The Two-System View of Cognition and Investor Choice*

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Abstract

This paper examines how investors' effortless intuition (System 1) and deliberative reasoning (System 2) jointly influence their decision-making. We construct a novel dataset of livestream promotional events linked to the initial offerings of mutual funds in China between 2020 and 2024. These events occur before any performance records or portfolio disclosures become available, providing a clean setting to isolate the effects of different cognitive processes. We find that investors' intuitive favorable responses to the dynamic emotional displays of livestream presenters, including vocal tone, facial expressiveness, and body movement, are positively and significantly associated with fund subscriptions. However, this effect weakens when livestreams convey (complex) information or feature fund managers that require investors' analytical processing. Our study provides novel evidence on how investors' intuition (System 1) and reasoning (System 2) interact to influence their choices, offering a foundation for developing a positive theory of investor behavior.

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

JEL classifications: G11; G14; G20; D83

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Abstract

This paper examines how investors' effortless intuition (System 1) and deliberative reasoning (System 2) jointly influence their decision-making. We construct a novel dataset of livestream promotional events linked to the initial offerings of mutual funds in China between 2020 and 2024. These events occur before any performance records or portfolio disclosures become available, providing a clean setting to isolate the effects of different cognitive processes. We find that investors' intuitive favorable responses to the dynamic emotional displays of livestream presenters, including vocal tone, facial expressiveness, and body movement, are positively and significantly associated with fund subscriptions. However, this effect weakens when livestreams convey (complex) information or feature fund managers that require investors' analytical processing. Our study provides novel evidence on how investors' intuition (System 1) and reasoning (System 2) interact to influence their choices, offering a foundation for developing a positive theory of investor behavior.

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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

"…two major hypotheses about the role of intuition in judgment and choice. The first is that most behavior is intuitive, skilled, unproblematic, and successful (Klein, 1998). The second is that behavior is likely to be anchored in intuitive impressions and intentions even when it is not completely dominated by them."

– Kahneman (2003b, p. 717) 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 investors' decisions, suggesting that economic agents are also "homo sapiens" and rely on intuition rather than deliberative reasoning 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 (2021), Huang, Ivković, Jiang, and Wang (2023), and Hu and Ma (2024) 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 deliberative reasoning (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 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 (2008), 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) further emphasizes that System 1 typically governs judgment unless modified or overridden by System 2, and that contextual factors—"the power of the situation"—help delineate the boundaries of System 1.

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

[1] There is substantial evidence across different fields showing that people are not accustomed to thinking hard 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 (2011) 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.

about a fund and/or the presence of a fund manager in a livestream, which are analyzed by System 2. We employ advanced video analytics and generative AI to separately capture presenters' dynamic and fluid behavior that determines investors' impression (System 1) and the information conveyed that engages investors' deliberative reasoning (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 alters 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' impressions (System 1) and their subscription decisions. Second, this setting allows us to examine new funds with limited information about the fund and/or its manager. As in many psychology studies and prior research in finance and accounting (see, for example, Blankespoor, Hendricks, and Miller 2017; Huang et al. 2023; Hu and Ma 2024), this environment enables us to accurately measure the amount (complexity) of information that engages investors' deliberative reasoning (System 2), and subsequently, to explore how System 1 and System 2 interact in a high-stakes, real-world setting.

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 daily 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,

This research also shows that such impressions and judgments can accurately predict medical assessments, educational, and job performance outcomes, especially when derived from dynamic and fluid behavior rather than static images (Ambady, Hallahan, and Connor 1999; Ambady, Bernieri, and Richeson 2000). Building on both strands of this research, we employ advanced machine learning (ML) techniques to analyze presenters' expressive dynamic behavior during livestreams that shape investors' rapid impressions, using this as a proxy for investors' positive perceptions of livestream presenters. We implement cutting-edge audio and computer vision models to capture presenters' vocal tone, facial expressiveness, and body motion as inputs to investors' impression formation (System 1). Simultaneously, we utilize natural language processing (NLP) methods to examine livestream transcripts, quantifying the amount and complexity of information conveyed and processed by System 2.

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. Our results indicate that investors' System 2, elaborate reasoning, can override their favorable System 1 impressions in making 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 fund launch livestreams from July 1, 2020, to May 31, 2024. The dataset includes 789 livestream events related to 1,422 funds. Like traditional e-commerce livestreams, fund livestreams feature live video feeds with hosts and guests (collectively, referred to as presenters), interactive text, and shopping

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

cart functions. Since 2020, fund families have begun livestreaming on social media platforms to compensate for investors' limited access to conventional financial advisors and fund information due to the COVID-19 pandemic. As a result, fund livestreams have gained increasing popularity and become one of the most common marketing tools for funds in China (deHaan, Huang, Kannan, and Qiu 2025). In 2023, over 140 fund companies hosted more than 54,000 livestreams, with total viewership reaching roughly 3.4 billion.[3] We focus on fund launch livestreams because this information-sparse environment (prior to the livestream) helps highlight the role of System 1 and explore how System 1 and System 2 interact in investors' decision-making.

Guided by the two-system view of cognition, we isolate livestream presenters' nonverbal visual and auditory signals that influence investors' quick impressions (System 1) by extracting the presenters' multidimensional expressive features (without any information content): vocal tone, facial expressiveness, and body motion.[4] To do this, we first obtain the full audio stream from the video. The audio file includes both a vocal component and a textual component (i.e., a transcript) generated by a speech-to-text algorithm. We then capture the two visual dimensions using a series of images taken at one frame per second (i.e., 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 algorithms, we develop a presenter expressive behaviour measure, *Impression Score*, that determines investors' System 1 processing.

To quantify the amount of information conveyed during livestreams, we use generative AI to analyze video transcripts. Specifically, we measure the information content of a livestream by comparing the amount of information in its transcript to that in the Fund

[3] For more details, see https://app-web.chnfund.com/jx/202402/t20240226_4328340.html.
[4] We rely on widely available computational services, including Speech Emotion Recognition, DeepFace, and YOLO11to construct investor impression measures and conduct the analysis.

Overview section on the Tiantian Fund website. The Fund Overview is a key feature of the platform that is easily accessible and widely read by investors. In addition to structured information about a fund (e.g., fund name and code), the Overview also provides a brief fund description under six topic categories: investment objectives, investment philosophy, investment scope, investment strategy, dividend policy, and risk-return characteristics.

We first perform text segmentation on a transcript and use generative AI (DeepSeek) to extract topics from each segment. We then assess whether each segment's content matches any of the six key topics in the Fund Overview section or the nine additional topics.[5] This step allows us to create the variable *Info*, which measures the amount of informational content conveyed during a livestream, beyond what is covered in the Fund Overview. For the six topics in the Fund Overview, we calculate the cosine similarity between each topic-specific segment and the relevant Overview content. Segments with similarity scores above a set threshold are classified as repetitive. For each topic, we then determine the variable *Info Ratio* as one minus the proportion of repetitive content within that topic's total segments. For the nine additional topics, *Info Ratio* is set to one for the relevant segment(s), as these topics differ from those in the Overview. Finally, we aggregate the topic-specific *Info Ratio* measures to the livestream level to construct the variable *Info*, which captures the amount of information shared with investors during a livestream.

We document several 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. This pattern holds across individual vocal, facial, and body-motion measures, even

[5] 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 topics in the Fund Overview as our additional topics. These nine additional topics 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.

after controlling for other livestream features (e.g., verbal tone, image clarity, and beauty score) as well as fund manager and fund characteristics (e.g., manager experience and fund fees). A one-standard-deviation increase in investors' favorable impressions (*Impression Score*) corresponds to a 17.3 percent increase in subscriptions and a 23.2 percent increase in subscription amount. Given the average subscription amount of RMB 839.50 million (USD 116.86 million) in our sample, this effect amounts to an extra RMB 194.76 million (USD 27.11 million). These findings support prior evidence that investors' favorable impressions are linked to their investment decisions (e.g., Blankespoor, Hendricks, and Miller 2017; Huang et al. 2023; Hu and Ma 2024).[6]

Second, we examine how investors' favorable impressions (System 1) interact with deliberative reasoning (System 2) to shape investment decisions. We find that higher information content in livestreams—which requires investors to engage in 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 net effect of *Impression Score* on the fund subscription amount is −0.066 and is not statistically different from zero. In other words, when livestreams contain information, investors' System 2 reasoning overrides their intuitive System 1 responses. These results align with Kahneman's two-system theory of cognition. To our knowledge, this is the first empirical evidence in finance that directly tests Kahneman's hypothesis and delineates the boundaries of System 1.

Third, we examine potential heterogeneity in how investors' System 2 overrides System 1. To do this, we apply DeepSeek to classify the information presented in livestreams as complex or non-complex. Complex topics are difficult for retail investors to understand and

[6] In the Online Appendix, we also show that more favorable investor impressions at launch are associated with poorer long-term fund performance, consistent with the findings in Hu and Ma (2024) and deHaan et al. (2025).

require interpretation by professionals, such as fund managers and analysts, whereas non-complex topics are easily understood by retail investors. We then measure the information content of different types of information conveyed. Our findings indicate that only when investors' System 2 is activated by complex information does it override System 1.

Relatedly, we examine whether the presence of fund managers in a livestream matters. We first show that livestreams with manager presence convey more, and specifically more complex, information than those without. 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. We find that when livestreams promote active funds with complex strategies, investors face greater informational complexity, slow down, and engage in deliberative reasoning. System 2 scrutiny overrides System 1's favorable impressions in shaping investment decisions.

The decision to livestream a fund launch is not random. However, since our main goal is to examine whether and how investors' System 2 analytical reasoning interacts with System 1 intuition during a fund launch livestream, it is unclear how this selection could significantly bias our conclusions. Similarly, a fund manager's decision to be present in a livestream is a conscious choice, potentially aimed at improving launch outcomes. We find no noticeable differences in background between fund managers who participate in fund launch livestreams and those who do not. Moreover, our findings indicate that a fund manager's presence in the livestream actually decreases—rather than enhances—the effectiveness of the livestream. In other words, the endogenous decision to include fund managers in livestreams works against us in detecting the negative impact of their presence.

In conclusion, our new evidence on the boundaries of System 1 supports the conjecture in Kahneman and Frederick (2002) and Kahneman (2011) that System 1 is the default for

governing judgment, unless modified by System 2, which is activated by the amount and complexity of information. Given the increasing importance of livestreaming in our daily lives, our findings have significant implications for disclosure choices and capital markets rule-making.

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 impression (System 1) and information processing (System 2) from livestreams. Section 5 presents the main findings, including the influence of fund livestreams, the role of investors' favorable impressions, and the interaction between investors' favorable impressions and information processing on fund issuance performance. Section 6 explores the role of investor inattention and provides robustness checks. 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 field of applying video analysis to examine how visual and auditory cues in communication influence investor behavior and asset prices (Blankespoor, Hendricks, and Miller 2017; Curti and Kazinnik 2023; Gorodnichenko, Pham, and Talavera 2023; Alexopoulos, Han, Kryvtsov, and Zhang 2024; Hu and Ma 2024; deHaan et al. 2025; Chang et al. 2025). We extend this work by applying the two-system framework of cognition (Kahneman 1973, 2011; Tversky and Kahneman 1974; Stanovich and West 2000) to examine mutual fund launch livestreams. To the best of our knowledge, we present the first evidence on how investors' System 1 intuition and System 2 information processing interact to shape their financial decisions in a large-scale, high-stakes setting. Furthermore, with the aid of advanced video analytics and

generative AI, we are among the first in the literature to use entire livestream videos (approximately 60 minutes on average), rather than brief snippets used in prior research as input to investors' System 1 judgment (e.g., Ambady and Rosenthal 1992; Blankespoor, Hendricks, and Miller 2017). Analyzing the entire video is crucial for our research question, as it helps us better capture the amount and complexity of information exchanged during a livestream that activates System 2.

Second, our paper contributes to the growing body of research on financial technology (fintech) platforms and investor behavior. Fintech channels increasingly influence how investors access and buy financial products, whether through online fund distribution, robo-advisors, or mobile trading apps. Recent research shows that these innovations broaden market participation and change 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 literature by examining livestreaming, a rapidly growing fund distribution channel that uniquely combines fund promotion with information disclosure. We show that retail investors, influenced by livestream presenters' nonverbal cues, may invest in funds that do not warrant such inflows—a behavioral bias. Importantly, we also find that investors' deliberative reasoning, triggered by the amount and complexity of information during livestreams, helps reduce the effect of their favourable impressions on fund subscription decisions.

Finally, our paper adds to the literature on mutual fund marketing. Early studies show that advertising can attract flows without enhancing risk-adjusted returns (Jain and Wu, 2000) and that fund families strategically market products with strong recent performance (Nanda, Wang, and Zheng, 2004; Gaspar, Massa, and Matos, 2006). More recent work highlights the strategic role of mutual fund marketing in influencing fund flows and market competition beyond simply lowering investors' participation or search costs (deHaan, Song, Xie, and Zhu,

2021; Roussanov, Ruan, and Wei, 2021; Chen, Jiang, and Xiaolan, 2023). We contribute to this literature by exploring livestreaming as a new and increasingly vital marketing channel in capital markets. Our study is among the first to examine this sensory- and information-rich channel, providing new evidence that investors' favorable impressions and information processing during these events collectively influence their capital allocation.

