Emotions and Fund Flows: Evidence from Managers' Live Streams *

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Abstract

We study whether real-time, unscripted communication by fund managers persuades public-market investors. Using live-streamed sessions by Chinese ETF managers, we apply a multimodal ML framework to quantify facial, vocal, and textual affect and summarize them in Affective Delivery Index (ADI). A one-standard-deviation increase in ADI raises next-day (two-week) fund flows by 0.1 pp (0.4 pp), with no predictability for subsequent returns, consistent with persuasion rather than information. Facial expressions are the dominant modality. Effects are stronger in down markets, for ETFs with higher retail ownership, and remain after controlling for contemporaneous/past returns and flows plus day, ETF-index-week, fund-month, and fund-day-of-the-week fixed effects. Investor reactions during the stream (likes/views) load positively on ADI, consistent with emotional contagion as a mechanism. Our results indicate that live manager delivery reallocates capital in the short run and moves trading and prices even absent new information.

Keywords: Fund Managers, Live Streaming, Affective Delivery Index, ETF Flows, Machine Learning

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1 Introduction

Capital flows do not respond only to information; they also respond to how that information is delivered. As real-time video has exploded, investor communication increasingly arrives with facial cues, voice tone, and on-screen interaction—not just words. Yet we know little about whether these delivery cues move capital allocation in asset management, where even small shifts in flows translate into fees and market impact.

We study this question in the setting of fund-manager live streams. Traditional fund communication is largely text-based (prospectuses, reports, shareholder letters), and prior work has focused on textual sentiment (Kostovetsky and Warner, 2020; Abis and Lines, 2024; Hillert, Niessen-Ruenzi, and Ruenzi, 2025); verbal delivery is better studied in corporate settings than in funds (Mayew and Venkatachalam, 2012; Allison et al., 2022). Live streaming—an integrated medium combining visual, vocal, and verbal elements—has become a common channel for managers to reach investors. Despite its rapid adoption, we know little about what these sessions convey and whether their delivery affects fund flows. Using a comprehensive sample of ETF managers' live-streamed videos from China, we bring multimodal machine-learning measures to this setting and link them to high-frequency flows.

Fund management companies in China have been leveraging live streams for marketing and investor education, with industry data showing that over 90% of fund families now conduct regular live sessions. Our analysis focuses primarily on ETF market, for the following reasons. First, live streaming activities in fund industry occur frequently—often once monthly or more—whereas fund flows for other fund types are only disclosed quarterly, limiting timely analysis. In contrast, ETFs offer access to daily fund flow and market trading data, enabling us to examine high-frequency investor responses. This granularity is critical given that the observed impact of live streaming is likely short-lived. Second, given that China's ETF market is dominated by passive funds, such setting allows us to systematically control for the simultaneous effects of performance and fund manager skill, as well as similarity in content, that are strong determinants for fund flows.

Following Hu and Ma (2025), we use machine learning (ML) algorithms to quantify features of the video data along visual, vocal, and verbal dimensions. We further apply factor analysis to all three features and create a unified measure, *Affective Delivery Index* (ADI), summarizing the affect with which the fund managers deliver the streaming to their audiences. Our measure

is derived for 101 fund managers managing 459 exchange-traded funds based on around 2000 live streaming episodes over the January 2021–December 2023 period.

We study the impact of these measures on individual fund outcomes. We find that ETFs managed by managers characterized by a greater value of ADI—that is, those whose managers are more positive in their videos—attract, on average, more fund flows. The results are significant, both statistically and economically. A one-standard-deviation increase in ADI is associated with a 0.1 percentage-point (0.4 pp) increase in next-day (two-week) fund flows, a sizable effect considering that the average daily fund flow in our sample is 0.04%. Further, this pattern is more significant along the visual dimension, whereas a vocal factor has a positive but insignificant effect; the verbal dimension plays a trivial role. This result stands in contrast to most studies in the literature, which use textual analysis and find strong predictive information from disclosed data, such as conference call scripts or fund letters. Two hypotheses are at play. On the one hand, if live streaming indeed conveys informative content about future market movement, we should expect at least the verbal content matter. On the other hand, if live streaming is purely for investor educational purpose but without any predictive information, the unified ADI, especially the visual dimension, should not affect investor behavior. Therefore, the observed fund flow effect is more likely to be persuasion-driven, rather than information-driven.

We next examine the extensive margin and test whether the decision to host a live stream activity affects fund flows. A baseline regression incorporating the occurrence of a live stream as a regressor yields an insignificant result, suggesting that a mere stream participation does not differentially affect investor behavior. This helps us alleviate concerns regarding sample selection bias, since the decision to host a live stream may be endogenous, for instance, shaped by a range of underlying factors that could otherwise confound our analysis. By establishing that participation in live streaming has no direct effect on fund flows, it is less likely that unobserved variables driving both the decision to stream and fund flows are distorting our results.

To further rule out the sample selection issue and mitigate potential endogeneity concerns, we conduct several other tests. The results are robust to controlling for a set of conventional variables, including fund manager characteristics, fund and fund family controls, including fund flows and fund performance. In addition, we control for the ETF index×week fixed effects, which allows us to effectively compare the effect for ETFs tracking the similar (or same) index, and largely avoid

contamination from the effect of fund performance, information content, or other index-related factors that are strongly related to fund flows. We also include fund×month fixed effects, which control for any lower-frequency time-varying fund characteristics and day fixed effects that absorb any daily variation in aggregate market news. Finally, results are robust to fund-day-of-the-week fixed effects, which flexibly absorb within-fund weekly seasonality in flows and content supply.

To further improve empirical identification in addition to the complete set of fixed effects, an alternative and more direct way to obtain a well-identified set of parameters can be through the use of instrumental variables. We use the air quality index (AQI) as an instrument for ADI during live streaming. Similar to the OLS regression results, we again find a strong positive effect of ADI on fund flows.

To further support the sentiment-driven channel, we also examine investor reactions by analyzing their emotional responses after viewing the videos. Viewers' emotions are likely to be influenced by the host's emotions (Lin, Yao, and Chen, 2021). We measure investor emotion as the ratio of video likes to total views. Our findings indicate that investor emotions are significantly and positively influenced by ADI. Aligning with the fund flow analysis, the visual component-specifically, facial expressions-emerges as the most robust driver of investor emotions. These results suggest that fund managers' positive expressions are contagious, capable of reshaping investors' emotional states and, in turn, their behavior. In contrast, the regression of future fund performance on ADI and its three sub-components returns an insignificant effect, suggesting that investors' trades are not induced by information content.

Next, we explore the heterogeneity of the ADI effect across different market regimes, live streaming characteristics, fund types, and fund investor clienteles. We find that the effect is more pronounced during market downturns, indicating that investors are more prone to being persuaded in bear markets. Moreover, longer videos amplify the emotional influence, which indicates that extended exposure to fund managers' emotional expressions enhances investors' emotional engagement and response. Live streaming conducted in the afternoon exhibits a stronger effect. Broad market index ETFs exhibit a weak effect compared to that of other ETFs. Last, ETFs with high retail investor ownerships produce larger effect than those with high institutional ownership. The result is quite intuitive since retail investors are likely to watch videos and are also typically more easily affected by fund managers.

Apart from the primary market fund flows, we also study the effect of ADI on the secondary market trading activity. ADI is significantly and positively related to net-buy volume of retail investors, consistent with our previous findings that retail investors respond more strongly to live streaming video factor. Within the three individual components, the visual element is still the strongest factor, followed by vocal and verbal elements. Besides the quantity effect, ADI is also significantly related to ETF price deviations. Higher absolute values of ADI (again the visual part) lead to larger price deviations of ETFs with respect to their underlying assets.

Finally, we conduct a series of robustness checks. Since live streaming sessions could last longer than half an hour and audiences may only watch parts of the videos, we randomly select half of each video content and repeat the baseline analysis. The result is still robust even with partial video-based measures. Different from typical machine learning based methods, we also apply new multi-modal AI models—Alibaba's open-source R1-Omni model—to the video data and use prompt to create an AI-based ADI measure. Again, the alternative factor generates a significant effect on fund flows.

Related Literature

A long-standing literature has documented that mutual fund flows are shaped by both performance and other fund characteristics. Classic studies find that investors chase returns, reacting asymmetrically to positive and negative performance (Sirri and Tufano, 1998; Berk and Green, 2004; Goldstein, Jiang, and Ng, 2017). More recent research identifies non-performance-related flow drivers, such as advertising (Jain and Wu, 2000), product design (Barber, Odean, and Zheng, 2005; Hartzmark and Sussman, 2019), and manager attributes (Bai et al., 2019; Niessen-Ruenzi and Ruenzi, 2019). Of particular note, recent applications of computer vision reveal that fund managers' facial attractiveness influences flows, especially when photos are public (Bai and Tian, 2023). These findings suggest that investors incorporate soft signals when allocating capital, although the role of real-time emotional communication in this context remains underexplored. We advance the literature on mutual fund flows by identifying fund managers' emotional expressions as a previously unexplored determinant of investor allocations. Our study shows that affective signals embedded in live streaming, including facial happiness and vocal tone, are strongly associated with subsequent capital inflows.

Mutual fund marketing plays a central role in shaping investor attention and reducing infor-

mation frictions. Fund companies dedicate a significant portion of their expenses to marketing and distribution (Roussanov, Ruan, and Wei, 2020), aiming to enhance fund visibility and appeal. Traditional marketing tools, such as advertisement, name changes, and branding efforts have all been shown to attract inflows-even absent performance justification (Cooper, Gulen, and Rau, 2005; Steven Gallaher and Starks, 2015; Espenlaub, ul Haq, and Khurshed, 2017). With the rise of FinTech platforms, new forms of communication are gaining prominence. For instance, Hong, Lu, and Pan (2025) find that platform entry increases performance-chasing tendencies, while Mayew and Venkatachalam (2012) show that persuasive cues, such as vocal tones can shape investor response. Yet, the marketing value and psychological impact of fund live streaming remains a relatively unexplored frontier. Our study introduces live streaming as a new form of affect-based marketing and expands the understanding of investor communication in digital finance. These insights contribute to the literature on mutual fund marketing and offer implications for the design of digital engagement strategies in asset management.

Our paper extends the literature on video-based information in financial decision-making by focusing on real-time and unscripted live communication and applying it to public market setting. Whereas prior studies have concentrated on structured video formats, such as startup pitches or corporate presentations (Blankespoor, Hendricks, and Miller, 2017; Hu and Ma, 2025), our research shifts the focus to live streaming, an increasingly popular communication tool used by fund managers to engage with retail investors. We apply our methodology to trading markets and provide novel empirical evidence that emotional cues conveyed during such live streaming influence investment behavior even if they do not contain tradable information.

Non-textual big data analysis in financial market becomes more and more popular nowadays. William and Mohan (2012) measure managerial affective states during earnings conference calls by analyzing conference call audio files using vocal emotion analysis software, and find that positive and negative affects displayed by managers are informative about the firm's financial future. Gorodnichenko, Pham, and Talavera (2023) develop a deep learning model to detect emotions embedded in press conferences after the Federal Open Market Committee meetings and find that, after controlling for the Federal Reserve's actions and the sentiment in policy texts, a positive tone in the voices of Federal Reserve chairs leads to significant increases in asset prices.

From the theory perspective, our paper also connects to the literature on persuasion and infor-

mation design (e.g. Kamenica and Gentzkow, 2011). In that framework, a sender optimally structures signals to shift receivers' actions. We study a complementary margin: delivery. Managers' live streams bundle facial and vocal affect with content, and we show that this affect moves flows even when informational content is held fixed, with no corresponding improvement in performance. Thus, our evidence is closer to persuasion via attention and affect (e.g., limited-attention/salience models; psychology of emotional contagion) than to canonical information-design tests. We therefore use persuasion in a broad sense and view our results as documenting a delivery channel that standard models of disclosure could embed.

The remainder of the paper is structured as follows. Section 2 describes the data and sample used in our paper. Section 3 shows how we employ ML algorithm to analyze live streaming data. Section 4 discusses the main findings related to ADI and other robustness tests. Section 5 concludes.

2 Data and Summary Statistics

This section introduces the dataset and reports summary statistics. The sample is a combination of two parts, live streaming data and the fund data, which are merged using fund manager names and fund IDs. The data spans 36 months, from January 2021 to December 2023.

