The Two-System View of Cognition and Investor Choice*

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Abstract

This paper examines how effortless intuition (System 1) and deliberative reasoning (System 2) jointly influence investor 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 responses—elicited by 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 the livestreams convey richer information or feature fund managers, conditions that engage more deliberative reasoning. Our study provides novel evidence on how intuitive (System 1) and deliberative (System 2) processes interact to influence investor choices, offering a foundation for developing a positive theory of investor behavior.

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

JEL classifications: G11; G14; G20; D83

"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 assumption of "homo economicus" in economics, an agent would be endowed with a single deliberative cognitive system that has the perfect ability to process information 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," relying on intuitive rather than deliberative reasoning in high-stakes decision-making. For example, Blankespoor, Hendricks, and Miller (2017) show that investor perception of a CEO, based on 30-second content-filtered video clips of initial public offering (IPO) roadshow presentations, is positively associated with IPO pricing. Huang, Ivković, Jiang, and Wang (2023) find positive associations between favorable first impressions based on video stills of entrepreneurs pitching and angel investment. Hu and Ma (2024) show that persuasive features extracted from startup pitch delivery—such as tone of voice and facial expression—significantly influence how angel investors allocate capital.

While these seminal studies highlight the role of effortless intuition (System 1) in influencing investor decisions, they leave an equally important question open: 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 monitors System 1 lightly 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 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 intuitive thinking.

In particular, we examine the interaction between System 1 and System 2 cognition by analyzing livestream promotional events for mutual fund launches in China. We employ

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[1] There is preponderous evidence across different fields showing that people are not accustomed to thinking hard and often rely on intuition that quickly comes to mind (System 1) to make a decision. 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) find 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 the political science domain, Todorov, Mandisodza, Goren, and Hall (2005) and Antonakis and Dalgas (2009) show that voters' impressions of candidates' faces predict electoral outcomes.

advanced video analytics and generative AI to separately capture investors' effortless intuition, proxied by content-filtered expressive behavior of livestream presenters, and their deliberative reasoning, triggered by information that transpires during a livestream. We then study whether, and how, investors' System 2 scrutiny alters their System 1 impressions of the fund at launch.

We examine these fund launch livestream events for two reasons. First, the fund launch livestream is the first major exposure of a fund and/or its manager to investors, providing a clear link between investors' impressions (System 1) and their subscription decisions. Second, the fund launch setting allows us to focus on new funds for which there is little information about the fund and/or its manager. This information-sparse environment, akin to many psychology studies and prior studies in finance and accounting (see, for example, Blankespoor, Hendricks, and Miller 2017; Huang et al. 2023; Hu and Ma 2024), allows us to cleanly quantify the amount (complexity) of information that engages deliberative reasoning (System 2), and, in turn, identify how System 1 and System 2 interact in a high-stakes, real-world setting.

To this end, we apply advanced machine learning (ML) techniques to capture investors' favorable impressions of livestream presenters and the information content conveyed during a livestream. We use state-of-the-art audio and computer vision models to extract overall impression measures from livestreaming videos, capturing vocal tone, facial expressiveness, and body motion. In parallel, we apply natural language processing (NLP) methods to livestream transcripts to quantify the amount (complexity) of information conveyed. Our analysis shows that investors' favorable impressions (System 1) are positively and significantly associated with the number and amount of fund subscriptions. However, this positive association is significantly attenuated when livestreams provide richer information or when fund managers are present, as these managers typically provide richer and more complex information than other guests in livestreams. Our results indicate that investors' System 2 scrutiny has the potential to override their System 1 favorable impressions in shaping financial decision-making.

Based on fund livestream videos from the Tiantian Fund website—the largest mutual fund distribution platform in China—we construct a novel dataset of fund launch livestreams between July 1, 2020 and May 31, 2024, covering 853 livestream events related to 1,422 funds. Similar to conventional e-commerce livestreams, fund livestreams feature live video feeds with hosts and guests (collectively, referred as presenters), interactive text, and shopping cart functionality. Due to the COVID-19 pandemic, fund families began livestreaming on social media platforms to compensate for investors' limited access to traditional financial advisors and fund information since 2020. Subsequently, fund livestreams gain increasing popularity and become one of the most common fund marketing tools in China (deHaan, Huang, Kannan, and Qiu 2025). In 2023, more than 140 fund companies hosted over 54,000 livestreams, with cumulative viewership totaling approximately 3.4 billion.[2] We focus on fund launch livestreams because this information-sparse environment (prior to the livestream) helps elevate the role of System 1 and uncover how System 1 and System 2 interact.

Guided by the two-system view of cognition, to isolate the nonverbal visual/auditory signals that determine rapidly formed impressions (System 1), we extract multi-dimensional expressive features of livestream presenters (devoid of any information content): vocal tone, facial expressiveness, and body motion.[3] To this end, we first extract the full audio stream

[2] For more details, see https://app-web.chnfund.com/jx/202402/t20240226_4328340.html.

[3] Prior research shows that people draw on a wide range of nonverbal information in forming their impressions, including change in tone of speech, facial expression, eye gaze, and general 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.

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 at one frame per second (i.e., 3,600 images for a one-hour livestream). With these steps, we construct investors' impression measures using ML algorithms.[4] Following Kaplan and Sorensen (2021), Huang et al. (2023), and Hu and Ma (2024), we also create an overall measure using Principal Component Analysis, *Impression Score*, that summarizes "how favorable" investors feel about livestream presenters.

To quantify the amount of information content conveyed during livestreams, we apply generative AI to video transcripts. Specifically, we construct the information measures of a livestream based on the amount of information its transcript contains relative to the Fund Overview section from 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 providing structured information about a fund (e.g., fund name and fund code), the Overview provides a brief fund description under six topic headings: investment objectives, investment philosophy, investment scope, investment strategy, dividend policy, and risk-return characteristics. As a robustness check, we also benchmark a fund's livestream information content against the Important Notices section of its prospectus, which appears at the front of the document and contains key disclosures for investors.

We first conduct text segmentation of a transcript and use generative AI (DeepSeek) to extract topics from each segment. We then assess whether each segment's content corresponds to any of the six key topics in the Fund Overview section, or any of the nine additional topics.[5] With this approach, we construct the variable *Info* to capture the amount

[4] We rely on widely available computational services, such as *DeepFace, OpenCV,* and *YOLO11,* to construct investor impression measures and conduct the analysis.
[5] We apply DeepSeek for unrestricted topic extraction on 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

of information content conveyed during a livestream (above and beyond the content in Fund Overview). For the six topics covered in the Fund Overview, we compute the cosine similarity between each topic-specific segment and the corresponding Overview content. Segments with similarity scores exceeding a predefined threshold are categorized as repetitive. For each topic, we then calculate *Info Ratio* as one minus the proportion of repetitive content in that topic's total segment content. For the nine additional topics, *Info Ratio* equals one for the corresponding segment(s), since these topics differ from those covered in the Overview. We aggregate the topic-specific *Info Ratio* measures to the livestream level to construct *Info*, which captures the amount of information conveyed in a livestream.

We document several key findings. First, fund launch livestreams are positively associated with issuance performance. Among funds with livestreams, investors' favorable impressions—capturing System 1 intuition—are positively associated with fund issuance outcomes. This pattern holds consistently across individual vocal, facial, and body motion measures, controlling for other features in livestreams (e.g., verbal tone and image clarity) 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*) is associated with a 17.0 percent increase in the number of subscriptions and a 21.3 percent increase in the subscription amount. Given the average subscription amount of RMB 839.50 million (USD 116.86 million) in our sample, this effect corresponds to an additional RMB 178.81 million (USD 25.12 million). These results align with prior evidence that investors' favorable impressions are positively correlated with their investment decisions (e.g., Blankespoor, Hendricks, and Miller 2017; Huang et al. 2023; Hu and Ma 2024).

Second, we examine the interaction between investors' intuitive impressions (System 1)

Overview as our additional topics. 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.

and deliberative reasoning (System 2) in affecting investment decisions. We find that greater information content in livestreams—by engaging investors' analytical processing—significantly attenuates the positive association between favorable impressions and fund issuance performance. When a livestream's information content falls in the top quintile of the sample, the net effect of *Impression Score* on fund subscription amount is −0.005 and statistically indistinguishable from zero. In other words, when information is sufficiently rich, System 2 overrides System 1. These findings are consistent with Kahneman's two-system view of cognition. To our knowledge, this is the first empirical evidence in finance that directly tests Kahneman's proposition and delineates the boundaries of intuitive thinking.

Third, we explore potential heterogeneity in the role of System 2 overriding System 1. To this end, we employ generative AI (DeepSeek) to classify information conveyed in livestreams into complex and non-complex topics. Complex topics are difficult to understand and require interpretation by professionals (e.g., fund managers and analysts), while non-complex topics are easily understood by retail investors. We then calculate the information content for different types of information conveyed (as defined above). We find that only investors' scrutiny triggered by complex information mitigates the impact of their favorable impressions.

Relatedly, we examine whether the presence of fund managers in a livestream matters. We first show that livestreams with manager participation convey more information and more complex information to investors than those without. In these cases, the positive association between investors' favorable impressions and fund issuance performance disappears, consistent with the conjecture in Kahneman and Frederick (2002) and Kahneman (2011) that the amount and complexity of information triggers System 2, which offsets the impact of System 1.

We also explore whether fund type moderates the interaction between System 1 and System 2 in changing investor choices. Passive funds follow established benchmarks and feature predictable portfolio compositions, while active funds adopt sophisticated investment strategies. By categorizing funds into active and passive types, we find that System 2 overrides System 1 only for active funds.

In the final part of the paper, we examine whether a fund's ability to elicit favorable investor impressions during livestreams correlates with subsequent return performance. We find that more positive impressions at launch are, in fact, associated with poorer long-run performance. These results suggest that retail investors, influenced by System 1 cues during livestreams, may direct capital to funds that do not warrant such inflows, indicating a behavioral bias. As System 2 deliberative reasoning counteracts the influence of System 1 on subscription decisions, our findings suggest that enhanced information disclosure can help mitigate this bias.