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 more than 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

[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://www.vidchina.cn/outcome/46.

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 (2025), 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 website (https://roadshow.eastmoney.com/list?type=1) 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, the setting is information-poor, allowing a clean analysis of the roles of investors' System 1 intuition and its interaction with System 2 information processing. Figure 1 provides a screenshot of the livestream interface and related details on the Tiantian Fund website.

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 2 lists the top 10 fund families by the number of fund launch livestreams during the sample period and the distribution of livestream start times. We show that the top three fund families have over 100 livestreams linked to fund launches. Figure 3, 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, and over 60% include a fund manager (Panel B).[8]

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.[9] Consequently, each livestream may be associated with two sets of outcome variables if the fund is available in both classes. For the subscription analysis, this increases the sample from 853 livestreams to 1,524 fund issuance observations. After requiring data availability for livestream, fund, and fund manager characteristics, the final sample comprises 789 livestreams associated with 1,422 launch outcome observations.[10] Table 1 outlines the sample construction process.

3.3. Summary Statistics

We gather fund and fund manager characteristics from the RESSET Database and the Wind Database. We measure a fund manager's performance using the average annualized net asset growth rate of the funds they previously managed, which aligns with a common manager performance measure displayed on the Tiantian Fund platform. We record gift-giving during livestreams through keyword searches and manual review. Additionally, we obtain livestream viewership and like counts via web scraping. Table 2, Panel A presents

[8] 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.

[9] 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.

[10] Among 789 livestreams, 488 are unique, and 301 are the first of multiple livestreams.

summary statistics for fund and fund manager characteristics. Variable definitions are provided in the Appendix.

Table 3, Panel A offers a comparative analysis of new funds that host livestreams (*Livestream = 1*) versus those that do not (*Livestream = 0*). Two-sample tests show significant differences across various fund characteristics. Both the mean and median number (amount) of subscriptions are substantially higher for funds that host livestreams (Mean = 25,689 [RMB 839.50 million], Median = 7,597 [RMB 217.70 million]) than for those that do not (Mean = 12,361 [RMB 707.92 million], Median = 2,263 [RMB 191.46 million]). These differences are statistically significant, as indicated by t-tests and Wilcoxon tests, suggesting that fund livestreams are positively linked to the number (amount) of subscriptions.

Table 3, Panel B presents the results from the linear probability model. Across all specifications, the coefficient on *Active Fund* is negative and statistically significant, indicating that actively managed funds are less likely to host a launch livestream. The coefficients on *Fund Fees* and *State-owned Fund Family* are positive and significant across all specifications, showing that new funds with higher fees and those affiliated with a state-owned fund family are more likely to host a launch livestream. Overall, the findings suggest that certain fund features, such as higher fees, are positively associated with the likelihood that a new fund will host a launch livestream.

4. Methodology: Constructing Impression and Information Measures in Livestreams

In this section, we explain how we apply machine learning and generative AI to capture investors' System 1 intuition and System 2 elaborate reasoning. Guided by seminal work in social and cognitive psychology (Strahan and Zytowski 1976; Rosenthal et al. 1979; Krauss, Morency, Wenzel, and Winton 1981; Ambady and Rosenthal 1992; Ambady, Hallahan, and Connor 1999; Kahneman and Frederick 2002; Kahneman 2003a, 2003b), we measure

livestream presenters' dynamic, fluid behavior in vocal tone, facial expressiveness, and body motion, which are processed by investors' System 1.[11]

Unique to our context, mutual fund livestreams let us explore how the information shared during livestreams—processed by investors' System 2—interacts with presenters' nonverbal cues—interpreted by investors' System 1. Specifically, the Fund Overview section on the Tiantian Fund website offers structured information about each new fund (for example, investment objectives and philosophy) sourced from the prospectus. We use this section as a benchmark and apply generative AI and machine learning algorithms to assess the amount and complexity of the conveyed information.

4.1. Constructing Investor Impression Measures Using Machine Learning

We construct investor impression measures from video data by leveraging recent advances in speech recognition and computer vision. To ensure replicability and transparency, we use established machine learning algorithms that are widely recognized and readily accessible. Figure 4 presents a flowchart outlining how we construct the impression measures, and Table IA1 in the Online Appendix provides the implementation details.

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).[12] These logs naturally preserve the audio's temporal dependency

[11] Since livestream transcripts include both information and emotional cues (i.e., sentiment), which could interfere with the functioning of System 1, our primary measure, *Impression Score*, uses content-filtered video and audio cues. As a robustness check, we also include verbal tone in our main measure and find that our key findings remain unchanged.

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

structure and align with human cognitive processes. We then use Speech Emotion Recognition, a Python package that includes deep-learning-based speech emotion recognition algorithms, to detect 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.

4.1.2. Facial expressiveness

Given that fund livestreams typically last about one hour—considerably longer than startup pitch videos (Hu and Ma 2024)—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 a speaker, tracks facial feature points (e.g., nose, eyes), and probabilistically classifies seven facial emotions: anger, disgust, fear, happiness, neutral, 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.

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.[13] We extract images at a rate of one 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.[14]

[13] Because our method captures what viewers see of presenters' upper-body movement in a livestream—unlike in-person pitches observed from the audience—camera-angle adjustments used by Davila and Guasch (2022) are not applicable. We therefore measure presenters' body movement using the raw (unadjusted) displacement magnitude.

[14] After converting each frame to grayscale, we apply the Farneback algorithm to calculate inter-frame optical flow, decompose the x- and y-direction components, and derive pixel displacement magnitudes using a polar coordinate transformation. Specifically, we divide the image into presenter-specific regions, extract displacement magnitudes by region, compute their average values, and sum the total displacement along with

Our variable, *Body Motion*, is calculated by first averaging across presenters within each frame and then across all frames in a livestream.

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). *Impression Score* is the first principal component of *Vocal Positive*, *Visual Positive,* and *Body Motion*.

Table 2, Panel B presents summary statistics for the investor impression measures, highlighting substantial cross-sectional variation. For example, the mean of *Visual Positive* is 0.080, indicating that presenters display positive visual features for approximately 8 percent of the total livestream duration. The 25th and 75th percentiles are 0.025 and 0.111, respectively, suggesting notable differences in the visual dimension. Panel B also reports each impression measure's loading on *Impression Score* and its "uniqueness." The former shows how strongly each measure contributes to the composite factor, while the latter indicates how much of each measure's variance is left unexplained by the composite factor.

To validate our measures of investors' favorable impressions of livestream presenters, we examine the association between our measures and investors' reactions to livestreams. Table IA2 presents the results. We show that *Impression Score* positively and significantly correlates with the number of likes and the ratio of the number of likes to the number of viewers during a livestream.[15] We conclude that, *Impression Score* can be viewed as a composite index that captures investors' overall favorable impressions.

4.2. Constructing Other Livestream Measures Using Machine Learning

Using Aliyun's speech-to-text API, we generate text transcripts from the audio data of

the number of frames. Finally, after processing all frames, we determine the average displacement variation by dividing each region's total displacement by the number of frames.

[15] Table IA3 presents 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.

each speaker in a livestream. We then use StructBERT (Wei et al. 2020) to classify the sentiment of these transcripts.[16] 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.

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.[17] Our variable, *Image Clarity*, is the average clarity score across all frames in a livestream.

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 Using Generative AI

In this section, we explain our approach to creating information measures for a livestream by using its transcript and the Fund Overview section of the Tiantian Fund website. The Fund Overview provides concise, structured information about a fund, including its name, code, manager, fee structure, and other key details. It also features a brief fund description under six topic headings: investment objectives, investment philosophy,

[16] 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.

[17] We measure image clarity using the Variance of Laplacian, which captures the sharpness of image edges.

investment scope, investment strategy, dividend policy, and risk-return characteristics, sourced from the 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 therefore use it as our benchmark for comparing and assessing the amount of information in livestreams. As a robustness check, we use the prospectus Important Notices section—located at the front and summarizing key investor disclosures—as an alternative benchmark. Figure 5 presents a flowchart illustrating how we construct the information measures, and Table IA1 in the Online Appendix provides the implementation details.

4.3.1. Step 1. Text segmentation

Text segmentation is a crucial part of natural language processing, enabling large documents to be divided into smaller, cohesive units for further analysis. Fund livestream transcripts are complex, lengthy texts featuring dialogue and covering a variety of topics. Traditional approaches, such as character-based or fixed-size chunking, often miss the subtleties of such content. To overcome this limitation, we use a method that employs semantic similarity from word embeddings to segment text into meaningful chunks. This approach ensures each chunk is semantically coherent and contextually relevant, enhancing the overall quality of the analysis.

To implement text segmentation, we use word embeddings to capture the semantic content of sentences. Specifically, we convert each sentence in the transcript into a high-dimensional vector and apply the GTE model developed by Alibaba DAMO Academy to measure the similarity between sentence embeddings.[18] We then assess the semantic relatedness of sentences and identify coherent segments within the text. The threshold is set

[18] 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 the GTE model for its efficiency and accuracy in processing complex textual data and its ability to provide robust semantic representations for our analysis. For further details on the GTE model, see https://huggingface.co/thenlper/gte-large-zh.

at 0.75, which is the minimum semantic difference needed to split the text into separate segments.[19]

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 on the TianTian Fund website 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 "others."

4.3.3. Step 3. Measuring the amount of information

Kahneman and Frederick (2002) and Kahneman (2011) argue that System 2 lightly monitors System 1 and activates when the novelty or complexity of information exceeds what System 1 can automatically manage, shifting decision-making from intuition to analytical reasoning. To test this conjecture, in this section, we explain how we construct the variable, *Info*, which measures the amount of information conveyed during a livestream. Our measure is based on the idea that, because the Fund Overview section is easily accessible and widely read by investors, livestream content that closely mirrors it is considered repetitive.

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

Conversely, content that deviates from the Fund Overview represents 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 algorithm. 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).[20] If the similarity score exceeds this threshold, the indicator *I(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*, *Info Ratio*$_{k,i}$, is constructed as follows:

$$Info\ Ratio_{k,i} = 1 - \frac{\sum_{s=1}^{S} Segment\ Length_{s,k,i} * I(Repetitive_{s,k,i})}{\sum_{s=1}^{S} Segment\ Length_{s,k,i}}, \quad (1)$$

where *Segment Length*$_{s,k,i}$ represents the number of words in segment *s* of livestream *i* on topic *k*, and *I(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 not repeating the Fund Overview content on the same topic.[21] 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 *Info Ratio*$_{k,i}$ to the livestream level using the following equation:

$$Info_i = \sum_{k=1}^{K} Topic\ Proportion_{k,i} \times Info\ Ratio_{k,i}, \quad (2)$$

where *Topic Proportion*$_{k,i}$ represents the share of word counts in livestream *i* attributed to topic *k* relative to the total word count of that livestream *i*'s transcript. When topic *k* is included in the Fund Overview, *Info Ratio*$_{k,i}$ is calculated as in Equation (1). When topic *k* is

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

not included 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 capture the complexity of information conveyed during a livestream, we first use generative AI to classify topics in livestreams into complex and non-complex topics. Complex topics require professional interpretation, such as by fund managers or analysts, whereas non-complex topics are easily understood by retail investors. Specifically, we employ DeepSeek to classify the 15 topics extracted from livestream transcripts into two groups: those easily understood by retail investors and those requiring professional interpretation. Based on DeepSeek's response, we categorize the topics as complex—including macroeconomic policy analysis, industry analysis, stock-picking strategy, quantitative modelling, investment philosophy, and market trend analysis—or non-complex: product features and trends, fund manager's professional background, investor education, index characteristics, investment objectives, investment scope, investment strategy, dividend policy, and risk-return characteristics.[22]

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

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

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

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

Table 2, Panel C presents summary statistics for our information measures. The mean of *Info* is 0.685, indicating that 68.5 percent of livestream content is novel to investors. Of this

[22] Figure IA6 provides examples of complex and non-complex topics. Figure IA7 presents a flowchart illustrating how we construct measures of complexity-related information.

information content, complex topics account for 53.1 percent (0.364/0.685), while non-complex topics account for 46.9 percent (0.321/0.685).[23]

5. Main Results

This section presents the main empirical analysis. We first examine the relationship between fund livestreams and issuance performance, focusing on the role of investors' System 1 intuition in shaping their purchase decisions. We then investigate whether and how investors' System 2 elaborate reasoning, activated by information shared during livestreams, modifies the effect of their favorable impressions on fund purchase decisions.

