Marketing for Flows, Paying with Alpha:

Evidence from Mutual Fund Manager Livestreaming[1]

Silu Cheng
East China University of Science and Technology

Yue Hu
Shanghai Jiao Tong University

Linlin Ma
Peking University

Zilu Wang
Fudan University

May 2026

[1] Cheng is at East China University of Science and Technology, email: y11230018@mail.ecust.edu.cn; Hu is at Shanghai Jiao Tong University, email: anthonyhy321@sjtu.edu.cn; Ma is at Peking University, email: linlin.ma@phbs.pku.edu.cn; and Wang is at Fudan University, email: zlwang22@m.fudan.edu.cn. All errors are ours.

Marketing for Flows, Paying with Alpha: Evidence from Mutual Fund Manager Livestreaming

Abstract

Mutual fund managers operate with dual objectives: producing risk-adjusted returns and expanding assets under management (AUM). Yet how managers allocate scarce time and attention across value creation versus asset gathering remains an empirical black box. We study this question using portfolio managers' livestreaming in China, which provides high-frequency, manager-level variation in marketing intensity. We document a robust tradeoff: livestreaming strengthens flow–performance sensitivity, but it predicts lower subsequent alpha. The pattern is consistent with production-side substitution of managerial attention away from research and implementation, with the performance drag concentrated in weekday streams and single-manager funds, and accompanied by fewer site visits and less informative narrative disclosures. We further show that marketing incentives can become self-reinforcing: managers with stronger historical marketing performance livestream more in the future, increasingly rely on star-style promotion, and experience greater performance erosion. Together, the estimates trace an AUM–alpha frontier and quantify the marginal rate at which chasing flows erodes alpha.

1. Introduction

Mutual fund managers are evaluated and compensated on two margins. They are rewarded for producing alpha through information acquisition and portfolio decisions, and they are also rewarded for acquiring assets by attracting flows beyond what past performance alone would justify. Yet the second margin, marketing effort and its effectiveness, remains largely a black box in empirical work. With costly search and limited attention, marketing shapes which funds investors notice, how they interpret performance signals, and how capital is allocated across managers. Consistent with its economic importance, marketing and distribution account for roughly one third of the costs of active management (Roussanov et al., 2021). Despite this, marketing is typically measured using coarse, fee-based proxies such as 12b-1 charges, which reveal little about the real-time technologies managers use to reach investors.

This paper studies a novel and economically salient marketing technology in asset management: portfolio managers' livestreaming in China. Since 2020, Chinese mutual fund managers have increasingly used livestreaming platforms to communicate with retail investors in real time, explain investment views, and cultivate a personal brand. Livestreaming moves managers to the front line of investor communication and generates high-frequency, manager-specific variation in marketing intensity. This setting allows us to directly measure manager-level marketing effort and to examine two foundational questions: (i) how marketing reshapes investors' flow responses to performance signals and, in turn, capital allocation across funds, and (ii) how marketing affects the production side of active management, including subsequent performance and information production.

We assemble a novel dataset from China's largest mutual fund livestreaming platform, covering fund manager livestreaming activity from 2020 to 2024, and merge it with fund flows, performance, portfolio holdings, and multiple proxies for information production. Conceptually, livestreaming can reduce investors' search frictions and strengthen performance-based capital allocation. At the same time, it may divert managerial time and attention away from research, monitoring, and portfolio

implementation. The empirical analysis that follows quantifies both margins and evaluates whether livestreaming induces a tradeoff between marketing effectiveness and value creation.

As a first step, and without imposing a causal interpretation, we examine time-series trends in industry-wide fund performance and cross-sectional dispersion in FPS surrounding livestreaming adoption. Panel A of Figure 2 demonstrates a significant reduction in FPS dispersion (SD_FPS), indicating a notable alleviation of search friction within the industry (Sirri and Tufano, 1998; Huang et al., 2007). In contrast, Panel B shows a significant erosion in overall fund performance following livestreaming adoption.

Motivated by Figure 2, we conduct three panel regressions to test the dual effects of fund livestreaming. First, we examine how engagement in livestreaming affects fund FPS. The results indicate that livestreaming significantly reinforces FPS by 0.259. In magnitude, this represents a 64.59% enhancement in investor responses, consistent with the search friction story (Sirri and Tufano, 1998; Guercio and Tkac, 2008). Second, in terms of fund performance, we find that livestreaming funds exhibit a marked deterioration in performance, consistent with the limited attention hypothesis. For each additional day of livestreaming, the Fama-French five-factor (hereafter as FF5) alpha decline by 0.093%.[2] The combined findings support our conjecture and suggest that fund managers, when deciding whether to livestream, are likely to face the tradeoff between FPS (search friction) and fund performance (value creation).

There exist two key reasons why limited attention (or effort) is particularly relevant in our setting. First, unlike e-commerce livestreaming that relies on hired promoters, a fund's core product is its managerial skill (Berk and Green, 2004). This inalienable feature necessitates the manager's personal involvement in livestreams to establish

2 One alternative for the negative correlation between livestreaming and performance is that livestreaming-driven inflows expand fund size and therefore erode fund performance. We address this issue by investigating whether livestreaming's impact on performance is concentrated in the inflow cohort, and find no supporting evidence as well. Detailed results see Table A2 of Appendix.

credibility, which significantly increases their workload.[3] Consequently, managers play a prominent role in the livestreaming decision, which is fundamentally different from traditional family-led marketing activities (Jain and Wu, 2000; Chen et al., 2022). Second, to prevent livestreaming from backfiring, fund managers have to persistently refine their on-camera professionalism, such as appearance management, verbal precision and interactive skills (Kacperczyk et al., 2025; Li et al., 2025; deHaan et al., 2026). These time-consuming activities, most of which occur during weekdays, probably occupy managers' substantial time and energy that would otherwise be allocated to investment research.[4] As anecdotal evidence suggests, multitasking and work overload from livestreaming have significantly impaired fund performance.[5]

To validate whether fund managers genuinely reduce their commitment to portfolio investment, we undertake four examinations. First, compared to those with multiple co-managers, the performance deterioration following livestreaming is more significant for funds managed by a single manager or those without any manager dedicated solely to the fund. Second, given manager's reliance on site visits to make sound investment decisions (Chen et al., 2022; Cicero et al., 2024), we test whether livestreaming leads to a reduction in site visits by fund managers in the current quarter. The results support our conjecture. Third, motivated by Hirshleifer and Sheng (2022), we document a significantly stronger impact of fund livestreaming on performance during weekdays than weekend. Finally, leveraging a textual analysis of fund quarterly reports, we find a statistically significant reduction in the information content of fund reports, aligning with our limited attention hypothesis.

Having established the tradeoff between production and marketing, a natural question arises: what motivates fund managers to participate in livestreaming? Intuitively, for an indifferent marginal manager, the livestreaming-induced marginal

3 News coverage highlights that it is now a common practice for fund managers to engage fre quently in livestreaming. More details see https://www.cqcb.com/zibenshichang/2024-05-07/5563370_pc.html.

4 Our data indicate that the majority of fund livestreaming take place on weekdays.

5 More details see https://mp.weixin.qq.com/s/fiWl2VF1DJHBHnP1SCCArg and https://www.cqcb.com/zibenshichang/2024-05-07/5563370_pc.html.

benefit, i.e. the search friction mitigation, should be equal to its marginal cost of effort diversion, i.e. the expected performance decline. It follows that a livestreaming fund should either be better able to mitigate search frictions or have a lower expected performance.

Focusing on the former, we hypothesize that two types of funds should benefit more from the search friction alleviation. First, funds with higher search costs can have larger potential to enhance their visibility among investors and increase their FPS (Sirri and Tufano, 1998). Measuring search cost by family size, we confirm this viewpoint. Second, with comparable visibility gains, high-performing funds are more likely to be perceived as skilled and thus receive greater inflows (Berk and Green, 2004). This motivates funds with superior performance to engage more in livestreaming activities. Consistent with this idea, we document a significant and positive correlation between fund performance and their livestreaming activities. This relationship holds for both short- and long-term performance horizons, suggesting that livestreaming is unlikely to be merely a strategy to capitalize on transient strong returns. Meanwhile, this evidence also eliminates a potential career concern story, where managers with worse past performance might wish to alleviate career pressures by livestreaming to attract fund flows (Chevalier and Ellison, 1999).

Turning to the other end of the spectrum, we test whether funds with lower expected performance are more likely to engage in livestreaming. To resolve the empirical challenge to measure such performance expectation, we utilize the well-established fact of decreasing return to scale and document a significant positive correlation between fund scale growth and their likelihood of being engaged in live activities (Berk and Green, 2004; Chen et al., 2004; Pástor et al., 2015; Zhu, 2018).

However, as Berk and van Binsbergen (2015) pointed out, skilled managers may manage larger scale in equilibrium, potentially blurring the relation between fund size and cost of value creation. To address this concern, we instrument fund size using Morningstar rating upgrades, which generate exogenous capital inflows unrelated to unobserved managerial motives for livestreaming (Grecico and Tkach, 2008; Ben-

Davis et al., 2022), and obtain similar conclusions. These findings collectively reveal that diseconomies of scale are probably another important driver of fund livestreaming.

Inspired by the fact that the likelihood of fund livestreaming is positively associated with historical while negatively with future performance, we hypothesize that fund livestreaming potentially creates an interesting flow dynamic: On the one hand, a combination of high past performance and enhanced FPS generate a larger contemporaneous inflow. On the other hand, however, the current performance erosion brought by livestreaming crystallize into a foreseeable future outflow. In line with this analysis, we confirm both a short-term inflow and a subsequent outflow. More importantly, we find that funds preferring current rather than deferred flows exhibit deeper involvement in livestreaming, reflecting investment horizons as another important driver of marketing (Gaspar et al., 2005; Ben-David et al., 2013).

In terms of marketing dynamics, we find that strong historical investor feedback (proxied by view counts) spurs future livestreaming activity. This self-reinforcing cycle generates more polarized managers, leading those marketing-oriented ones to conduct a star-promotion strategy and experience a larger decline of performance.

Last but not least, we discuss how livestreaming reshapes mutual fund industry's structure and its implications for overall market efficiency. Firstly, we examine the potential market efficiency implications. As is emphasized before, livestreaming funds spend more effort in mitigating search costs while simultaneously reducing their input in value generation. Consequently, compared to the pre-live period, the industry has invested less effort in delivering superior performance. Along this idea, we find that while mutual fund ownership is associated with a lower stock post-earnings-announcement drift (PEAD), this efficiency-enhancing impact vanishes after a fund is engaged in livestreaming. This points to a potential negative externality of manager's marketing—the market efficiency loss.