2.1 Fund manager live streaming

Fund managers' live streaming has emerged on the strength of China's large, mature, and commerce-oriented ecosystem.[1] Live streaming, as an instantaneous form of interaction that transcends the limitations of time and space, has become a key medium for content dissemination among financial institutions. Fund management companies now use live streaming as a routine channel for information and investor education. Unlike entertainment or product promotion, fund managers' live streaming emphasizes compliance and information density. According to the requirements of the Asset Management Association of China ($AMAC$), live streaming by fund managers should primarily serve the purpose of investor education rather than fund marketing. In 2023, more than 140 firms hosted about 54,000 sessions on Ant Fortune, Tiantian Fund, Jravity, Yunjilink, and

[1] By Q4 2023, live streaming had reached nearly 30% of global internet users on a weekly basis, underscoring its widespread adoption as a key channel for investor interaction. According to Digital 2024: April Global Statshot Report, live streaming recorded an audience reach of 28.5% among internet users worldwide in Q4 2023, up by 2.8% from the previous quarter. A 2023 survey by Censuswide and Wunderman Thompson Commerce revealed that eight in ten online shoppers in China have already purchased products via live streaming.

Sina Finance, up roughly 21.4% from 2022, with total views near 3.36 billion and year-on-year growth around 12%.[2]

We obtain fund managers' live streaming videos from Tiantian Fund APP, one of China's top online fund sales platforms. Tiantian Fund platform had equity fund sales and hybrid fund sales retention reaching 402.9 billion RMB in 2023, maintaining its position as the third-largest in the industry. To collect live streaming data, we compile a list of ETF fund managers and use their names as search keywords. We develop a mobile app crawler in Python, which retrieves a list of live streaming videos associated with these fund managers based on predefined keywords. We download 1,980 live streaming videos, totaling approximately 1,952 hours. In addition to the video content, we collect metadata including the timestamp, number of views, number of likes, and associated fund codes. Hereafter, *likes* refers to the platform-reported number of like interactions for a video. Since the platform does not provide real-time counters, the reported view and like counts reflect the snapshot at the time of data download, rather than the final totals at the end of the live streaming.

We apply the following criteria in selecting samples: (1) track a stock index; (2) fund age more than one month at the time of live streaming; (3) conduct live streaming at least two times per month; (4) at least two ETFs tracking similar index. The final sample includes 29 fund management companies, 101 ETF fund managers, and 459 managed ETFs.

Our data is structured at the fund-day level. When the date of live streaming coincides with a trading day, fund characteristics are recorded on the day of live streaming, and fund flow is measured on the next trading day. When live streaming occurs on a non-trading day, fund characteristics are taken from the most recent previous trading day, while fund flow is still measured on the next trading day. All continuous variables are winsorized at 1%.

Table 1 presents summary statistics of the main variables based on managed funds sample used in main analysis. The multimodal emotion variables and ADI are all standardized to have a mean of zero and a standard deviation of one. The average duration of live streaming conducted by fund managers is 59 minutes (approximately one hour), ranging from 25 minutes to 231 minutes, depending on the topic of live streaming. The videos receive a substantial number of views and likes, indicating significant investor engagement. On average, each video receives 50,156 views and 34,246 likes. To examine which types of fund managers are more likely to conduct live streaming,

[2]The data is from the 2023 Annual Report on Live Streaming in the Financial Sector, published by the Jubilee Data Institute.

we also perform a t-test that compares fund characteristics with and without a live-streaming record. The results are reported in Table A4.

2.2 Fund characteristics

China's rapidly growing fund market and live streaming industry offer a unique research setting. First, the Chinese large fund market has attracted a large influx of global capital. The current data from Investment Company Institute (ICI) for Q1 2024 shows a boost in the Chinese fund market, with a total size of 3.52 trillion USD, ranked fourth globally.[3] As an emerging mutual fund market, China's market environment offers comprehensive data to study fund manager's live streaming practices and fund flows.

Second, different from the U.S., the Chinese market is mainly dominated by individual investors. Compared with institutional investors, these are more likely to be uninformed and thus trade on sentiment (Nofsinger and Sias, 1999). They are more prone to being influenced by external information, creating behavioral biases and altering investment decisions.

The financial data on fund, as well as the fund manager information, are primarily sourced from the Wind Economic Database (Wind), China Stock Market & Accounting Research (CSMAR) Database, and iFinD Database (iFinD). For each fund, we collect the tracked index, turnover rate, net asset value, outstanding shares, fund age, and daily returns. Following the methodology of Sirri and Tufano (1998), the fund flow is calculated using the following equation:

$$Flow_{it} = \frac{TNA_{it} - TNA_{it-1} \times (1 + r_{it})}{TNA_{it-1}} * 100\% \tag{1}$$

In equation 1, TNA_{it} refers to the total net assets of fund i at time t, calculated as net asset values (NAV) multiplied by total shares. r_{it} represents the fund's return on NAV, which accounts for cash dividends and fund splits. In addition, we collect two secondary-market data series. First, we take retail net buying using Wind's trade-size classification, in which institutional orders are those exceeding RMB 1 million, large orders range from RMB 200,000 to 1 million, medium orders from RMB 40,000 to 200,000, and small orders are below RMB 40,000. We define retail orders as all non-institutional orders, that is, the sum of small, medium, and large orders. Second, we use ETFs' minute-by-minute close prices via iFinD to construct intraday price volatility.

[3]Source: https://www.ici.org/statistics

Table 1 also provides summary statistics of variables related to both funds and fund managers. Regarding fund-level features, the sample funds are on average 729 days (approximately two years) old, their average size is 2,118 million RMB, and mean turnover rate of 7.20%. Daily returns on the event day t and the cumulative returns over the ten days leading up to the event $(t-10, t-1)$ are both negative. The benchmark indices that funds track exhibit an average volatility of 1.37, indicating a moderate level of underlying market fluctuation.

At the fund family level, we compute weighted average flows by aggregating the ETF fund flows under each fund management company using fund size as weights. The resulting average family-level flow ratio is approximately 0.12% at live streaming days.

3 Methodology

This section describes the methodological framework to analyze fund live streaming. The procedure consists of three main stages: video pre-processing, extraction of multimodal features, and construction of a composite factor to measure how positive the fund manager is in the live streaming.

In this paper, we apply machine learning algorithms to extract three key dimensions from fund managers' live streaming: facial expressions (e.g., happy, sad, angry, fearful, disgusted, surprised, neutral), vocal tone (e.g., angry, sad, neutral, happy), and textual sentiment (positive or negative). This framework closely follows the 3-V model, visual, vocal, and verbal features, proposed by Hu and Ma (2025), which is designed to quantify expressive behaviors in online entrepreneurial pitches. Similarly, Curti and Kazinnik (2023) applies a comparable methodology to analyze nonverbal cues in central bank press conferences, linking facial and vocal signals to market responses.

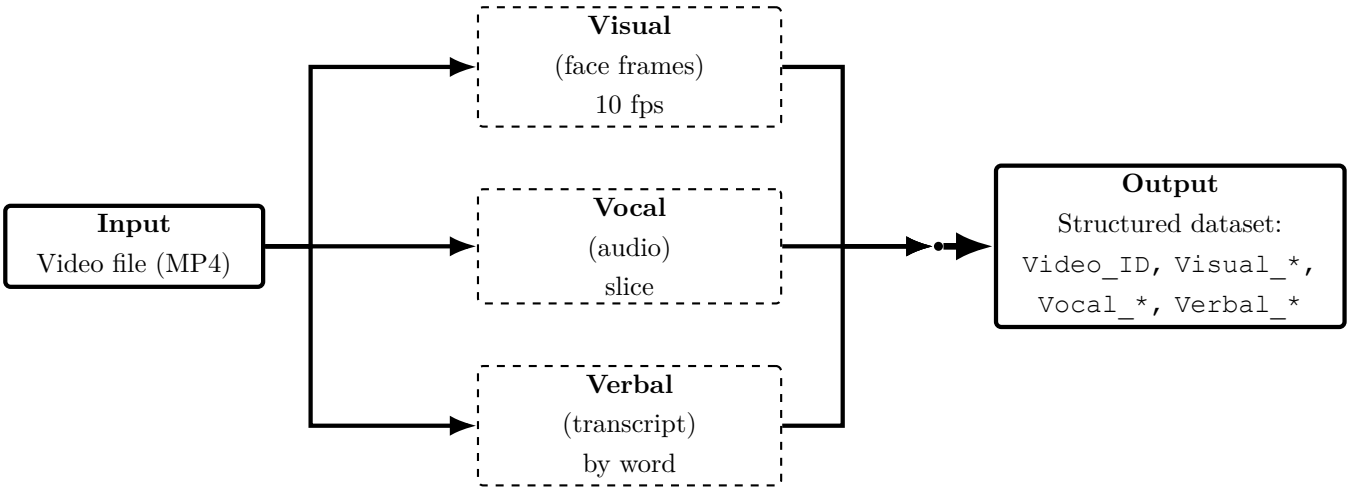


Figure 1: Framework for processing the live streaming

Our implementation consists of multiple modules: the *face_recognition* module for identifying fund managers, Face++ for facial expression detection, the SenseVoice model for vocal tone analysis, and a sentiment dictionary for verbal sentiment extraction. All models are pre-trained, offering high classification accuracy and ease of deployment. This approach allows us to generate consistent, scalable, and replicable emotion metrics across thousands of live streaming videos.

3.1 Video Pre-Processing

The first step of our analysis is to pre-process the live streaming in order to produce structured multimodal inputs that serve as the raw materials for subsequent machine learning analysis.

Each video file is decomposed into three synchronized streams: visual, vocal, and verbal. The visual stream consists of facial frames extracted at a fixed sampling rate of 10 frames per second, as the mean length of live streaming is about 1 hour. Our first step is to identify fund managers' faces from multiple individuals in live streaming. We crop fund managers' images from the historical live streaming and create a folder with one image per manager. We then extract frames from live streaming in chronological order. For each frame, the *face_recognition* module is used for face identification and cropping. To avoid multiple matches for the same person, we set the tolerance value of 0.5 to ensure stricter face comparisons.[4]

The audio stream retains the continuous speech of the fund manager and provides the basis for vocal tone analysis. To ensure that downstream measures reflect the fund manager rather than other speakers or background noise, we first perform speaker diarization, which consists of speaker

[4]The default tolerance value is 0.6 and lower numbers make face comparisons more strict.

recognition and voiceprint verification. We extract the audio track from the live streaming and collect short utterances from each fund manager to construct a voice library. Using a PyTorch-based voiceprint recognition model, we then identify, segment, and cluster the fund managers' speech segments from the live streaming recordings.

As for the textual stream, we convert the managers' speech into transcripts using the iFLYTEK speech recognition engine, and subsequently represent the transcripts and then analyze the transcripts to identify the vocabulary and topics conveyed in the verbal content.[5]

3.2 Facial expressions

After pre-processing, we obtain a series of cropped facial images of fund managers, each containing the complete set of facial features. For the visual dimension, we adopt the established method provided by Face++, which offers APIs for facial expression recognition. The system first detects faces within the images and assigns a unique `face_token` to each detected face, which is then used in subsequent analyses. This step also provides detailed facial attribute information, including gender, age, head pose, face quality, and mouth status.

Based on the generated `face_token`, the system further identifies and returns the emotional state of the detected face. The model classifies faces into seven discrete categories: happy, sad, angry, disgusted, fearful, surprised, and neutral. Each category is associated with a confidence score, with higher values indicating greater confidence in the classification. In addition, Face++ provides other facial features such as the beauty score, which measures facial attractiveness.

Our independent variable, *Visual*, is constructed from the set of frames with assigned emotion scores. For each live streaming session, we compute the average score for each emotion across all frames and use these averages as the representation. Referring to Chang et al. (2024), *Visual* is the difference between happy facial expressions and sad facial expressions, which measures the intensity of fund managers' net-positive emotion. A higher *Visual* score denotes a happier fund manager during live streaming. The specific definition for *Visual* is outlined in Table A1.

3.3 Tone of voice

For the voice dimension, we focus exclusively on the acoustic information conveyed by speech rather than its textual content, which is addressed in the verbal dimension. After clustering

[5]iFLYTEK is a listed company specializing in intelligent speech and AI technologies. As of April 2025, its Open Platform had reached more than 4.17 billion terminal devices.

fund managers' audio segments, we subsequently employ SenseVoice-Small, a multilingual voice understanding model open-sourced by Alibaba (An et al., 2024).