5.1. Fund Launch Livestream and Issuance Performance

To examine whether a fund's launch livestream is significantly associated with its issuance performance, we estimate the following specification:

$$Y_{i,t} = \beta_0 + \beta_1 LiveStream_{i,t} + \gamma Controls_{i,t} + StyleFE + YearFE + TimeofDayFE + \varepsilon_{i,t}, \quad (5)$$

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 subscription period, and the latter indicates the number of launch livestreams. To control for potential confounding factors, we include fund and fund manager characteristics, collectively denoted as *Controls*. Furthermore, we control for style fixed effects, year fixed effects, and

[23] Table IA3 presents 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, whereas the fund issuance amount is negatively correlated with two of the three information measures.

time-of-day fixed effects.[24,25] Standard errors are clustered at the fund level.

Table 4, Panel A presents the regression results for Equation (5). Regardless of whether we use the livestream indicator or the number of livestreams, the coefficients on *Livestream Indicator* (*Number of Livestreams*) are significantly positive at the 1% level across all specifications. This finding underscores that fund launch livestreams significantly improve issuance performance.

To provide supplemental evidence on the role of launch livestreams in fund issuance outcomes, we explore the correlation between livestream viewership and the issuance performance of a new fund. Table 4, Panel B presents the regression results. The coefficient on *LnViewers* is significantly positive in column (1), indicating a positive correlation between livestream viewership and fund issuance performance. However, when the dependent variable is the amount of subscriptions, there is no significant association between livestream viewership and the amount of subscriptions, suggesting that livestream viewers are likely small retail investors who are swayed by the livestream to participate with a small investment.[26]

5.2. System 1 Intuition and Fund Issuance Performance

Under the two-system framework, "agents often act intuitively…guided… by what they happen to see at a given moment" (Kahneman 2003a, p. 1469). In our setting, fund launch livestreams featuring positive nonverbal cues—engaging visuals and vocal affect—processed by investors' System 1, stimulate subscriptions.

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[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] 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.

[26] 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.

In this section, we examine how investors' favorable impressions, proxying for their System 1 intuition, formed during livestreams can enhance fund issuance performance.[27] We run the following cross-sectional regression using 1,422 fund issuance observations:

$$Y_{i,t} = \beta_0 + \beta_1 Impression\ Measures_{i,t} + \gamma Controls_{i,t} + StyleFE + YearFE + \\ + TimeofDayFE + \varepsilon_{i,t}, \quad (6)$$

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 measure of impression (*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, and fund manager characteristics as control variables.[28] Furthermore, we control for style fixed effects, year fixed effects, and time-of-day fixed effects. Standard errors are clustered at the fund level.

Table 5 presents the regression results for Equation (6). In Panel A, we use the number of subscriptions (*LnSubscriptions*) as the dependent variable. Columns (1) to (3) present 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* and *Visual Positive* are statistically significant. For example, in column (1), the coefficient on *Vocal Positive* is 0.167 and significant at the 1% level, suggesting that a one-standard-deviation increase in positive vocal features is associated with a 16.7 percent increase in the

[27] 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).

[28] 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*).

number of subscriptions. In column (4), we show that *Impression Score* positively and significantly correlates with the number of accounts subscribing to a fund issuance. In terms of economic significance, the coefficient of 0.173 means that a one-standard-deviation increase in *Impression Score* is associated with a 17.3 percent increase in the number of subscriptions. The average number of subscriptions in our sample is 25,689 accounts. A 17.3 percent increase means there are 4,444 additional subscriptions to the new fund.

In Table 5, Panel B, we use the subscription amount (*LnAmount*) as the performance measure and find very similar results. All individual impression measures have positive loadings, and the coefficient on *Vocal Positive* is statistically significant. The coefficient of 0.232 in column (4) indicates that a one-standard-deviation increase in *Impression Score* is associated with a 23.2 percent increase in the subscription amount. The average subscription amount in our sample is RMB 839.50 million (USD 116.86 million). The 23.2 percent increase corresponds to RMB 194.76 million (USD 27.11 million).

Social perceptions are formed from nonverbal and paralinguistic cues—tone of voice, facial expressions, and body language (Rosenthal et al. 1979; Ambady et al. 1999)—that engage System 1 (intuitive, automatic) processing. In this section, we show that investors' System 1 intuition can influence their choices and is positively associated with the issuance performance of newly launched funds.[29] The effects are economically large, underscoring the importance of delivery features in mutual-fund livestreams and aligning with evidence that investors' favorable impressions shape their decision-making (Blankespoor, Hendricks, and Miller 2017; Huang et al. 2023; Hu and Ma 2024). What is missing from the above analysis is that during fund livestreams, material and complex information is shared, which activates

[29] In Table IA4, we also investigate whether a fund's ability to generate favorable investor impressions during livestreams is linked to its subsequent return performance. Consistent with Hu and Ma (2024) and deHaan et al. (2025), we find that more favorable investor impressions at launch are associated with poorer long-term fund performance. These findings suggest that retail investors, influenced by System 1 cues during livestreams, may allocate capital to funds that do not justify such inflows, revealing a behavioral bias.

System 2 (Kahneman and Frederick, 2002; Kahneman, 2011). We examine whether and how investors' System 2 elaborate reasoning modifies their favorable impressions (System 1) in the next section.

5.3. The Impact of System 2 Information Processing

To our knowledge, this is the first study to examine the interaction between System 1 and System 2 in a high-stakes, real-world setting. Specifically, we test whether disclosing information during livestreams, which engages investors' System 2, attenuates the effectiveness of their effortless intuition (a System 1 process).

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

During fund livestreams, presenters such as fund managers share information on macroeconomics, market trends, industry developments, and fund specifics. For retail investors, this content is often novel and complex, activating System 2 cognition and prompting deliberative processing (Kahneman and Frederick, 2002; Kahneman, 2011).

Our research setting thus raises an important question about the interplay between the two systems: does information (which activates System 2) weaken or strengthen the influence of investors' favorable impressions (primarily associated with System 1) on fund issuance performance? We measure the amount of information in livestreams using two proxies: (1) *Info*, the share of information content conveyed during a livestream relative to the Fund Overview on Tiantian; (2) *High Info*, an indicator variable that equals one if the value of *Info* is in the top quintile, and zero otherwise.

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

$$Y_{i,t} = \beta_0 + \beta_1 Impression\ Score_{i,t} + \beta_2 Info_{i,t} + \gamma Controls_{i,t} + StyleFE + YearFE + TimeofDayFE + \varepsilon_{i,t}, \quad (7)$$

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 effects of System 1 and System 2 cognition on investors' choices. Given that our information measures are sentiment-neutral, we do not predict a directional effect from activating System 2 cognition.

Table 6, Panel A presents the regression results for Equation (7). Across all four columns, the coefficient on *Impression Score* is positive and statistically significant, indicating that investors' favorable impressions are positively and significantly associated with fund issuance outcomes. However, our two information measures do not load.

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

$$Y_{i,t} = \beta_0 + \beta_1 Impression\ Score \times Info_{i,t} + \beta_2 Impression\ Score_{i,t} + \beta_3 Info_{i,t} + \gamma Controls_{i,t} + StyleFE + YearFE + TimeofDayFE + \varepsilon_{i,t}, \quad (8)$$

where the coefficient on the interaction term captures whether and how System 2 moderates the positive impact of System 1 on fund issuance performance.

Table 6, Panel B presents the regression results for Equation (8). Columns (1) and (3) use the interaction *Impression Score* × *Info*; columns (2) and (4) use *Impression Score* × *High Info*. Across all specifications, the interaction coefficient is negative and statistically significant, 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 net effect of *Impression Score* on *LnAmount* is −0.066 (0.157 − 0.223 × 1), and is not statistically different from zero, indicating that *Impression Score*'s impact shifts from a statistically significant positive effect to no significant effect.

Our findings provide new evidence in support of Kahneman's two-system framework of

cognition. Nonverbal cues such as gestures, body movements, and dynamic facial expressions primarily engage System 1—intuitive and affect-driven—so when substantive cues are scarce, investors rely on heuristic impressions (e.g., positive affect). By contrast, information that supplies decision content engages System 2—deliberative and analytical—requiring careful processing. Accordingly, when livestreams convey little information, System 1 dominates and impression effects emerge; when livestreams are information-rich, System 2 dominates, and System 1 effects are attenuated.

5.3.2. The impact of System 2 information processing: Information type

In this section, we examine how different types of information influence the role of System 1 in fund issuance performance. We focus on information complexity, a critical factor that activates System 2 (Kahneman and Frederick 2002; Kahneman 2011). Using generative AI, we classify information into complex versus non-complex topics. Section 4.3.4 details the classification procedure.

We interact *Impression Score* with two types of information in livestreams (*Info Complex* and *Info NonComplex*). The coefficients on the interaction terms indicate whether complex or non-complex information in livestreams significantly affects the role of investors' favorable impressions in fund issuance performance. Table 6, Panel C presents the results.

In columns (3) and (6), the coefficient on *Impression Score* × *Info Complex* is negative and highly significant, whereas the coefficient on *Impression Score* × *Info NonComplex* is not statistically significant. The results indicate that complex information shared during livestreams mitigates the effect of investors' favorable impressions on fund issuance performance, whereas non-complex information shows no significant effect. For example, in column (6), when *Info Complex* takes a value of 0.666 (the top quartile (standardized)), the net effect of *Impression Score* on *LnAmount* is −0.019 (−0.174 × 0.666 − 0.016 × (−0.697) + 0.086) (−0.697 is the bottom quartile (standardized) of *Info NonComplex*). The effect of

System 1 turns negative and is not statistically different from zero, suggesting that investors' System 2 offsets favorable System 1 impressions in their decision-making.

Complex information requires cognitive effort and activates System 2, leading investors to base decisions on content rather than delivery. As attention shifts to analysis, the influence of investors' favorable impressions on fund-issuance outcomes is mitigated. By contrast, non-complex information can be processed quickly by System 1 without additional effort. Investors need not engage in deep analysis and therefore continue to rely on heuristic impressions from nonverbal cues. Consequently, non-complex information does little to dampen the impact of investors' favorable impressions on their decision-making. Our findings thus far are consistent with the above framework.

5.3.3. The impact of System 2 information processing: Fund manager presence

We study fund managers' presence in livestreams for three reasons. First, their presence alters how viewers interpret the event: host-only sessions are perceived as entertainment or promotion—engaging System 1—whereas sessions with a fund manager resemble a formal lecture that demands information processing and thus engages System 2 (as conjectured by Kahneman and Frederick 2002; Kahneman 2011). Second, a fund manager's presence alters the content: these sessions contain more technical and complex information, which requires deeper cognitive processing and activates System 2. Third, due to disclosure regulations, fund managers are required to discuss their fund characteristics truthfully, which contrasts with the cheerful persona exhibited by hosts and other guests during a livestream—the potential conflict between (grim) information delivered by a fund manager and general favorable impressions of other presenters in a livestream engages System 2 (as conjectured by Kahneman and Frederick 2002; Kahneman 2011).

Table 7, Panel A compares investor impressions, the amount and complexity of information in livestreams, the timing of livestreams, and fund manager characteristics with

and without a fund manager's presence. The results indicate that a fund manager's presence in a livestream has no significant effect on *Impression Score*, but significantly increases the amount and complexity of information shared in a livestream. This suggests that fund managers play an important role in increasing the information content and the degree of complexity of the information conveyed during livestreams. We further note that fund managers are more likely to join livestreams before the subscription period, indicating that their presence is not necessarily driven by difficulties in selling the fund. Moreover, we do not find that fund managers who present in livestreams differ from those who do not in their demographic characteristics. However, we note that managers who participate in livestreams are slightly more experienced (based on the Wilcoxon test) and have better past performance (based on the t-test) than managers who do not.

We estimate Equation (8) by replacing *Info* with *Manager Present* (an indicator variable for whether at least one manager joins a livestream). In Table 7, Panel B, column (1), the negative coefficient on *Impression Score* × *Manager Present* indicates that a fund manager's presence in a livestream attenuates the positive impact of investors' impressions on fund issuance performance. In column (2), when *Manager Present* takes a value of one, the net effect of *Impression Score* is −0.021 (0.292 − 0.313), and it is not significantly different from zero. These results suggest that the positive effect of investors' impressions on fund issuance performance disappears when a fund manager is present, consistent with the notion that such livestreams trigger investors' System 2 cognition, which overrides System 1. Interestingly, the coefficient on the standalone variable *Manager Present* is negative and significant at the 1% level, consistent with our setting, characterized by overly positive delivery features in livestreams and generally more material information provided by professional managers.

A fund manager's decision to participate in a livestream is a conscious choice, presumably intended to improve launch performance. However, our empirical evidence

suggests that manager presence actually decreases—rather than enhances—livestream effectiveness. Because managers are likely to select into livestreams when they expect they could provide a "boost" to fund subscription, this selection bias may lead us to underestimate the true negative impact of their involvement. In addition, Figure IA8 shows a decrease in manager participation over time, indicating that managers may have adjusted their participation decisions in livestreams as they recognize that their involvement may weaken, rather than strengthen, investor impressions. In summary, using an alternative measure of the amount and degree of complexity of information conveyed during livestreams, we continue to find that System 2 cognition offsets System 1 in influencing investor behaviour.