The remainder of the paper is organized as follows. Section 2 discusses our contribution to the extant literature. Section 3 provides institutional background and describes our sample. Section 4 details the construction of investor impression (System 1) and information processing (System 2) measures from livestreams. Section 5 presents the main results, including the impact of fund livestreams, the role of investors' impressions in fund issuance performance, and the interaction between investors' impressions and information scrutiny. Section 6 conducts robustness checks and examines the long-run performance implications of System 1 and 2. Section 7 concludes. Additional technical details and supplementary materials appear in the Online Appendix.

2. Relation to Prior Literature

Our paper contributes to several strands of the literature. First, our study contributes to the emerging literature applying video analysis to examine the role of visual and auditory cues in communication in affecting 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; Chang et al. 2025). We add to this literature by applying the two-system framework of cognition (Kahneman 1973, 2011; Tversky and Kahneman 1974; Stanovich and West 2000) to study mutual fund launch livestreams—a large-scale, high-stakes retail setting. We provide the first evidence on how System 1 intuition and System 2 information processing interact to shape investors' financial decisions. Moreover, aided by advanced video analytics and generative AI, we are also the first in the literature to examine System 1 and 2 using the entire livestream video (on average, roughly 60 minutes long), rather than "thin slices" used in prior literature as reasonable proxies for judgment (e.g., Ambady and Rosenthal 1992; Blankespoor, Hendricks, and Miller 2017). Using the entire video is important for our analysis as we want to capture the scope and complexity of information transpired during a livestream.

Second, our study contributes to the growing literature on financial technology (fintech) platforms, social media, and investor behavior. Fintech channels increasingly shape how investors access and purchase financial products, whether through online fund distribution, robo-advisors, or mobile trading apps. Recent studies show that these innovations expand market participation and alter investment patterns (D'Acunto, Prabhala, and Rossi 2019; Barber, Huang, Odean, and Schwarz 2022; Rossi and Utkus 2024; Hong, Lu, and Pan, 2025). Relatedly, Cookson, Mullins, and Niessner (2024) survey the growing literature on the role of social media in financial markets and conclude that social media may exacerbate behavioral biases that are harmful to retail trading performance. We add to 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 System 1 cues during livestreams, may invest in funds that do not warrant such inflows—a behavioral bias. Importantly, we further show that deliberative reasoning (System 2) helps attenuate the impact of these intuitive impressions on fund subscription decisions.

Finally, our study contributes to the literature on mutual fund marketing. Early studies show that advertising can attract flows even without improving risk-adjusted returns (Jain and Wu, 2000) and that fund families strategically market products with superior recent performance (Nanda, Wang, and Zheng 2004; Gaspar, Massa, and Matos 2006). More recent work emphasizes the strategic role of mutual fund marketing in shaping fund flows and fund market competition beyond lowering investors' participation or search cost (deHaan, Song, Xie, and Zhu 2021; Roussanov, Ruan, and Wei 2021; Chen, Jiang, and Xiaolan 2023). We add to this literature by examining livestreaming as a novel and increasingly important marketing channel in capital markets. While marketing scholars have analyzed livestreaming in consumer product markets (Bharadwaj et al. 2022; Gu, Zhang, and Kannan 2024; Huang and Morozov 2025), our study is among the first to study the sensory-rich channel of livestreams and finds evidence that investors' impressions and information processing during such events jointly shape their capital allocation.

3. Institutional Background and Sample Formation

3.1. Institutional Background

The mutual fund industry in China started in 2001, with the first mutual fund, Hua'an Innovation Mixed Fund, launched in September 2001. Retail investors purchase mutual fund products mainly through commercial banks and independent fund distributors. At the onset of the COVID-19 pandemic in early 2020, investors' access to traditional information channels (e.g., financial advisors at local bank branches and broker branches) was severely curtailed. To make up for retail investors' lost access to financial advisors and fund information, fund families started to provide livestreams of fund managers and/or other finance professionals (e.g., analysts, investment advisors) on social media platforms. For example, in 2023, more than 140 fund companies—representing over 80% of all fund families in China—conducted more than 54,000 livestreams.[6]

Livestream channels are generally managed 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 a variety of topics, including industry developments, market trends, investment strategies, risk-return characteristics, and fund investment philosophies. Sessions typically last about an hour. Speakers and topics are announced up to a week in advance, and viewers may submit questions either beforehand or in real time.

Our primary 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, cumulative fund sales on the platform had exceeded 10 trillion yuan, with an average of more than 1.5 million daily active users. According to Hong, Lu, and Pan (2025), the platform exerts significant influence on retail investors and market trends in China.

3.2. Sample Formation

We downloaded fund livestream videos from the Tiantian Fund website (https://roadshow.eastmoney.com/list?type=1) in early June 2024. We then construct 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 test of investors' System 1

[6] 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.

effects in livestreams and their interaction with System 2 information processing. Figure 1 provides a screenshot of the livestream interface and accompanying details on the Tiantian Fund website.

We begin with an initial sample of 2,786 livestream videos potentially related to newly launched funds during the sample period based on 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 livestream videos over the sample period. Figure 2 lists the top 10 fund families by their 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 videos, livestreams have an average of 1.88 speakers (untabulated); 72.7% feature at least two presenters, and over 60% include at least a fund manager (Panel B).[7]

To ensure consistency across our analyses and avoid duplicating information already conveyed in a fund's first launch livestream (if we were to analyze subsequent livestreams of the same new fund), we retain only the first livestream for each new fund, reducing the sample to 853 livestreams. Mutual funds in China are typically marketed in two share classes (A and C), which are identical except for load and service fees.[8] As a result, each livestream video may be linked to two sets of outcome variables if the fund is offered in both classes. For the subscription analysis, this expands the sample from 853 livestream videos to 1,524

[7] We obtain participant names and job titles from the livestream introductions on the TianTian Fund website, and we double-check and supplement this information by manually viewing the videos and recording participant names and job titles.

[8] Load and service fees are typically charged upfront or annually, whereas management and custodian fees are deducted from fund assets on an ongoing basis. In addition, fund distribution intermediaries may waive or discount load and service fees.

fund issuance observations. After requiring data availability for livestream, fund, and fund manager characteristics, the final sample consists of 1,422 observations. Table 1 summarizes the sample construction process.

3.3. Summary Statistics

We obtain fund characteristics from the RESSET Database and the Wind Database.[9] Specifically, we gather basic information about a fund and its fund managers, including fund type, investment style, fund return, assets under management (AUM), fund fees (management fee and custodian fee), fund manager's demographic characteristics and educational background, and their industry experience from RESSET. We get fund family's ownership information and size (i.e., assets under management) from Wind. We measure the past performance of a fund manager as the average annualized net asset growth rate of funds that the manager previously managed, which aligns with one of the fund manager performance measures commonly displayed on the Tiantian Fund platform. We also record gift-giving behaviors during livestreams by using keyword searches in conjunction with manual viewing. Additionally, we obtain viewership and like counts from livestream videos through web scraping. We report summary statistics for livestream, fund, and fund manager characteristics in Table 2, Panel A. Variable definitions are provided in the Appendix.

As a first step, we analyze the determinants of whether a fund hosts a launch livestream, relating fund- and fund manager-level characteristics to the probability that a new fund hosts one.

Table 3, Panel A provides a comparative analysis of new funds that host livestreams (*Livestream* = 1) versus those that do not (*Livestream* = 0). The two-sample tests reveal significant differences across various fund characteristics. Both the mean and median number

[9] RESSET is a leading financial database in China, offering detailed financial data and analytical tools. Wind is a comprehensive financial database that provides a wide range of financial market data, including stock, bond, futures, and macroeconomic data.

(amount) of subscriptions are notably higher for funds that host livestreams (Mean = 25,689 (RMB 839.50 million), Median = 7,597 (RMB 217.70 million)) compared to those that do not host livestreams (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 associated with the number (amount) of subscriptions.

Table 3, Panel B presents the results from the linear probability model. Across all specifications, the coefficients on *Active Fund* are 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, indicating that new funds with higher fees and funds affiliated with a state-owned fund family are more likely to host a launch livestream. Overall, the results indicate that certain fund characteristics, such as being actively managed and charging higher fees, are positively associated with the likelihood of a new fund hosting a launch livestream.

4. Methodology: Constructing Impression and Information Measures in Livestreams

In this section, we explain how we analyze fund livestream videos using machine learning and generative AI.

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) and recent application in accounting (Blankespoor, Hendricks, and Miller 2017; Davila and Guasch 2022), we aim to capture investors' System 1 effortless intuition based on observing livestream presenters' vocal cues, dynamic facial expressions, gestures, and body motion as follows: vocal tone, facial expressiveness, and body motion.[10] For each dimension, we use machine learning algorithms to extract vocal and visual measures from the raw data. We then aggregate these measures across presenters and units of analysis to characterize each livestream video.

Unique to our setting, mutual fund livestreams allow us to examine how investor scrutiny (System 2) triggered by information conveyed during livestreams interacts with their impressions (System 1). Specifically, the Fund Overview section on the Tiantian Fund website provides structured information about each new fund (e.g., investment objectives and investment philosophy) sourced from the prospectus. We use this section as a benchmark to identify the scope and complexity of information conveyed during a fund's livestream—they are important conditions that engage System 2 (Kahneman and Frederick 2002; Kahneman 2011). To operationalize this, we employ generative AI and machine learning algorithms to construct a set of information measures.

4.1. Constructing the Impression Measures Using Machine Learning

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

We first extract the three dimensions from the sound and image streams of the fund livestream videos. For the vocal dimension, we extract the audio files from the video and segment the audio into speaker logs based on the dialogue presenters (Wang et al. 2023). The unit for vocal analysis is at the level of each speaker log. For the two visual (facial

[10] Given that livestream transcripts contain both information and emotional cues (i.e., sentiment), which may confound the identification of System 1, our main measure, *Impression Score*, employs content-filtered video/audio cues, excluding verbal-related measures. As a robustness check, we add verbal tone in our main measure and find that our main findings remain.

expressiveness and body motion) dimensions, we represent the video using images sampled at one frame per second and employ face-detection and body-detection machine learning algorithms to identify presenters' faces and bodies in each video frame. The unit for visual analysis is at the level of each video frame.