Secondly, we focus on the competition in the fund livestreaming market and relate it to the observed time-series intensity of fund livestreaming. Specifically, we

demonstrate a significantly lower FPS enhancement during high-competition period—highlighting the strategic substitution of fund livestreaming and an unstable share of livestreaming funds in equilibrium, as shown in Figure 1. In this case, a pattern of universal but excessive engagement — similar to the open-end structure in this industry—is less likely to occur (Stein, 2005).

Finally, we briefly analyze the impacts of fund livestreaming on FPS concavity. As previously discussed, livestreaming significantly mitigate search frictions and contributes to an increasing cross-fund equality in terms of search frictions, thereby weakening the salience and edge of top-performing funds (Sirri and Tufano, 1998). Following this logic, we find a less convex FPS during post-livestreaming period, suggesting a lower dispersion of search costs and a more evenly capital redistribution across funds in this industry.

Our paper contributes to several strands of literature. First, we advance research on mutual fund marketing by directly measuring manager-level marketing effort and its economic consequences. Because marketing effort is typically unobserved and proxied by coarse, largely time-invariant variables such as distribution fees or advertising expenses, existing work has limited ability to study marketing as a managerial choice (Huang et al., 2007; Roussanov et al., 2021; Chen et al., 2022). Using managers' livestreaming as a high-frequency, manager-specific measure, we open this black box and document a fundamental marketing-production tradeoff: marketing strengthens investors' reliance on performance signals but can crowd out research and information production, lowering subsequent risk-adjusted performance, consistent with a multitasking agency view in which managers allocate scarce effort between asset gathering and alpha production.

Second, we contribute to the broader literature on fintech adoption by showing how a new communication technology changes behavior on the supply side of asset management. While much of the fintech literature emphasizes improvements in screening and decision-making as well as potential distortions (Berg et al., 2020; D'Acunto et al., 2019; Reher and Sokolinski, 2024; Fuster et al., 2022; Chu et al., 2023;

Dai et al., 2025), we highlight a mechanism specific to delegated portfolio management: fintech can expand the marketing technology set and reallocate managerial effort between asset gathering and alpha production. Our results complement emerging work on fintech in mutual funds by documenting a technology-induced tradeoff at the core of active management (Cen, 2024; Hong et al., 2025).

Third, our findings speak to the literature on search frictions and the flow-performance relation in mutual funds. Prior work shows that search costs shape flow-performance sensitivity and its convexity (Sirri and Tufano, 1998; Huang et al., 2007; Chevalier and Ellison, 1997; Goldstein et al., 2017). We show that livestreaming mitigates search frictions and increases fund-level flow-performance sensitivity, and we provide industry-level evidence that the flow-performance relation becomes less convex in the post-livestreaming period.

Finally, our paper is closely related to contemporaneous work studying mutual fund livestreaming as a persuasion technology (Kaperczyk et al., 2025; Li et al., 2025; deHaan et al., 2026). We complement their analysis by emphasizing manager- and family-level incentives and by documenting the supply-side consequences of livestreaming through the marketing-research tradeoff.

2. Data Description and Sample Statistics

2.1 Sample Selection and Data Sources

Our study focuses on Chinese open-end equity funds from the Q2 2020 to Q4 2024, excluding structured funds, fund of funds (FOF), qualified domestic institutional investor (QDII) funds, umbrella funds, and index funds, leaving a final sample of 3,061 funds. Our analysis relies on three main datasets: (1) fund livestreaming information, (2) fund performance and other characteristics, and (3) listed companies' characteristics and corresponding stock data.

Livestreaming data are hand-collected from *Tian Tian Fund*, one of China's largest fund livestreaming platforms, including fund codes, livestreaming dates, viewership

numbers, guest name, and guest tags. Although the earliest livestream on *Tian Tian Fund*'s website dates back to August 2020, livestreams on its mobile app began as early as May 2020. We supplement the website data with app-based livestream records from May 2020 to December 2024, in line with deHaan et al. (2026).

Fund performance and characteristics, as well as listed company and stock data, are sourced from the China Stock Market & Accounting Research (CSMAR) Database, Wind Database, and Chinese Research Data Services (CNRDS) Database. Specifically, we collect fund performance, holdings, fee structures, and manager information from CSMAR, along with firm-specific and stock return data. Fund and family characteristics come from Wind, manager site visit data from CNRDS, and Morningstar ratings from the Asset Management Association of China's official website.

2.2 Measurement of Key Variables

Below, we define the key variables used in our study. Definitions of other variables can be found in Appendix Table A1.

2.2.1 Livestreaming Variables

We measure fund livestreaming activity using two variables: *D*(*live*) and *Live_day*. *D*(*live*) is an indicator that equals 1 if a fund manager conducts at least one livestream in a quarter, and 0 otherwise. *Live_day* counts the number of days in a quarter on which a fund manager livestreams. For overnight livestreams, we record the event based on the start date and count it as a single livestream day.

2.2.2 Star-promotion Variables

To examine star-promotion practices, we extract guest tags of each livestream from *Tian Tian Fund* and classify them based on a predefined keyword list. We consider tags describing fund managers' educational background, personality, or awards—characteristics unrelated to performance—as evidence of star-promotion. The keyword categories are listed in Table A6.

For each livestream, we construct dummy variables: (1) *D*(*Live_Edu*) equals 1 if any

education-related keyword appears; (2) *D*(*Live_Per*) equals 1 for personality-related keywords; (3) *D*(*Live_Awd*) equals 1 for award-related keywords. If a livestream guest tag contains any keyword from Table A6, *D*(*Live_Star*) is set to 1. These dummy variables are not mutually exclusive, as a single tag may include multiple keywords.

We then aggregate these livestream-level indicators to the fund-quarter level. Specifically, *D*(*Star_promotion*) equals 1 if a fund has at least one livestream with *D*(*Live_Star*) equal to 1 in a quarter, and 0 otherwise. Similar procedures are applied to construct *D*(*Education*), *D*(*Personality*), and *D*(*Awards*).

2.3 Descriptive Statistics

Table 1 reports descriptive statistics for the main variables at the fund-quarter level, including the number of observations, mean, standard deviation, minimum, median, and maximum. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate outlier influence.

Since livestreaming's adoption in Q2 2020, the average quarterly participation rate of fund managers has been 7.9%, with a peak of 45 livestream days in a single quarter. Regarding star-promotion behavior, 18.8% of funds use at least one star-promotion keyword in guest tags to attract audiences. Additionally, average fund performance during the sample period is negative, consistent with findings in deHaan et al. (2026) for a similar sample period.

[Insert Table 1 about here]

3 Main results

3.1 The impacts of managerial livestreaming

3.1.1 Tradeoff between marketing and production

We begin by examining the impact of livestreaming on fund FPS. Specifically, we estimate the following model at the fund-quarter level:

$$Flow_{i,t} = \beta_1 Perf_{i,t-4\sim t-1} \times Live_{i,t} + \beta_2 Perf_{i,t-4\sim t-1} + \beta_3 Live_{i,t} + Controls$$

$$+Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (1)$$

where $Flow_{i,t}$ is the net percentage growth of fund i during quarter t, measured as the percentage change in fund's assets after adjusting for fund returns:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + Return_{i,t})}{TNA_{i,t-1}} \quad (2)$$

where $TNA_{i,t}$ denotes the total net assets, and $Return_{i,t}$ is the net return for fund i during quarter t.

In Eq. (1), $Live_{i,t}$ is measure by two variables: a binary indicator $D(Live)_{i,t}$ and a continuous variable $Live_day_{i,t}$, which records the number of manager livestreaming days during the quarter. Fund-level long-term performance ($Perf_{i,t\text{-}4\sim t\text{-}1}$) is measured by the cumulative four-quarter excess return over the risk-free rate ($Exc_Return_{i,t\text{-}4\sim t\text{-}1}$) and the cumulative Fama-French five-factor alpha ($FF5_Alpha_{i,t\text{-}4\sim t\text{-}1}$). The main coefficient of interest, β_1, quantifies the additional FPS generated by livestreaming activities. The control variables includes: fund size ($Size_{i,t\text{-}1}$), fund age ($Age_{i,t\text{-}1}$), management fee ($Manage_fee_{i,t\text{-}1}$), load fee ($Load_{i,t\text{-}1}$), manager gender ($D(Male)_{i,t\text{-}1}$) and educational background ($D(Phd)_{i,t\text{-}1}$), family size ($Size_family_{i,t\text{-}1}$), and rolling volatility of daily FF5 alpha ($FF5_Alpha_SD_{i,t\text{-}4\sim t\text{-}1}$). Detailed definitions of the variables are provided in Table A1 in the Appendix. We also include fund fixed effects, year-quarter fixed effects, and cluster standard errors by fund family.

Columns (1)–(4) of Table 2 present the estimation results. The positive and statistically significant coefficients on the interaction terms β_1 indicate that investors respond more strongly to past performance when fund managers engage in livestreaming. In economic terms, fund livestreaming raises the FPS by 64.59% (0.259/0.401), highlighting its substantial impact.

Next, we estimate the following regression to examine the impact of livestreaming on fund performance:

$$Perf_{i,t} = \beta_1 Live_{i,t-1} + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (3)$$

where $Perf_{i,t}$ is defined as before. *Controls* refers to a series of lagged fund-level

variables and managerial characteristics, including $Perf_{i,t-1}$, $Flow_{i,t-1}$, $Size_{i,t-1}$, $Manage_fee_{i,t-1}$, $Load_{i,t-1}$, $Age_{i,t-1}$, $D(phd)_{i,t-1}$, and $D(Male)_{i,t-1}$.

As shown in Columns (5)–(8) of Table 2, livestreaming activities significantly impair subsequent fund performance. Compared to its counterparts, a livestreaming fund exhibit an average decrease in FF5 alpha of 62.9 basis points in the following quarter.[6]

[Insert Table 2 about here]

3.1.2 Source of the tradeoff: Attention diversion

We provide several direct evidence supporting an attention diversion channel.

First, we investigate whether the performance erosion is more pronounced for managers with pre-existing attention constraints. Specifically, we partition our sample by whether a fund is co-managed or if at least one manager of a fund is dedicated solely to the fund. We then re-estimate Eq. (3) for each subsample, with results shown in Panel A of Table 3.