In our application, we use the speech emotion recognition (SER) function of SenseVoice-Small to obtain the probability distributions of four vocal expressions—angry, sad, neutral, and happy. SenseVoice accepts audio inputs of up to 30 seconds in length. Therefore, we divide each audio file into 500 parts of equal duration. After segmentation, the raw chunks are processed by the Transformer-based encoder to capture prosodic features, such as pitch and rhythm, as well as spectral patterns, such as timbre and energy distribution. The encoded representations are then passed through classification layers and generate both the predicted emotion label and the corresponding probability distribution. Finally, for each audio file, we compute the average probability of each emotion across all parts to obtain live streaming-level emotion measures.

Based on these predicted probabilities, we construct another key independent variable *Vocal*, to measure the emotion in the voice, which is also the difference between happy speech expression and sad speech expression.

3.4 Text sentiment analysis

To capture the semantic orientation of fund managers in their live streaming, we then apply a rule-based sentiment scoring approach based on the HowNet sentiment dictionary (Dong and Dong, 2003).[6]

Each sentence is tokenized and scanned for positive and negative words. Existing dictionary-based methods typically rely on word polarity, ignoring the role of linguistic modifiers, which reduces the accuracy of sentiment estimation (Shapiro and Wilson, 2021; Hillert, Niessen-Ruenzi, and Ruenzi, 2025). Our approach addresses this limitation by incorporating degree adverbs, negation words, and punctuation, each assigned specific weights to capture their effect on emotional intensity. The detailed weighting scheme and calculation procedure are documented in the Appendix 5. Sentence-level scores are first averaged to obtain transcript-level sentiment measures, which are then rescaled to the [0,1] interval to ensure comparability across videos. In this way, we obtain a positive and a negative sentiment score for each video.

From this analysis, we construct the third key independent variable, *Verbal*, which measures

[6]HowNet (China National Knowledge Infrastructure) is a benchmark sentiment dictionary that has been widely adopted in Chinese sentiment analysis (Du et al., 2021).

the sentiment in the text. The variable is also measured by the difference between the positive and the negative sentiment scores of fund managers in the videos.

3.5 Affective Delivery Index (ADI)

Apart from the three individual emotion variables, we create a composite indicator to summarize the overall positive level of live streaming. Using a method similar to Hu and Ma (2025), we employ principal component analysis (PCA) to categorize three dimensions of emotion variables, thereby reducing the dimensionality and enhancing our understanding of the data. PCA transforms the original data into a set of linearly independent representations, which can be used to extract the main characteristic components.

In this study, we ultimately reduce the variables to obtain *Affective Delivery Index*. *ADI* can be viewed as a composite index that represents the positive level reflected in live streaming, integrating information from the three dimensions and providing clear and intuitive weights for each variable. Both *ADI* and multimodal emotion variables are standardized into a zero-mean variable with a standard deviation of one. Since the underlying features have already been standardized and winsorized prior to PCA, no additional winsorization is applied to the factor.

4 Empirical Findings

In this section, we examine how fund managers' live streamings influence their fund flows. We begin in Section 4.1 with reporting results from the baseline specification that quantifies the average effect of streaming, both on an extensive margin, driven by managers' streaming participation, as well as the intensive margin, driven by variation in manager ADI. Section 4.2 investigates temporal effects of *ADI* and its sub-components. In Section 4.3, we delve into the underlying mechanisms that drive the flow relationship. Section 4.4 uses instrument variable method to mitigate the potential endogeneity concern. Section 4.5 evaluates various aspects of heterogeneity in the flow effects. In Section 4.6, we examine whether *ADI* influences ETF secondary market trading activities. Finally, in Section 4.7, we report a battery of robustness results to ensure the stability of our findings.

4.1 Live streaming and fund flows

Our first test examines whether live-streaming event predicts next-day capital flows of related funds. A fund is considered related if it is managed by the streamer. Formally, we estimate the following regression model:

$$Flow_{i,t+1} = \alpha + \beta \cdot Streaming_{i,t} + \boldsymbol{\gamma} \cdot Controls_{i,t} + FEs + \varepsilon_{i,t+1} \tag{2}$$

The dependent variable is net flow of fund i on the next trading day following live streaming event on day t. The main independent variable, $Streaming_{it}$, is an indicator variable equal to one if a fund i is managed by a manager streaming on day t, and equal to zero, otherwise. In our regressions, we control for characteristics of funds and fund management companies, including $fund\ age$, $fund\ size$, $turnover$, $Return$, $Flow$, $index\ volatility$, and $family\ flow$.[7] We also alternately include a rich set of fixed effects (FEs) to control for any unobservable omitted variables driving the flow predictability. Day FEs absorb any common macroeconomic conditions driving variation in flows on day t; fund FEs control for any time-invariant fund characteristics; index $\times$ week FEs ensure that the comparisons are made within groups of funds that share the similar (same) tracking index and trading week, thereby allowing for comparisons among funds with similar content of information. This fixed effect is leveraging the fact that passive funds with similar benchmark are likely to feature similar discussion topics. Fund $\times$ month FEs account for any slower moving time-varying unobservable characteristics at the fund level, which may simultaneously affect fund flows. Finally, fund $\times$ day-of-the-week (DOW) FEs absorb stable weekly patterns in both investor activity and streaming supply. We double cluster standard errors at the fund family and day level to allow for serial correlation in investment decisions within the same fund family over time.

Table 2 presents the results. Columns 1 to 6 report the results using different combinations of fixed effects. The coefficients of *Streaming* are all negative but statistically insignificant, indicating that live streaming has little predictive effect for flows of funds managed by the streamer. As robustness, we study whether funds that stream are systematically different from the non-streaming funds prior to the streaming events. We use propensity score matching to match the streaming fund-day pairs to control groups. We consider two groups of non-streaming funds: (a)

[7] Detailed definitions of the control variables are described in Appendix A1.

not streaming funds at day t; and (b) not streaming at whole sample. Figure 2 reports coefficients of differences in fund flows over the event window, controlling for the same variables and fixed effects as in Table 2. Propensity score matching (PSM) is based on fund characteristics including age, size, turnover, past returns, past flows, index volatility, and family flows. Our results indicate no pre-trends prior to the reporting dates, irrespective of the control group we use. Consistent with the earlier results, we also do not find any systematic differences in flows after the streaming date. We conclude that the flow effects we document for the streaming vs. non-streaming funds are not driven by any pre-trends surrounding the event. Also, this result suggests that funds do not choose their streaming dates strategically to attract extra amount of flows.

We further turn our attention to an intensive-margin analysis in which we explore the impact of emotions in live streaming on the movement of fund flows. By applying deep learning algorithms, we decompose live streaming content into three dimensions: visual, vocal, and verbal, corresponding to the streamer's facial expressions, tone of voice, and text sentiment, respectively. To summarize the degree of happiness due to live streaming, we construct *ADI* through PCA using three dimensions variables, similar to Hu and Ma (2025) and Tetlock, Saar-Tsechansky, and Macskassy (2008). We analyze whether *ADI* and its individual features predict fund flows. For each fund i at time t, we estimate the following regression model:

$$Flow_{i,t+1} = \alpha + \beta \cdot ADI/Features_{i,t} + \boldsymbol{\gamma} \cdot Controls_{i,t} + FEs + \varepsilon_{i,t+1} \tag{3}$$

In this model, $Features \in [Visual, Vocal, Verbal]$. We further control for live streaming variables, including *video length*, and *video views*. Similar as before, here and thereafter, we cluster standard errors at the fund family and day level, which allows for potential intra-company correlation in the errors, recognizing that funds in same family might experience similar shocks over time.[8]

Table 3 presents the results. We present estimates across different specifications using different sets of fixed effects and various dimensions of the measures. The coefficients of *ADI* and *Visual* positively and strongly correlate with future fund flows across all columns, suggesting a robust relationship between emotion and fund flows.

Column 1 includes fund FEs and day FEs. In column 2, we additionally control for and index ×

[8]In Table A9, we also show alternative ways to cluster standard errors: at fund and time, and fund manager and time. The results are robust across different settings.

week FEs; in column 3 for fund-month FEs; column 4, fund × DOW FEs; in column 5, we present the most comprehensive specification. In all specifications, the coefficient of *ADI* is positive and statistically significant at the 1% level. In column 1, the estimated coefficient is 0.057. Given that *ADI* is standardized, this indicates that a one standard deviation increase in *ADI* is associated with an increase of 0.057 percentage points in daily fund flow, which amounts to 85% of the average fund flow (0.057/0.067). This sizable effect highlights the economic importance of fund managers' emotional displays.

In columns 6 to 9, we further disaggregate *ADI* into three channels: visual (facial expressions), vocal (tone of voice), and verbal (text sentiment). Across specifications, we consistently find that positive facial expressions yield a significant impact on fund flows. As an example, in column 6, the coefficient of *Visual* is 0.096 and significant at the 5% level, suggesting that a one-unit increase in positive facial expression is associated with a change equivalent to 143% of the average daily fund flow (0.096/0.067). In contrast, the effect of *Vocal* and *Verbal* is statistically insignificant, underscoring the fact that facial expression is the dominant emotional channel predicting investor behavior. While the coefficients of *Vocal* are positive, they are statistically insignificant, indicating limited contribution to fund attraction. Similarly, the coefficients of *Verbal* are negative and insignificant, contrary to prior findings suggesting that textual content conveys valuable information for fund investors. Our results also hold when we include fund × DOW FEs. Because fund × DOW FEs absorb stable weekly patterns in both investor activity and streaming supply, the remaining verbal effect reflects within-fund, within-week deviations in delivery, consistent with persuasion rather than timing.

To further improve our empirical identification and mitigate the concerns of spurious correlations, we implement two placebo designs: (a) assigning each stream date to a non-streaming, index-matched ETF and (b) randomly re-assigning stream dates within fund. We then repeat the analysis in Table 3. Both tests produce null effects, as reported in Table 4. We further expand this test by producing an empirical distribution of t-statistics based on 1000 placebo tests, in Figure 3. The red vertical bar shows the t-statistic of our baseline regression. We can see that the empirical distribution of t-statistics centers on zero and the red bar falls outside 95% confidence interval, both for ADI and Visual. Overall, the placebo results alleviate concerns that timing or slow-moving sectoral conditions drive our results.

In summary, *ADI* is positively related to fund flows, and this effect remains significant after controlling for time, fund, index × week, fund × month, and fund × DOW FEs. Specifically, more happiness in facial expressions expressed in live streaming predicts significantly higher future fund flows for funds. Meanwhile, happiness expressed through the tone of voice or text sentiment has a minimal effect on future capital movement.

4.2 Investor affect and flow horizon

Live streaming greatly reduces the marketing costs of fund management companies, making it more convenient for fund management companies to communicate with investors, which stimulates the frequency of fund managers' live streaming. Thus, a natural question to ask is how long the positive effect of live streaming persists. We test for the duration of the impact of *ADI* in our next analysis. To this end, we employ the following regression specifications:

$$Flow_{i,t,t+k} = \alpha + \beta \cdot ADI/Features_{i,t} + \boldsymbol{\gamma} \cdot Controls_{i,t} + FEs + \varepsilon_{i,t} \tag{4}$$

Compared to equation 3, we vary the time horizon of future fund flows in equation 4. Specifically, we examine the effect on future 1-, 10-, 20-, and 40-trading day fund flows.

Table 5 presents the regression results. Column 1 presents our baseline result in Table 3, showing the result of $Flow_{i(t,t+1)}$, that is, future one-day trading day flows. Column 2 displays the result of the future 10-trading day fund flows and yields coefficients that are significant at the 5% level. Column 3 reports the coefficient for the 20- trading-day horizon, which is statistically insignificant. The coefficient in column 4, corresponding to 40-day flows, continues to exhibit positive but also insignificant effect, suggesting that the effect of *ADI* diminishes over longer horizons. For completeness, we also examine similar effects for the three individual dimensions and report their results in Table A6.