4.1.1. Vocal tone

We focus on vocal cues that are not captured by the textual content of the fund's livestream videos. Unlike images, which can independently provide rich information, splitting audio into fixed high-frequency segments, similar to a series of images, may lead to the loss of information embedded in the audio's temporal dependency structure. Instead, we divide each audio stream into speaker logs.[11] These units naturally preserve the auto-dependent information structure in the audio and align with human cognitive processes. We then use S*peech Emotion Recognition*, a well-established 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, as determined by *Speech Emotion Recognition*. We compute this as the average across all speaker logs in a livestream.

4.1.2. Facial expressiveness

Because fund livestreams typically last about one hour—much 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 analyze presenters' emotional expressions. The algorithm identifies a speaker, tracks the movement of facial feature points (e.g., nose, eyes), and

[11] Speaker logs are generated by a speaker logging system developed by Alibaba DAMO Academy, based on CAM++ and clustering techniques. When given an audio segment containing a multi-person conversation as input, the model can automatically identify the number of speakers and distinguish and output each individual speaker.

probabilistically classifies seven facial emotions: anger, disgust, fear, happiness, neutral, sadness, and surprise. For each image, the probabilities of these seven emotions sum to one. 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 averaging across all frames in a livestream.

4.1.3. Body motion

Nonverbal behaviors such as body movements often arise unconsciously and convey information that can influence important decisions (Burgoon, Birk, and Pfau 1990; Chartrand and Bargh 1999; Hall, Coats, and LeBeau 2005). Following Chen, Yao, and Kotha (2009) and Davila and Guasch (2022), we measure the movement magnitude of presenters in a livestream. We extract images at a rate of one frame per second and use *YOLO11*, developed by Ultralytics, to detect skeletal key points and construct skeletons. We then apply the optical flow method to calculate displacement magnitudes.[12] Our variable, *Body Motion*, is computed by first averaging across presenters within a frame and then averaging across all frames in a livestream.

4.1.4. Summary measure

Beyond the individual impression measures, we construct a summary measure of livestream 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 impression measures of livestream videos, highlighting substantial cross-sectional variations across these measures. For example, the mean of *Visual Positive* is 0.080, indicating that presenters display positive visual features

[12] After converting each frame to grayscale, we use the Farneback algorithm to compute inter-frame optical flow, decompose the x- and y-direction components, and obtain pixel displacement magnitudes through polar coordinate transformation. We then divide an image into participant-specific regions, extract displacement magnitudes by region, compute their average values, and accumulate total displacement along with the number of frames. Finally, after processing all frames, we calculate the average displacement variation by dividing each region’s total displacement by the number of frames.

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* as well as 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. Overall, *Impression Score* can be viewed as a composite index that aggregates information from the impression measures, capturing investors' overall impressions of a launch livestream.

4.2. Constructing Other Livestream Measures Using Machine Learning

We also construct verbal and video image measures for livestreams. We first extract the verbal and image dimensions from the sound and image streams of a livestream video. For the verbal measure, a speech-to-text machine learning algorithm is used to extract speech from the sound. For the clarity measure, we represent the video using images sampled at one frame per second. The unit for visual analysis is at the level of each video frame.

4.2.1. Verbal (text)

Using Aliyun's *speech-to-text* API, we generate text transcripts from the audio data of each speaker log in the livestream videos. We then use *StructBERT* (Wei et al. 2020), developed by Alibaba DAMO Academy, to classify the sentiment of these transcripts. *StructBERT* is a Chinese sentiment classification model designed for general-domain applications. It takes natural language text as input and produces both a sentiment label (0 = negative, 1 = positive) and an associated probability. Our variable, *Verbal Positive*, is defined as the probability, calculated by *StructBERT*, that a livestream transcript expresses positive sentiment. We compute this measure as the text-length-weighted average across all speaker logs in a livestream.

4.2.2. Image clarity

Studies in computer vision show that a video's aesthetic quality is an important determinant of 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 assess the image quality of livestream videos. We extract images at a rate of one frame per second and use *OpenCV* to evaluate their clarity.[13] Our variable, *Image Clarity*, is calculated as the average clarity score across all frames in a livestream. The code used to construct the individual livestream features is listed in Table IA1, Panel A of the Online Appendix.

4.3. Constructing the Information Measures Using Generative AI

In this section, we describe our method for constructing information measures for a livestream using its transcript and the Fund Overview section of the Tiantian Fund website. The Fund Overview provides structured and concise information about a fund, including its name, code, manager, fee structure, and other basic details. It also contains a brief fund description under six topic headings: investment objectives, investment philosophy, investment scope, investment strategy, dividend policy, and risk-return characteristics, largely sourced from the prospectus. For newly launched funds without a performance history, the Fund Overview is 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 evaluating 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 disclosure—as an alternative benchmark. Figure 5 presents a flowchart illustrating how we construct the information measures from livestream transcripts and textual data from the Tiantian Fund website and Table IA1 in the Online Appendix provides implementation details.

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

4.3.1. Step 1. Text segmentation

Text segmentation is a key component of natural language processing, allowing large documents to be divided into smaller, coherent units for further analysis. Fund livestream transcripts are complex, lengthy texts that contain dialogic structures and cover diverse topics. Traditional methods, such as character-based or fixed-size chunking, often fail to capture the nuances of such content. To address this limitation, we adopt a method that uses semantic similarity derived from word embeddings to segment text into meaningful chunks. This method ensures that each chunk is semantically coherent and contextually relevant, thereby improving the overall quality of the analysis.

To implement semantic segmentation, we utilize word embeddings to capture the semantic content of sentences. Specifically, we convert each sentence in the transcript into a high-dimensional vector representation and apply the GTE model developed by Alibaba DAMO Academy to measure the similarity between sentence embeddings.[14] We then quantify the semantic relatedness of sentences and identify coherent segments within the text. The threshold is set to 0.75, defined as the minimum semantic difference required to split the text into separate segments.[15] The code for text segmentation is listed in Table IA1, Panel B.

4.3.2. Step 2. Topic classification

We use DeepSeek to extract topics from each segment. Specifically, we assess whether each segment's content corresponds to any of the six topics covered in the Fund Overview on the TianTian Fund website, or any of the nine additional topics.

To do this, we apply DeepSeek for unrestricted topic extraction on 20 livestream transcripts representing various fund types (e.g., index funds, equity funds, bond funds, and

[14] GTE is a transformer-based, pre-trained language model specifically designed to produce high-quality text embeddings that capture both semantic and contextual information. We choose 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.

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

hybrid funds). 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 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 merely serve to fill gaps between more substantive discussions, are categorized as "others." The prompt used is listed in Table IA1, Panel C.

4.3.3. Step 3. Measuring the amount of information

Next, we describe how we construct the variable, *Info,* which captures the amount of information content conveyed during a livestream (above and beyond the content in Fund Overview).

First, for the six topics covered in the Fund Overview section (investment objectives, investment philosophy, investment scope, investment strategy, dividend policy, and risk-return characteristics), we calculate the proportion of livestream content on each topic that is repetitive relative to the Fund Overview.

Specifically, for each topic, we compare a relevant segment obtained in the first step with the corresponding content in the Fund Overview and compute 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).[16] 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. The code used is listed in Table IA1, Panel D. The rationale for our measure is that since the Fund Overview section is easily accessible and widely read by investors, livestream content that closely mirrors it is considered repetitive. Conversely, content that deviates from

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

the Fund Overview represents information.

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

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

where $Segment\ Length_{s,k,i}$ represents the number of words in segment *s* of livestream *i* on topic *k*, and $I(Repetitive_{s,i,k})$ 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.[17] 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:

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

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 livestream *i*'s transcript. When topic *k* is included in the Fund Overview, $Info\ Ratio_{k,i}$ is computed as in Equation (1). When topic *k* is not included in the Fund Overview, $Info\ Ratio_{k,i}$ is set to 1, since information on that topic is relative to the Fund Overview.

4.3.4. Step 4. Measuring the complexity of information

Kahneman and Frederick (2002) and Kahneman (2011) argue that System 2 monitors System 1 lightly and is activated when the complexity of information exceeds what System 1 can handle automatically, shifting decision-making from intuition to analytical processing. To test this conjecture in a real-world setting, we employ generative AI to classify information into complex and non-complex topics. Complex topics require professional interpretation

[17] 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.

(e.g., by fund managers or analysts), whereas non-complex topics are easily understood by retail investors. A priori, complex information could either distract viewers from System 1 or make them more deliberative a la System 2 (Ambady and Rosenthal 1992; Kahneman and Frederick 2002; Evans 2008). Either or both could lead to interaction, triggering System 2 scrutiny.

Specifically, we use 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: 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.[18]

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

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

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

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. Within this 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).

[18] Figure IA6 presents a flowchart illustrating how we construct the information complexity measures.

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' impressions in shaping their purchase decisions. We then investigate whether and how investor System 2 scrutiny triggered by information disclosed during livestreams modifies the effect of their System 1 impressions on fund purchase decisions.

5.1. Livestream and Fund Issuance Performance

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

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

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 mentioned in Section 3.3, collectively denoted as *Controls*. Furthermore, we control for style fixed effects, year fixed effects, and time-of-day fixed effects.[19,20] Standard errors are clustered at the fund level.

Table 4, Panel A presents the regression results of Equation (5). Irrespective of whether we employ the livestream dummy or the number of livestreams, the coefficients on

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[19] 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.

[20] 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.

Livestream Indicator (*Number of Livestreams*) are significantly positive at the 1% level across all specifications. This finding underscores that fund launch livestreams significantly improve their issuance performance.

To provide supplemental evidence on the role of launch livestreams on 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, we also note that 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.