5.3.4. The impact of System 2 information processing: Fund type

We next examine how fund type moderates the interaction between System 1 and System 2 in influencing investor choices. Passive funds track well-defined benchmarks and have transparent, predictable portfolios, requiring little investor scrutiny. In contrast, active funds employ complex strategies that heighten informational demands and, in turn, are more likely to engage investors' deliberative reasoning (System 2) (Kahneman and Frederick 2002; Kahneman 2011).

We estimate Equation (8) separately for active and passive fund subsamples. Table 8 presents the results. For active funds in columns (1) and (3), the coefficient on *Impression Score* × *High Info* is negative and statistically significant. By contrast, the corresponding coefficient for passive funds in columns (2) and (4) is insignificant. These results indicate that when investors face greater informational complexity, they naturally slow down and engage in deliberative reasoning. Under such conditions, System 2 scrutiny overrides System 1's favorable impressions in shaping investment decisions.

6. Supplemental Analyses

In this section, we conduct additional analyses to explore the role of investor inattention caused by concurrent livestreaming events and to assess the robustness of our main findings.

6.1. The Role of Investor Distraction in Two-System Cognition

We examine whether the distraction experienced by investors plays a role in System 1 and System 2 cognition. Under the two-system view, System 1 is automatic and effortless, requiring few cognitive resources. In contrast, System 2 is slower and more effortful. It is an empirical question whether and how the distraction experienced by investors alters the interaction between investors' System 1 and System 2 in influencing their choices.

In our setting, concurrent livestreams compete for investors' limited attention and are distracting. Following Hirshleifer, Lim, and Teoh (2009), we sort sample livestreams by the number of concurrent fund livestreams on the Tiantian platform into quintiles, and set the indicator variable *High Distraction* to equal one if the number of concurrent livestreams is in the top quintile, and zero otherwise. We conduct our analysis using the following model:

$$Y_{i,t} = \beta_0 + \beta_1 Impression\ Score \times High\ Info \times\ High\ Distraction_{i,t} + \beta_2 Impression\ Score \times High\ Info_{i,t} + \beta_3 Impression\ Score \times\ High\ Distraction_{i,t} + \beta_4 High\ Info \times High\ Distraction_{i,t} + \beta_5 Impression\ Score_{i,t} + \beta_6 High\ Info_{i,t} + \beta_7 High\ Distraction_{i,t} + \gamma Controls_{i,t} + StyleFE + YearFE + TimeofDayFE + \varepsilon_{i,t}, \quad (9)$$

where the coefficient β_1 captures whether and how investor distraction moderates the interaction between System 1 and System 2 in influencing investor choices, β_3 captures whether and how investor distraction moderates the positive impact of System 1, and β_4 captures whether and how investor distraction moderates the role of System 2.

Table 9 presents the regression results for Equation (9). Across both specifications, we find that the coefficient on the standalone variable *Impression Score* is positive and significant. Moreover, the coefficient on the interaction term *Impression Score* × *High*

Distraction is significantly positive. These findings suggest that when investors are distracted by concurrent livestreams, the positive effect of favorable impressions is amplified. We further show that the coefficient on the standalone variable *High Info* is not statistically significant. Moreover, the coefficient on the interaction term *High Info* × *High Distraction* is significantly negative when the dependent variable is the amount of subscription. These findings suggest that when investors are distracted by concurrent livestreams, their System 2 cognition is negatively and significantly associated with the amount of fund issuance. Importantly, we find no significant moderating role of investor inattention in the interaction of System 1 and System 2 in affecting issuance outcomes.

Faced with distraction, investors instinctively offload cognitive effort by relying more on the automatic, heuristic processing of System 1, which requires little effort. Meanwhile, distraction accentuates the effect of System 2 on fund subscription. We conclude that distraction is a double-edged sword, increasing investors' reliance on both systems.

6.2. Robustness Checks

First, we reconstruct the summary measure *Impression Score* using *Vocal Positive*, *Verbal Positive*, *Visual Positive,* and *Body Motion* as the first principal component of PCA analysis. Table IA5 presents the results. The results are similar to those in Table 6.

Second, we measure livestream information content relative to a prospectus' Important Notices section rather than the Tiantian Fund Overview used earlier. The Important Notices section is concise and highlights key investor disclosures.[30] We then repeat the analyses of Sections 5.3.1 and 5.3.2 using this alternative measure of information in livestreams. Table IA6 presents the results. We find very similar results to those in Table 6.

Finally, to examine whether there are any temporal changes in the roles of System 1 and

[30] The Important Notices section appears at the front of the fund prospectus. It records the issuer's attestation to the authenticity, accuracy, and completeness of the prospectus and provides key investor disclosures. These notices help investors understand the product's features and make informed investment decisions.

System 2 during livestreams, we take three 10-minute slices at the beginning, middle, and end of a livestream. We compute *Impression Score* and *Info* from these three segments and re-estimate Equation (8). Table IA7 shows that the coefficients on the interaction term are negative and significant for the first 10-minute segment. The coefficients become marginally significant for the middle 10-minute segment. There is no significant effect of either System 1 or System 2 toward the end of a livestream. Several factors may be at play: increased cognitive overload, viewer fatigue, or viewers may have left. Future work is needed to differentiate among these possible explanations.

7. Conclusion

Guided by Kahneman's two-system framework of cognition, this paper is the first in finance to delineate the boundaries of intuitive thinking in a high-stakes, real-world setting. We construct and analyze a novel dataset of livestream promotional events linked to the initial offerings of mutual funds in China. By focusing on fund launches with limited prior information, our empirical design cleanly identifies how investors' intuitive thinking (System 1) and deliberative reasoning (System 2) interact in their decision-making.

We find that livestream presenters' vocal tone and facial expressiveness, which are processed by investors' System 1, significantly improve fund subscription outcomes, highlighting livestreaming as an effective promotional channel that captures attention and shifts investment decisions. However, information shared during livestreams activates investors' System 2. As more information is conveyed during livestreams, the effect of investors' favorable impressions on fund subscriptions disappears. This moderating role of System 2 emerges with more complex information, the presence of fund managers in livestreams, and in active fund launch livestreams. Overall, our paper presents novel evidence on the important interdependence of System 1 and System 2 cognition in affecting investor

choices, and our findings could serve as a basis for developing a positive theory of investor behavior.

Appendix
Variable Definitions

All continuous variables are winsorized at the 1st and 99th percentiles.

Variable	Definition and Construction
Issuance Performance	
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.
Livestream Characteristics	
Vocal Positive	Probability that the vocal emotion of presenters in a livestream is happiness or surprise by *Speech Emotion Recognition*. The unit of analysis is a speaker log. The algorithm assigns a probability of anger, disgust, fear, happiness, neutrality, sadness, and surprise to each speaker log. We take the average across the entire set of speaker logs in a livestream.
Visual Positive	Probability that the facial emotion of presenters in a livestream is happiness or surprise by DeepFace's emotion recognition Application Programming Interface (API). The algorithm assigns a probability of anger, disgust, fear, happiness, neutrality, sadness, and surprise to each presenter at one frame/sec. We take the average across presenters in a frame, and then the average across frames in a livestream.
Body Motion	Movement magnitude of presenters in a livestream. Use skeletal key points from *YOLO11* to construct the skeleton, then apply the optical flow method to calculate displacement magnitudes. The algorithm computes the measure at one frame/sec. We take the average across presenters in a frame, and then the average across frames in a livestream.
Impression Score	First principal component of *Vocal Positive*, *Visual Positive*, and *Body Motion*.
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 *Info* is in the top quintile, and zero otherwise.
Info Complex	Share of information content in a livestream related to the six complex topics that require interpretation by investment professionals, including macroeconomic policy analysis, industry analysis, stock-picking strategy, quantitative modeling, investment philosophy, and market trend analysis, relative to the Tiantian Fund Overview. See detailed variable construction in Section 4.3.
Info NonComplex	Share of informational in a livestream related to topics outside the six complex topics that are easy for retail investors to understand, including product features and trends, fund manager's professional background, investor education, index characteristics, investment objectives, investment scope, investment strategy, dividend policy, and risk-return characteristics, relative to the Tiantian Fund Overview. See detailed variable construction in Section 4.3.
Manager Present	Indicator variable that takes a value of one if at least one fund manager is present during the livestream, and zero otherwise.
High Distraction	Indicator variable that takes a value of one if the number of concurrent livestreams on the Tiantian platform is in the top quintile, and zero otherwise.
Verbal Positive	Probability that the sentiment of a livestream is positive by StructBERT. The unit of analysis is a speaker log. The algorithm assigns a probability of positive sentiment to each speaker log. We take the text-length-weighted average across the entire set of speaker logs in a livestream.
Image Clarity	Clarity score of a livestream by *OpenCV*. The algorithm computes the measure at one frame/sec. We take the average across frames in a livestream.
Beauty Score	Beauty score assigned by DeepFace's facial analysis API. The algorithm assigns a value between 0 and 5 (where 5 indicates the highest level of attractiveness) to each presenter at one frame/sec. We take the average across presenters in a frame, and then the average across frames in a livestream.
Number of Presenters	The number of presenters in a livestream.
Share of Female Presenters	The share of female presenters in a livestream.

Gift	Indicator variable that takes a value of one if during a livestream, any of the following is mentioned related to coupons, points, gifts, presents, prizes, red envelopes, lotteries, or gift packs, and zero otherwise.
LnLength	Natural logarithm of one plus the number of minutes that a livestream lasts.
LnLivetoClose	Natural logarithm of one plus the number of days from a fund's (first) launch livestream to the end of its subscription period.
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.
LnViewers	Natural logarithm of one plus the number of viewers of a livestream.
LnLikes	Natural logarithm of one plus the number of likes of a livestream.
Like Ratio	Ratio of the number of likes to the number of viewers.
Fund Characteristics	
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. They include non-index funds and enhanced index funds.
Fund Fees	Sum of annual fund management fee and custodian fee, expressed in percentage points (there is no load when purchasing new funds on the Tiantian Fund platform).
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 ten fund families based on assets under management in a year, and zero otherwise.
Fund Manager Characteristics	
Female Manager	Indicator variable that takes a value of one if at least one fund manager is a 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.

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Figure 1. A Snapshot of Fund Livestreams on the Tiantian Fund Platform

This figure presents a snapshot of the livestream format and additional details from the Tiantian Fund website.



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: conservative, aggressive, and enterprising.

Participant name & job title:
Huaqing Su (fund manager) || Yi Yi (host)

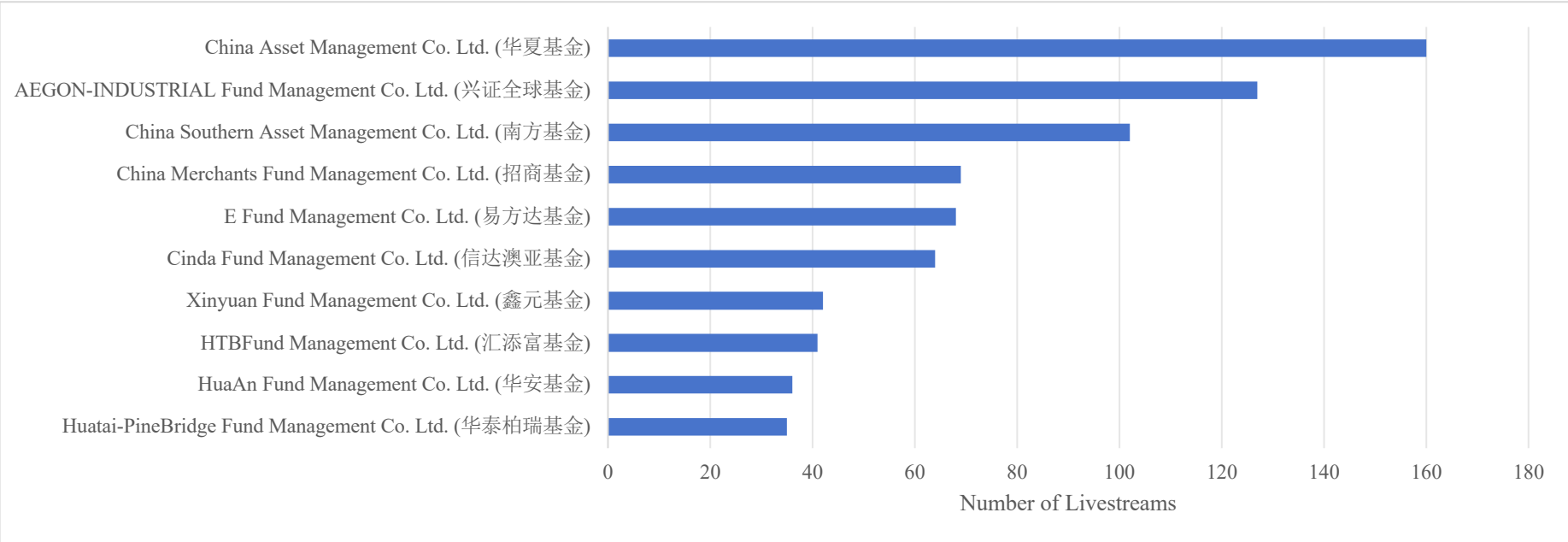
Fund family:
- Fullgoal Fund Management Co. Ltd.
- Established in 1999, one of China's "Old Ten" fund companies with a full suite of licenses.