4.3 Economic mechanism

In this analysis, we explore channels through which *ADI* may affect fund flows. We consider two broad categories: emotion and signal theory. To distinguish between the two channels we focus on future fund performance. If the effect of fund managers' happiness is purely behavioral we should expect no significant effect on future performance. In turn, if managers' affect is a reflection of a

positive signal they want to convey we should expect a positive impact on future fund performance.

4.3.1 Investor emotions

A large literature on behavioral finance over the last few decades has argued that investors in their decisions are not always rational and are often subject to emotional and cognitive biases when making financial decisions, a phenomenon referred to as cognitive illusions (Kahneman and Riepe, 1998). Investor emotions, therefore, may play a critical role in shaping investment behavior.

Prior research has shown that individuals in positive emotional states tend to make more optimistic judgments and are more receptive to both strong and weak information, whereas negative moods are associated with more cautious and analytical processing (Hirshleifer and Shumway, 2003). Moreover, emotional states can influence risk preferences in complex ways. For example, positive affect can foster both risk-averse and risk-seeking behavior depending on the framing of the decision context: when potential losses are emphasized, individuals in a positive mood tend to avoid risk, but when such losses are downplayed, they may become more risk-prone (Arkes, Herren, and Isen, 1988).

Importantly, investor emotions are not formed in isolation. They can be shaped by others through emotional contagion. When watching live streaming, investors not only listen to the words fund managers say but also observe their facial expressions and physical presence on screen. Fund managers' positive emotions are contagious and can alter investors' emotional states and, in turn, influence their behavior (Pugh, 2001; Hochschild, 2019). We examine whether live streaming affects investor emotions using regression analysis. We use viewer reactions as a proxy for investor emotions, calculated as follows:

$$Investor\ Reaction_{i,t} = \frac{likes_{i,t}}{video\ views_{i,t}} \tag{5}$$

In this measure, *likes* refers to the number of positive reactions a video receives, while *video views* captures the total number of views. Both variables are recorded at the time the video is downloaded from the platform. We use $Investor\ Reaction_{i,t}$ in equation 5 as the dependent variable and continue with the regression in equation 3 to estimate whether ADI can spread to investors' emotions. The regression results are summarized in Table 6. Column 1 and 2 report the results for ADI , while columns 3 and 4 present the results for the multimodal variables. We find a positive

and statistically significant relationship between the *ADI* and investor emotions, with significance at the 5% and 1% level. For the multimodal variables, the coefficient of *Visual* is significantly positive at the 1% level, demonstrating that positive facial expressions significantly enhance investor emotions. The coefficient of *Vocal* is positive, while that of *Verbal* is negative. However, both are statistically insignificant, indicating their limited impact on investors' reactions.

Overall, investor emotions, particularly facial expressions, are positively correlated with the positivity of fund managers' emotion. Fund managers' *ADI* effectively provokes positive emotions in investors, in line with the emotion contagion theory (ECT), and thereby influences investors' investment decisions.

4.3.2 Future fund performance

We further propose and test an alternative channel, through which investors interpret *ADI* . Specifically, investors may perceive positive facial expressions, vocal tones, and textual sentiments displayed during live streaming as indicators of the fund managers' favorable outlooks on the market. In their view, such optimism suggests that the managers are not only competent and professional but may also possess private information regarding future fund performance. An optimistic demeanor in live streaming is thus interpreted as a strong sign of confidence in the future market. Based on this interpretation, we expect *ADI* to positively predict future fund returns. We examine whether *ADI* is associated with fund returns over the subsequent 1-, 10-, 20-, and 40-trading-day windows. We present the results from this model in Table 7.

We choose the daily raw return and index-adjusted return as the measure of fund performance. The results reveal an insignificant relationship between *ADI* and future fund performance across all regression specifications, indicating that *ADI* lacks predictive power. This suggests that the increase in fund flows due to *ADI* is a manifestation of investor affect. Similar results for multimodal features are reported in Table A6. We also examine whether three-dimensional features in live streaming are associated with performance-flow sensitivity. Results in Table A7 show no such result.

4.4 Instrumental Variable (IV)

Our results so far indicate strong support for emotion-based mechanism driving fund flows. The above results clearly point out to a specific mechanism but they do not necessarily provide precise

answers to all challenges behind their empirical identification. In particular, one may still worry about potential issues related to endgoneity concerns due to omitted variables or reverse causality. The high-dimensional set of fixed effects makes it unlikely that our results can be attributed to an unspecified omitted variable. An alternative and more direct way to obtain a well-identified set of parameters can be through the use of instrumental variables.

Inspired by the recent health science findings that air pollution affects mental health and cognition, studies in finance literature also find significant effect of air pollution on financial market dynamics, for instance, Li et al. (2021) find that air pollution significantly increases investors' behavioral biases based on a proprietary data set obtained from a large Chinese mutual fund family consisting of complete trading information. Therefore, we use the air quality index (AQI)[9] as an instrument for *ADI* during live streaming. Specifically, we create a AQIscore (8 to 1) based on AQI value (from 0 to 400 with a interval of 50). For instance, a AQIscore with 8 indicates highest air quality based on AQI between 0 and 50. We then use AQIscore as the instrument for ADI in regressions.

We report the results from the estimation in Table 8. Column 1 provides the estimates for the first-stage equation. The F-statistic for the coefficient is above 10, implying the strength of our instrument. In columns 2, we estimate the average effect of ADI on fund flows using the fitted values from stage one to capture the exogenous variation in ADI and a set of different fixed effects as before. Similar to the results in baseline analysis, we again find a strong positive effect of ADI on fund flows. The magnitudes of the effects are larger than the estimates reported before, thus suggesting a possibility of downward bias in the original estimates.

4.5 Heterogeneity analysis

Market regime. In 4.1, we have shown that *ADI* positively predicts future fund flows. We further investigate the impact of *ADI* conditional on different market regimes. Our motivation for the test is driven by a broad observation that investors' emotional state is sensitive to market conditions. We define two indicator variables, *Up* and *Down*. *Up* equals one if the monthly return of the market index in the previous month is positive, and zero otherwise. *Down* equals one if the

[9]AQI focuses on common, harmful pollutants that have well-documented health impacts. While specific pollutants may vary slightly by country/region, the core pollutants monitored globally include: PM2.5, PM10, O_3, NO_2, SO_2, CO. AQI is not a simple average of pollutant concentrations. Instead, it uses a breakpoint-based formula to convert the concentration of each pollutant into a "sub-index," then selects the highest sub-index as the final AQI value. Most countries use a 0–500 scale for AQI, but breakpoint values for pollutants may differ slightly.

monthly return of the market index in the previous month is negative, and zero otherwise. We use China Securities Index 300 Index (CSI 300) as the market. The data comes from Wind database. We report the results in Table 9.

To report the flow predictability of *ADI* in different market regimes, we divide Table 9 into two columns: column 1 corresponds to rising markets while column 2 to declining markets. We find that in up market the coefficient is positive and statistically insignificant. In contrast, the effect is positive and statistically and economically strong in down markets. Hence, in adverse market conditions, *ADI* is expected to bring relatively more flows into the funds, as investors' emotions are less rational and more prone to being affected by a declining market.

Length of streaming. It is possible that the response of investors to managers' emotion depends on the length of exposure to such treatment. In our sample, the duration of fund managers' live streaming sessions varies considerably, with an average length of approximately one hour. To explore whether the emotional effect differs by video length, we divide the sample into two groups. Live streaming longer than the median is classified as long videos; those shorter than the median are categorized as short videos. We estimate the same regression model in the two sub-samples.

The results are presented in Table 10. Column 1 shows the results for short-length live streaming, while column 2 shows the results for long-length live streaming. The coefficients indicate that the positive impact of fund managers' *ADI* on fund flows is more pronounced in long-length streaming. This could be attributed to the fact that longer videos offer more ample emotional cues, allowing investors to better perceive, interpret, and internalize managers' emotions. Moreover, longer durations facilitate stronger emotional contagion from managers to investors.

Time of streaming. We also investigate whether the timing of fund managers' live streaming influences the effect of *ADI*. Prior studies have shown that attention to emotional cues may depend on the time at which they are presented to investors. Live streaming in our sample occurs at various times, from as early as 8:00 a.m. to as late as 9:00 p.m., extending well beyond the ETF trading hours of 9:30 a.m. to 3:00 p.m. To capture the timing effect, we construct an indicator variable, $Morning$, following the methodology in Chen, Demers, and Lev (2018). This variable is assigned a value of 1 for live streaming ending before 12:00 p.m. and 0 for those ending at or after 12:00 p.m. Since we aggregate video-day level data to the fund-day level by their means, the observation can be included in the Morning group if its averaged $Morning$ value is greater than zero, and in the

Afternoon group if its averaged $Afternoon$ value is greater than zero. Observations may belong to both groups.

Columns 3 and 4 report the results on the differential effects of live streaming across time periods. Column 3 presents the estimate for live streaming in the morning. The coefficient of ADI is negative and statistically insignificant. In contrast, the coefficient for the afternoon subsample, in column 4, becomes substantially larger and is statistically significant at the 1% level. These results suggest that ADI is more effective in live streaming that takes place in the afternoon.

Fund types. Our results may also depend on the types of funds for which live streaming is being conducted. Based on index descriptions from Wind and CSMAR, we adopt a two-step classification procedure. In the first step, we assigning each ETF to one of 18 specific categories according to its description. In the second step, we consolidate these into two overarching categories: Index ETFs, which include ETFs that track broad-based indexes such as large cap, medium cap, and small cap; and Other ETFs, which include all remaining categories, such as sectoral or thematic indexes. Table A3 details the summary of indexes. We then conduct subsample regressions based on this classification to examine whether ADI acts differently across fund types.

Columns 5 and 6 present the regression outcomes across different fund categories. For index ETFs, the estimated coefficient of ADI is negative and insignificant. Conversely, the result for Other ETFs, in column 6, indicates a significantly positive coefficient at the 1% level. This pattern implies that ADI tends to manifest primarily in funds that track industry-specific or style-based indices, rather than broad-based indexes.

Fund investor clienteles. It is conceivable that the emotion effect depends on the degree of sophistication of fund investors. We examine how the emotional effect differs between ETFs with varying levels of institutional ownership. To account for the semi-annual disclosure frequency of institutional holdings and the strong correlation between institutional preference and fund size, we construct institutional ownership groups by comparing institutional holding ratios within each semi-annual period and the median fund size. Specifically, ETFs are classified as having high or low institutional ownership depending on whether their holding ratio is above or below the median value within their corresponding subgroup. We then assess whether ADI and multimodal features during live streaming lead to differential impact on one-day future fund flows across these two groups. We present the results in Table 11.

The coefficient of *ADI* in column 2, corresponding to a sample of ETFs with low institutional ownership, is positive and statistically more significant than the one in column 1, corresponding to high institutional ownership. These results suggest that the emotional signals conveyed through fund managers' live streaming are more effective in influencing flows of funds dominated by retail investors. One possible explanation is that retail investors have limited access to fundamental information and tend to rely more on affective cues in their decisions. In contrast, institutional investors typically exhibit greater rationality and information processing capabilities, which dampens the behavioral effect of live streaming.

4.6 ADI in the ETF secondary market

ETF markets are characterized by a dual-layer structure. The primary market allows large investors and market makers to purchase or redeem ETF shares based on their NAV, while the secondary market is where ETF units are traded intraday on stock exchanges at market prices. Most retail investors participate in the secondary market. Hence, emotions conveyed in live streaming can affect trading activity, particularly in the secondary market. In this section, we study whether fund managers' *ADI* influences ETF trading behavior in the secondary market by analyzing retail net buying volumes and intraday price volatility.

ADI/features and volumes. We begin by investigating the relationship between *ADI*, and the three individual features, and secondary market trading activity, measured as net buying volumes. To assess retail-driven demand and supply, we construct the *netbuy ratio* as the ratio of net buying volume by non-institutional investors to total trading volume. To assess the impact of *ADI* on subsequent non-institutional trading activity, we use *netbuyratio* at time $t+1$ as the dependent variable and control for its value at time t. Panel A in Table 12 reports a significantly positive relationship between *ADI*, *Visual*, and *Vocal* on *netbuy ratio*. This result indicates that greater emotional positivity in live streaming induces stronger net buying activities by retail investors in the secondary market.