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). This insight spurs the large advertising literature, whereby sellers' communications can create perceived product differentiation even in the absence of substantive differences—an effect especially pronounced among less-informed or less-sophisticated consumers (e.g., Braithwaite 1928; Hurwitz and Caves 1988; Bagwell 2007). In our setting, fund livestreams with positive nonverbal cues—engaging visuals and vocal affect—may capture investor attention, triggering System 1, and stimulate subscriptions.[21]

In this section, we explore the extent to which investors' impressions formed during livestreams can enhance fund issuance performance. We run the following cross-sectional

[21] To explore the immediate impact of System 1, we examine the association between investors' impression and their reactions during livestream events. Table IA2 presents the results. *Impression Score* positively and significantly correlates with the number of likes of the livestream and the ratio of the number of likes to the number of viewers.

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 zero mean and unit standard deviation for the ease of interpretation. We also include livestream, fund, and fund manager characteristics as control variables.[22] 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 of 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. Columns (4) employs *Impression Score* instead. All individual impression measures have positive loadings; the coefficients on *Vocal Positive* and *Visual Positive* are statistically significant. As an 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 number of subscriptions. In column (4), we show *Impression Score* positively and significantly correlates with the number of accounts subscribing to a fund issuance. In terms of economic significance, the coefficient 0.170 means that a one-standard-deviation increase in *Impression Score* is associated with a 17.0 percent increase in the number of subscriptions. The average number of subscriptions in our sample is 25,689 accounts. A 17.0

[22] We include the following livestream characteristics as control variables: positive verbal measure (*Verbal Positive*), video image quality (*Image Clarity*), the number of presenters (*Number of Participants*), 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*).

percent increase means that there are 4,367 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; the coefficient on *Vocal Positive* is statistically significant. The coefficient 0.213 in column (4) means that a one-standard-deviation increase in *Impression Score* is associated with a 21.3 percent increase in the subscription amount. The average subscription amount in our sample is RMB 839.50 million. The 21.3 percent increase corresponds to RMB 178.81 million (USD 25.12 million).

Social perceptions are formed based on 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. By activating System 1, these cues can influence decisions without extensive deliberation and are positively associated with the issuance performance of newly launched funds. The effect is economically large, underscoring the importance of delivery features in mutual-fund livestreams and aligning with evidence that investors' impressions shape their decision-making (Blankespoor, Hendricks, and Miller 2017; Huang et al. 2023; Hu and Ma 2024).

5.3. The Impact of System 2 Information Processing

In this section, we exploit the mutual fund–livestream setting—where material information may be disclosed—to test whether and how investor scrutiny modifies their favorable impressions. 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 the disclosure of information during livestreams, which engages System 2, attenuates the effectiveness of effortless intuition (a System 1 channel).

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

During fund livestreams, presenters such as fund managers convey information on macroeconomics, market trends, industry developments, and fund specifics. For retail investors, this content is often complex and novel, activating System 2 cognition and prompting deliberative processing.

This raises an important question about the interplay between the two systems: does more information (which activates System 2) weaken or strengthen the influence of 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*, a dummy 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 in livestreams (*Info* and *High Info*). *Info* is standardized to have zero mean and unit standard deviation for the ease of interpretation. The coefficients on *Impression Score* and information measures indicate the separate effects of System 1 and System 2 cognition on investors' choices.

Table 6, Panel A presents the results. Across all four columns, the coefficients on *Impression Score* are positive and statistically significant, indicating that investors' favorable impressions are positively and significantly associated with fund issuance outcomes. Information measures do not load. Because our information measures are sentiment-neutral, we do not predict a directional effect from activating System 2 cognition.

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

$$Y_{i,t} = \beta_0 + \beta_1 Impression\ Score_{i,t} + \beta_2 Impression\ Score \times Info_{i,t} + \beta_3 Info_{i,t} +$$

$$\gamma Controls_{i,t} + StyleFE + YearFE + TimeofDayFE + \varepsilon_{i,t}, \tag{8}$$

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 results. Columns (1) and (3) use the interaction *Impression Score* × *Info*; columns (2) and (4) use *Impression Score* × *High Info*. Across all specifications, the interaction coefficients are negative and statistically significant, indicating that issuance outcomes become less responsive to *Impression Score* when a livestream conveys (more) information. Take column (4) as an example, when *High Info* takes a value of 1, the net effect of *Impression Score* on *LnAmount* is −0.078 (0.150 − 0.228 × 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 are consistent with Kahneman's two-system framework of cognition. Nonverbal information such as gestures, body movement, and dynamic facial expressions primarily engages System 1—intuitive and affect-driven—so when substantive cues are scarce, investors lean on heuristic impressions (e.g., positive affect). By contrast, information supplies decision content that 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. As far as we are aware, we are the first in the literature to test Kahneman's proposition and delineate the boundaries of intuitive thinking.

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

In this section, we examine how different types of information, proxying for the different levels of investors' scrutiny, influence the role of System 1 in fund issuance performance. We focus on information complexity, given that complexity is a critical factor activating 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 livestream (*Info Complex* and *Info NonComplex*). The coefficients on the interaction terms reveal whether complex or non-complex information in livestreams significantly affects the role of investors' impressions in fund issuance performance. Table 6, Panel C presents the results. In columns (3) and (6), the coefficients on *Impression Score* × *Info Complex* are negative and highly significant, whereas the coefficients on *Impression Score* × *Info NonComplex* are not statistically significant. The results indicate that complex information mitigates the effect of investors' impressions on fund issuance performance, while non-complex information shows no significant effect. Take column (6) as an example, when *Info Complex* takes a value of 0.666 (the 75th percentile), the net effect of *Impression Score* on *LnAmount* is −0.005 (0.076 − 0.177 × 0.666 − 0.018 × 0.725). The effect of System 1 turns negative and is not statistically different from zero, suggesting that investors' System 2 scrutiny offsets System 1 favorable impressions in their decision-making.

Complex information demands 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' 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' impressions on their decision-making.

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

We study fund managers' participation in livestreams for three reasons. First, their presence changes 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 participation alters content: these sessions contain more technical and complex information, which requires deeper cognitive processing, activating System 2. Third, due to disclosure regulations, fund managers are bound by truthful discussion of their fund characteristics, which is in stark contrast to 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 a fund engages System 2 (as conjectured by Kahneman and Frederick 2002; Kahneman 2011).

Table 7, Panel A compares inverstors' impression and the amount and complexity of information in livestreams with the participation of a fund manager versus those without. The results indicate that fund managers' participation has no significant effects on *Impression Score*, but significantly increases the amount and complexity of information in livestreams. Both measures—*Info* and *Info Complex*—show higher values when a manager is present, with statistically significant differences confirmed by both t-tests and Wilcoxon tests. This suggests that fund managers play a crucial role in increasing the information content and the degree of complexity in information conveyed during livestreams.

We estimate Equation (8) replacing *Info* by *Manager Present* (an indicator variable for whether at least one manager joins a livestream). In Table 7, Panel B, column (1), the negative coefficients on *Impression Score* × *Manager Present* indicate that managers' participation in livestreams 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 −0.033 (0.285 − 0.318), and is not significantly different from zero. These results suggest that the positive effect of investors' impressions on fund issuance performance disappears when fund managers are present, consistent with the notion that such livestreams trigger investors' System 2 cognition, which overrides System 1. Interestingly, we note that the coefficient on the standalone variable *Manager Present* is negative and significant at the 1% level, consistent with our setting, characterized by overly positive features in livestreams and generally risky basic information provided by professional managers.

In summary, by using an alternative measure for the amount of and the degree of complexity in information conveyed during livestreams, we continue to find that System 2 cognition offsets System 1 in affecting investor behavior.

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 with transparent and predictable portfolios, requiring little investor scrutiny. In contrast, active funds employ complex strategies that increase 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 coefficients on *Impression Score* × *High Info* are negative and statistically significant. By contrast, the corresponding coefficients for passive funds in columns (2) and (4) are 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 influencing investment decisions.

6. Supplemental Analyses

6.1. 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 IA3 presents the results. The results are similar to Table 6.

Second, we measure livestream information content relative to the prospectus Important Notices section rather than the Tiantian Fund Overview used earlier. The Important Notices section is concise and highlights key investor disclosure.[23] Then we repeat the analyses of Sections 5.3.1 and 5.3.2 using this alternative measure of information in livestreams. Table IA4 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 System 2 during livestreams, we take three 10-minute slices in the beginning, middle and end of a livestream. We compute *Impression Score* and *Info* from these three segments, and re-estimate Equation (8). Table IA5 shows that the coefficients on the interaction term are negative and significant when using the first 10-minute segments. The coefficients become marginal significant with the middle 10-minute segments. 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 called for to differentiate these possible explanations.

6.2. Long-term Performance Implications of System 1 and System 2

In this section, we examine whether a fund's ability to elicit favorable impressions among investors during fund launch livestreams correlates with its ability to deliver superior investment performance.

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[23] 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.

We conduct our analysis using the following model:

$$Return_{i,t} = \beta_0 + \beta_1 Impression\ Score_{i,t} + \beta_2 Impression\ Score \times High\ Info_{i,t} + \beta_3 High\ Info_{i,t} + \gamma Controls_{i,t} + StyleFE + YearFE + TimeofDayFE + \varepsilon_{i,t}, \quad (9)$$

where we use net-of-fee returns as the dependent variable, which is the return received by investors. We measure cumulative fund return over the next three months (*Return 3m*), six months (*Return 6m*), or one year (*Return 12m*) after a fund's lock-up period.[24] The key variables of interest are *Impression Score* and its interaction with *High Info*. All regressions include fund characteristic, manager characteristic, and livestream characteristic controls. Style fixed effects, year fixed effects, and time-of-day fixed effects are included. Standard errors are clustered at the fund level.

Table 9, Panel A presents the results. In columns (1) to (4), we find the coefficients on *Impression Score* are significantly negative. The findings show that funds associated with investors' favorable impressions underperform after the end of the lock-up period. Next, we limit the sample to those with a manager present, and reconstruct the *Impression Score* and related measures only based on managers (not including other presenters in a livestream). We re-estimate Equation (9), and Table 9, Panel B presents the results. In columns (1) to (4), we find that the coefficients on *Impression Score* remain significantly negative, and the magnitudes are larger than those in Panel A.

These findings suggest that retail investors, relying on intuitive rather than deliberative cognition during livestreams, allocate capital to funds that do not warrant such inflows, indicating a potential bias. Because System 2 counteracts the influence of investors' favorable impressions (System 1) on subscription decisions, enhanced information disclosure can help mitigate this bias.