Columns (1)–(4) of Panel A reveal that the negative impact of livestreaming on performance is statistically significant only for funds with a single manager. This suggests that a sole manager is more affected by the time demands of livestreaming. Column (5)–(8) exhibit the similar pattern, where a dedicated manager shields the fund from the post-live performance decline, aligning with the attention diversion channel.

Second, we directly test the impact of livestreaming on fund managers' information production through the lens of site visits, a time-consuming and non-compulsory source of private information (Chen et al., 2022; Cicero et al., 2024). Given the time demands of livestreaming, managers may reduce site visits. To verify this potential crowd-out effect, we employ the following model:

$$Site_Visit_{i,t} = \beta_1 Live_day_{i,t} + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (4)$$

where $Site_Visit_{i,t}$ includes both the quarterly change in the number of site visits, $Site_visit_change_{i,t}$, and the growth rate of site visits, $Site_visit_growth_{i,t}$. By comparing

6 Our findings are robust to conducting matching technique; see Appendix Table A3 and Figure A1.

a manager's site visit intensity relative to her own historical baseline, we can control for confounders like personal traits and preference and isolate livestreaming effect. To purge the contamination of COVID-19 lockdowns (Zhao et al., 2023), we exclude observations for Q2 2020 (nationwide) and Q2 2022 (Shanghai).

To further investigate the potentially non-linear impacts, we extend Eq. (4) by categorizing livestreaming days into three intensity levels:

$$Site_Visit_{i,t} = \beta_1 D(Live_day_high)_{i,t} + \beta_2 D(Live_day_med)_{i,t} + \beta_3 D(Live_day_low)_{i,t} + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (5)$$

where $D(Live_day_high)$, $D(Live_day_med)$, and $D(Live_day_low)$ indicate high (≥7 days), medium (3-7 days), and low (1-3 days) livestreaming intensity per quarter, respectively. The results are presented in Panel B of Table 3.

[Insert Table 3 about here]

As expected, the relationship between livestreaming and site visits is convexly increasing. Specifically, columns (3) and (4) indicate that a lower frequency of livestreaming does not significantly crowd out managers' site visit activities. However, when managers livestream for seven or more days in a quarter, their site visits decline significantly relative to their own past levels.

Next, we separate the fund livestreaming dates into weekdays ($D(Live_W)_{i,t}$ and $Live_day_W_{i,t}$) versus non-weekdays ($D(Live_NW)_{i,t}$ and $Live_day_NW_{i,t}$), since fund managers primarily conduct research and trading on weekdays (Hirshleifer and Sheng, 2022). Panel C of Table 3 shows that only weekday livestreaming significantly impairs fund performance, further supporting our crowd-out hypothesis.

Finally, we conduct a textual analysis of fund quarterly reports to assess whether livestreaming crowds out research activities. We classify sentences as either informative (containing specific details or insights) or generic (vague, boilerplate statements like general market commentary). The proportion of generic sentences

(*No_infor*) in each report is used as the dependent variable. Panel D of Table 3 indicates that livestreaming is associated with a significant increase in generic sentences, suggesting that during quarters with livestreaming activity, the information content of fund reports declines, replaced by vaguer and boilerplate language. This shift provides further evidence that livestreaming substantially encroaches on the fundamental research activities that underlie fund performance.

A potential alternative explanation is that livestreaming may attract flows that are more sensitive to short-term returns and market sentiment, potentially increasing flow-induced trading and liquidity costs, thereby impairing performance (Cen, 2024). If this were the case, we would expect higher future flows and flow volatility. However, as shown in Appendix Table A4, we observe no such pattern, ruling out this alternative for the negative effect of livestreaming on fund performance.

3.2 Managerial incentives of livestreaming

3.2.1 Mitigate search friction

Given the attention demands and performance costs, why do managers continue to livestream? One potential explanation is that livestreaming helps reduce search friction, a well-documented challenge in the industry (Sirri and Tufano, 1998; Barber et al., 2005; Huang et al., 2007; Rossanov et al., 2021). In contrast, livestreaming offers fund managers a real-time, scalable platform to reach a broader investor base. Thus, managers benefiting more from reduced search friction are more likely to engage in a livestreaming activity. We assess this motivation by examining whether fund livestreaming decision is associated with (1) a fund's ex-ante level of search cost (potential to enhance visibility) and (2) its historical performance (potential to attract flows when searched).

To test search costs, we estimate the following regression:

$$Live_{i,t} = \beta_1 Size_family_{i,t-1} + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (6)$$

where $Size_family_{i,t\text{-}1}$, the natural logarithm of the fund family's assets, serves as a proxy for search cost, as smaller families typically face greater search costs (Sirri and Tufano,

1998; Huang et al., 2007).

Regarding the historical performance, we estimate the following regression:

$$Live_{i,t} = \beta_1 FF5_Alpha + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (7)$$

where *FF5_Alpha* includes historical performance over different horizons (*FF5_Alpha*$_{i,t\text{-}1}$, *FF5_Alpha*$_{i,t\text{-}4\sim t\text{-}1}$ and *FF5_Alpha*$_{i,t\text{-}8\sim t\text{-}1}$).

Panel A of Table 4 reports results from Eq. (6). Column (1) and (2) show significantly negative coefficients on *Size_family*. This indicates that funds from smaller families—which face higher search costs—are more active in livestreaming. In contrast, for funds with negative past performance (columns (3) and (4)), the coefficients are insignificant, suggesting that managers of underperforming funds are less inclined to use livestreaming to reduce search friction.

[Insert Table 4 about here]

Panel B of Table 4 further confirms the complementary relationship between performance and livestreaming (Roussanov et al., 2021). Consistent coefficients on *FF5_Alpha* across both short- and long-term performance suggest that livestreaming is less likely a strategy to highlight temporary strong returns. Strong past performance, as a credible signal of managerial skill, enhances the fund's ability to attract inflows when searched, thereby incentivizing livestreaming (Berk and Green, 2004). Meanwhile, this also eliminates an alternative career concern story, where poorly performing managers might livestream to attract inflows and avoid termination (Chevalier and Ellison, 1999).

3.2.2 Diseconomies of scale

For fund managers, another potential incentive for livestreaming is a low expected marginal benefit of research. To circumvent the empirical challenge to directly measure such expectation, we build on the well-documented fact of diminishing returns to scale at the fund level (Berk and Green, 2004; Chen et al., 2004; Pástor et al., 2015; Pástor et al., 2020). We test whether funds with higher growth are more likely to adopt livestreaming. Specifically, we estimate the effect of recent fund growth on

livestreaming decisions, using two measures of growth: net inflows ($Flow_{i,t\text{-}1}$) and changes in fund size ($\Delta Size_{i,t\text{-}1}$), where $\Delta Size_{i,t}=TNA_{i,t}-TNA_{i,t\text{-}1}\times(1+Return_{i,t})$. [7] Specifically, we estimate the following model:

$$Live_{i,t} = \beta_1 Flow_{i,t-1} \,/\, \Delta Size_{i,t-1} + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (8)$$

However, fund growth may be endogenous to managerial skill and strategy (Berk and van Binsbergen, 2015). To isolate the exogenous growth driven by factors unrelated to managerial skill, we use Morningstar's rating upgrade ($D(Upgrade)_{i,t\text{-}2}$) as an instrumental variables (IV) for the growth of fund scale. A rating upgrade plausibly induces exogenous inflows but is unrelated to unobserved managerial motives for livestreaming (Guercio and Tkac, 2008; Ben-David et al., 2022).

Table 5 presents the results. Columns (1) and (2) report the estimate results for Eq. (8). Both coefficients are positive and significant, indicating that recent fund growth is associated with a higher likelihood of livestreaming.

[Insert Table 5 about here]

Columns (3) through (6) present the IV estimates. Columns (3) and (5) confirm that a Morningstar rating upgrade is strongly associated with higher flows and greater fund size growth (the first stage). The second-stage results in columns (4) and (6) show that the instrumented, upgrade-driven increases in $Flow_{i,t\text{-}1}$ and $\Delta Size_{i,t\text{-}1}$ significantly raise the probability of livestreaming. This indicates that exogenous scale growth—likely pushing a fund beyond its optimal scale and lowering expected performance—significantly incentivize managers to livestream. In economic terms, a one-standard-deviation increase in instrumented $\Delta Size_{i,t\text{-}1}$ raises the probability of livestreaming by approximately 7.9% (0.036 × 2.195). Taken together, these results support the view that diseconomies of scale constitute another key driver of fund managers' decision to

7 Our measure of $\Delta Size$ purges the impact of past performance, thus essentially capturing the flow-induced change in size. We also considered the total change in size (without this adjustment), and the results are qualitatively similar.

livestream.

3.2.3 Flow dynamics and fund horizon

As presented in Table 2 and Panel B of Table 4, livestreaming is positively associated with historical while negatively with future performance. Given investor's flow-chasing behavior, we can anticipate that livestreaming triggers an intertemporal substitution of fund flow: a contemporaneous inflow (from the combination of superior past performance and reduced search friction) followed by an outflow (driven by livestreaming-induced performance erosion). If the divergent short- and long-term effects hold, then livestreaming should be more attractive to managers with shorter investment horizons, as they prioritize immediate inflows over long-term sustainability.

To test this hypothesis, we estimate the following model:

$$Flow_{i,t+j} = \beta_1 Live_{i,t} + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (9)$$

where $Flow_{i,t+j}$ denotes the fund flows in the current quarter (j=0) and the subsequent four quarters (j=1, 2, 3, 4). The coefficient β_1 over these horizons estimates the dynamic effects of livestreaming on fund flows.

The results in Table 6 support our conjectures.[8] Columns (1) and (2) show that livestreaming significantly increases fund flow in the current (j=0) and the subsequent (j=1) quarters, reflecting the boost from enhanced FPS for high-performing funds. However, this positive effect begins to fade in the second quarter (j=2) and finally reverses into significant outflows by the fourth quarter (j=4), as shown in columns (3) to (5). This finding also aligns with our prediction that livestreaming erodes performance, which in turn negatively impacts future fund flows.

[Insert Table 6 about here]

To further test the investment horizon channel, we test this idea using the following model:

8 The results using the quarterly number of livestreaming days as the dependent variable are presented in Appendix Table A5 and are qualitatively similar.

$$Live_{i,t} = \beta_1 Short_horizon_{i,t} + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (10)$$

where $Short_horizon_{i,t}$ is measured in two ways: (1) the fund's turnover rate over the past four quarters, $Churn_GMM_{t\text{-}4\sim t\text{-}1}$ (Gaspar et al., 2005); and (2) a dummy variable $D(Pumping)_{t\text{-}4\sim t\text{-}1}$ indicating fund pumping intensity (Ben-David et al., 2013).[9]

The results in columns (6) and (7) confirm our conjecture: both $Churn_GMM_{t\text{-}4\sim t\text{-}1}$ and $D(Pumping)_{t\text{-}4\sim t\text{-}1}$ are significantly positive. This suggests that the incentive to livestream is partly driven by its immediate marketing benefits and the delayed outflows, making it particularly appealing to managers with shorter horizons.