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

Figure 2. 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 presents 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

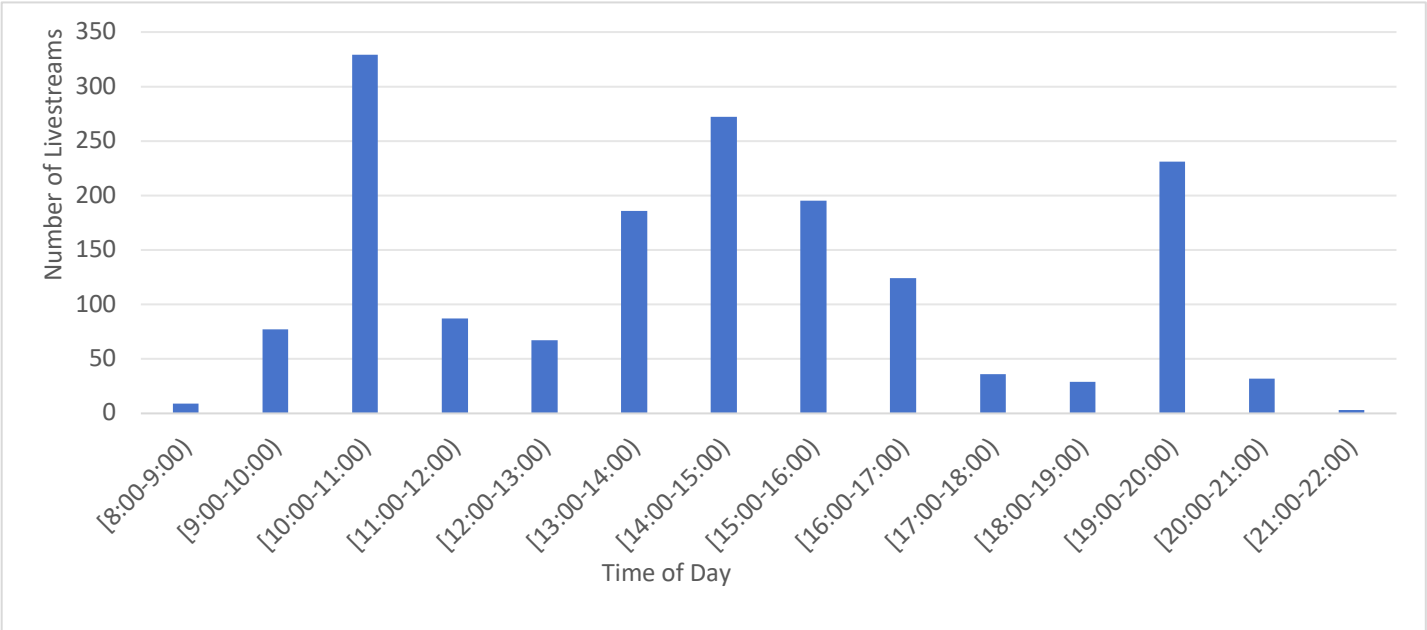
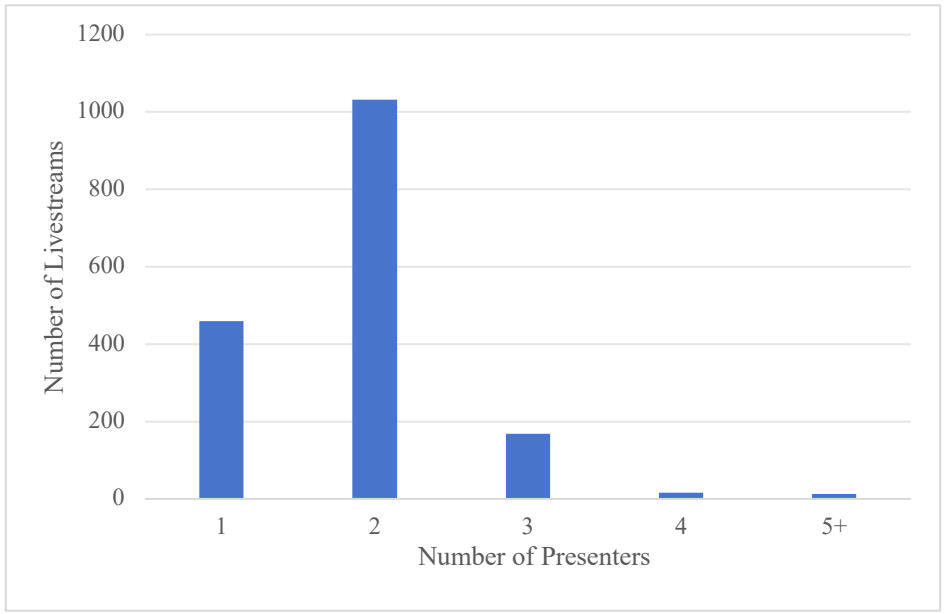


Figure 3. Fund Livestream Presenters

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

Panel A: Number of Presenters



Panel B: Fund Manager Participation

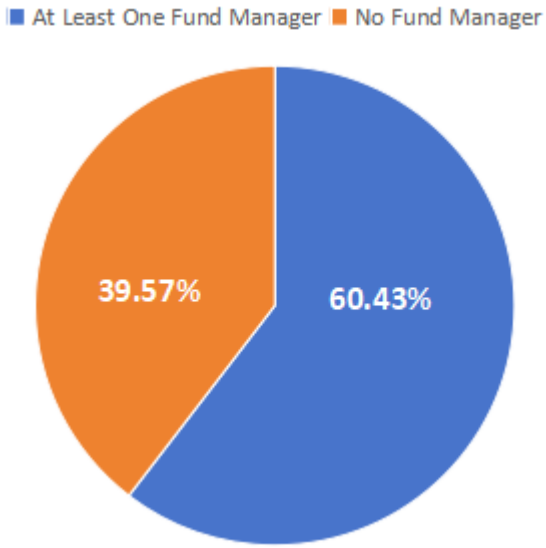


Figure 4. Flowchart for Constructing the Impression Measures

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*.

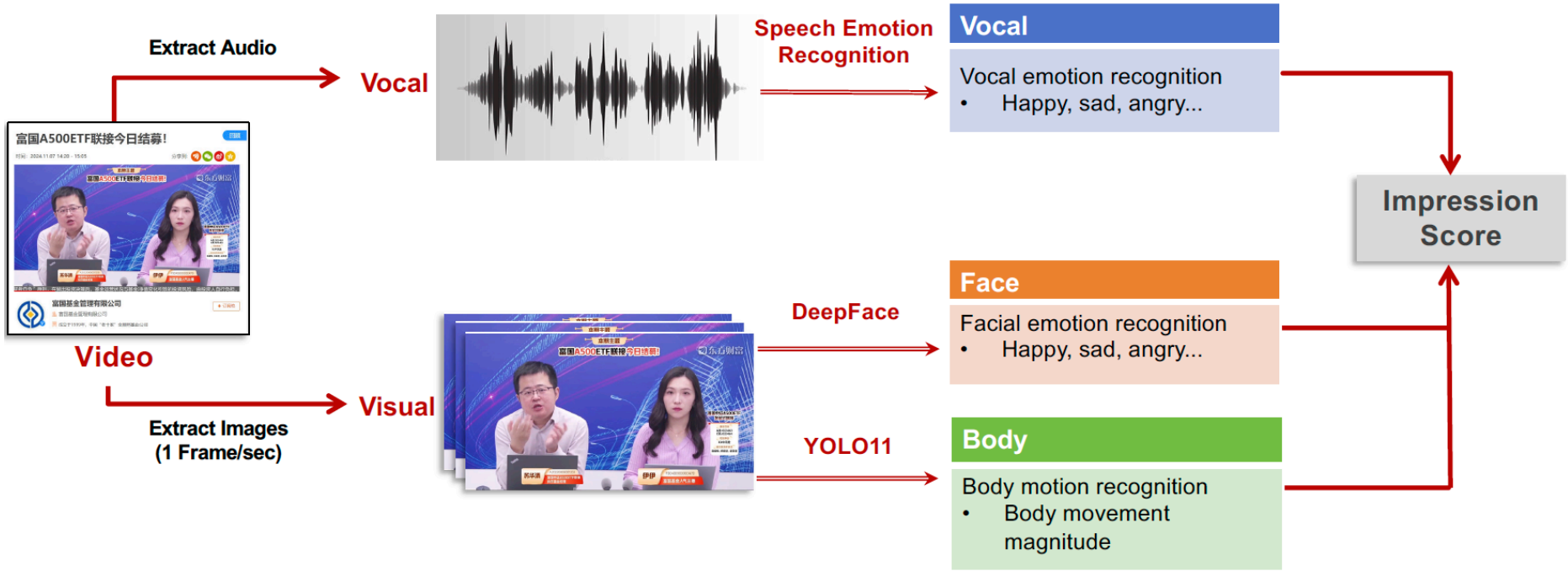


Figure 5. Flowchart for Constructing the Information Measure (*Info*)

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 ten topics not covered by the Fund Overview.

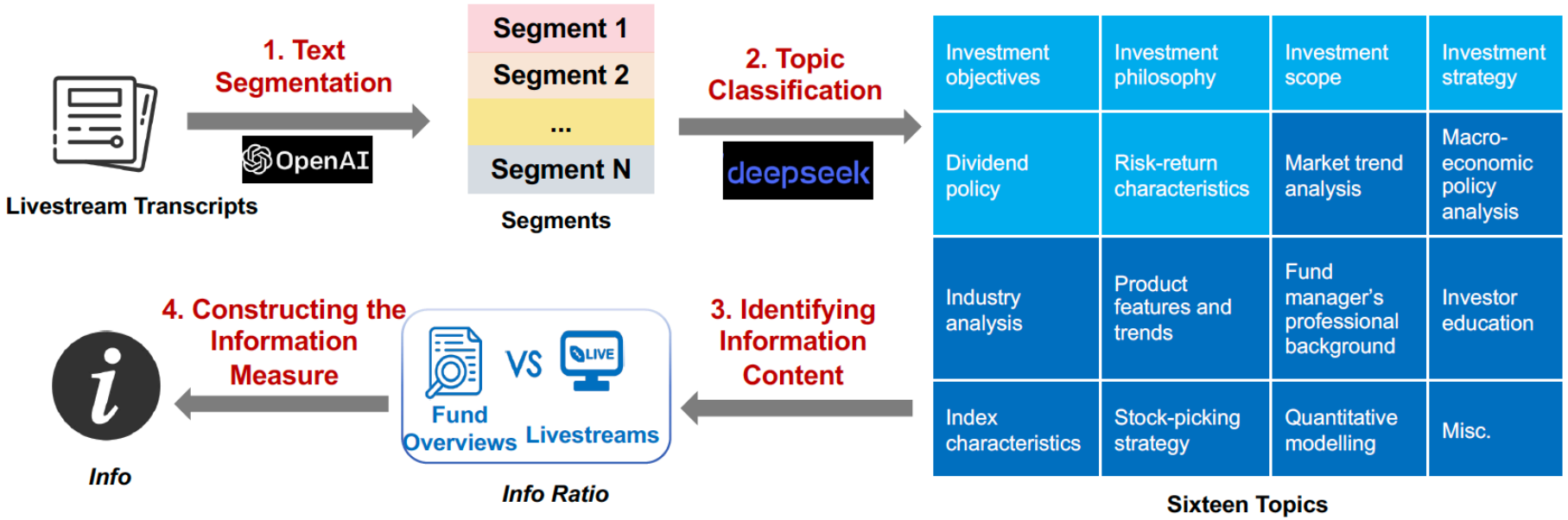


Table 1. Sample Formation

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.