[24] The lock-up period is the interval after a fund's inception during which investors cannot redeem shares or place new subscription orders. During this period, fund managers gradually acquire assets to build the target portfolio.

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 little prior information, our empirical design achieves a clean identification of the interaction between intuitive thinking (System 1) and deliberative reasoning (System 2) in retail investors' decision-making.

We find that vocal tone and facial expressiveness significantly increase investor subscriptions, highlighting livestreaming as an effective promotional channel that captures attention and shifts investment decisions. However, information in livestreams triggers System 2, and dominates System 1's (favorable impressions') influence. With richer information conveyed during livestreams, the net effect of investors' impressions on subscriptions disappears. This dominating role of System 2 emerges with more complex information, fund manager participation 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 be the 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 *Speech Emotion Recognition* 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* emotion recognition Application Programming Interface (API). The *DeepFace* model assigns a probability of anger, disgust, fear, happiness, neutrality, sadness, and surprise to each participant 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 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 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.
Verbal Positive	Probability that the sentiment of a livestream is positive by the *StructBERT* model. The unit of analysis is a speaker log. The *StructBERT* model 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.
Number of Participants	The number of 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 launch livestream to the end of its subscription period.
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., two for a master's degree, and one 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.
Flow and Return Variables	
Return 3m	Fund net-of-fee return over the three-month period after the lock-up period, calculated as the change in a fund's net asset value per share (with reinvested dividend).
Return 6m	Fund net-of-fee return over the six-month period after the lock-up period, calculated as the change in a fund's net asset value per share (with reinvested dividend).
Return 12m	Fund net-of-fee return over the twelve-month period after the lock-up period, calculated as the change in a fund's net asset value per share (with reinvested dividend).

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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)

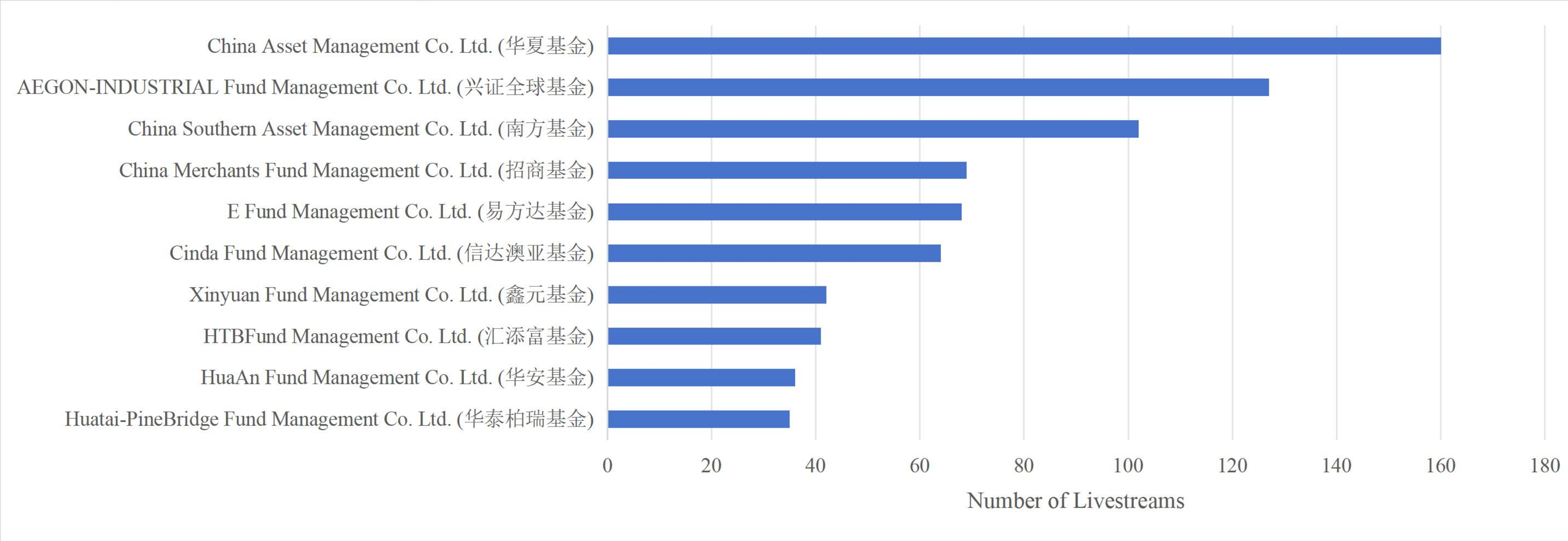
Fund family:
- Fullgoal Fund Management Co. Ltd.
- Established in 1999, one of China's "Old Ten" fund companies with a full suite of licenses.

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

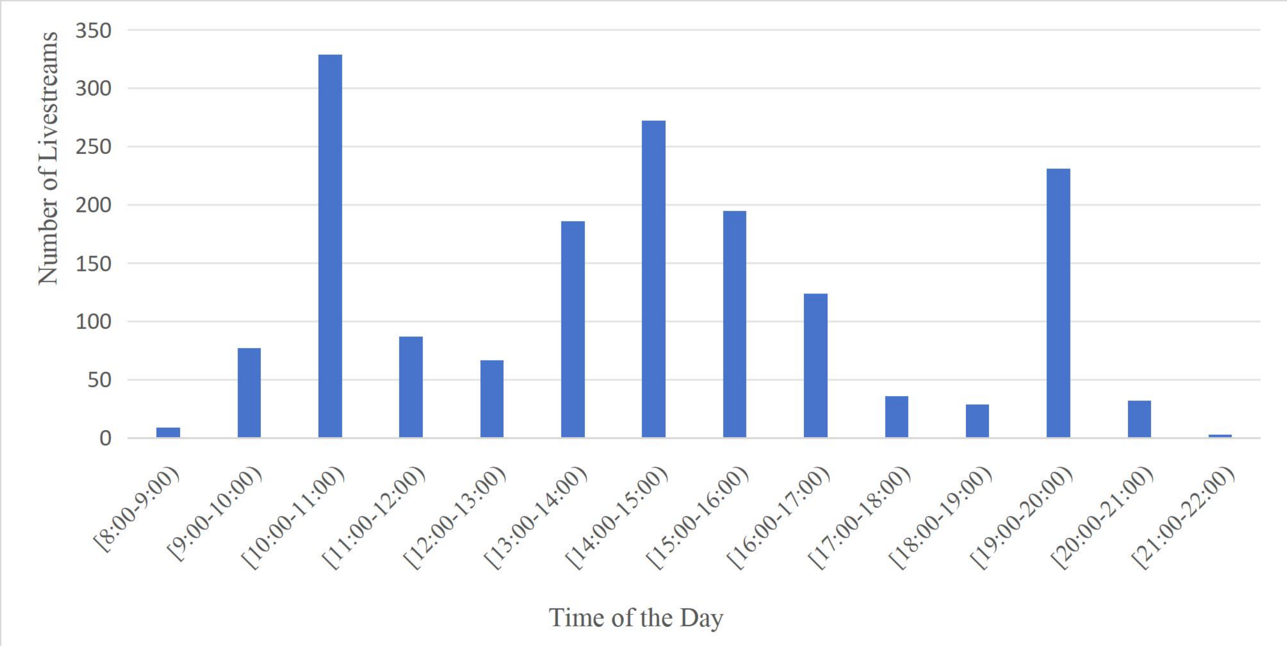
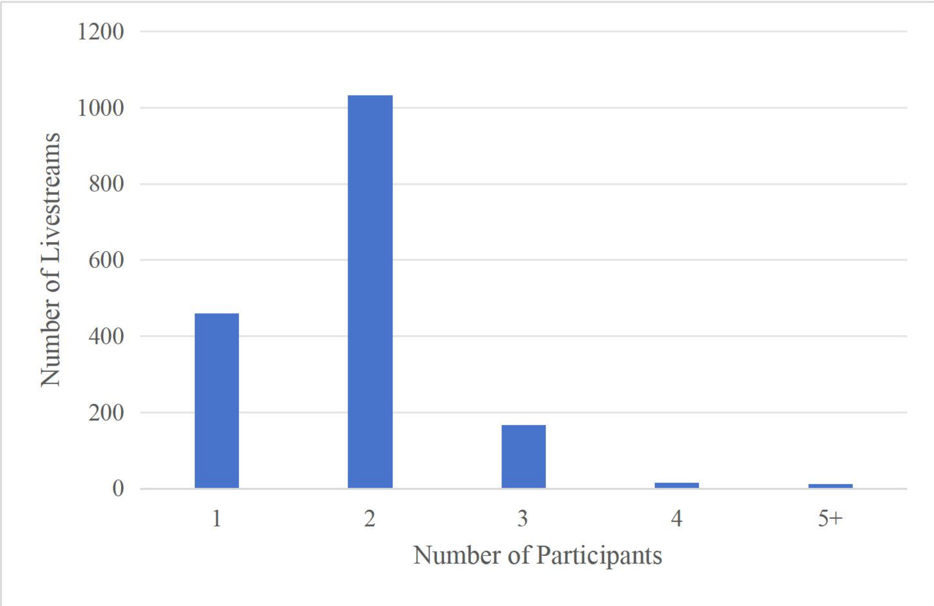


Figure 3. Participants of Fund Livestreams

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

Panel A: Number of Participants



Panel B: Fund Manager Participation

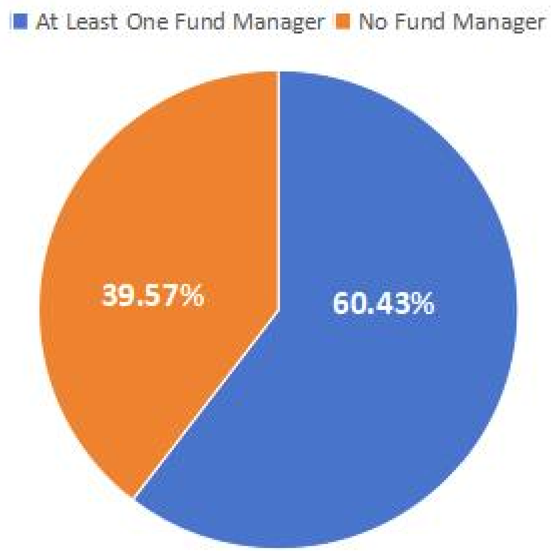


Figure 4. Flowchart for Constructing the Impression Measures

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.