3.3 Livestreaming Dynamics

This section examines how manager's marketing strategy evolve over time. We first examine how historical marketing performance reshapes manager's future livestreaming decision and, in turn, fund performance. More concretely, we estimate following regression model:

$$Live_{i,t}/Perf_{i,t} = \beta_1 D(View)_{i,t-1} + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (11)$$

where $D(View)_{i,t\text{-}1}$ represents fund i's prior marketing performance in quarter t-1, measured by investor feedback. We use two variables: (1) $D(View_top1)_{i,t\text{-}1}$, a dummy variable equal to 1 if fund i had the highest viewership within its fund family and style in quarter t-1, and 0 otherwise; and (2) $D(View_top50\%)_{i,t\text{-}1}$, a binary indicator equal to 1 if fund i's viewership ranked in the top 50% within its fund family and style in quarter t-1. The sample is restricted to funds that conducted livestreaming in the previous quarter.

[Insert Table 7 about here]

As presented in columns (1) to (4) of Table 7, the coefficients on $D(View_top1)$ and

9 $D(Pumping)_{t\text{-}4\sim t\text{-}1}$ is derived by first measuring quarterly pumping intensity based on Ben-David et al. (2013), computed as the difference between the FF5 alpha on the last day of the quarter and the FF5 alpha on the first day of the next quarter. The average pumping intensity over the past four quarters is then calculated. This dummy variable takes a value of 1 if the average pumping intensity falls within the top tercile among all funds in that quarter, and 0 otherwise.

D(*View_top50%*) are significantly positive at the 1% level. This suggests that funds with stronger investor feedback (higher viewership) are more likely to engage in livestreaming in the next quarter. Dynamically, this self-reinforcing cycle is likely to polarize fund managers, leading popular managers to increasingly bias towards marketing. Columns (5) and (6) further examine fund performance implications. Consistent with our prediction, a strong historical livestreaming performance leads to worse future performance due to managers' greater propensity for marketing.

Motivated by literature on star fund (Nanda et al., 2004; Gaspar et al., 2005; Wang, 2025), we hypothesize that marketing-oriented managers likely craft a distinctive personal brand during livestreams to attract investors. To test this, we analyze the keywords used in the guest tags during livestream and estimate the following model:

$$Promote_star_{i,t} = \beta_1 D(View)_{i,t-1} + \beta_2 FF5_Alpha_{i,t-4\sim t-1} + \beta_3 FF5_Alpha_{i,t-8\sim t-1} + Controls + Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (12)$$

where $Promote_star_{i,t}$ represents a set of dummy variables indicating whether the manager used a skill-unrelated tags, such as educational background, personality, or awards ($D(Education)_{i,t}$, $D(Personality)_{i,t}$, $D(Awards)_{i,t}$). $D(Star_promoting)_{i,t}$ equals 1 if any of these tags were used.

Table 8 results confirm our hypothesis: managers with strong past viewership are more likely to add skill-unrelated tags to promote a star persona. Interestingly, long-term performance does not significantly correlate with the use of these tags, suggesting they are more about branding than skill. A closer examination, as shown in columns (3)–(8), reveals that managers are particularly likely to highlight their education or personality for their investors, consistent with recent works on trust and persuasion in the financial markets (Gennaioli et al., 2015; Li et al., 2025; deHaan et al., 2026).

[Insert Table 8 about here]

To further explore the incentives and outcomes of star-promoting strategy utilization, we test this using:

$$Live_{i,t}/Perf_{i,t} = \beta_1 D(Live_star)_{i,t-1} + \beta_2 D(Live_nostar)_{i,t-1} + Controls$$
$$+Fund\ FE + Year - Quarter\ FE + \varepsilon_{i,t} \quad (13)$$

where we separate $D(Live)_{i,t\text{-}1}$ into two separate variables, $D(Live_star)_{i,t\text{-}1}$ and $D(Live_star)_{i,t\text{-}1}$, based on whether managers used star tags during livestreaming.

Table 9 presents the regression results. For funds that livestreamed in the previous quarter, columns (1) and (2) show that using star tags leads to a 10 percent increase in the likelihood of subsequent livestreaming (an additional 0.8 days), a 66.22% (117.06%) rise. This pattern suggests that it is marketing-oriented managers that primarily use star tags. In terms of performance, columns (3) and (4) reveal that funds with star tags experience more significant performance deterioration in the following quarter, reinforcing the idea that star tags are a marketing tool rather than a performance enhancer.

[Insert Table 9 about here]

4 Discussion: industry implication

In this section, we explore the broader industrial implications of fund livestreaming. We address three main areas: first, the impact on market efficiency; second, the role of competition in fund livestreaming; and third, the effect of livestreaming on capital allocation, with a focus on the flow-performance relationship.

4.1 Livestreaming and market efficiency

Previous analysis suggests that livestreaming diverts managerial effort from investment towards marketing. If this comes at the expense of informed trading, it could weaken the price discovery process in the stock market. We test this hypothesis by comparing the price efficiency of stocks held by livestreaming versus non-livestreaming funds. Use post-earnings-announcement drift (PEAD) as our key measure of price efficiency, we first estimate the following model:

$$CAR_{j,t} = \beta_1 Fundshare_{j,t} \times Rank_SUE_{j,t} + \beta_2 Fundshare_{j,t} + \beta_3 Rank_SUE_{j,t}$$

$$+Controls + Stock\ FE + Year - Quarter\ FE + Industry\ FE + \varepsilon_{j,t} \quad (14)$$

where $CAR_{j,t}$ is the cumulative abnormal return from the first to the 30th trading day after an earnings announcement. $Rank_SUE_{j,t}$ represents the quintile rank of *SUE*, taking values from -2 (lowest quintile) to +2 (highest quintile). *SUE* is the earnings surprises as the standardized unexpected earnings, calculated as $SUE_{j,t}=(EPS_{j,t}-EPS_{j,t-4})/P_{j,t}$, where $EPS_{j,t}$ is the earnings per share for stock j in quarter t and $P_{j,t}$ is the price per share of stock j at the end of quarter t. $Fundshare_{j,t}$ is the proportion of stock j's total shares outstanding held by all mutual funds in quarter t. Following Huang et al. (2021), we control for the natural logarithm of total assets (*Size_Stock*), the book-to-market ratio (*BM*), institutional ownership excluding the holdings of the fund (*IO_ExpFund*), the number of analysts following the stock (*# Analysts*), and the idiosyncratic volatility measured over the four quarters preceding earnings announcements (*IVOL*). The coefficient β_1 captures whether higher fund ownership mitigates the sensitivity of PEAD to earnings surprises—that is, whether fund ownership helps improve market efficiency by reducing the PEAD.

To test whether livestreaming hampers the role of mutual funds in promoting market efficiency, we further decompose $Fundshare_{j,t}$ into proportions of stock j's total shares held by livestreaming funds ($Fundshare_Live_{j,t}$) and non-livestreaming funds ($Fundshare_NoLive_{j,t}$) and estimate the following regression:

$$CAR_{j,t} = \beta_1 Fundshare_Live_{j,t} \times Rank_SUE_{j,t} + \beta_2 Fundshare_NoLive_{j,t} \times Rank_SUE_{j,t}$$
$$+\beta_3 Fundshare_Live_{j,t} + \beta_4 Fundshare_NoLive_{j,t} + \beta_5 Rank_SUE_{j,t} + Controls$$
$$+Stock\ FE + Year - Quarter\ FE + Industry\ FE + \varepsilon_{j,t} \quad (15)$$

Columns (1)–(2) and (3)–(4) of Table 10 present the estimation results from these models. In columns (1) and (2), the coefficient on the interaction term is significantly negative at the 1% level. However, in columns (3) and (4), only the interaction term involving the holding share of non-livestreaming funds (*Fundshare_NoLive* × *Rank_SUE*) is significantly negative. This implies that mutual fund ownership generally reduces PEAD, but this efficiency-enhancing effect is confined to non-livestreaming

funds. The findings carry an important implication: manager livestreaming not only harms value creation but also undermines the market efficiency.

[Insert Table 10 about here]

4.2 The role of competition

Livestreaming competes for investor attention, so we explore whether its positive effect on a fund's FPS is stronger during periods of lower competition. We measure competition intensity in two ways: the number of funds livestreaming and the total number of livestreaming days, both measured quarterly. We split the sample into high- and low-competition periods based on the median of these measures and re-run Eq. (1) separately on each subsample.

The results in Table 11 show that, in less competitive markets, fund livestreaming raises FPS by 0.307 on average—45.50% greater than in highly competitive markets. This suggests that the marginal benefit of livestreaming depends on the livestreaming intensity of peer funds.

This pattern aligns with the idea that excessive, universal engagement—similar to the open-end structure in this industry—is less likely to occur (Stein, 2005). This reasoning also resonates with Figure 1: initially, few funds livestreamed, resulting in a high marginal benefit and rapid growth in livestreaming activity. However, as competition intensified, the marginal benefit declined while marginal costs remained stable. [10] Eventually, as livestreaming became overcrowding, funds gradually recognized that focusing on performance rather than livestreaming was more rational, leading to a subsequent decline in sector-wide livestreaming participation and stabilization at an equilibrium—where marginal returns and costs are balanced.

10 There is no evidence suggesting that increased market intensity of livestreaming will reduce its associated costs. Instead, increasing competition in the livestreaming market may even lead to higher marginal costs of livestreaming due to rising quality requirements. To explore this, we conduct subgroup regressions on the performance impact of livestreaming during high- versus low-competition periods. A test of coefficient differences between the two groups shows no significant divergence, which partly supports the absence of cost reduction effects.

[Insert Table 11 about here]

4.3 FPS concavity and industrial capital allocation

While mitigating search friction, livestreaming can also weaken the salience and competitive edge of top performers, leading to a convergence of search friction as observed in Panel A of Figure 2. The resulting reduction of search friction inequality likely alters the pattern of capital allocation across funds, thereby reshaping industry-wide concavity of flow-performance relationship.