		Remaining
Possible livestreams featuring new funds over the period from July 1, 2020 to May 31, 2024. 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.		2,786
Less observations not meeting these criteria:		
The livestream is verified to promote a new fund.	– 129	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 2. Summary Statistics

This table presents summary statistics. Our sample period is from July 1, 2020 to May 31, 2024. Panel A presents summary statistics for livestream, fund, and fund manager characteristics. Panel B presents summary statistics for the impression measures; the last two columns report the factor loadings and uniqueness of each measure from the principal component factor analysis used to construct *Impression Score*. Panel C presents summary statistics for the information measures. Variable definitions are provided in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fund, Fund Manager, and Livestream Characteristics

	Mean	*SD*	*P25*	*Median*	*P75*
Active Fund	0.835	0.371	1.000	1.000	1.000
Fund Fees	1.305	0.534	0.750	1.700	1.750
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
Verbal Positive	0.793	0.109	0.730	0.811	0.877
Image Clarity	1.688	1.145	0.835	1.503	2.228
Beauty Score	2.876	0.321	2.869	2.651	3.115
Number of Presenters	1.911	0.632	2.000	2.000	2.000
Share of Female Presenters	0.502	0.362	0.333	0.500	1.000
Gift	0.114	0.318	0.000	0.000	0.000
Number of Viewers	47,000	35,000	28,000	39,000	52,000
LnViewers	10.57	0.566	10.24	10.57	10.86
Video Length	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 B: Impression Measures (Unstandardized)

	Mean	*SD*	*P25*	*Median*	*P75*	*Loading*	*Uniqueness*
Vocal Positive	0.229	0.185	0.083	0.181	0.325	0.693	0.519
Visual Positive	0.080	0.076	0.025	0.056	0.111	0.737	0.456
Body Motion	0.944	0.716	0.520	0.749	1.123	0.503	0.747
Impression Score	-0.008	0.788	-0.587	-0.184	0.397		

Panel C: Information Measures (Unstandardized)

	Mean	*SD*	*P25*	*Median*	*P75*
Info	0.685	0.102	0.616	0.694	0.753
Info Complex	0.364	0.149	0.257	0.364	0.463
Info NonComplex	0.321	0.106	0.247	0.309	0.379

Table 3. Determinants of Funds Having a Launch Livestream

This table presents 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 presents linear probability regression estimates examining the association between fund and fund manager characteristics and the likelihood of hosting a launch livestream. Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Comparing Funds With a Launch Livestream to Those Without

	Livestream = 1		*Livestream = 0*		*Test of Difference*	
	Mean	*Median*	*Mean*	*Median*	*t-test*	*Wilcoxon text*
	(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***

Panel B: Explaining Whether a Fund Hosts a Launch Livestream

	Livestream Indicator		
	(1)	(2)	(3)
Active Fund	-0.065***	-0.062***	-0.042***
	(0.009)	(0.009)	(0.014)
Fund Fees	0.177***	0.177***	0.123***
	(0.007)	(0.007)	(0.016)
State-owned Fund Family	0.054***	0.051***	0.050***
	(0.007)	(0.007)	(0.007)
Large Fund Family	0.009	0.010	0.012
	(0.008)	(0.008)	(0.008)
Female Manager	0.008	0.006	0.010
	(0.008)	(0.008)	(0.008)
Rookie Manager	0.019	0.032	0.013
	(0.039)	(0.039)	(0.039)
Highest Degree	-0.009	-0.009	-0.006
	(0.010)	(0.010)	(0.010)
Top2 University	0.011	0.015	0.014
	(0.011)	(0.011)	(0.011)
Manager Experience	-0.015	-0.006	-0.004
	(0.013)	(0.013)	(0.013)
Manager Past Performance	-0.010**	0.002	0.003
	(0.004)	(0.006)	(0.007)

Style FE	NO	NO	YES
Year FE	NO	YES	YES
Observations	9,855	9,855	9,855
Adjusted R^2	0.069	0.091	0.109

Table 4. Fund Livestream and Issuance Performance

This table presents multiple regression estimates examining 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 effect of livestreaming on 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) present 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) present 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,* and *Manager Past Performance*. Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Whether Hosting a Launch Livestream and Fund Issuance Performance

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Livestream Indicator	0.823***		0.562***	
	(0.059)		(0.057)	
Number of Livestreams		0.253***		0.182***
		(0.027)		(0.019)
Active Fund	-0.589***	-0.605***	-0.637***	-0.644***
	(0.113)	(0.113)	(0.174)	(0.174)
Fund Fees	1.312***	1.352***	0.956***	0.979***
	(0.127)	(0.127)	(0.146)	(0.146)
State-owned Fund Family	-0.018	-0.006	0.198***	0.204***
	(0.053)	(0.053)	(0.062)	(0.062)
Large Fund Family	0.595***	0.609***	0.260***	0.271***
	(0.054)	(0.054)	(0.059)	(0.059)
Female Manager	-0.003	-0.004	-0.013	-0.014
	(0.058)	(0.058)	(0.071)	(0.071)
Rookie Manager	1.519***	1.588***	1.689***	1.738***
	(0.305)	(0.306)	(0.342)	(0.342)
Highest Degree	-0.025	-0.022	-0.067	-0.064
	(0.067)	(0.067)	(0.075)	(0.075)
Top2 University	-0.120*	-0.124*	-0.051	-0.055
	(0.069)	(0.069)	(0.073)	(0.073)
Manager Experience	0.818***	0.834***	0.963***	0.974***
	(0.099)	(0.099)	(0.114)	(0.114)
Manager Past Performance	0.224	0.223	0.275**	0.275**
	(0.163)	(0.165)	(0.121)	(0.122)
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	5,861	5,861	9,855	9,855
Adjusted R^2	0.474	0.474	0.132	0.132

Panel B: Number of Livestream Viewers and Fund Issuance Performance

	LnSubscriptions	*LnAmount*
	(1)	(2)
LnViewers	0.214**	0.087
	(0.091)	(0.090)
Active Fund	-0.517*	-0.658**
	(0.288)	(0.325)
Fund Fees	0.388	0.212

	(0.290)	(0.308)
State-owned Fund Family	0.110	0.264**
	(0.123)	(0.112)
Large Fund Family	0.479***	0.138
	(0.109)	(0.111)
Female Manager	0.254**	0.124
	(0.124)	(0.119)
Rookie Manager	-0.709***	-0.181
	(0.257)	(0.257)
Highest Degree	-0.250*	-0.182
	(0.134)	(0.127)
Top2 University	0.043	-0.055
	(0.127)	(0.121)
Manager Experience	0.242	0.865***
	(0.229)	(0.251)
Manager Past Performance	1.788***	1.684***
	(0.412)	(0.346)
Style FE	YES	YES
Year FE	YES	YES
Observations	783	1,422
Adjusted R^2	0.360	0.233

Table 5. Investor Impressions and Fund Issuance Performance

This table presents multiple regression estimates examining the association between investors' impressions and fund issuance performance. Our sample period is from July 1, 2020 to May 31, 2024. Panel A presents the results using the number of subscriptions as the dependent variable. Panel B presents 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,* and *Manager Past Performance.* Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Investor Impressions and Number of Fund Subscriptions

	LnSubscriptions			
	(1)	(2)	(3)	(4)
Vocal Positive	0.167***			
	(0.049)			
Visual Positive		0.108**		
		(0.049)		
Body Motion			0.049	
			(0.044)	
Impression Score				0.173***
				(0.046)
Verbal Positive	0.057	0.087	0.076	0.082
	(0.053)	(0.054)	(0.053)	(0.054)
Image Clarity	0.070	0.080	0.088*	0.078
	(0.052)	(0.053)	(0.053)	(0.053)
Beauty Score	-0.057	-0.091	-0.039	-0.115
	(0.157)	(0.160)	(0.157)	(0.158)
Number of Presenters	-0.123	-0.121	-0.109	-0.142*
	(0.083)	(0.084)	(0.084)	(0.084)
Share of Female Presenters	0.120	0.087	0.129	0.082
	(0.142)	(0.142)	(0.142)	(0.140)
Gift	-0.113	-0.104	-0.105	-0.105
	(0.164)	(0.162)	(0.162)	(0.161)
LnViewers	0.197**	0.223**	0.214**	0.205**
	(0.097)	(0.097)	(0.097)	(0.096)
LnLength	0.120	0.090	0.124	0.123
	(0.195)	(0.193)	(0.193)	(0.193)
LnLivetoClose	-0.016	-0.022	-0.011	-0.024
	(0.053)	(0.053)	(0.053)	(0.053)
Active Fund	-0.628**	-0.597**	-0.599**	-0.618**
	(0.292)	(0.297)	(0.297)	(0.295)
Fund Fees	0.395	0.394	0.407	0.398
	(0.292)	(0.299)	(0.298)	(0.296)
State-owned Fund Family	0.151	0.110	0.117	0.118
	(0.124)	(0.125)	(0.125)	(0.124)
Large Fund Family	0.401***	0.466***	0.464***	0.415***
	(0.122)	(0.120)	(0.121)	(0.121)
Female Manager	0.192	0.223*	0.215*	0.191
	(0.129)	(0.128)	(0.130)	(0.129)
Rookie Manager	1.507	1.271	1.329	1.318
	(0.942)	(0.945)	(0.947)	(0.942)
Highest Degree	-0.245*	-0.262*	-0.259*	-0.270**
	(0.135)	(0.135)	(0.134)	(0.134)
Top2 University	0.050	0.073	0.078	0.052
	(0.127)	(0.128)	(0.129)	(0.127)

Manager Experience	1.709**	1.532**	1.583**	1.549**
	(0.696)	(0.698)	(0.700)	(0.696)
Manager Past Performance	1.836***	1.852***	1.890***	1.837***
	(0.424)	(0.426)	(0.430)	(0.423)
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time of Day FE	YES	YES	YES	YES
Observations	783	783	783	783
Adjusted R^2	0.362	0.357	0.353	0.363

Panel B: Investor Impressions and Fund Issuance Amount

	LnAmount			
	(1)	(2)	(3)	(4)
Vocal Positive	0.130***			
	(0.045)			
Visual Positive		0.054		
		(0.046)		
Body Motion			0.025	
			(0.042)	
Impression Score				0.232**
				(0.095)
Verbal Positive	0.016	0.034	0.029	0.034
	(0.049)	(0.049)	(0.049)	(0.049)
Image Clarity	0.161***	0.171***	0.175***	0.169***
	(0.050)	(0.049)	(0.049)	(0.049)
Beauty Score	-0.151	-0.159	-0.133	-0.185
	(0.150)	(0.153)	(0.149)	(0.153)
Number of Presenters	-0.058	-0.048	-0.042	-0.067
	(0.081)	(0.081)	(0.081)	(0.081)
Share of Female Presenters	0.054	0.041	0.059	0.029
	(0.133)	(0.134)	(0.134)	(0.133)
Gift	-0.018	-0.009	-0.010	-0.009
	(0.152)	(0.152)	(0.152)	(0.151)
LnViewers	0.124	0.144	0.140	0.134
	(0.095)	(0.094)	(0.094)	(0.094)
LnLength	0.119	0.094	0.110	0.117
	(0.190)	(0.190)	(0.191)	(0.191)
LnLivetoClose	-0.054	-0.056	-0.051	-0.058
	(0.051)	(0.051)	(0.051)	(0.051)
Active Fund	-0.719**	-0.696**	-0.700**	-0.715**
	(0.328)	(0.330)	(0.330)	(0.330)
Fund Fees	0.206	0.210	0.217	0.213
	(0.310)	(0.313)	(0.313)	(0.313)
State-owned Fund Family	0.290**	0.263**	0.266**	0.265**
	(0.113)	(0.112)	(0.113)	(0.112)
Large Fund Family	0.022	0.070	0.068	0.039
	(0.118)	(0.118)	(0.118)	(0.118)
Female Manager	0.080	0.107	0.102	0.087
	(0.124)	(0.125)	(0.125)	(0.125)
Rookie Manager	2.016**	1.842**	1.881**	1.872**
	(0.896)	(0.896)	(0.896)	(0.896)
Highest Degree	-0.167	-0.177	-0.174	-0.185
	(0.126)	(0.126)	(0.126)	(0.126)
Top2 University	-0.031	-0.010	-0.008	-0.024
	(0.119)	(0.120)	(0.120)	(0.120)

Manager Experience	2.346***	2.220***	2.254***	2.228***
	(0.659)	(0.660)	(0.660)	(0.660)
Manager Past Performance	1.751***	1.777***	1.793***	1.767***
	(0.351)	(0.351)	(0.351)	(0.350)
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time of Day FE	YES	YES	YES	YES
Observations	1,422	1,422	1,422	1,422
Adjusted R^2	0.247	0.244	0.243	0.246

Table 6. Investor Impressions, Information, and Fund Issuance Performance

This table presents multiple regression estimates examining 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 separately examines the effects of investors' impressions and information processing on fund issuance performance. Panel B examines whether information conveyed during the livestream modifies the positive effect of investors' impressions on fund issuance outcomes. Columns (1) and (2) present the results using the number of subscriptions as the dependent variable. Columns (3) and (4) present the results using the total subscription amount as the dependent variable. Panel C distinguishes between complex information—topics requiring interpretation by professionals like fund managers and analysts—and non-complex information which can be easily understood by retail investors. Columns (1) to (3) present the results using the number of subscriptions as the dependent variable. Columns (4) to (6) present 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,* and *Manager Past Performance.* Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Investor Impressions, Information, and Fund Issuance Performance