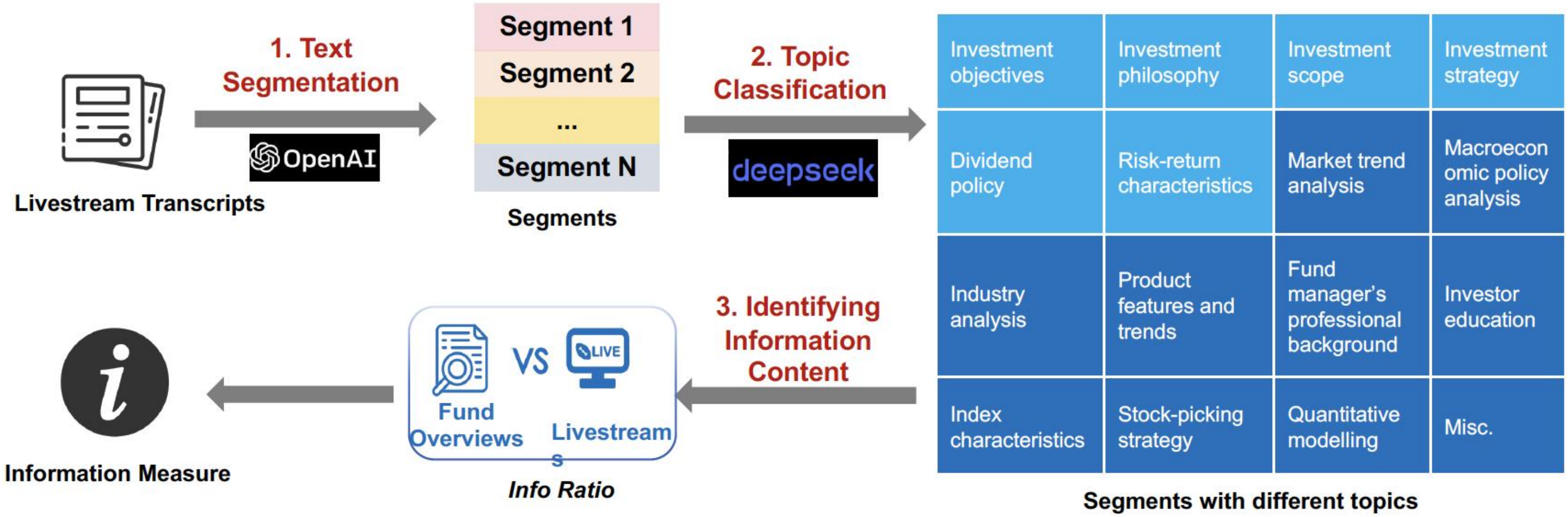


Table 1. Sample Formation

This table lists the steps taken to form the livestream sample for newly launched funds in China and 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.		2,786
We use keywords including "new fund," "launch," "set sail," "on sale," "get on board," "new issuance," and "first launch" in the introduction of a fund livestream to filter livestreams.		
Less observations 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
Final Livestream Sample		1,688
Keep the first livestream of each fund.	− 835	853
Split a fund into different share classes (A and C)[25].	+ 671	1,524
Drop observations with missing data on livestream, fund, or fund manager characteristics.	− 102	1,422
Final Fund Issuance Sample		1,422

[25]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 not service fees while class C charges service fees but not front-end loads.

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 when performing 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: Livestream, Fund, and Fund Manager Characteristics

	Mean	*SD*	*P25*	*Median*	*P75*
Verbal Positive	0.793	0.109	0.730	0.811	0.877
Image Clarity	1.688	1.145	0.835	1.503	2.228
Number of Participants	1.911	0.632	2.000	2.000	2.000
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
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

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 Accounts	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, Number of Participants*, *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		0.106**		
		(0.047)		
Body Motion			0.048	
			(0.045)	
Impression Score				0.170***
				(0.045)
Verbal Positive	0.060	0.088	0.079	0.082
	(0.053)	(0.054)	(0.053)	(0.053)
Image Clarity	0.071	0.082	0.090*	0.079
	(0.052)	(0.053)	(0.053)	(0.053)
Number of Participants	-0.140*	-0.135	-0.126	-0.155*
	(0.081)	(0.082)	(0.082)	(0.082)
Gift	-0.103	-0.096	-0.094	-0.097
	(0.163)	(0.161)	(0.162)	(0.160)
LnViewers	0.194**	0.220**	0.211**	0.203**
	(0.097)	(0.097)	(0.097)	(0.097)
LnLength	0.114	0.087	0.118	0.119
	(0.194)	(0.193)	(0.192)	(0.192)
LnLivetoClose	-0.014	-0.020	-0.009	-0.022
	(0.053)	(0.053)	(0.053)	(0.053)
Active Fund	-0.626**	-0.591**	-0.599**	-0.609**
	(0.291)	(0.296)	(0.297)	(0.295)
Fund Fees	0.399	0.394	0.412	0.397
	(0.291)	(0.298)	(0.297)	(0.295)
State-owned Fund Family	0.150	0.111	0.115	0.119
	(0.124)	(0.125)	(0.125)	(0.124)
Large Fund Family	0.397***	0.463***	0.460***	0.413***
	(0.121)	(0.120)	(0.120)	(0.120)
Female Manager	0.227*	0.251**	0.253**	0.219*
	(0.124)	(0.125)	(0.125)	(0.125)
Rookie Manager	1.499	1.283	1.313	1.339
	(0.938)	(0.941)	(0.943)	(0.939)
Highest Degree	-0.251*	-0.264*	-0.267**	-0.270**
	(0.135)	(0.135)	(0.133)	(0.134)
Top2 University	0.046	0.073	0.074	0.054
	(0.127)	(0.128)	(0.129)	(0.127)
Manager Experience	1.704**	1.542**	1.573**	1.566**
	(0.693)	(0.695)	(0.698)	(0.694)
Manager Past Performance	1.868***	1.878***	1.924***	1.863***
	(0.417)	(0.419)	(0.422)	(0.415)

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	0.363	0.358	0.355	0.364

Panel B: Investor Impressions and Fund Issuance Amount

	LnAmount			
	(1)	(2)	(3)	(4)
Vocal Positive	0.127***			
	(0.045)			
Visual Positive		0.046		
		(0.044)		
Body Motion			0.022	
			(0.042)	
Impression Score				0.213**
				(0.092)
Verbal Positive	0.016	0.032	0.028	0.031
	(0.049)	(0.049)	(0.049)	(0.049)
Image Clarity	0.162***	0.172***	0.175***	0.170***
	(0.049)	(0.049)	(0.049)	(0.049)
Number of Participants	-0.070	-0.058	-0.054	-0.076
	(0.079)	(0.079)	(0.080)	(0.080)
Gift	-0.014	-0.005	-0.005	-0.006
	(0.152)	(0.152)	(0.152)	(0.151)
LnViewers	0.121	0.141	0.137	0.132
	(0.095)	(0.095)	(0.095)	(0.095)
LnLength	0.117	0.094	0.108	0.115
	(0.190)	(0.190)	(0.191)	(0.190)
LnLivetoClose	-0.053	-0.055	-0.051	-0.057
	(0.051)	(0.051)	(0.051)	(0.051)
Active Fund	-0.707**	-0.684**	-0.690**	-0.699**
	(0.327)	(0.329)	(0.329)	(0.329)
Fund Fees	0.204	0.208	0.216	0.209
	(0.310)	(0.312)	(0.312)	(0.312)
State-owned Fund Family	0.294***	0.268**	0.269**	0.270**
	(0.113)	(0.112)	(0.113)	(0.112)
Large Fund Family	0.023	0.070	0.067	0.043
	(0.117)	(0.117)	(0.118)	(0.118)
Female Manager	0.100	0.124	0.123	0.103
	(0.119)	(0.119)	(0.119)	(0.119)
Rookie Manager	2.055**	1.894**	1.916**	1.931**
	(0.891)	(0.890)	(0.890)	(0.891)
Highest Degree	-0.166	-0.173	-0.173	-0.179
	(0.127)	(0.126)	(0.126)	(0.126)
Top2 University	-0.025	-0.004	-0.004	-0.015
	(0.119)	(0.120)	(0.120)	(0.119)
Manager Experience	2.374***	2.259***	2.280***	2.273***
	(0.655)	(0.655)	(0.655)	(0.655)
Manager Past Performance	1.770***	1.794***	1.811***	1.783***
	(0.347)	(0.347)	(0.347)	(0.346)
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	0.248	0.244	0.244	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. *Info* is the share of information content in a livestream relative to the Tiantian fund overview. *High Info* is an indicator variable that takes a value of one if this share is in the top quintile, and zero otherwise. 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, Number of Participants*, *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	0.164***	0.168***	0.098**	0.102**
	(0.046)	(0.045)	(0.044)	(0.044)
Info	-0.061		-0.050	
	(0.053)		(0.051)	
High Info		-0.172		-0.079
		(0.134)		(0.130)
Verbal Positive	0.082	0.084	0.031	0.032
	(0.053)	(0.053)	(0.049)	(0.049)
Image Clarity	0.080	0.082	0.170***	0.171***
	(0.053)	(0.053)	(0.049)	(0.049)
Number of Participants	-0.143*	-0.156*	-0.065	-0.076
	(0.083)	(0.082)	(0.080)	(0.080)
Gift	-0.099	-0.100	-0.007	-0.006
	(0.160)	(0.160)	(0.151)	(0.151)
LnViewers	0.201**	0.204**	0.130	0.132
	(0.096)	(0.096)	(0.095)	(0.095)
LnLength	0.129	0.119	0.125	0.116
	(0.192)	(0.192)	(0.190)	(0.190)
LnLivetoClose	-0.023	-0.027	-0.058	-0.059
	(0.053)	(0.053)	(0.051)	(0.051)
Active Fund	-0.631**	-0.634**	-0.719**	-0.714**
	(0.297)	(0.296)	(0.330)	(0.331)
Fund Fees	0.394	0.393	0.209	0.210
	(0.296)	(0.295)	(0.314)	(0.313)
State-owned Fund Family	0.116	0.122	0.267**	0.271**
	(0.124)	(0.124)	(0.112)	(0.112)
Large Fund Family	0.410***	0.405***	0.041	0.040
	(0.120)	(0.120)	(0.118)	(0.118)
Female Manager	0.218*	0.228*	0.101	0.106
	(0.125)	(0.125)	(0.119)	(0.119)
Rookie Manager	1.402	1.354	1.976**	1.934**
	(0.944)	(0.935)	(0.893)	(0.890)
Highest Degree	-0.277**	-0.283**	-0.185	-0.186