In the spirit of Chevalier and Ellison (1997) and Goldstein et al. (2017), we test this idea by estimating the shape of the flow-performance relationship separately for the pre-livestreaming (Q1 2018-Q1 2020) and post-livestreaming (Q2 2020-Q4 2024) periods. As plotted in Figure 3, following the introduction of livestreaming, the flow-performance relationship became less convex, suggesting that livestreaming has weakened the salience that top-performing funds have previously enjoyed (Sirri and Tufano, 1998; Huang et al., 2007). As a result, investor flows are now spread more linearly across the performance spectrum, rather than being heavily concentrated in top-performing funds.

[Insert Figure 3 about here]

In other words, by reducing search friction, livestreaming has greatly reshaped investor capital allocation in the asset management market, as manifested in a less convex flow-performance relationship.

5 Conclusion

We show that fund managers face a marketing-production trade-off: while livestreaming reduces search costs and increases flow-performance sensitivity, it also impairs fund performance by diverting managerial attention from investment activities. Search friction, diminishing return to scale, and shorter investment horizons are three main channels responsible for managers' preference for livestreaming. Positive investor feedback from prior livestreaming sessions spurs future marketing effort, which often leads to performance erosion and an adoption of star-promotion marketing strategy. As

livestreaming becomes widespread, the flow-performance relationship flattens, but this occurs at the expense of industry-wide performance decline and a potential market efficiency loss.

References

Agarwal V, Ma L, and Mullally K, 2023, Managerial multitasking in the mutual fund industry, *Financial Analysts Journal* 79, 65–75.

Barber B M, Odean T, and Zheng L, 2005, Out of sight, out of mind: The effects of expenses on mutual fund flows, *The Journal of Business* 78, 2095–2120.

Beck T, Levine R, and Levkov A, 2010, Big bad banks? The winners and losers from bank deregulation in the United States, *The Journal of Finance* 65, 1637–1667.

Ben-David I, Franzoni F, Landier A, and Moussawi R, 2013, Do hedge funds manipulate stock prices? *The Journal of Finance* 68, 2383–2434.

Ben-David I, Li J, Rossi A, and Song Y, 2022, What do mutual fund investors really care about? *The Review of Financial Studies* 35, 1723–1774.

Berg T, Burg V, Gombović A, and Puri M, 2020, On the rise of fintechs: Credit scoring using digital footprints, *The Review of Financial Studies* 33, 2845–2897.

Berk J B, and Green R C, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Berk J B, and van Binsbergen J H, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1–20.

Bhattacharya U, Lee J H, and Pool V K, 2013, Conflicting family values in mutual fund families, *The Journal of Finance* 68, 173–200.

Buchak G, Matvos G, Piskorski T, and Seru A, 2018, Fintech, regulatory arbitrage, and the rise of shadow banks, *Journal of Financial Economics* 130, 453–483.

Cen X, 2024, Smartphone trading technology, investor behavior, and mutual fund performance, *Management Science* 70, 6897–6916.

Chen H, Qu Y, Shen T, Wang Q, and Xu D X, 2022, The geography of information acquisition, *Journal of Financial and Quantitative Analysis* 57, 2251–2285.

Chen J, Jiang W, and Xiaolan M Z, 2022, The economics of mutual fund marketing, *Working Paper*.

Chen J, Hong H, Huang M, and Kubik J D, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review* 94, 1276–1302.

Chen Y J, Gallego G, Gao P, and Li Y, 2025, Position auctions with endogenous product information: Why live-streaming advertising is thriving, *Management Science*.

Chevalier J, and Ellison G, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Chevalier J, and Ellison G, 1999, Career concerns of mutual fund managers, *The Quarterly Journal of Economics* 114, 389–432.

Chu Y, Sun C, Zhang B, and Zhao D, 2023, Fintech and gender discrimination, *Working Paper*.

Cicero D C, Puckett A, Wang A Y, and Zhang S, 2024, TAXI! Do mutual funds pursue and exploit information on local companies? *Journal of Financial and Quantitative Analysis* 59, 3340–3375.

D'Acunto F., Prabhala N., and Rossi A G, 2019, The promises and pitfalls of robo-advising, *The Review of Financial Studies* 32, 1983–2020.

Dai L, Han J, Shi J, and Zhang B, 2025, Fintech Lending and Debt Spiral, *Working Paper*.

Dannhauser C D, and Spilker III H D, 2023, The modern mutual fund family, *Journal of Financial Economics* 148, 1–20.

deHaan E, Huang A H, Kannan S, and Qiu L, 2026, Social media livestreaming: Investor information or persuasion? *Journal of Accounting and Economics*, 101861.

Donze J, and Dubec I, 2009, Paying for ATM usage: good for consumers, bad for banks? *The Journal of Industrial Economics* 57, 583–612.

Egan M, 2019, Brokers versus retail investors: Conflicting interests and dominated products, *The Journal of Finance* 74, 1217–1260.

Fuster A, Goldsmith-Pinkham P, Ramadorai T, and Walther A, 2022, Predictably unequal? The effects of machine learning on credit markets, *The Journal of Finance* 77, 5–47.

Gârleanu N, and Pedersen L H, 2018, Efficiently inefficient markets for assets and asset management, *The Journal of Finance* 73, 1663–1712.

Gaspar J M, Massa M, and Matos P, 2005, Shareholder investment horizons and the market for corporate control, *Journal of Financial Economics* 76, 135–165.

Gaspar J M, Massa M, and Matos P, 2006, Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization, *The Journal of Finance* 61, 73–104.

Gennaioli N, Shleifer A, and Vishny R, 2015, Money doctors, *The Journal of Finance* 70, 91–114.

Goldstein I, Jiang H, and Ng D T, 2017, Investor flows and fragility in corporate bond funds, *Journal of Financial Economics* 126, 592–613.

Guercio D D, and Tkac P, 2008, Star power: the effect of Morningstar ratings on mutual fund flow, *Journal of Financial and Quantitative Analysis* 43, 907–936.

Hirshleifer D, and Sheng J, 2022, Macro news and micro news: Complements or substitutes? *Journal of Financial Economics* 145, 1006–1024.

Hu A, and Ma S, 2025, Persuading investors: A video-based study, *The Journal of Financ* 80, 2639–2688.

Hong C Y, Lu X, and Pan J, 2025, FinTech platforms and mutual fund distribution, *Management Science* 71, 488–517.

Huang J, Wei K D, and Yan H, 2007, Participation costs and the sensitivity of fund flows to past performance, *The Journal of Finance* 62, 1273–1311.

Huang S, O'Hara M, and Zhong Z, 2021, Innovation and informed trading: Evidence from industry ETFs, *The Review of Financial Studies* 34, 1280–1316.

Jain P C, and Wu J S, 2000, Truth in mutual fund advertising: Evidence on future performance and fund flows, *The Journal of Finance* 55, 937–958.

Jayaratne J, and Strahan P E, 1996, The finance-growth nexus: Evidence from bank branch deregulation, *The Quarterly Journal of Economics* 111, 639−670.

Kacperczyk M, Nieuwerburgh S V, and Veldkamp L, 2014, Time-varying fund manager skill, *The Journal of Finance* 69, 1455–1484.

Kacperczyk M, Van Nieuwerburgh S, and Veldkamp L, 2016, A rational theory of mutual funds' attention allocation, *Econometrica* 84, 571–626.

Kroszner R S, and Strahan P E, 1999, What drives deregulation? Economics and politics of the relaxation of bank branching restrictions, *The Quarterly Journal of Economics* 114, 1437–1467.

Li K, Song Y, Xu N, and Zu C, 2025, The two-system view of cognition and investor choice, *Working Paper*.

Nanda V, Wang Z J, and Zheng L, 2004, Family values and the star phenomenon: Strategies of mutual

fund families, *The Review of Financial Studies* 17, 667–698.

Pástor L, Stambaugh R F, and Taylor L A, 2015, Scale and skill in active management, *Journal of Financial Economics* 116, 23–45.

Pástor L, Stambaugh R F, and Taylor L A, 2020, Fund tradeoffs, *Journal of Financial Economics* 138, 614–634.

Reher M, and Sokolinski S, 2024, Robo advisors and access to wealth management, *Journal of Financial Economics* 155, 103829.

Roussanov N, Ruan H, and Wei Y, 2021, Marketing mutual funds, *The Review of Financial Studies* 34, 3045–3094.

Sirri E R, and Tufano P, 1998, Costly search and mutual fund flows, *The Journal of Finance* 53, 1589–1622.

Song Y, 2020, The mismatch between mutual fund scale and skill, *The Journal of Finance* 75, 2555–2589.

Stein J C, 2005, Why are most funds open-end? Competition and the limits of arbitrage, *The Quarterly Journal of Economics* 120, 247–272.

Stoughton N M, Wu Y, and Zechner J, 2011, Intermediated investment management, *The Journal of Finance* 66, 947–980.

Wang P, 2024, Portfolio pumping in mutual fund families, *Journal of Financial Economics* 156, 103839.

Zhao P, Liu Q, Ma T, Kang T, Zhou Z, Liu Z, Zhang M, and Wan J, 2023, Policy instruments facilitate China's COVID-19 work resumption, *Proceedings of the National Academy of Sciences* 120, e2305692120.

Zhu M, 2018, Informative fund size, managerial skill, and investor rationality, *Journal of Financial Economics* 130, 114–134.

Figure1: Time Trend of Mutual Funds Livestreaming: 2020-2024

This figure shows the time-series pattern of fund livestreaming from Q1 2020 to Q4 2024. Livestreaming data are obtained from the *Tiantian Fund Platform*, where the first fund livestream appeared in Q2 2020. *Live Num* denotes the number of funds conducting manager livestreams each quarter, while *Live Day* represents the average number of manager livestream days among the livestreaming funds each quarter.