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Impression Score	0.168***	0.172***	0.107**	0.111**
	(0.046)	(0.046)	(0.045)	(0.045)
Info	-0.061		-0.051	
	(0.053)		(0.051)	
High Info		-0.181		-0.089
		(0.134)		(0.130)
Verbal Positive	0.081	0.084	0.033	0.035
	(0.053)	(0.053)	(0.049)	(0.049)
Image Clarity	0.078	0.080	0.170***	0.170***
	(0.053)	(0.053)	(0.049)	(0.049)
Beauty Score	-0.118	-0.128	-0.187	-0.191
	(0.158)	(0.158)	(0.153)	(0.153)
Number of Presenters	-0.130	-0.142*	-0.057	-0.067
	(0.085)	(0.084)	(0.082)	(0.081)
Share of Female Presenters	0.082	0.089	0.028	0.033
	(0.141)	(0.141)	(0.133)	(0.133)
Gift	-0.107	-0.108	-0.009	-0.010
	(0.161)	(0.160)	(0.151)	(0.151)
LnViewers	0.203**	0.206**	0.132	0.135
	(0.096)	(0.096)	(0.094)	(0.094)
LnLength	0.133	0.123	0.126	0.118
	(0.193)	(0.193)	(0.191)	(0.191)
LnLivetoClose	-0.025	-0.029	-0.059	-0.061
	(0.053)	(0.052)	(0.051)	(0.051)
Active Fund	-0.641**	-0.646**	-0.736**	-0.732**
	(0.297)	(0.296)	(0.331)	(0.332)
Fund Fees	0.395	0.395	0.213	0.214
	(0.297)	(0.295)	(0.314)	(0.314)
State-owned Fund Family	0.114	0.121	0.261**	0.265**
	(0.124)	(0.124)	(0.113)	(0.112)
Large Fund Family	0.412***	0.406***	0.038	0.037
	(0.121)	(0.121)	(0.118)	(0.118)
Female Manager	0.190	0.198	0.086	0.090
	(0.130)	(0.130)	(0.125)	(0.125)
Rookie Manager	1.381	1.332	1.916**	1.874**

	(0.947)	(0.937)	(0.898)	(0.895)
Highest Degree	-0.277**	-0.284**	-0.191	-0.192
	(0.134)	(0.134)	(0.126)	(0.126)
Top2 University	0.050	0.047	-0.026	-0.025
	(0.127)	(0.127)	(0.120)	(0.120)
Manager Experience	1.600**	1.560**	2.263***	2.229***
	(0.700)	(0.692)	(0.661)	(0.660)
Manager Past Performance	1.816***	1.791***	1.749***	1.743***
	(0.423)	(0.423)	(0.350)	(0.350)
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	0.364	0.364	0.246	0.246

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

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.122***		-0.118***	
	(0.038)		(0.042)	
Impression Score × High Info		-0.262**		-0.223**
		(0.104)		(0.106)
Impression Score	0.164***	0.230***	0.101**	0.157***
	(0.045)	(0.051)	(0.045)	(0.051)
Info	-0.061		-0.047	
	(0.051)		(0.051)	
High Info		-0.208		-0.106
		(0.131)		(0.129)
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	0.368	0.249	0.247

Panel C: Interaction Between Investor Impressions and Complex (NonComplex) Information and Fund Issuance Performance

	LnSubscriptions			*LnAmount*		
	(1)	(2)	(3)	(4)	(5)	(6)
Impression Score × Info Complex	-0.142***		-0.188***	-0.160***		-0.174***
	(0.039)		(0.055)	(0.043)		(0.062)
Impression Score × Info NonComplex		0.071	-0.063		0.115**	-0.016
		(0.051)	(0.065)		(0.052)	(0.071)
Impression Score	0.144***	0.156***	0.144***	0.087*	0.098**	0.086*
	(0.045)	(0.046)	(0.045)	(0.045)	(0.046)	(0.045)
Info Complex	-0.169***		-0.102	-0.160***		-0.079
	(0.061)		(0.074)	(0.056)		(0.074)
Info NonComplex		0.159**	0.099		0.168***	0.122
		(0.063)	(0.077)		(0.058)	(0.077)
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	0.376	0.370	0.377	0.256	0.253	0.256

Table 7. Investor Impressions, Information, and Fund Issuance Performance: The Role of Fund Manager Presence in Livestreams

This table presents multiple regression estimates examining the association between livestream characteristics and fund issuance performance, with a focus on whether a fund manager is present during the livestream. Our sample period is from July 1, 2020 to May 31, 2024. Panel A conducts two-sample t-tests and Wilcoxon tests comparing investor impressions, the amount and complexity of information content in a livestream, timing of livestreams, and fund manager characteristics with and without a fund manager's presence. Panel B presents the regression results, with a focus on the role of fund manager participation during her 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,* and *Manager Past Performance*, and are omitted for brevity. Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Comparing Impression, Information, Timing of Livestreams, and Fund Manager Characteristics With Fund Manager Presence to Those Without (Unstandardized)

	Manager Present = 1		*Manager Present = 0*		*Test of Difference*	
	Mean	*Median*	*Mean*	*Median*	*t-test*	*Wilcoxon text*
	(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
Impression Score	0.007	-0.095	-0.021	-0.123	0.028	0.028
Info	0.698	0.708	0.670	0.678	0.028***	0.030***
Info Complex	0.387	0.387	0.314	0.303	0.073***	0.084***
Before Subscription	0.254	0.000	0.208	0.000	0.045**	0.000
Female Manager	0.227	0.000	0.260	0.000	-0.033	0.000
Rookie Manager	0.089	0.000	0.077	0.000	0.012	0.000
Highest Degree	2.070	2.000	2.075	2.000	-0.005	0.000
Top2 University	0.165	0.000	0.161	0.000	0.004	0.000
Manager Experience	1.218	1.311	1.218	1.306	0.000	0.005
Manager Past Performance	0.087	0.046	0.064	0.038	0.022*	0.008

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

	LnSubscriptions	*LnAmount*
	(1)	(2)
Impression Score × Manager Present	-0.157*	-0.313***
	(0.087)	(0.087)
Impression Score	0.259***	0.292***
	(0.066)	(0.067)
Manager Present	-0.383***	-0.396***
	(0.128)	(0.125)
Controls	YES	YES
Style FE	YES	YES
Year FE	YES	YES
Time of Day FE	YES	YES
Observations	783	1,422
Adjusted R^2	0.372	0.256

Table 8. Investor Impressions, Information, and Fund Issuance Performance: By Fund Type

This table replicates the analysis in Panel B of Table 6, using sub-samples of different fund types: active funds 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,* and *Manager Past Performance*, and are omitted for brevity. Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	LnSubscriptions		*LnAmount*	
	Active	Passive	Active	Passive
	(1)	(2)	(3)	(4)
Impression Score × High Info	-0.301***	-0.063	-0.312***	0.362
	(0.109)	(0.279)	(0.112)	(0.318)
Impression Score	0.209***	0.249	0.138***	0.042
	(0.053)	(0.177)	(0.052)	(0.174)
High Info	-0.203	-0.140	-0.180	0.016
	(0.151)	(0.257)	(0.145)	(0.244)
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	0.419	0.260	0.243	0.449

Table 9. Investor Impressions and Fund Issuance Performance

This table presents multiple regression estimates examining the association between investor attention, investors' impressions, information processing, and fund issuance performance. Our sample period is from July 1, 2020 to May 31, 2024. We examine whether investors' distraction caused by concurrent livestreams alters the effects of their impressions and information processing on fund issuance outcomes. Columns (1) presents the results using the number of subscriptions as the dependent variable. Column (2) presents 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,* and *Manager Past Performance.* Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

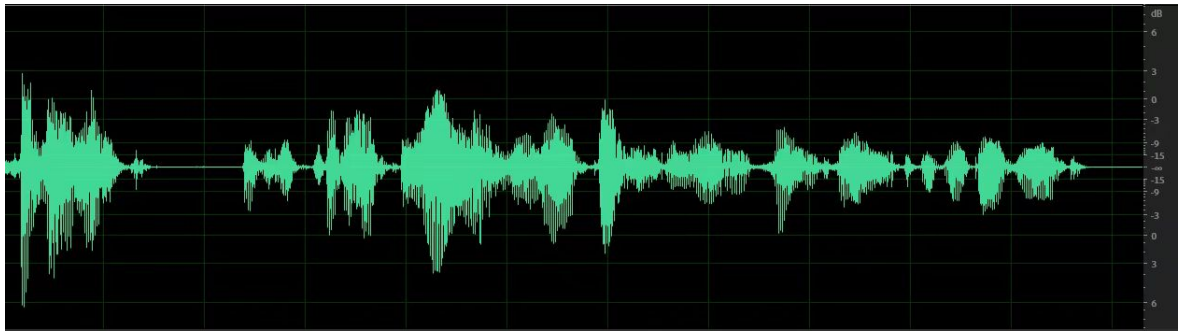
	LnSubscriptions	*LnAmount*
	(1)	(2)
Impression Score × High Info × High Distraction	-0.366	-0.247
	(0.245)	(0.241)
Impression Score × High Info	-0.183	-0.170
	(0.121)	(0.121)
Impression Score × High Distraction	0.246**	0.228**
	(0.115)	(0.116)
High Info × High Distraction	-0.196	-0.597**
	(0.299)	(0.287)
Impression Score	0.181***	0.111*
	(0.057)	(0.058)
High Info	-0.146	0.040
	(0.142)	(0.142)
High Distraction	-0.139	0.048
	(0.139)	(0.126)
Controls	YES	YES
Style FE	YES	YES
Year FE	YES	YES
Observations	783	1,422
Adjusted R^2	0.370	0.250

Online Appendix for "The Two-System View of Cognition and Investor Choice"

Figure IA1. 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 IA2. 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 IA3. 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 IA4. 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

首先第一是汇聚了优质的龙头。然后第二是行业均衡不偏科。第三点是历史收益优异。第四点，长期的表现优于同类的指数。第五个是聪明钱的浓度高，第六第七是成长速度快和盈利能力强。那么我们认为投资做长期的投资，要买好公司，买龙头，才能够更好的去分享到时代发展的红利。

Firstly, it gathers high-quality leading companies. Secondly, it maintains industry balance without favoring any particular sector. Thirdly, it has an excellent historical performance. Fourthly, its long-run performance surpasses that of similar indices. Fifthly, it has a high concentration of "smart money". Sixth and seventh, it features rapid growth and strong profitability. We believe that for long-run investment, one should invest in good companies and leaders to better share in the dividends of era development.

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 current valuation of central state-owned enterprises (SOEs) is indeed in a state of chronic undervaluation. Investors who pay attention to relevant research reports or follow Yinhua's official account may find related materials for reference, which include some discussions on this topic. In fact, over an extended period, the valuation of central SOEs has consistently been undervalued. It is possible that the valuation of central SOEs is chronically lower than that of local state-owned enterprises.

Figure IA5. 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 IA6. Complex and NonComplex 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。

For the new energy sector, I mainly focus on innovation and application. In terms of innovation, I'm following the progress of the 4680 battery in lithium battery technology, which may reach an inflection point this year. This is a battery technology path led by Tesla. Last year, its planned capacity reached about 4 GWh, already a significant scale. Whether capacity can advance to the 30 GWh level this year and further approach 100 GWh next year is something to watch. On March 1, Musk is expected to speak at the Investment Day event at the Texas factory. Earlier reports mentioned Tesla's "Master Plan Part 3," and there is speculation about its content. My personal prediction is that it may center on the 4680 battery combined with energy storage, possibly accompanied by a low-priced model around 100,000 yuan. I believe this will create a multiplier effect—once battery costs come down, energy storage applications will also expand significantly.

Panel B: Example of NonComplex 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。

There are several index systems we currently use to describe market styles. The first is the broad-based index system. For example, the SSE 50 represents the 50 largest stocks by market capitalization on the Shanghai Stock Exchange, while the CSI 300 covers the 300 largest stocks across both the Shanghai and Shenzhen stock exchanges. These are typically defined as large-cap style indices. Moving further within the broad-based indices, we have the CSI 500 and the CSI 1000. The CSI 500 includes the top 500 stocks by market capitalization after excluding those already part of the CSI 300. The CSI 1000, in turn, covers the next 1,000 largest stocks after excluding both the CSI 300 and CSI 500 constituents.

Figure IA7. Flowchart for Constructing the Complex and Non-complex Information Measures (*Info Complex* and *Info NonComplex*)

This figure presents a flowchart illustrating the process of constructing the complex and non-complex information measures. Topics in orange refer to the six 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.