ADI/features and volatility. Next, we assess whether emotional signals in live streaming affect intraday price volatility. Volatility is calculated as the standard deviation of minute-by-minute log returns. We use the absolute value of *ADI* and individual variables as explanatory variables. We use volatility at time $t+1$ as the dependent variable, controlling for volatility at time t. The absolute value of *ADI* and *Visual* is significantly positively associated with intraday

price volatility, as reported in Panel B of Table 12. This suggests that investors' trading amplifies short-term price fluctuations in the secondary market.

4.7 Robustness tests

To ensure the robustness of the benchmark results, we conducted the following robustness tests. The conclusions of these tests are align with our previous regressions.

Random selection of video content. In our main analysis, we utilize the *ADI* derived from the entire video as a measure of emotions based on the assumption that investors watch the full live streaming videos. In our first robustness test, we recalculate the emotion variable using a randomly selected 50% subset of the content instead of the entire video. Specifically, we recalculate $Visual$, $Vocal$, and $Verbal$ as the averages of emotional scores captured through facial expressions, tone of voice, and text sentiment, respectively, from 50% of the content in each dimension. The *ADI* is also reconstructed using PCA on the *Visual*, *Vocal*, and *Verbal* scores. The results are reported in Table 13. The coefficients for ADI and $Visual$ are both positive and statistically significant and do not alter the inferences of our main results. $Vocal$ and $Verbal$ still do not display significant effects. These findings confirm that *ADI*, particularly those derived from facial expressions, has a positive and significant influence on fund flows.

AI-based emotion extraction. In previous sections, we employed machine learning techniques to analyze fund managers' emotions. The emergence of generalized AI (GAI) has fundamentally changed how people produce and analyze data. In this part, we leverage GAI to conduct video-based emotion analysis.

Specifically, we use Alibaba's open-source R1-Omni model, a state-of-the-art multimodal large language model that integrates RLVR for enhanced emotion recognition. To extract fund managers' emotional expressions from live streaming videos, we design customized prompts tailored for the R1-Omni model. The prompt is as follows:

As a mutual fund investor, you are watching the fund manager's live streaming; throughout the video, which emotion conveyed by the characters is the most obvious to you? Output the thinking process in <think> </think> and final emotion in <answer> </answer> tags.

We segment each video into 5-minute clips throughout its duration. For each clip, the model identifies a single dominant emotion selected from the following seven categories: happy, sad, angry, fearful, disgusted, surprised, and neutral. Based on the classification results across all clips within

a video, we calculate the proportion of each emotion. We then construct adjusted *ADI* variable, defined as the difference between the logarithm of one plus the proportion of clips classified as happy and that of clips classified as sad, reflecting the video's overall emotional tone. Table 14 presents the results based on this clip-level analysis. Consistent with our previous findings we find the coefficient of *ADI* is significantly positive.

Other Robustness. Table A8 reports the results for different measure of verbal content and still finds insignificant role played by information channel. Table A9 investigates the robustness of different clustering methods for standard errors. Table A10 further add time-varying topic-related fixed effects to remove text-related factors. Controlling for topic-month fixed effects–constructed from transcripts via Latent Dirichlet Allocation (LDA)–leaves the ADI coefficient virtually unchanged. These tests imply the flow response is unlikely driven by changing informational content but by affective delivery. Overall, we confirm the robustness of the main findings.

5 Conclusion

In this paper we investigate the impact of the positive emotion expressed by fund managers during live streaming on fund flows, providing a novel perspective on how real-time investor communication shapes investment decisions and behavior. Our analysis reveals that *Affective Delivery Index (ADI)*, especially facial expressions, during live streaming significantly influence short-term fund flows, while vocal tone and verbal content play comparatively minor roles.

To explore the underlying mechanisms, we propose two potential channels through which *ADI* affects fund flows: investor emotions and positive signaling. Through the emotions channel, managers' positive emotions are transmitted to investors, altering their emotional state and investment behavior. Our empirical evidence supports this channel, as *ADI* in live streaming is positively associated with investors' reaction. However, since *ADI* does not predict future performance, the resulting fund flows appear to reflect irrational investor behavior rather than rational learning process. The signaling channel, which posits that positive emotions convey favorable private information about future performance, is not supported by our findings.

The impact of *ADI* appears to be more salient under specific conditions, including market downturns, extended video duration, afternoon sessions, and ETFs characterized by lower institutional ownership. It is insignificant for broad-index ETFs but it becomes evident for ETFs targeting spe-

cific industries or styles. *ADI* also positively influences secondary market activities by improving the net buying ratio and intraday price volatility. These findings are robust across various model specifications and robustness checks, including checks using newly developed AI-based techniques.

Collectively, our paper sheds light on how emotions influence fund flows, emphasizing the critical role of communication with investors in affecting their decision making. With significant changes in communication channel, we expect this area of research to become more fruitful in the future.

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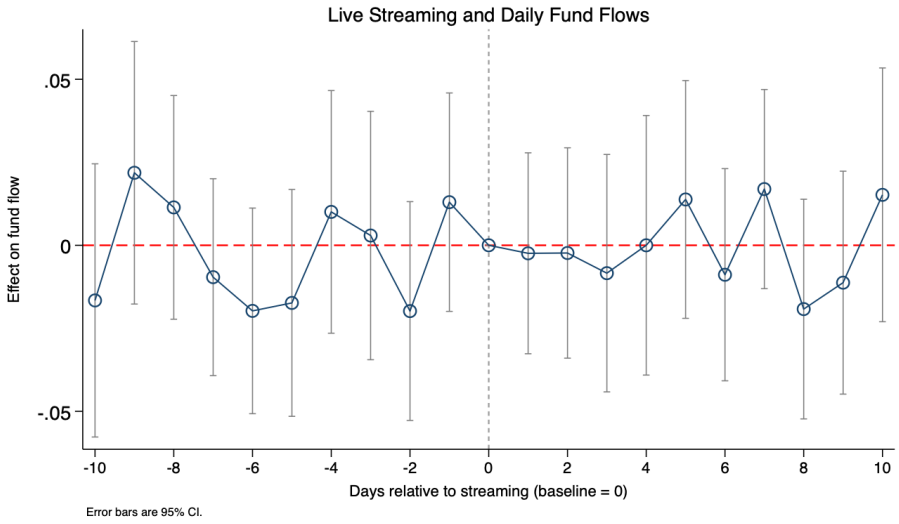
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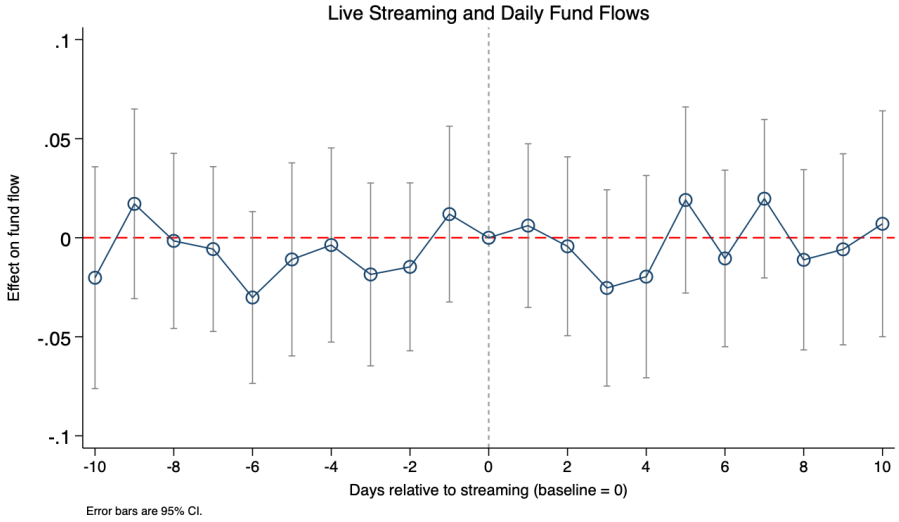
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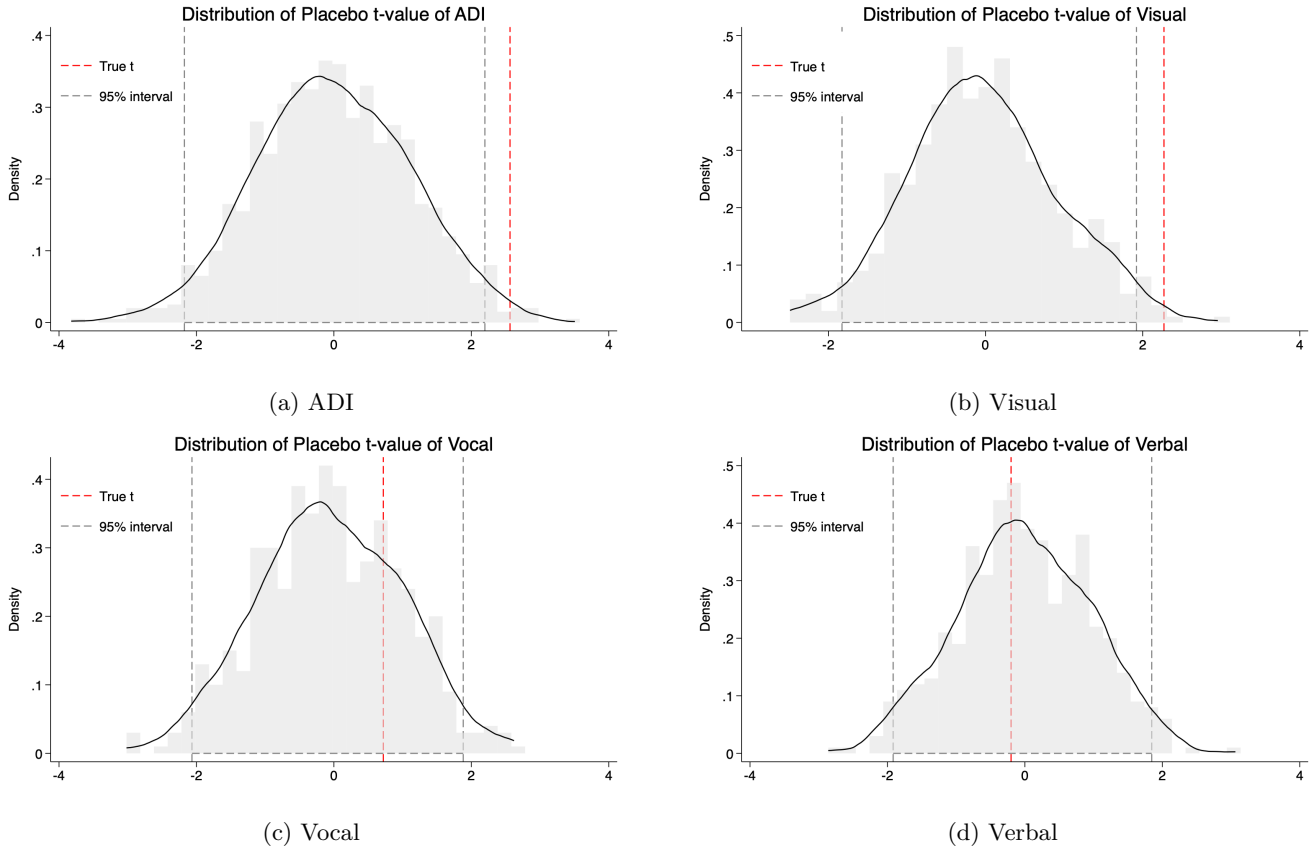
(a) Whole Sample Match



(b) Match to Non-Streaming Funds

Figure 2: **Fund Flows around Streaming Days**

This figure shows event-time estimates of live streaming on daily fund flows, with day 0 (the streaming day) normalized to zero. Treated fund-days (live streaming fund-day pairs) are matched to all other non-streaming funds at time t (Panel A) or funds have never done any streaming in whole sample periods (Panel B) at same days using propensity score matching. 95% confidence intervals are shown.



(a) ADI

(b) Visual

(c) Vocal

(d) Verbal

Figure 3: **Random Dates and Funds: Placebo Test**

This figure shows the distribution of t-statistics across *ADI* and multimodal variables. Our specification follows that in Table 3. In each test, *ADI* and its three features are randomly assigned to periods with different fund × month groups. We draw 1,000 samples, with replacement, of such groups. The dashed red lines mark the true t-statistic and dashed gray lines indicate the 95% interval.