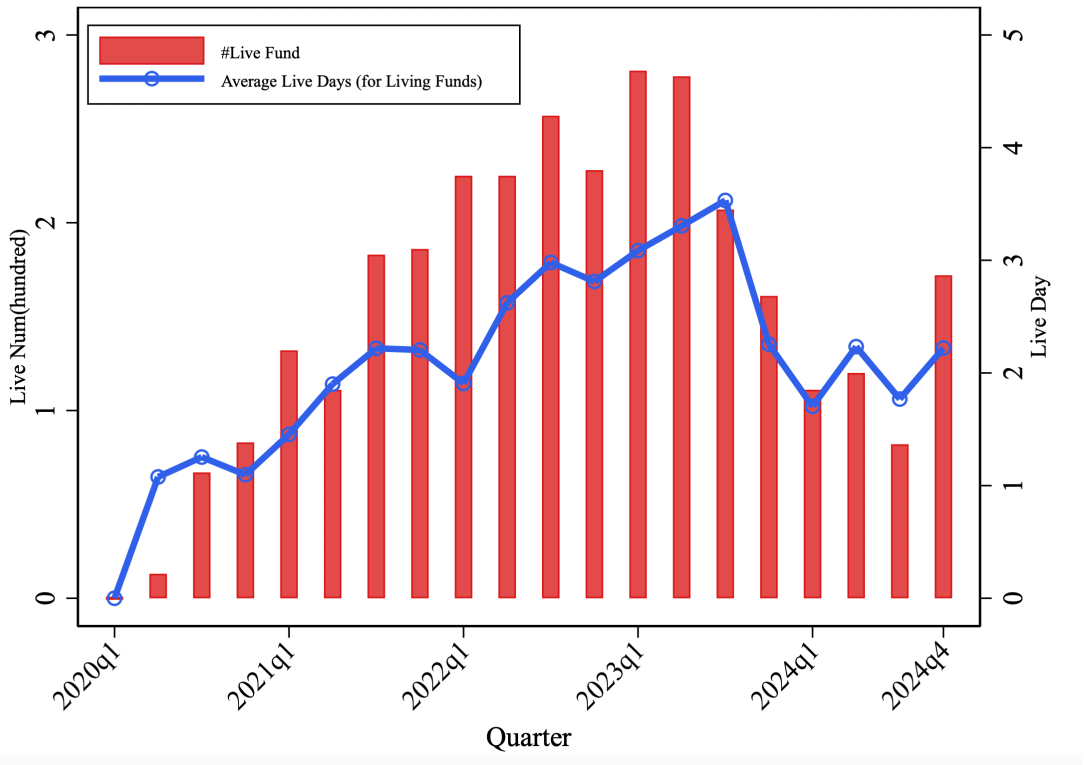
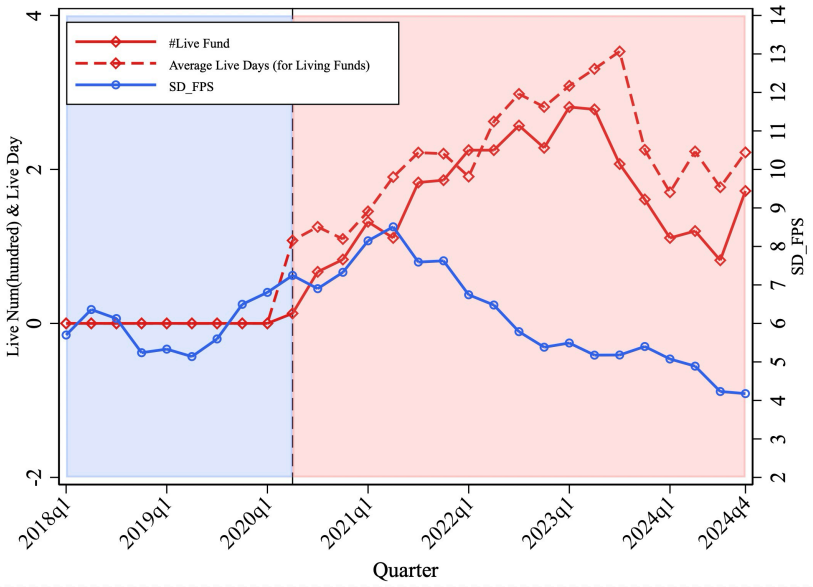


Figure 2: Tradeoff Induced by Livestreaming: Performance vs. Search Friction

This figure illustrates the time-series pattern of funds' FPS difference, performance and livestreaming from Q1 2018 to Q4 2024. In Panel A, the horizontal axis represents quarters. The right vertical axis represents the standard deviation of FPS across all sample funds (SD_FPS), while the left vertical axis indicates livestreaming activity (measured by the number of funds livestreaming and the average livestreaming days). In Panel B, the horizontal axis represents quarters. The right vertical axis indicates fund performance, measured by value-weighted FF5 alpha and the median of FF5 alpha, and the left vertical axis indicates livestreaming activity. The blue- and red-shaded areas mark the pre- and post-initiation periods of fund livestreaming, which began in Q2 2020.

Panel A: Time Trend of Mutual Funds' FPS Dispersion and Livestreaming



Panel B: Time Trend of Mutual Funds' Performance and Livestreaming

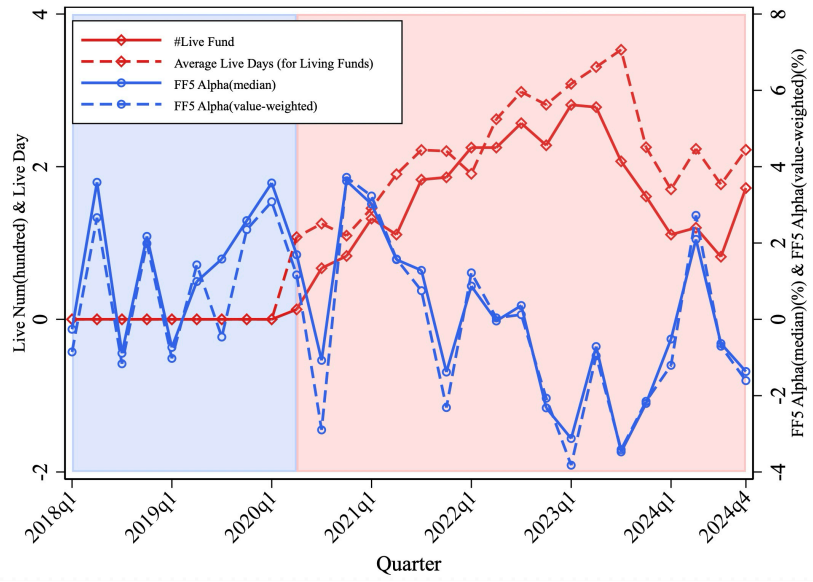
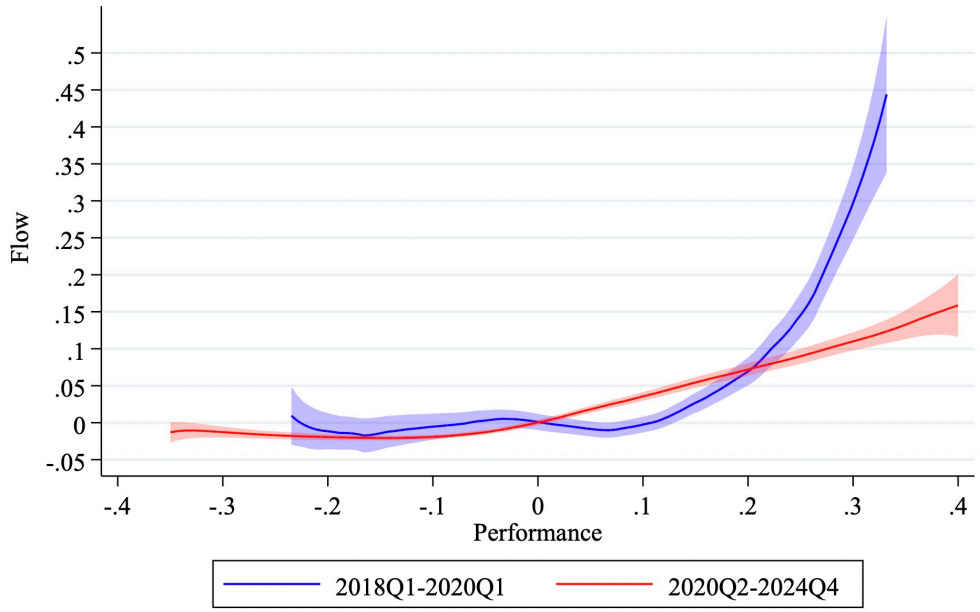


Figure 3: The Impact of Livestreaming on the Industry—Reduced Search Inequality

This figure depicts the changes in the shape of the flow-performance relationship following the entry of livestreaming technology into the fund industry in Q2 2020. The horizontal axis represents fund performance, and the vertical axis represents fund flows. The blue line depicts the flow-performance relationship estimated using the subsample from Q1 2018 to Q1 2020, while the red line shows the relationship estimated using the subsample from Q2 2020 to Q4 2024. The shaded areas represent 90% confidence intervals. To facilitate comparison, both lines are vertically shifted to pass through the origin (0, 0).



Bandwidth: optimal from npregress kernel, Confidence level: 90%, Adjusted to pass through (0,0)

Table 1: Summary Statistics

This table reports the summary statistics for key variables in our data sets at the fund-quarter level. The sample covers the period from Q2 2020 to Q4 2024. For each variable, we report the total number of observations (N), the sample mean (Mean), the sample standard deviation (SD), the sample minimum (Min), median (Med) and maximum (Max). Panel A summarizes fund characteristics variables, and Panel B displays fund manager characteristics variables. Variable definitions are provided in Table A1.

	N	Mean	SD	Min	Med	Max
Panel A: Fund-quarter variables						
Return (%)	37328	-0.320	10.113	-23.414	-0.894	28.607
Exc_Return (%)	37328	-0.564	10.116	-23.652	-1.143	28.408
FF5_Alpha (%)	33080	-0.313	5.929	-14.532	-0.621	18.221
D(*Live*)	37328	0.079	0.269	0.000	0.000	1.000
Live_day	37328	0.198	1.229	0.000	0.000	45.000
Size	37328	19.780	1.664	15.468	19.905	23.254
Δ*Size* (hundred million)	37328	-0.338	2.195	-11.925	-0.085	10.412
Flow	37328	-0.009	0.241	-0.554	-0.029	1.630
Age	37328	2.712	0.820	0.693	2.639	4.500
Manage_fee (%)	37328	0.912	0.677	0.000	1.200	2.000
Load (%)	37328	0.710	0.544	0.000	1.000	2.750
Size_family	37328	7.710	1.496	2.676	8.107	9.715
FF5_Alpha_SD	31173	0.008	0.003	0.002	0.007	0.017
D(Upgrade)	37328	0.046	0.209	0.000	0.000	1.000
Churn_GMM	33425	0.880	0.403	0.155	0.842	1.874
Pumping	30322	0.001	0.011	-0.027	0.000	0.029
Panel B: Fund manager variables						
D(*Phd*)	37328	0.085	0.279	0.000	0.000	1.000
D(*Male*)	37328	0.613	0.487	0.000	1.000	1.000
Num_Site_visit	37328	1.035	2.289	0.000	0.000	12.000
D(*Star_promoting*)	4971	0.188	0.391	0.000	0.000	1.000
D(*Education*)	4971	0.115	0.319	0.000	0.000	1.000
D(*Personality*)	4971	0.052	0.223	0.000	0.000	1.000
D(*Awards*)	4971	0.053	0.225	0.000	0.000	1.000