	(0.134)	(0.134)	(0.126)	(0.127)
Top2 University	0.052	0.050	-0.016	-0.016
	(0.127)	(0.127)	(0.119)	(0.119)
Manager Experience	1.617**	1.579**	2.308***	2.275***
	(0.698)	(0.691)	(0.657)	(0.655)
Manager Past Performance	1.842***	1.822***	1.765***	1.763***
	(0.415)	(0.415)	(0.346)	(0.346)
Style FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Time of Day FE	YES	YES	YES	YES
Observations	783	783	1,422	1,422
Adjusted R^2	0.365	0.365	0.246	0.246

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

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Impression Score	0.161***	0.228***	0.093**	0.150***
	(0.044)	(0.050)	(0.043)	(0.050)
Impression Score × Info	-0.124***		-0.121***	
	(0.037)		(0.042)	
Info	-0.061		-0.046	
	(0.051)		(0.051)	
Impression Score × High Info		-0.266**		-0.228**
		(0.104)		(0.106)
High Info		-0.201		-0.097
		(0.131)		(0.128)
Verbal Positive	0.088*	0.094*	0.038	0.041
	(0.053)	(0.054)	(0.049)	(0.049)
Image Clarity	0.087*	0.084	0.175***	0.172***
	(0.052)	(0.052)	(0.049)	(0.049)
Number of Participants	-0.147*	-0.155*	-0.069	-0.073
	(0.083)	(0.083)	(0.080)	(0.080)
Gift	-0.114	-0.115	-0.020	-0.018
	(0.160)	(0.161)	(0.151)	(0.152)
LnViewers	0.215**	0.213**	0.138	0.138
	(0.095)	(0.095)	(0.094)	(0.095)
LnLength	0.116	0.098	0.118	0.099
	(0.190)	(0.191)	(0.190)	(0.190)
LnLivetoClose	-0.021	-0.024	-0.056	-0.056
	(0.053)	(0.052)	(0.051)	(0.051)
Active Fund	-0.667**	-0.647**	-0.740**	-0.710**
	(0.296)	(0.294)	(0.328)	(0.329)
Fund Fees	0.422	0.365	0.228	0.174
	(0.296)	(0.295)	(0.312)	(0.314)
State-owned Fund Family	0.105	0.125	0.255**	0.273**
	(0.123)	(0.123)	(0.112)	(0.112)
Large Fund Family	0.395***	0.386***	0.024	0.021
	(0.120)	(0.120)	(0.118)	(0.118)
Female Manager	0.218*	0.239*	0.105	0.118
	(0.125)	(0.125)	(0.119)	(0.118)
Rookie Manager	1.394	1.388	1.986**	1.961**
	(0.942)	(0.935)	(0.892)	(0.889)
Highest Degree	-0.264**	-0.274**	-0.170	-0.174
	(0.133)	(0.133)	(0.125)	(0.126)
Top2 University	0.061	0.062	-0.003	-0.002

	(0.126)	(0.126)	(0.119)	(0.119)
Manager Experience	1.624**	1.610**	2.327***	2.301***
	(0.698)	(0.692)	(0.656)	(0.655)
Manager Past Performance	1.820***	1.803***	1.749***	1.756***
	(0.414)	(0.414)	(0.345)	(0.345)
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	0.370	0.369	0.250	0.248

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

	LnSubscriptions			*LnAmount*		
	(1)	(2)	(3)	(4)	(5)	(6)
Impression Score	0.140***	0.150***	0.139***	0.077*	0.087*	0.076*
	(0.044)	(0.045)	(0.044)	(0.044)	(0.045)	(0.044)
Impression Score × Info Complex	-0.143***		-0.190***	-0.161***		-0.177***
	(0.039)		(0.055)	(0.043)		(0.062)
Impression Score × Info NonComplex		0.071	-0.065		0.115**	-0.018
		(0.051)	(0.065)		(0.052)	(0.071)
Info Complex	-0.170***		-0.102	-0.159***		-0.077
	(0.060)		(0.074)	(0.055)		(0.074)
Info NonComplex		0.160***	0.099		0.167***	0.120
		(0.061)	(0.076)		(0.057)	(0.076)
Verbal Positive	0.099*	0.090*	0.096*	0.051	0.044	0.050
	(0.053)	(0.053)	(0.053)	(0.049)	(0.049)	(0.049)
Image Clarity	0.081	0.074	0.082	0.171***	0.164***	0.169***
	(0.052)	(0.052)	(0.052)	(0.049)	(0.049)	(0.049)
Number of Participants	-0.099	-0.106	-0.093	-0.026	-0.028	-0.017
	(0.083)	(0.082)	(0.083)	(0.081)	(0.081)	(0.081)
Gift	-0.133	-0.124	-0.144	-0.035	-0.031	-0.047
	(0.159)	(0.160)	(0.159)	(0.151)	(0.151)	(0.151)
LnViewers	0.185*	0.179*	0.190**	0.115	0.108	0.113
	(0.094)	(0.096)	(0.095)	(0.094)	(0.095)	(0.094)
LnLength	0.159	0.161	0.162	0.154	0.151	0.157
	(0.192)	(0.195)	(0.193)	(0.190)	(0.190)	(0.190)
LnLivetoClose	-0.016	-0.014	-0.012	-0.052	-0.051	-0.049
	(0.052)	(0.053)	(0.053)	(0.050)	(0.051)	(0.051)
Active Fund	-0.687**	-0.615**	-0.677**	-0.781**	-0.720**	-0.763**
	(0.294)	(0.294)	(0.294)	(0.326)	(0.326)	(0.325)
Fund Fees	0.515*	0.530*	0.565*	0.319	0.344	0.369
	(0.298)	(0.301)	(0.300)	(0.311)	(0.313)	(0.312)
State-owned Fund Family	0.100	0.109	0.092	0.246**	0.259**	0.242**
	(0.121)	(0.122)	(0.121)	(0.111)	(0.111)	(0.111)

Large Fund Family	0.374***	0.396***	0.376***	0.003	0.022	0.005
	(0.119)	(0.119)	(0.119)	(0.117)	(0.117)	(0.117)
Female Manager	0.192	0.195	0.192	0.071	0.065	0.067
	(0.125)	(0.126)	(0.125)	(0.119)	(0.119)	(0.119)
Rookie Manager	1.365	1.329	1.402	1.943**	1.877**	1.956**
	(0.933)	(0.938)	(0.940)	(0.888)	(0.891)	(0.891)
Highest Degree	-0.288**	-0.282**	-0.277**	-0.193	-0.192	-0.184
	(0.133)	(0.134)	(0.133)	(0.126)	(0.126)	(0.125)
Top2 University	0.034	0.032	0.039	-0.029	-0.042	-0.029
	(0.126)	(0.127)	(0.125)	(0.118)	(0.119)	(0.118)
Manager Experience	1.616**	1.570**	1.643**	2.309***	2.250***	2.322***
	(0.691)	(0.695)	(0.697)	(0.655)	(0.658)	(0.658)
Manager Past Performance	1.872***	1.906***	1.858***	1.804***	1.855***	1.813***
	(0.413)	(0.417)	(0.415)	(0.343)	(0.347)	(0.346)
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	0.378	0.371	0.378	0.256	0.253	0.256

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

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 the inverstors' impression and the amount and complexity of information content in a livestream with fund manager participation to those without. *Info* is the share of information content in a livestream relative to the Tiantian fund overview. *Info Complex* is the share of information in a livestream related to the six complex topics that require interpretation by investment professionals. 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. *Manager Present* is an indicator variable that takes a value of one if at least one fund manager is present during the livestream, and zero otherwise. The control variables include *Verbal Positive, Image Clarity, Number of Participants*, *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 Information Measures 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***

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

	LnSubscriptions	*LnAmount*
	(1)	(2)
Impression Score	0.255***	0.285***
	(0.066)	(0.066)
Impression Score × Manager Present	-0.158*	-0.318***
	(0.087)	(0.086)
Manager Present	-0.386***	-0.396***
	(0.122)	(0.122)
Controls	YES	YES
Style FE	YES	YES
Year FE	YES	YES
Time of Day FE	YES	YES
Observations	783	1,422
Adjusted R^2	0.373	0.257

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. *High Info* is an indicator variable that takes a value of one if the share of information is in the top quintile, and zero otherwise. The control variables include *Verbal Positive, Image Clarity, Number of Participants*, *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	0.221***	0.197	0.137***	-0.067
	(0.053)	(0.191)	(0.051)	(0.194)
Impression Score × High Info	-0.300***	-0.060	-0.318***	0.343
	(0.110)	(0.271)	(0.112)	(0.313)
High Info	-0.205	-0.144	-0.173	-0.017
	(0.150)	(0.264)	(0.144)	(0.254)
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	0.239	0.244	0.421

Table 9. Investor Impressions, Information, and Long-term Performance

This table presents multiple regression estimates examining the association between livestream characteristics and fund performance. Our sample period is from July 1, 2020 to May 31, 2024. In Panel A, we use the full sample. In Panel B, we limit the sample to those with manager present during the livestream, and reconstruct *Impression Score* and related measures only based on manager (not including hosts and other presenters). 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, Number of Participants*, *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: Full Sample

