panel H: Interaction Between Investor Impressions and Information and Fund Issuance Performance (*Impression Score* is based on the median values of *Vocal Positive*, *Visual Positive*, and *Body Motion* within each livestream)

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.124*** (0.039)		-0.124*** (0.040)	
Impression Score × High Info		-0.320*** (0.112)		-0.290** (0.128)
Impression Score	0.078 (0.066)	0.159** (0.077)	0.026 (0.067)	0.100 (0.073)
Info	-0.081 (0.060)		-0.075 (0.070)	
High Info		-0.214 (0.135)		-0.138 (0.156)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	783	783	1,422	1,422
Adjusted R ²	0.359	0.360	0.246	0.245

Table IA10. Investor Impressions, Information, and Fund Issuance Performance: Using Alternative Information Measures

This table replicates the analysis in Table 4, Panel B, using alternative information measures by comparing livestream transcripts with the Important Notice section of the fund prospectus. Our sample period is from July 1, 2020 to May 31, 2024. We examine whether the association between investors' impressions and fund issuance outcomes varies with the information conveyed during the livestream. Columns (1) and (2) report the results using the number of subscriptions as the dependent variable. Columns (3) and (4) report the results using the total subscription amount as the dependent variable. *Info* is the share of information content in a livestream that is new relative to the Important Notice section of the fund prospectus. The control variables include *Verbal Positive*, *Image Clarity*, *Beauty Score*, *Number of Presenters*, *Share of Female Presenters*, *Gift*, *LnViewers*, *LnLength*, *LnLiveToClose*, *Active Fund*, *Fund Fees*, *State-owned Fund Family*, *Large Fund Family*, *Female Manager*, *Rookie Manager*, *Highest Degree*, *Top2 University*, *Manager Experience*, *Manager Past Performance*, *Market Return*, *Market Volatility*, and *Number of Fund Launches*, and are omitted for brevity. Variable definitions are provided in Online Appendix A. For specifications in which the dependent variable is *LnSubscriptions*, heteroskedasticity-robust standard errors clustered at the fund family level are reported in parentheses. For specifications in which the dependent variable is *LnAmount*, heteroskedasticity-robust standard errors clustered at the fund family level and livestream level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>LnSubscriptions</i>		<i>LnAmount</i>	
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.075* (0.043)		-0.110** (0.052)	
Impression Score × High Info		-0.188* (0.105)		-0.284** (0.110)
Impression Score	0.166*** (0.050)	0.208*** (0.052)	0.119** (0.058)	0.186*** (0.064)
Info	-0.130** (0.055)		-0.154*** (0.058)	
High Info		-0.346** (0.142)		-0.280** (0.132)
Controls	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time-of-Day FE	YES	YES	YES	YES
Observations	770	770	1,400	1,400
Adjusted R ²	0.362	0.363	0.251	0.249