Table 2: Tradeoff between Flow-Performance Sensitivity and Fund Performance

This table investigates the tradeoff resulting from fund livestreaming. Columns (1) – (4) examine the impact of manager livestreaming activities on FPS, while columns (5) – (8) analyze their effect on fund performance. In columns (1) – (4), the coefficient on the interaction term captures the marginal effect of livestreaming on FPS. Fund performance is measured using two alternative approaches; detailed variable definitions are provided in Table A1. The odd-numbered columns examine the effect of the livestreaming indicator (a dummy variable) on FPS or performance, whereas the even-numbered columns examine the effect of the intensity of livestreaming (measured by the number of manager livestreaming days) on FPS or performance. Controls for column (1) – (4) are $Size_{t-1}$, $Manage_fee_{t-1}$, $Load_{t-1}$, $FF5_Alpha_sd_{t-4\sim t-1}$, $Size_family_{t-1}$, Age_{t-1}, $D(phd)_{t-1}$, $D(Male)_{t-1}$. Controls for column (5) – (8) are *corresponding performance variable of t*, $Flow_t$, $Size_t$, $Manage_fee_t$, $Load_t$, Age_t, $D(phd)_t$, $D(Male)_t$. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	$Flow_t$				Exc_Return_{t+1}		$FF5_Alpha_{t+1}$	
$D(Live)_t \times Exc_Return_{t-4\sim t-1}$	0.154***							
	(0.036)							
$Live_day_t \times Exc_Return_{t-4\sim t-1}$		0.127***						
		(0.026)						
$D(Live)_t \times FF5_Alpha_{t-4\sim t-1}$			0.259***					
			(0.075)					
$Live_day_t \times FF5_Alpha_{t-4\sim t-1}$				0.202***				
				(0.046)				
$D(Live)_t$	0.069***		0.068***		-0.794***		-0.629***	
	(0.009)		(0.009)		(0.182)		(0.172)	
$Live_day_t$		0.008***		0.005***		-0.102***		-0.093***
		(0.002)		(0.002)		(0.037)		(0.033)
$Exc_Return_{t-4\sim t-1}$	0.383***	0.389***						
	(0.024)	(0.024)						
$FF5_Alpha_{t-4\sim t-1}$			0.401***	0.404***				
			(0.026)	(0.026)				
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31924	31924	26442	26442	38216	38216	31957	31957
R^2	0.236	0.232	0.231	0.228	0.687	0.687	0.227	0.226

Table 3: Source of the Tradeoff: Attention Diversion Channel

This table investigates whether fund managers reduce their research activities due to livestreaming activities. In Panel A, columns (1) and (2) present results for the subsample of funds with more than one manager in period *t*. Columns (3) and (4) present results for the subsample of funds with only one manager in period *t*. Columns (5) and (6) present results for the subsample where at least one of the fund's managers exclusively manages this single fund in period *t*. Columns (7) and (8) present results for the subsample where none of the fund's managers exclusively manages a single fund in period *t*. In Panel B, the dependent variable in columns (1) and (3) is *Site_visit_change*, defined as the quarterly change in the number of site visits, calculated as $Site_visit_t - Site_visit_{t-1}$. Columns (2) and (4) use *Site_visit_growth* as the dependent variable, measuring the growth rate of quarterly site visits, computed as $(Site_visit_t - Site_visit_{t-1}) / Site_visit_{t-1}$. *D*(*Live_day_high*) equals 1 if the number of livestreaming days in a quarter is greater than or equal to 7, and 0 otherwise; *D*(*Live_day_median*) equals 1 if livestreaming days are between 3 (inclusive) and 7, and 0 otherwise; *D*(*Live_day_low*) equals 1 if livestreaming days range from 1 to 3, and 0 otherwise. Columns (3) and (4) use non-livestreaming funds as the control group. Note that we exclude Q2 2020, due to the COVID-19 pandemic delaying the resumption of normal economic activity in China until mid-April (Zhao et al., 2023), and Q2 2022, due to the comprehensive lockdown in Shanghai—the headquarters city for many fund families. In Panel C, $D(Live_W)_{i,t}$ and $Live_day_W_{i,t}$ are the dummy variable for manager weekday livestreaming and the number of manager weekday livestreaming days for fund *i* in quarter *t*, respectively. Conversely, $D(Live_NW)_{i,t}$ and $Live_day_NW_{i,t}$ are the corresponding variables for non-weekday livestreaming. In Panel D, No_infor_t represents the proportion of generic sentences to the total number of sentences in the quarterly report. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

Panel A Livestreaming and performance: the role of managerial attention constraints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Multiple managers		Single manager		With single-fund manager		Without single-fund manager	
Dependent Variable:	$FF5_Alpha_{t+1}$							
$D(Live)_t$	-0.398		-0.652***		-0.201		-0.657***	
	(0.438)		(0.195)		(0.653)		(0.182)	
$Live_day_t$		0.017		-0.113***		-0.103		-0.093***
		(0.071)		(0.035)		(0.115)		(0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6118	6118	25373	25373	3226	3226	28623	28623
R^2	0.308	0.307	0.238	0.237	0.311	0.311	0.234	0.234

Panel B Livestreaming and site visit

	(1)	(2)	(3)	(4)
Dependent Variable:	*Site_visit_change*$_t$	*Site_visit_growth*$_t$	*Site_visit_change*$_t$	*Site_visit_growth*$_t$
Live_day $_t$	-0.019	-0.026***		
	(0.017)	(0.008)		
D(*Live_day_high*)$_t$			-0.624**	-0.404***
			(0.287)	(0.110)
D(*Live_day_median*)$_t$			0.017	-0.039
			(0.107)	(0.096)
D(*Live_day_low*)$_t$			-0.063	-0.052
			(0.067)	(0.057)
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	29621	7844	29621	7844
R^2	0.150	0.259	0.150	0.259

Panel C Weekday livestreaming and fund performance

	(1)	(2)	(3)	(4)
Dependent Variable:	*Exc_Return*$_t$		*FF5_Alpha*$_t$	
D(*Live_W*)$_{t-1}$	-0.809***		-0.654***	
	(0.181)		(0.172)	
Live_day_W $_{t-1}$		-0.108***		-0.099***
		(0.038)		(0.035)
D(*Live_NW*)$_{t-1}$	1.322		1.335	
	(1.059)		(1.297)	
Live_day_NW $_{t-1}$		1.466*		1.276
		(0.836)		(1.006)
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	38216	38216	31957	31957
R^2	0.687	0.687	0.227	0.226

Panel D Livestreaming and the information content of quarterly reports

	(1)	(2)	(3)	(4)
Dependent Variable:	*No_infor*$_t$			
D(*Live*)$_t$	1.689***		1.267**	
	(0.514)		(0.520)	
Live_day$_t$		0.300***		0.213**
		(0.089)		(0.086)
Controls	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	39672	39672	30799	30799
R^2	0.478	0.478	0.501	0.501

Table 4: Search Friction and Fund Livestreaming

This table examines whether historically high search friction serves as an incentive for funds to conduct livestreaming. In the columns (1) - (2) and (3) - (4) of Panel A, we restrict the sample to funds with non-negative and negative past one-year FF5 alpha, respectively. In Panel B, the independent variables are fund's historical performance. $FF5_Alpha_{t\text{-}8\sim t\text{-}1}$ are the sums of the FF5 alpha over the past eight quarters. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

Panel A Search cost and Fund Livestreaming

	(1)	(2)	(3)	(4)
	$FF5\ \ Alpha_{t\text{-}4\sim t\text{-}1}\geq 0$		$FF5\ \ Alpha_{t\text{-}4\sim t\text{-}1}<0$	
Dependent	$D(live)_t$	$Live\ \ day_t$	$D(live)_t$	$Live\ \ day_t$
$Size_family_{t\text{-}1}$	-0.062***	-0.189**	-0.008	0.027
	(0.022)	(0.084)	(0.021)	(0.065)
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	17641	17641	14197	14197
R^2	0.335	0.320	0.328	0.309

Panel B Historical Performance and Fund Livestreaming

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$D(live)_t$	$Live_day_t$	$D(live)_t$	$Live_day_t$	$D(live)_t$	$Live_day_t$
$FF5_Alpha_{t-1}$	0.003***	0.006***				
	(0.000)	(0.002)				
$FF5_Alpha_{t-4\sim t-1}$			0.003***	0.007***		
			(0.000)	(0.002)		
$FF5_Alpha_{t-8\sim t-1}$					0.002***	0.008***
					(0.000)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31964	31964	26442	26442	19948	19948
R^2	0.264	0.262	0.276	0.272	0.287	0.304

Table 5: Diseconomies of Scale and Fund Livestreaming

This table examines whether funds facing higher costs of generating alpha are more inclined to engage in livestreaming. *D*(*Upgrade*) is a dummy variable indicating whether a fund's Morningstar rating has improved. Specifically, it equals 1 if the fund's three-year Morningstar rating in the current quarter is higher than in the previous quarter, and 0 otherwise. $\Delta Size_{i,t-1}$ is calculated as $\Delta Size_{i,t}=TNA_{i,t}-TNA_{i,t-1}\times(1+Return_{i,t})$. In columns (3) through (6), we employ *D*(*Upgrade*) as an instrumental variable for *Flow* and Δ*Size*. Columns (3) and (5) report the first-stage regression results, while columns (4) and (6) present the corresponding second-stage results. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Stage 1	Stage 2	Stage 1	Stage 2
Dependent Variable:	$D(live)_t$	$D(live)_t$	$Flow_{t-1}$	$D(live)_t$	$\Delta Size_{t-1}$	$D(live)_t$
$Flow_{t-1}$	0.030**			0.393**		
	(0.012)			(0.194)		
$\Delta Size_{t-1}$		0.003**				0.036**
		(0.001)				(0.017)
$D(Upgrade)_{t-2}$			0.050***		0.542***	
			(0.010)		(0.087)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21766	21766	20941	20941	20941	20941
R^2	0.308	0.307	0.195	-0.105	0.151	-0.079