	Return 3m		*Return 6m*		*Return 12m*	
	(1)	(2)	(3)	(4)	(5)	(6)
Impression Score	-0.005**	-0.008***	-0.004*	-0.006***	-0.003	-0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Impression Score × High Info		0.013**		0.011*		0.007
		(0.006)		(0.006)		(0.006)
High Info	0.009	0.010	0.009	0.010*	-0.010	-0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
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	1,416	1,416	1,367	1,367	1,240	1,240
Adjusted R^2	0.750	0.751	0.105	0.108	0.972	0.972

Panel B: Fund Manager Presence Sample (Impression score only based on fund manager)

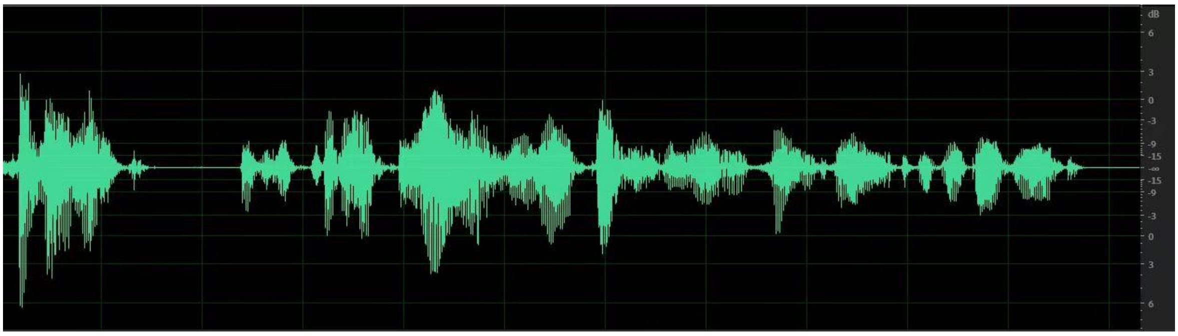
	Return 3m		*Return 6m*		*Return 12m*	
	(1)	(2)	(3)	(4)	(5)	(6)
Impression Score	-0.009***	-0.012***	-0.008**	-0.010***	-0.005	-0.005
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)
Impression Score × High Info		0.013*		0.011		0.000
		(0.007)		(0.007)		(0.009)
High Info	0.010	0.010	0.005	0.005	-0.016	-0.016
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)
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	771	771	751	751	686	686
Adjusted R^2	0.759	0.760	0.148	0.150	0.973	0.973

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. Flow Chart for Constructing The Complexity of Information (Info Complex and Info NonComplex)

This figure presents a flowchart illustrating the process of constructing the information complexity measure.

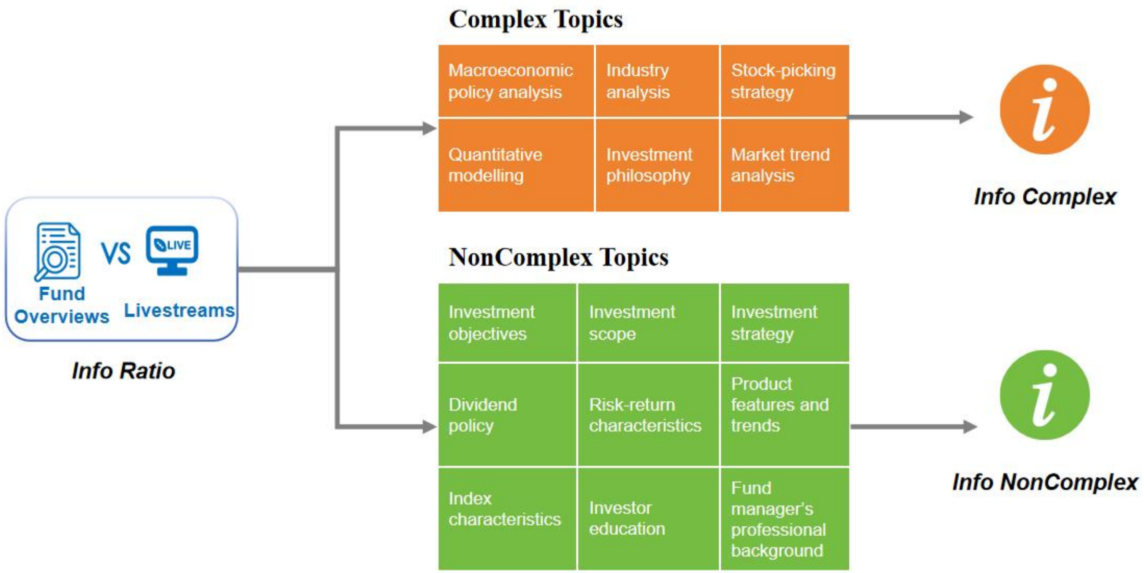


Table IA1. Implementation Details

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. Investor Impressions and Reactions

This table presents multiple regression estimates examining the association between investor impressions and investor 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, Number of Participants*, *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	0.003			
	(0.010)			
Visual Positive		0.022**		
		(0.010)		
Body Motion			0.013	
			(0.012)	
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			0.004*	
			(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	0.739	0.738	0.739

Table IA3. 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. *Info* is the share of information content in a livestream relative to the Tiantian fund overview. *High Info* is an indicator variable that takes a value of one if this share is in the top quintile, and zero otherwise. 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, Number of Participants*, *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***	0.115**	0.119**
	(0.054)	(0.054)	(0.048)	(0.048)
Info	-0.067		-0.053	
	(0.052)		(0.051)	
High Info		-0.187		-0.089
		(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	0.365	0.366	0.247	0.247

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

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Impression Score	0.189***	0.271***	0.112**	0.158***
	(0.053)	(0.061)	(0.047)	(0.055)
Impression Score × Info	-0.141***		-0.111**	
	(0.042)		(0.043)	
Info	-0.067		-0.051	
	(0.050)		(0.051)	
Impression Score × High Info		-0.310***		-0.171
		(0.115)		(0.111)
High Info		-0.187		-0.086
		(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	0.372	0.371	0.250	0.248

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

	LnSubscriptions			*LnAmount*		
	(1)	(2)	(3)	(4)	(5)	(6)
Impression Score	0.182***	0.186***	0.179***	0.109**	0.114**	0.107**
	(0.053)	(0.053)	(0.052)	(0.048)	(0.048)	(0.048)
Impression Score × Info Complex	-0.131***		-0.210***	-0.130***		-0.162**
	(0.047)		(0.060)	(0.047)		(0.063)
Impression Score × Info NonComplex		0.042	-0.106		0.083	-0.036
		(0.054)	(0.067)		(0.052)	(0.069)
Info Complex	-0.175***		-0.103	-0.159***		-0.074
	(0.059)		(0.073)	(0.055)		(0.074)
Info NonComplex		0.170***	0.102		0.174***	0.123
		(0.060)	(0.075)		(0.056)	(0.075)
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	0.377	0.371	0.379	0.254	0.252	0.255

Table IA4. 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 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. *High Info* is an indicator variable that takes a value of one if this share is in the top quintile, and zero otherwise. 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, Number of Participants*, *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	0.159***	0.159***	0.096**	0.100**
	(0.047)	(0.047)	(0.045)	(0.045)
Info	-0.127**		-0.140***	
	(0.052)		(0.049)	
High Info		-0.315**		-0.221*
		(0.125)		(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	0.365	0.366	0.251	0.249

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

	LnSubscriptions		*LnAmount*	
	(1)	(2)	(3)	(4)
Impression Score	0.155***	0.187***	0.093**	0.148***
	(0.047)	(0.052)	(0.045)	(0.051)
Impression Score × Info	-0.065*		-0.090**	
	(0.038)		(0.040)	
Info	-0.128**		-0.139***	
	(0.051)		(0.049)	
Impression Score × High Info		-0.155		-0.261**
		(0.117)		(0.107)
High Info		-0.331***		-0.243**
		(0.125)		(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	0.366	0.366	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	0.142***	0.168***	0.144***	0.086*	0.108**	0.088*
	(0.045)	(0.046)	(0.045)	(0.045)	(0.045)	(0.045)
Impression Score × Info Complex	-0.155***		-0.113***	-0.157***		-0.130***
	(0.038)		(0.042)	(0.041)		(0.046)
Impression Score × Info NonComplex		0.137***	0.084		0.110**	0.048
		(0.048)	(0.054)		(0.051)	(0.058)
Info Complex	-0.165***		-0.184***	-0.132**		-0.175***
	(0.058)		(0.064)	(0.055)		(0.060)
Info NonComplex		0.043	-0.032		-0.011	-0.081
		(0.056)	(0.061)		(0.058)	(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	0.375	0.367	0.376	0.256	0.249	0.256

Table IA5. 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 based on the beginning 10 minutes, middle 10 minutes, and ending 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) 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. *High Info* is an indicator variable that takes a value of one if this share is in the top quintile, and zero otherwise. The control variables include *Verbal Positive, Image Clarity, Number of Participants*, *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	0.528***			0.394**	0.454**			0.369*
	(0.181)			(0.195)	(0.181)			(0.190)
Impression Score Beginning × Info Beginning	-0.539**			-0.484**	-0.513**			-0.459*
	(0.233)			(0.242)	(0.240)			(0.243)
Info Beginning	-0.130			-0.104	0.230			0.303
	(0.253)			(0.258)	(0.233)			(0.235)
Impression Score Middle		0.363**		0.246		0.331**		0.292*
		(0.149)		(0.171)		(0.144)		(0.156)
Impression Score Middle × Info Middle		-0.271		-0.238		-0.322		-0.290
		(0.213)		(0.214)		(0.204)		(0.204)
Info Middle		-0.134		-0.116		-0.343		-0.332
		(0.229)		(0.231)		(0.220)		(0.220)
Impression Score Ending			0.010	-0.109			0.063	-0.039
			(0.174)	(0.188)			(0.186)	(0.199)
Impression Score Ending × Info Ending			0.249	0.300			0.033	0.056
			(0.243)	(0.243)			(0.258)	(0.258)
Info Ending			-0.363	-0.343			-0.395	-0.377
			(0.253)	(0.257)			(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	0.362	0.365	0.366	0.367	0.247	0.248	0.246	0.249