Table 1: **Summary Statistics**

Our data spans 36 months of (daily) observations, from January 2021 to December 2023. For each variable, we provide the number of observations, mean, standard deviation, minimum, and maximum values. The last two columns display the factor loadings and uniqueness of three-dimension variables used to generate the ADI through PCA, which captures the overall positive level of live streaming.

	N	Mean	STD	Min	Max	Factor Loading	Uniqueness
$Visual_{i,t}$	9,013	0	1	-2.835	2.121	0.464	0.442
$Vocal_{i,t}$	9,013	0	1	-2.455	2.548	0.335	0.861
$Verbal_{i,t}$	9,013	0	1	-2.713	2.441	0.101	0.560
$ADI_{i,t}$	9,013	0	1	-3.287	3.444		
$beauty_{i,t}$	9,013	58.42	6.964	42.19	73.37		
$length_{i,t}$ *(minute)*	9,013	59.165	29.55	24.75	231.17		
number of video views$_{i,t}$	9,013	50,156	47,655	11,275	321,204		
number of likes$_{i,t}$	9,013	34,246	44,048	2,590	291,954		
stream gap$_{i,t}$ *(day)*	9,013	13.476	25.340	0	705		
$fund\ age_{i,t}$ *(day)*	9,013	729	736.9	45	3,344		
$fund\ size_{i,t}$ *(million)*	9,013	2,118	5,271	13.31	34,699		
$turnover_{i,t}$ *(%)*	9,013	7.204	8.166	0.016	41.19		
$Return_{i,t}$ *(%)*	9,013	-0.009	1.433	-3.685	4.63		
$Return_{i,t-10,t-1}$ *(%)*	9,013	-0.149	4.254	-10.72	12.24		
$Flow_{i,t+1}$ *(%)*	9,013	0.067	1.640	-6.122	7.843		
$Flow_{i,t}$ *(%)*	9,013	0.034	1.585	-6.065	7.375		
$Flow_{i,t-10,t-1}$ *(%)*	9,013	0.779	8.626	-24.8	47.14		
index vol$_{i,t}$	9,013	1.37	0.76	0	3.92		
$family\ flow_{i,t}$ *(%)*	9,013	0.116	0.610	-1.962	2.241		
$family\ flow_{i,t-10,t-1}$ *(%)*	9,013	1.716	3.443	-5.577	17.197		

Table 2: **Live Streaming and Daily Fund Flows**

The dependent variable is *Flow*. Definitions of independent variables are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Streaming_{i,t}$	-0.017	-0.015	-0.007	-0.008	-0.004	-0.005
	(0.019)	(0.018)	(0.017)	(0.020)	(0.016)	(0.019)
$fund\ age_{i,t}$	0.122***	0.126***	0.125***	0.740**	0.125***	0.720**
	(0.020)	(0.023)	(0.022)	(0.282)	(0.022)	(0.279)
$fund\ size_{i,t}$	-0.230***	-0.237***	-0.251***	-3.088***	-0.250***	-3.087***
	(0.020)	(0.020)	(0.017)	(0.308)	(0.018)	(0.309)
$turnover_{i,t}$	0.003	0.002	0.001	-0.003	0.002	-0.003
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
$Return_{i,t}$	-0.003	0.006	0.023**	0.043***	0.025***	0.044***
	(0.007)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
$Return_{i,t-10,t-1}$	-0.004*	-0.008**	-0.005	0.013***	-0.005	0.012***
	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
$Flow_{i,t}$	0.121***	0.121***	0.102***	0.033***	0.105***	0.035***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)
$Flow_{i,t-10,t-1}$	0.016***	0.015***	0.014***	-0.011***	0.014***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
$index\ vol_{i,t}$	-0.006	0.038**	0.052***	0.029*	0.051***	0.028*
	(0.017)	(0.016)	(0.015)	(0.015)	(0.014)	(0.014)
$family\ flow_{i,t}$	0.027***	0.017***	0.014**	0.014**	0.014**	0.014**
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$family\ flow_{i,t-10,t-1}$	-0.001	-0.001	-0.001	0.004***	-0.001	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	NO	NO	NO
Day FE	NO	YES	YES	YES	YES	YES
*Index*Week FE*	NO	NO	YES	YES	YES	YES
*Fund*Month FE*	NO	NO	NO	YES	NO	YES
*Fund*DOW FE*	NO	NO	NO	NO	YES	YES
Obs.	301,685	301,685	301,674	301,610	301,674	301,610
R^2	0.046	0.072	0.102	0.207	0.110	0.214

Table 3: **ADI, Features, and Fund Flows**

The dependent variable is *Flow*. Definitions of independent variables are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ADI_{i,t}$	0.057***	0.076***	0.106***	0.072**	0.160***				
	(0.019)	(0.021)	(0.030)	(0.029)	(0.044)				
$Visual_{i,t}$						0.096**	0.117**	0.086**	0.178***
						(0.036)	(0.048)	(0.033)	(0.054)
$Vocal_{i,t}$						0.019	0.041	0.026	0.048
						(0.028)	(0.036)	(0.029)	(0.047)
$Verbal_{i,t}$						-0.012	-0.013	-0.017	0.003
						(0.037)	(0.039)	(0.037)	(0.062)
$beauty_{i,t}$	-0.008**	-0.011**	-0.015**	-0.011**	-0.018*	-0.012***	-0.016**	-0.011**	-0.020*
	(0.003)	(0.004)	(0.007)	(0.005)	(0.010)	(0.004)	(0.008)	(0.005)	(0.010)
$video\ length_{i,t}$	0.103*	0.123	0.004	0.111	0.126	0.129	0.010	0.116	0.141
	(0.053)	(0.091)	(0.136)	(0.090)	(0.142)	(0.090)	(0.136)	(0.088)	(0.142)
$video\ views_{i,t}$	0.000	-0.037	0.087	-0.043	0.120	-0.038	0.087	-0.045	0.113
	(0.058)	(0.072)	(0.081)	(0.079)	(0.083)	(0.072)	(0.080)	(0.078)	(0.083)
$stream\ gap_{i,t}$	-0.058*	-0.065*	-0.105***	-0.080*	-0.125**	-0.068*	-0.107***	-0.082*	-0.129**
	(0.030)	(0.037)	(0.029)	(0.042)	(0.051)	(0.037)	(0.029)	(0.043)	(0.050)
$fund\ age_{i,t}$	0.054	0.035	2.637	0.131	4.683**	0.042	2.626	0.140	4.675**
	(0.114)	(0.115)	(1.916)	(0.159)	(1.715)	(0.121)	(1.919)	(0.165)	(1.691)
$fund\ size_{i,t}$	-0.024	-0.007	4.877***	-0.018	5.635***	-0.002	4.869***	-0.014	5.629***
	(0.062)	(0.066)	(0.958)	(0.086)	(1.239)	(0.065)	(0.955)	(0.086)	(1.234)
$turnover_{i,t}$	0.008	0.008	-0.013	0.008	-0.003	0.008	-0.012	0.008	-0.003
	(0.009)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.012)	(0.010)	(0.010)
$Return_{i,t}$	-0.016	0.011	-0.000	0.033	-0.010	0.011	0.000	0.032	-0.010
	(0.024)	(0.035)	(0.031)	(0.028)	(0.024)	(0.035)	(0.031)	(0.028)	(0.025)
$Return_{i,t-10,t-1}$	-0.015	-0.009	-0.024	-0.010	-0.032	-0.008	-0.024	-0.009	-0.031
	(0.012)	(0.015)	(0.018)	(0.014)	(0.019)	(0.015)	(0.018)	(0.014)	(0.019)
$Flow_{i,t}$	0.220***	0.187***	0.046	0.205***	0.093**	0.187***	0.047	0.205***	0.093**
	(0.022)	(0.024)	(0.030)	(0.028)	(0.040)	(0.024)	(0.030)	(0.028)	(0.040)
$Flow_{i,t-10,t-1}$	0.018***	0.015***	-0.041***	0.014***	-0.046***	0.015***	-0.041***	0.014***	-0.046***
	(0.004)	(0.005)	(0.007)	(0.004)	(0.010)	(0.005)	(0.007)	(0.004)	(0.010)
$index\ vol_{i,t}$	0.044	0.092	0.116	0.096	0.103	0.093	0.117	0.096	0.102
	(0.042)	(0.057)	(0.074)	(0.063)	(0.080)	(0.058)	(0.074)	(0.063)	(0.080)
$family\ flow_{i,t}$	0.050	0.056	-0.015	0.018	0.039	0.054	-0.019	0.015	0.032
	(0.032)	(0.039)	(0.060)	(0.045)	(0.057)	(0.039)	(0.061)	(0.045)	(0.056)
$family\ flow_{i,t-10,t-1}$	0.019**	0.022**	0.021	0.019**	0.016	0.022**	0.021	0.019**	0.016
	(0.008)	(0.009)	(0.015)	(0.008)	(0.017)	(0.009)	(0.015)	(0.008)	(0.017)
Fund FE	YES	YES	NO	NO	NO	YES	NO	NO	NO
Day FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Index × Week FE	NO	YES	YES	YES	YES	YES	YES	YES	YES
Fund × Month FE	NO	NO	YES	NO	YES	NO	YES	NO	YES
Fund × DOW FE	NO	NO	NO	YES	YES	NO	NO	YES	YES
Obs.	9,013	9,013	9,013	8,358	8,068	9,013	9,013	8,358	8,068
R^2	0.237	0.394	0.627	0.483	0.711	0.394	0.628	0.483	0.711

Table 4: **Placebo Tests**

The dependent variable is *Flow* of fund i. In *Panel A*, we assign *ADI* to a randomly selected non-streaming fund of the same index type on the corresponding streaming day, whereas in *Panel B* we re-assign *ADI* to a random non-streaming date of the same streaming fund. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

Panel A. Assign ADI to Non-Streaming Funds

	$Flow_{i,t+1}$			
	(1)	(2)	(3)	(4)
$ADI_{i,t}$	0.004	0.026		
	(0.014)	(0.053)		
$Visual_{i,t}$			-0.001	0.010
			(0.019)	(0.053)
$Vocal_{i,t}$			0.013	0.025
			(0.021)	(0.0573
$Verbal_{i,t}$			-0.020	0.012
			(0.031)	(0.049)
Obs.	8,589	3,184	8,589	3,184
R^2	0.392	0.769	0.393	0.769

Panel B. Assign ADI to Non-Streaming Days

	$Flow_{i,t+1}$			
	(1)	(2)	(3)	(4)
$ADI_{i,t}$	0.038	-0.035		
	(0.023)	(0.032)		
$Visual_{i,t}$			0.058	0.008
			(0.041)	(0.048)
$Vocal_{i,t}$			-0.014	-0.053
			(0.020)	(0.037)
$Verbal_{i,t}$			0.019	-0.022
			(0.024)	(0.038)
Obs.	8,454	5,382	8,454	5,382
R^2	0.409	0.741	0.409	0.741
Controls	YES	YES	YES	YES
Fund FE	YES	NO	YES	NO
Day FE	YES	YES	YES	YES
Index × Week FE	YES	YES	YES	YES
Fund × Month FE	NO	YES	NO	YES

Table 5: **ADI and Flow Horizon**

The dependent variable is $Flow$. We examine flows with the horizons of 1, 10, 20, and 40 trading days. Definitions of independent variables are provided in Table A1. All regressions control for Day FE, Index × Week FE, and Fund × Month FE. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$	$Flow_{i,t+1,t+10}$	$Flow_{i,t+1,t+20}$	$Flow_{i,t+1,t+40}$
	(1)	(2)	(3)	(4)
$ADI_{i,t}$	0.105***	0.400**	0.072	0.114
	(0.030)	(0.158)	(0.190)	(0.215)
Controls	YES	YES	YES	YES
Day FE	YES	YES	YES	YES
Index × Week FE	YES	YES	YES	YES
Fund × Month FE	YES	YES	YES	YES
Obs.	9,013	9,013	9,013	9,013
R^2	0.627	0.826	0.908	0.946