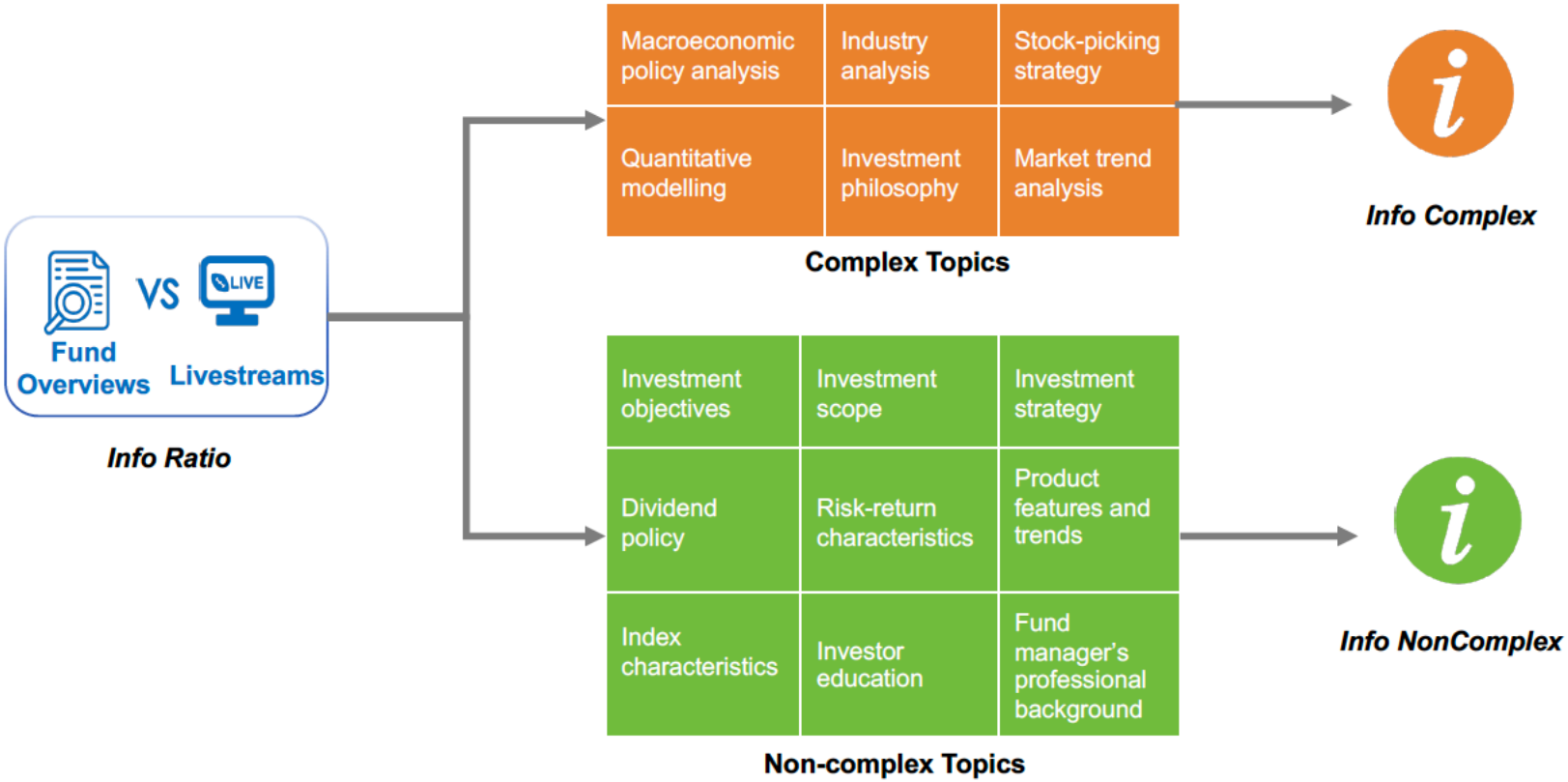


Figure IA8. Fund Manager Participation in Livestreaming Over Time

This figure presents 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. Implementation Details

We provide more details on the steps to perform video analysis used in our paper. This appendix proceeds with a more practical approach with information on our code structure, key functions, and notes on important steps.

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 constructinhg 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[videoid] = 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] {videoid} - {cat}: {e}")
                result_row[cat + "_match"] = None

        result_dict[videoid] = result_row
```

```
# Matching complete, results written to the target column
...
```

Table IA2. Validating Our Investor Impression Measures

This table presents multiple regression estimates examining the association between investors' impressions and reactions. Our sample period is from July 1, 2020 to May 31, 2024. Panel A presents the results using the number of likes as the dependent variable. Panel B presents the results using the ratio of likes to viewers 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,* and *Manager Past Performance*, and are omitted for brevity. Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Investor Impressions and Number of Likes

	LnLikes			
	(1)	(2)	(3)	(4)
Vocal Positive	0.000			
	(0.010)			
Visual Positive		0.024**		
		(0.011)		
Body Motion			0.014	
			(0.013)	
Impression Score				0.021*
				(0.011)
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	1,422	1,422	1,422	1,422
Adjusted R^2	0.842	0.842	0.842	0.842

Panel B: Investor Impressions and Like Ratio

	Like Ratio			
	(1)	(2)	(3)	(4)
Vocal Positive	0.001			
	(0.002)			
Visual Positive		0.005**		
		(0.002)		
Body Motion			0.003*	
			(0.002)	
Impression Score				0.005**
				(0.002)
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	1,412	1,412	1,412	1,412
Adjusted R^2	0.737	0.738	0.738	0.738

Table IA3. Correlation Matrix

This table presents 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	0.167***	0.101***	1						
(4) Vocal Positive	0.074**	0.037	0.737***	1					
(5) Visual Positive	0.186***	0.110***	0.693***	0.209***	1				
(6) Body Motion	0.061*	0.052*	0.503***	0.118***	0.076***	1			
(7) Info	0.002	-0.066**	-0.089***	-0.094***	-0.033	-0.042	1		
(8) Info Complex	-0.061*	-0.108***	-0.071***	-0.068**	-0.021	-0.052**	0.702***	1	
(9) Info NonComplex	0.085**	0.088***	0.015	0.005	-0.001	0.032	-0.025	-0.729***	1

Table IA4. Investor Impressions and Long-term Performance

This table presents multiple regression estimates examining the association between investor impressions and 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,* and *Manager Past Performance*, and are omitted for brevity. Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Return 3m	*Return 6m*	*Return 12m*
	(1)	(2)	(3)
Impression Score	-0.005**	-0.004*	-0.003
	(0.002)	(0.002)	(0.003)
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	0.750	0.104	0.972

Table IA5. Investor Impressions, Information, and Fund Issuance Performance: Using Alternative Impression Measures

This table replicates the analysis in Table 6, using alternative impression measures by including *Verbal Positive, Vocal Positive, Visual Positive, and Body Motion* in the PCA analysis. Our sample period is from July 1, 2020 to May 31, 2024. Panel A separately examines the effects of investors' impressions and information processing on fund issuance performance. Panel B examines whether information conveyed during the livestream modifies the positive effect of investors' impressions on fund issuance outcomes. Columns (1) and (2) present the results using the number of subscriptions as the dependent variable. Columns (3) and (4) present the results using the total subscription amount as the dependent variable. Panel C distinguishes between complex information—topics requiring interpretation by professionals like fund managers and analysts—and non-complex information which can be easily understood by retail investors. Columns (1) to (3) present the results using the number of subscriptions as the dependent variable. Columns (4) to (6) present 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,* and *Manager Past Performance,* and are omitted for brevity. Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Investor Impressions, Information, and Fund Issuance Performance

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Impression Score	0.192***	0.197***	0.122**	0.126***
	(0.054)	(0.054)	(0.048)	(0.048)
Info	-0.067		-0.055	
	(0.053)		(0.051)	
High Info		-0.195		-0.099
		(0.134)		(0.130)
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	0.364	0.365	0.247	0.247

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

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.139***		-0.109**	
	(0.042)		(0.044)	
Impression Score × High Info		-0.305***		-0.166
		(0.114)		(0.111)
Impression Score	0.189***	0.270***	0.118**	0.163***
	(0.053)	(0.061)	(0.048)	(0.055)
Info	-0.068		-0.052	
	(0.051)		(0.051)	
High Info		-0.194		-0.095
		(0.131)		(0.130)
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	0.371	0.370	0.249	0.247

Panel C: Interaction Between Investor Impressions and Complex (NonComplex) Information and Fund Issuance Performance

	LnSubscriptions			*LnAmount*		
	(1)	(2)	(3)	(4)	(5)	(6)
Impression Score × Info Complex	-0.131***		-0.209***	-0.130***		-0.160**
	(0.047)		(0.060)	(0.047)		(0.064)
Impression Score × Info NonComplex		0.043	-0.105		0.083	-0.035
		(0.054)	(0.067)		(0.053)	(0.070)
Impression Score	0.184***	0.189***	0.182***	0.117**	0.122**	0.115**
	(0.053)	(0.054)	(0.053)	(0.048)	(0.049)	(0.049)
Info Complex	-0.173***		-0.103	-0.160***		-0.076
	(0.060)		(0.073)	(0.055)		(0.074)
Info NonComplex		0.168***	0.101		0.175***	0.124
		(0.062)	(0.076)		(0.057)	(0.076)
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	0.376	0.370	0.378	0.254	0.252	0.254

Table IA6. Investor Impressions, Information, and Fund Issuance Performance: Using Alternative Information Measures

This table replicates the analysis in Table 6, using alternative information measures by comparing livestream transcripts with the Section of Important Information of fund prospectuses. Our sample period is from July 1, 2020 to May 31, 2024. fund issuance performance. Panel A separately examines the effects of investors' impressions and information processing on fund issuance performance. Panel B examines whether information conveyed during the livestream modifies the positive effect of investors' impressions on fund issuance outcomes. Columns (1) and (2) present the results using the number of subscriptions as the dependent variable. Columns (3) and (4) present the results using the total subscription amount as the dependent variable. *Info* is the share of information content in a livestream relative to the Tiantian Fund Overview. Panel C distinguishes between complex information—topics requiring interpretation by professionals like fund managers and analysts—and non-complex information which can be easily understood by retail investors. Columns (1) to (3) present the results using the number of subscriptions as the dependent variable. Columns (4) to (6) present 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,* and *Manager Past Performance,* and are omitted for brevity. Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Investor Impressions, Information, and Fund Issuance Performance

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Impression Score	0.161***	0.162***	0.106**	0.109**
	(0.047)	(0.047)	(0.046)	(0.046)
Info	-0.118**		-0.138***	
	(0.052)		(0.049)	
High Info		-0.307**		-0.225**
		(0.125)		(0.113)
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	0.363	0.363	0.252	0.249

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

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Impression Score × Info	-0.056		-0.084**	
	(0.039)		(0.040)	
Impression Score × High Info		-0.123		-0.239**
		(0.118)		(0.107)
Impression Score	0.158***	0.183***	0.102**	0.152***
	(0.047)	(0.052)	(0.046)	(0.051)
Info	-0.120**		-0.137***	
	(0.052)		(0.049)	
High Info		-0.319**		-0.245**
		(0.126)		(0.114)
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	0.363	0.363	0.253	0.251

Panel C: Interaction Between Investor Impressions and Complex (NonComplex) Information and Fund Issuance Performance

	LnSubscriptions			*LnAmount*		
	(1)	(2)	(3)	(4)	(5)	(6)
Impression Score × Info Complex	-0.146***		-0.102**	-0.151***		-0.123***
	(0.038)		(0.043)	(0.041)		(0.046)
Impression Score × Info NonComplex		0.137***	0.088		0.110**	0.051
		(0.048)	(0.055)		(0.051)	(0.058)
Impression Score	0.144***	0.167***	0.146***	0.094**	0.116**	0.096**
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Info Complex	-0.160***		-0.174***	-0.131**		-0.172***
	(0.059)		(0.065)	(0.055)		(0.061)
Info NonComplex		0.046	-0.023		-0.011	-0.078
		(0.055)	(0.061)		(0.057)	(0.063)
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	770	770	770	1,400	1,400	1,400
Adjusted R^2	0.372	0.364	0.372	0.256	0.250	0.256

Table IA7. Investor Impressions, Information, and Fund Issuance Performance: By Livestream Slices

This table replicates the analysis in Table 6, Panel B, using investor impression and information measures for the first 10 minutes, middle 10 minutes, and last 10 minutes. Our sample period is from July 1, 2020 to May 31, 2024. We examine whether information conveyed during the livestream modifies the positive effect of investors' impressions on fund issuance outcomes. Columns (1) to (4) present the results using the number of subscriptions as the dependent variable. Columns (5) to (8) present 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 Presenter*, *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,* and *Manager Past Performance*, and are omitted for brevity. Variable definitions are provided in the Appendix. Heteroskedasticity robust standard errors clustered at the fund level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	LnSubscriptions				*LnAmount*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Impression Score Beginning × Info Beginning	-0.525**			-0.470*	-0.495**			-0.444*
	(0.235)			(0.246)	(0.242)			(0.245)
Impression Score Beginning	0.514***			0.382*	0.443**			0.359*
	(0.182)			(0.198)	(0.181)			(0.190)
Info Beginning	-0.114			-0.094	0.232			0.301
	(0.258)			(0.262)	(0.234)			(0.236)
Impression Score Middle × Info Middle		-0.264		-0.235		-0.308		-0.280
		(0.214)		(0.215)		(0.204)		(0.204)
Impression Score Middle		0.357**		0.247		0.326**		0.288*
		(0.150)		(0.172)		(0.144)		(0.156)
Info Middle		-0.079		-0.062		-0.318		-0.309
		(0.229)		(0.231)		(0.218)		(0.218)
Impression Score Ending × Info Ending			0.248	0.297			0.034	0.054
			(0.246)	(0.246)			(0.260)	(0.260)
Impression Score Ending			0.008	-0.110			0.066	-0.037
			(0.175)	(0.189)			(0.188)	(0.200)
Info Ending			-0.343	-0.334			-0.380	-0.368
			(0.254)	(0.258)			(0.257)	(0.257)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
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	0.359	0.362	0.363	0.364	0.247	0.248	0.246	0.248