Table 6: **ADI and Investors' Reaction**

The dependent variable is investors' Reaction, measured as $Investor\ Reaction_{it} = \frac{likes_{it}}{video\ views_{it}}$, where $likes_{it}$ denotes the total number of likes received by the video, and $video\ views_{it}$ denotes the total number of times the video was viewed. Columns 1 and 2 show the impact of *ADI*, while columns 3 and 4 report the impact of three-dimension variables on investors' reaction. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$InvestorReaction_{i,t}$			
	(1)	(2)	(3)	(4)
$ADI_{i,t}$	0.245**	0.352***		
	(0.103)	(0.115)		
$Visual_{i,t}$			0.389***	0.542***
			(0.112)	(0.136)
$Vocal_{i,t}$			0.032	0.038
			(0.101)	(0.125)
$Verbal_{i,t}$			-0.140	-0.163
			(0.097)	(0.104)
Controls	YES	YES	YES	YES
Fund FE	YES	NO	YES	NO
Day FE	YES	YES	YES	YES
Index × *Week FE*	YES	YES	YES	YES
Fund × *Month FE*	NO	YES	NO	YES
Obs.	9,013	9,013	9,013	9,013
R^2	0.950	0.978	0.950	0.978

Table 7: **ADI and Future Fund Performance**

The dependent variable is future 1-, 10-, 20-, and 40-trading day fund performance. *Panel A* presents the results of daily raw returns and *Panel B* reports the results of index-adjusted returns, which are defined as the difference between the ETF's daily return and the tracking index return. All regressions control for Day FE, Index × Week FE, and Fund × Month FE, . Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

Panel A. Raw Return

	$Ret_{i,t+1}$	$Ret_{i,t+1,t+10}$	$Ret_{i,t+1,t+20}$	$Ret_{i,t+1,t+40}$
	(1)	(2)	(3)	(4)
$ADI_{i,t}$	0.019	0.073	-0.013	-0.005
	(0.031)	(0.045)	(0.073)	(0.053)
Obs.	9,013	9,013	9,013	9,013
R^2	0.788	0.918	0.956	0.976

Panel B. Index-Adjusted Return

	$Adj_Ret_{i,t+1}$	$Adj_Ret_{i,t+1,t+10}$	$Adj_Ret_{i,t+1,t+20}$	$Adj_Ret_{i,t+1,t+40}$
	(1)	(2)	(3)	(4)
$ADI_{i,t}$	0.019	0.011	0.006	0.036
	(0.031)	(0.032)	(0.034)	(0.037)
Obs.	9,013	9,013	9,013	9,013
R^2	0.788	0.758	0.861	0.936
Controls	YES	YES	YES	YES
Day FE	YES	YES	YES	YES
Index × Week FE	YES	YES	YES	YES
Fund × Month FE	YES	YES	YES	YES

Table 8: **Instrumental Variable (IV)**

This table examines the results using a weather-based instrumental variable approach. We use the Air Quality Index (AQI) score of the city where the fund management company is registered as the instrument for the endogenous variable *ADI*. Column 1 presents the first-stage regression of *ADI* on the instrument *AQIscore*, while column 2 reports the second-stage regression of fund flows on the instrumented *ADI*. Variable definitions are provided in Table A1. Standard errors, in parentheses, and clustered at the fund level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$ADI_{i,t}$	$Flow_{i,t+1}$
	(1)	(2)
$AQIscore_{c,t}$	0.082***	
	(0.025)	
$ADI_{i,t}$		1.989**
		(1.007)
Controls	YES	YES
Day FE	YES	YES
Index × *Week FE*	YES	YES
Fund × *Month FE*	YES	YES
Fund × *Dow FE*	YES	YES
Obs.	8,068	8,068
F-statistics	10.64	

Table 9: **The Role of Market Conditions**

We choose the CSI 300 performance to measure market conditions. An *Up* market is defined as a market condition with a positive monthly return in the previous month, while a *Down* market is defined as a market condition with a negative monthly return in the previous month. Both regressions control for Fund FE, Day FE, and Index × Week FE. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$	
	CSI 300 Up	*CSI 300 Down*
	(1)	(2)
$ADI_{i,t}$	0.030	0.118***
	(0.041)	(0.029)
Controls	YES	YES
Fund FE	YES	YES
Day FE	YES	YES
Index × Week FE	YES	YES
Obs.	3,713	5,261
R^2	0.441	0.420

Table 10: **Subsamples of Videos and Fund Types**

The dependent variable is $Flow$. Columns 1 and 2 examine whether the effect of ADI on fund flows varies with video length. We divide the sample into short and long videos and re-estimate the regressions separately. Columns 3 and 4 explore potential differences across times of day. *Morning* includes live streaming ending before 12:00 p.m., while *Afternoon* includes live streaming ending at or after 12:00 p.m. Columns 5 and 6 investigate whether the effect differs across fund types. The sample is split into index ETFs and other ETFs, and regressions are estimated separately. All regressions control for Fund FE, Day FE, and Index × Week FE. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$					
	Short Video	*Long Video*	*Morning*	*Afternoon*	*Index ETFs*	*Other ETFs*
	(1)	(2)	(3)	(4)	(5)	(6)
$ADI_{i,t}$	0.026	0.146***	-0.031	0.116***	-0.027	0.103***
	(0.067)	(0.051)	(0.135)	(0.032)	(0.077)	(0.021)
Controls	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES
Index × Week FE	YES	YES	YES	YES	YES	YES
Obs.	4,028	4,018	1,467	7,005	1,569	7,265
R^2	0.497	0.521	0.534	0.443	0.547	0.387

Table 11: **Fund-Investor Clienteles**

The dependent variable is $Flow$. In each semi-annual period, funds are first split into two groups by the median of fund size. Within each size group, we further divide funds into high and low institutional ownership (IO) groups based on the median value of institutional holding ratios. This grouping approach accounts for the fact that institutional holdings are disclosed semiannually and strongly correlated with fund size. Both regressions control for Fund FE, Day FE, and Index × Week FE. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Flow_{i,t+1}$	
	High IO	*Low IO*
	(1)	(2)
$ADI_{i,t}$	-0.004	0.102**
	(0.055)	(0.047)
Controls	YES	YES
Fund FE	YES	YES
Day FE	YES	YES
Index × Week FE	YES	YES
Obs.	4,020	4,149
R^2	0.528	0.477

Table 12: **Secondary Market Volume and Volatility**

Panel A reports the effect of *ADI* and features on net buying activity by retail investors. Specifically, we use the net buying volumes of retail investors divided by the corresponding trading volume, to construct the *netbuy ratio*. *Panel B* examines the impact of the absolute value of *ADI* and its features on intraday price volatility. Volatility is measured as the standard deviation of minute-by-minute log returns within the trading day, capturing subsequent intraday price fluctuations. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. ADI/Features and Volumes

	$netbuy\ ratio_{i,t+1}$			
	(1)	(2)	(3)	(4)
$ADI_{i,t}$	0.215**	0.462***		
	(0.094)	(0.076)		
$Visual_{i,t}$			0.163*	0.397***
			(0.092)	(0.081)
$Vocal_{i,t}$			0.110	0.260***
			(0.074)	(0.078)
$Verbal_{i,t}$			0.078	0.015
			(0.070)	(0.083)
$netbuy\ ratio_{i,t}$	0.115***	0.057	0.115***	0.057
	(0.027)	(0.034)	(0.027)	(0.035)
Obs.	9,013	9,013	9,013	9,013
R^2	0.369	0.602	0.369	0.602

Panel B. ADI/Features and Volatility

	$Vol_{i,t+1}$			
	(1)	(2)	(3)	(4)
$\lvert ADI_{i,t}\rvert$	0.279***	0.291**		
	(0.081)	(0.130)		
$\lvert Visual_{i,t}\rvert$			0.362***	0.132
			(0.125)	(0.090)
$\lvert Vocal_{i,t}\rvert$			-0.061	0.034
			(0.071)	(0.083)
$\lvert Verbal_{i,t}\rvert$			0.011	-0.069
			(0.059)	(0.100)
$Vol_{i,t}$	0.190***	0.008	0.191***	0.009
	(0.021)	(0.023)	(0.020)	(0.023)
Controls	YES	YES	YES	YES
Fund FE	YES	NO	YES	NO
Day FE	YES	YES	YES	YES
Index × Week FE	YES	YES	YES	YES
Fund × Month FE	NO	YES	NO	YES
Obs.	9,013	9,013	9,013	9,013
R^2	0.759	0.861	0.759	0.861

Table 13: **Random Selection of Video Content**

The dependent variable is *Flow*. We randomly selected 50% of the facial expression frames, speech segments, and textual content to recalculate the averaged facial expressions, tone of voice, and text sentiments, as well as the *ADI*. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$			
	(1)	(2)	(3)	(4)
$ADI_{i,t}$	0.071***	0.089**		
	(0.024)	(0.036)		
$Visual_{i,t}$			0.091**	0.111**
			(0.037)	(0.050)
$Vocal_{i,t}$			0.008	0.019
			(0.028)	(0.035)
$Verbal_{i,t}$			0.010	0.002
			(0.040)	(0.036)
Controls	YES	YES	YES	YES
Fund FE	YES	NO	YES	NO
Day FE	YES	YES	YES	YES
Index $\times$ *Week FE*	YES	YES	YES	YES
Fund $\times$ *Month FE*	NO	YES	NO	YES
Obs.	9,013	9,013	9,013	9,013
R^2	0.393	0.626	0.394	0.627

Table 14: **AI-based Emotion Extraction**

The dependent variable is *Flow*. We split each video into 5-minute pieces and conduct emotion analysis using Alibaba's open-source R1-Omni model on the pieces. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$	
	(1)	(2)
$ADI_{i,t}$	0.059**	0.093***
	(0.027)	(0.033)
Controls	YES	YES
Fund FE	YES	NO
Day FE	YES	YES
Index $\times$ *Week FE*	YES	YES
Fund $\times$ *Month FE*	NO	YES
Obs.	9,013	9,013
R^2	0.393	0.627

Online Appendix

A. Tables

Table A1: **Variable Definition**

Variable	Definition
Streaming	Indicator variable equal to 1 if the fund is managed by a fund manager who conducts live streaming on day t, and 0 otherwise.
Visual	The difference between the logarithmic values of one plus the happy and sad facial expression ratios of fund managers. This variable is standardized to have a zero mean and unit variance after winsorized at 1%.
Vocal	The difference between the logarithmic values of one plus the happy and sad vocal expression ratios of fund managers. This variable is standardized to have a zero mean and unit variance afterwinsorized at 1%.
Verbal	The difference between the logarithmic values of one plus the positive and negative sentiment scores derived from fund managers' verbal sentiment. This variable is standardized to have a zero mean and unit variance after winsorized at 1%.
Affective Delivery Index (ADI)	A composite index constructed using PCA on the visual, vocal, and verbal emotional indicators. This variable captures the overall positive affect conveyed in live streaming and is standardized to have a zero mean and unit variance.
netbuy ratio	The net buying volume of non-institutional investors–defined as the sum of net buy volumes from large, medium, and small trades –divided by the total trading volume and multiplied by 100. Net buying volume is calculated as the difference between buy and sell volumes.
Vol	Intraday volatility, measured as the standard deviation of log returns from minute-level closing prices, multiplied by 10,000.
Return	Raw return of the fund, measured using the adjusted NAV with reinvested dividends.
Adj_Return	Adjusted return of the fund, measured using the difference between the fund's daily raw return and tracking index return.
fund age	The natural logarithm of the fund's age.
fund size	The natural logarithm of the fund's size.
turnover	Turnover rate of the fund.
index vol	Weekly volatility of the ETF's benchmark index.
family flow	Size-weighted aggregate fund flow across all ETFs managed by the same fund company over t and $t-1$ to $t-10$.
beauty	Average beauty score of fund managers appearing in live streaming, evaluated using Face++ API.
stream gap	Natural logarithm of one plus the number of days since the last live streaming event.
video length	Natural logarithm of the total minutes of video.
video views	Natural logarithm of total video views.

Continued on next page

Variable	Definition
likes	Total number of likes received by the video.
Investor Reaction	Ratio of *likes* to raw (non-logarithmic) *video views*.

Table A2: **ETF Types**

This table presents summary statistics for the indexes tracked by the ETFs. Based on the index descriptions provided by Wind and CSMAR.

Index ETFs		Other ETFs	
Large Cap	7	*Environmental Protection*	12
Mid Cap	16	*Pharmaceuticals and Health*	31
Small Cap	5	*Traditional Energy*	7
		New Energy	10
		Innovation-Oriented Boards	10
		Dividend and Low-Volatility Strategies	6
		Military and Aerospace	4
		Growth and Value	15
		State-Owned Enterprises	5
		Consumer Goods	20
		Specialized Industries	12
		Manufacturing and Resource-Based	7
		Semiconductors	5
		Technology and Internet	38
		Finance and Real Estate	34
Total	28	Total	216

Table A3: **Summary Statistics of Full Sample**

This table reports the summary statistics of the full sample, which consists of both streaming and non-streaming funds.

	N	Mean	STD	Min	Max
$Streaming_{i,t}$	370,548	0.036	0.185	0	1
$fund\ age_{i,t}$ *(day)*	370,548	1,102	1,114	47	4,858
$fund\ size_{i,t}$ *(million)*	370,548	2,056	5,278	13.587	34,525
$turnover_{i,t}$ *(%)*	370,548	6.67	8.186	0.003	43.964
$Return_{i,t}$ *(%)*	370,548	-0.041	1.454	-4.003	4.227
$Return_{i,t-10,t-1}$ *(%)*	370,548	-0.377	4.246	-11.06	11.60
$Flow_{i,t+1}$ *(%)*	370,548	0.031	1.544	-6.257	7.129
$Flow_{i,t}$ *(%)*	370,548	0.025	1.555	-6.377	7.116
$Flow_{i,t-10,t-1}$ *(%)*	370,548	0.484	8.05	-26.49	38.48
$index\ vol_{i,t}$	370,548	1.31	0.76	0	3.87
$family\ flow_{i,t}$ *(%)*	370,548	0.117	0.664	-2.172	2.625
$family\ flow_{i,t-10,t-1}$ *(%)*	370,548	1.58	4.19	-7.52	25.75

Table A4: **Difference of Streaming and Non-streaming Funds**

This table compares the characteristics of ETF funds that were involved in fund managers' live streaming (Streaming) and those that were not (Non-Streaming) over the sample period. We conduct two-sample t-tests for key fund-level and manager-level variables, including fund age, size, turnover rate, past returns, and past flows. The final column reports the difference in means between the two groups along with the associated significance levels. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Streaming	Non-Streaming	Diff
$fund\ age_{i,t}$ *(ln)*	6.539	6.541	-0.002
	(0.002)	(0.004)	(0.004)
$fund\ size_{i,t}$ *(ln)*	19.804	19.245	0.559***
	(0.003)	(0.007)	(0.008)
$turnover_{i,t}$ *(%)*	7.001	5.220	1.781***
	(0.015)	(0.028)	(0.034)
$Return_{i,t}(\%)$	-0.041	-0.037	-0.004
	(0.003)	(0.005)	(0.006)
$Flow_{i,t}(\%)$	0.038	-0.032	0.070***
	(0.003)	(0.006)	(0.007)

Table A5: **Features and Flow Horizon**

The dependent variable is $Flow$ of fund i at different horizons. All regressions control for Day FE, Index × Week FE, and Fund × Month FE. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$	$Flow_{i,t+1,t+10}$	$Flow_{i,t+1,t+20}$	$Flow_{i,t+1,t+40}$
	(1)	(2)	(3)	(4)
$Visual_{i,t}$	0.108**	0.412**	0.114	-0.206
	(0.050)	(0.191)	(0.182)	(0.209)
$Vocal_{i,t}$	0.045	0.118	-0.030	0.309
	(0.036)	(0.132)	(0.186)	(0.231)
$Verbal_{i,t}$	-0.006	0.095	0.040	0.135
	(0.041)	(0.125)	(0.136)	(0.230)
Controls	YES	YES	YES	YES
Day FE	YES	YES	YES	YES
Index × Week FE	YES	YES	YES	YES
Fund × Month FE	YES	YES	YES	YES
Obs.	9,013	9,013	9,013	9,013
R^2	0.627	0.826	0.908	0.946

Table A6: **Features and Future Fund Performance**

The dependent variable is index-adjusted return (*Adj_Ret*) of fund i at different horizons. All regressions control for Day FE, Index × Week FE, and Fund × Month FE. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Adj_Ret_{i,t+1}$	$Adj_Ret_{t+1,t+10}$	$Adj_Ret_{t+1,t+20}$	$Adj_Ret_{t+1,t+40}$
	(1)	(2)	(3)	(4)
$Visual_{i,t}$	0.026	0.050	0.050	0.022
	(0.039)	(0.035)	(0.032)	(0.048)
$Vocal_{i,t}$	-0.007	-0.043	-0.025	0.022
	(0.028)	(0.039)	(0.043)	(0.037)
$Verbal_{i,t}$	0.019	0.020	-0.036*	0.016
	(0.023)	(0.027)	(0.020)	(0.021)
Controls	YES	YES	YES	YES
Day FE	YES	YES	YES	YES
Index × Week FE	YES	YES	YES	YES
Fund × Month FE	YES	YES	YES	YES
Obs.	9,013	9,013	9,013	9,013
R^2	0.788	0.758	0.861	0.936

Table A7: **Performance-Flow Sensitivity**

This table reports how ADI and multimodal features affects the performance-flow sensitivity. We choose the daily raw return on the day t as the measurement of the fund's performance. All regressions control for Fund FE, Day FE, and Index × Week FE. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$			
	(1)	(2)	(3)	(4)
$Return_{i,t} \times ADI_{i,t}$	-0.026			
	(0.018)			
$Return_{i,t} \times Visual_{i,t}$		-0.009		
		(0.022)		
$Return_{i,t} \times Vocal_{i,t}$			-0.033*	
			(0.017)	
$Return_{i,t} \times Verbal_{i,t}$				-0.012
				(0.013)
$Return_{i,t}$	0.011	0.011	0.010	0.012
	(0.033)	(0.034)	(0.033)	(0.036)
Controls	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES
Day FE	YES	YES	YES	YES
Index × Week FE	YES	YES	YES	YES
Obs.	9,013	9,013	9,013	9,013
R^2	0.394	0.394	0.394	0.393

Table A8: **Alternative Weighting of Verbal**

We re-estimate the baseline regressions by applying a different weighting scheme for *Verbal*. Variable definitions are provided in Table A1. Standard errors, in parentheses, are clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$ADI_{i,t}$	0.065***	0.098***	0.144***			
	(0.020)	(0.026)	(0.041)			
$Visual_{i,t}$				0.092**	0.108**	0.169***
				(0.036)	(0.051)	(0.055)
$Vocal_{i,t}$				0.018	0.045	0.057
				(0.029)	(0.036)	(0.047)
$Verbal_{i,t}$				0.012	-0.007	0.014
				(0.033)	(0.037)	(0.047)
Controls	YES	YES	YES	YES	YES	YES
Fund FE	YES	NO	NO	YES	NO	NO
Day FE	YES	YES	YES	YES	YES	YES
Index × Week FE	YES	YES	YES	YES	YES	YES
Fund × Month FE	NO	YES	YES	NO	YES	YES
Fund × DOW FE	NO	NO	YES	NO	NO	YES
Obs.	9,013	9,013	8,068	9,013	9,013	8,068
R^2	0.393	0.627	0.710	0.394	0.627	0.711

Table A9: **Alternative Clustered Standard Errors**

The dependent variable is *Flow*. Variable definitions are provided in Table A1. In Panel A, standard errors are clustered at fund and day level. In Panel B, standard errors are clustered at fund manager and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

Panel A: Cluster at the fund and day level

	$Flow_{i,t+1}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ADI_{i,t}$	0.057**	0.075***	0.105***	0.070**	0.160***				
	(0.025)	(0.027)	(0.039)	(0.031)	(0.054)				
$Visual_{i,t}$						0.093**	0.108**	0.079**	0.168***
						(0.042)	(0.052)	(0.038)	(0.059)
$Vocal_{i,t}$						0.019	0.045	0.027	0.057
						(0.031)	(0.042)	(0.034)	(0.052)
$Verbal_{i,t}$						-0.007	-0.006	-0.015	0.004
						(0.033)	(0.037)	(0.035)	(0.045)
Obs.	9,013	9,013	9,013	8,358	8,068	9,013	9,013	8,358	8,068
R^2	0.237	0.393	0.627	0.483	0.710	0.394	0.627	0.483	0.711

Panel B: Cluster at the manager and day level

$ADI_{i,t}$	0.060**	0.076***	0.107***	0.068**	0.161***				
	(0.024)	(0.025)	(0.039)	(0.035)	(0.060)				
$Visual_{i,t}$						0.091**	0.107*	0.073*	0.164**
						(0.038)	(0.057)	(0.039)	(0.071)
$Vocal_{i,t}$						0.022	0.049	0.030	0.062
						(0.035)	(0.049)	(0.037)	(0.059)
$Verbal_{i,t}$						-0.005	-0.007	-0.011	0.006
						(0.031)	(0.048)	(0.036)	(0.066)
Obs.	9,322	9,322	9,322	8,682	8,428	9,322	9,322	8,682	8,428
R^2	0.238	0.395	0.628	0.485	0.713	0.395	0.628	0.485	0.713
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	NO	NO	NO	YES	NO	NO	NO
Day FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Index × Week FE	NO	YES	YES	YES	YES	YES	YES	YES	YES
Fund × Month FE	NO	NO	YES	NO	YES	NO	YES	NO	YES
Fund × DOW FE	NO	NO	NO	YES	YES	NO	NO	YES	YES

Table A10: **Control for Stream Topic**

This table examines the results after controlling for the topic of each live streaming using LDA. The dependent variable is $Flow$. Variable definitions are provided in Table A1. Standard errors, in parentheses, and clustered at the fund family and day level. ***, ** , and * denote statistical significance at the 1% , 5% and 10% levels, respectively.

	$Flow_{i,t+1}$			
	(1)	(2)	(3)	(4)
$ADI_{i,t}$	0.144**	0.210***		
	(0.062)	(0.071)		
$Visual_{i,t}$			0.158**	0.227***
			(0.064)	(0.063)
$Vocal_{i,t}$			0.058	0.078
			(0.043)	(0.073)
$Verbal_{i,t}$			-0.016	-0.005
			(0.063)	(0.084)
Controls	YES	YES	YES	YES
Day FE	YES	YES	YES	YES
Index × *Week FE*	YES	YES	YES	YES
Fund × *Month FE*	YES	YES	YES	YES
Fund × *DOW FE*	NO	YES	NO	YES
Topic × *Month FE*	YES	YES	YES	YES
Obs.	9,295	8,396	9,295	8,396
R^2	0.650	0.736	0.650	0.736

B. Analyse text using HowNet Dictionary

This part introduces how to perform text sentiment analysis in Python using the HowNet sentiment dictionary, which offers word lists for positive and negative sentiments, as well as degree adverbs and negation words. Unlike traditional approaches that focus solely on word polarity, our method additionally takes into account the effects of degree adverbs, negators, and punctuation. These linguistic modifiers are assigned specific weights to reflect their emotional intensity. The weighting procedure is described as follows.

- **Degree adverbs:** The base sentiment score is multiplied by a predefined coefficient depending on the strength of the modifier. Specifically, "more" increases the score to 2.0, "very" to 3.0, and "most" to 4.0. Weaker modifiers such as "slightly" (`ish`) reduce the score to 0.5. "Insufficiently" and "over" represent weakening modifiers, applying scaling factors of -0.3 and -0.5, respectively. If multiple modifiers appear consecutively, all applicable weights are applied cumulatively.
- **Negation words:** Negation terms are identified if they appear before a sentiment word. If the number of negators is odd, the sentiment polarity is reversed by multiplying the score by -1; if even, the polarity remains unchanged.
- **Punctuation and Connectives:** If a sentence ends with an exclamation mark, all sentiment scores in that sentence are amplified by a factor of 2. If a sentence ends with a question mark, it is interpreted as weakly negative and assigned a fixed negative sentiment score of 2. If the conjunction "but" appears, sentiment scores after the conjunction are multiplied by 5.

After weighting, we aggregate scores at the sentence level and compute their average to obtain document-level positive and negative sentiment scores. To ensure comparability across texts, we apply a piecewise rescaling scheme.

- If the scores exceed a fixed threshold (set to 4 in this case), the stronger score is rescaled to 1, and the weaker one is expressed as a proportion of the stronger.
- Otherwise, each score is divided by the threshold or capped at 1 if it exceeds it.

This rescaling procedure ensures all sentiment scores fall within the [0,1] interval, mitigating the impact of sentence length and extreme intensity values.