Table 6: Flow Dynamics and Fund Horizon

This table examines the intertemporal flow dynamics resulting from livestreaming and identifies the types of funds that engage in livestreaming under such flow patterns. In column (6), $Churn_GMM_{t\text{-}4\sim t\text{-}1}$ represents the fund's turnover rate over the past four quarters, constructed following the methodology of Gaspar et al. (2005). In column (7), $D(Pumping_{t\text{-}4\sim t\text{-}1})$ is derived by first measuring quarterly pumping intensity based on Ben-David et al. (2013), computed as the difference between the FF5 alpha on the last day of the quarter and the FF5 alpha on the first day of the next quarter. The average pumping intensity over the past four quarters is then calculated. This dummy variable takes a value of 1 if the average pumping intensity falls within the top tercile among all funds in that quarter, and 0 otherwise. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$Flow_t$	$Flow_{t+1}$	$Flow_{t+2}$	$Flow_{t+3}$	$Flow_{t+4}$	$D(live)_t$	
$D(live)_t$	0.083***	0.016*	0.003	-0.007	-0.013**		
	(0.010)	(0.008)	(0.006)	(0.006)	(0.005)		
$Churn_GMM_{t\text{-}4\sim t\text{-}1}$						0.032***	
						(0.010)	
$D(Pumping_{t\text{-}4\sim t\text{-}1})$							0.009**
							(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26442	26442	25705	24950	24164	31949	26445
R^2	0.230	0.224	0.234	0.236	0.231	0.264	0.271

Table 7: Livestreaming Dynamics

This table tests whether the quality or outcome of past livestreaming affects managers' future decisions to livestream and subsequent fund performance. *D*(*View_top1*) is a dummy variable equal to 1 if the fund's livestream had the highest number of views among all livestreaming funds within the same fund family and style, and 0 otherwise. *D*(*View_top50%*) equals 1 if the fund's livestream ranked in the top 50% by viewership within the same fund family and style, and 0 otherwise. In this table, the sample is restricted to funds that conducted livestreaming in the previous quarter; thus, these regressions use a subsample of the data. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$D(live)_t$	$Live_day_t$	$D(live)_t$	$Live_day_t$	$FF5_Alpha_t$	
$D(View_top1)_{t-1}$	0.054^{***}	0.478^{***}			-0.619^{*}	
	(0.018)	(0.152)			(0.343)	
$D(View_top50\%)_{t-1}$			0.064^{***}	0.540^{***}		-0.707^{***}
			(0.020)	(0.178)		(0.263)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3921	3921	3921	3921	3921	3921
R^2	0.383	0.414	0.384	0.414	0.325	0.326

Table 8: Fund Families' Star-Promoting: Historical livestreaming performance and Non-Skill Feature Promotion

This table tests whether fund families engage in star-promoting practices for managers of livestreaming funds. *D*(*Education*) is a dummy variable that equals 1 if the livestream's guest tag includes descriptions related to the fund manager's educational background, and 0 otherwise. *D*(*Personality*) equals 1 if the tag describes personality of the manager, and 0 otherwise. *D*(*Awards*) equals 1 if the tag highlights any awards received by the manager, and 0 otherwise. *D*(*Star_promoting*) is defined as 1 if any of *D*(*Education*), *D*(*Personality*), or *D*(*Awards*) equals 1, and 0 otherwise. In this table, the sample is restricted to funds that conducted livestreaming in the previous quarter; thus, these regressions use a subsample of the data. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	*D*(*Star_promoting*)		*D*(*Education*)		*D*(*Personality*)		*D*(*Awards*)	
$D(View_top1)_{t-1}$	0.079***		0.061***		0.033**		0.016	
	(0.025)		(0.023)		(0.015)		(0.018)	
$D(View_top50\%)_{t-1}$		0.084***		0.074***		0.031**		0.018
		(0.026)		(0.022)		(0.014)		(0.018)
$FF5_Alpha_{t-4\sim t-1}$	-0.051	-0.052	-0.003	-0.004	0.096	0.096	-0.159*	-0.159*
	(0.194)	(0.194)	(0.133)	(0.133)	(0.090)	(0.090)	(0.083)	(0.083)
$FF5_Alpha_{t-8\sim t-1}$	0.108	0.107	0.106	0.104	-0.072	-0.072	0.098	0.098
	(0.137)	(0.137)	(0.081)	(0.081)	(0.077)	(0.077)	(0.083)	(0.082)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1744	1744	1744	1744	1744	1744	1744	1744
R^2	0.415	0.416	0.456	0.457	0.378	0.378	0.394	0.394

Table 9: Future Livestreaming and Performance of Star-Tagged Funds

This table examines the future livestreaming activity and performance of funds that received star tags. $D(Live_star)_{i,t-1}$ equals 1 if the managers of fund i both livestream and receive star tags in quarter t-1, and 0 otherwise. $D(Live_nostar)_{i,t-1}$ equals 1 if the managers of fund i livestream but receive no star tags in quarter t-1, and 0 otherwise. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	$D(Live)_t$	$Live_day_t$	Exc_Return_t	$FF5_Alpha_t$
$D(Live_star)_{t-1}$	0.246***	1.463***	-1.151***	-0.711**
	(0.040)	(0.471)	(0.343)	(0.316)
$D(Live_nostar)_{t-1}$	0.148***	0.674***	-0.683***	-0.596***
	(0.018)	(0.158)	(0.217)	(0.192)
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	31964	31964	31957	31957
R^2	0.288	0.294	0.685	0.227

Table 10: Livestreaming and Market Efficiency

This table examines the impact of fund livestreaming on market efficiency. *Fundshare* represents the proportion of a stock's shares held by all funds (number of shares held by funds divided by total shares outstanding). *Fundshare_Live* refers to the proportion held by funds that managers conducted livestreaming during the quarter, while *Fundshare_NoLive* denotes the proportion held by funds that managers did not livestream during the quarter. *Rank_SUE* is constructed as follows: We first calculate the standardized unexpected earnings (SUE) for each stock, defined as the difference between the current quarter's earnings per share (EPS) and the EPS from four quarters prior, divided by the stock price at the end of the current quarter. Each quarter, stocks are sorted into quintiles based on SUE and assigned a value of 2, 1, 0, –1, or –2 from the highest to the lowest quintile. Following Huang et al. (2020), *CAR* is measured as the cumulative abnormal return from the first to the 30th trading day after the earnings announcement. If a stock has multiple earnings announcements within a quarter, we average the *CAR* across all events. Following Huang et al. (2020), the control variables include the natural logarithm of total assets (*Size_Stock*), the book-to-market ratio (*BM*), institutional ownership excluding the holdings of the fund (*IO_ExpFund*), the number of analysts following the stock (*#Analysts*), and the idiosyncratic volatility measured over the four quarters preceding earnings announcements (*IVOL*). Standard errors are clustered at the stock level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	CAR_t			
$Fundshare_t \times Rank_SUE_t$	-0.122***	-0.129***		
	(0.046)	(0.046)		
$Fundshare_Live_t \times Rank_SUE_t$			-0.542	-0.954
			(0.784)	(0.768)
$Fundshare_NoLive_t \times Rank_SUE_t$			-0.301**	-0.246*
			(0.121)	(0.133)
$Fundshare_t$	0.077	0.197**		
	(0.071)	(0.100)		
$Fundshare_Live_t$			-1.720*	-0.798
			(0.980)	(1.023)
$Fundshare_NoLive_t$			0.351**	0.004
			(0.171)	(0.260)
$Rank_SUE_t$	-0.747***	-0.771***	-0.908***	-0.957***
	(0.241)	(0.252)	(0.223)	(0.238)
Controls	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Cluster	Stock	Stock	Stock	Stock
Observations	63238	63060	63053	62878
R^2	0.188	0.329	0.188	0.330

Table 11: The Role of Competition

This table examines whether livestreaming competition among funds diminishes the benefits of livestreaming. The classification is based on the quarterly time series of market-wide livestreaming activity. Specifically, for each quarter, we calculate the number of unique funds that conducted livestreaming and the total number of livestreaming days. A quarter is classified as a high-competition period if this value is above the median value across all quarters in our sample; otherwise, it is classified as a low-competition period. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

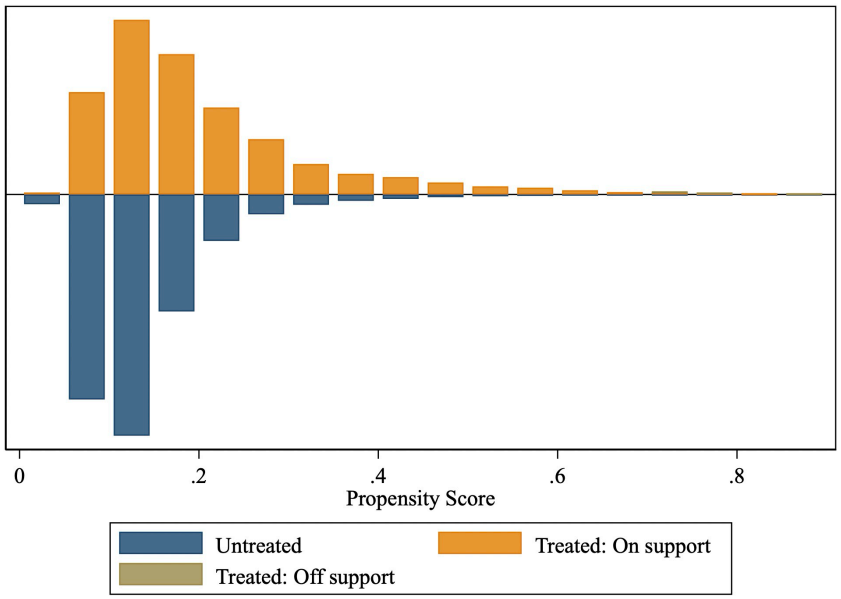
	(1)	(2)	(3)	(4)
	Fierce	Not Fierce	Fierce	Not Fierce
Dependent Variable:	$Flow_t$			
$FF5_Alpha_{t\text{-}4\sim t\text{-}1} \times D(live_m)_t$	0.211**	0.307**		
	(0.087)	(0.129)		
$FF5_Alpha_{t\text{-}4\sim t\text{-}1} \times Live_day_m_t$			0.166***	0.247***
			(0.044)	(0.086)
$D(live_m)_t$	0.061***	0.063***		
	(0.012)	(0.014)		
$Live_day_m_t$			0.007***	0.008*
			(0.002)	(0.004)
$FF5_Alpha_{t\text{-}4\sim t\text{-}1}$	0.348***	0.448***	0.346***	0.452***
	(0.043)	(0.035)	(0.042)	(0.035)
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	11388	14919	11388	14919
R^2	0.334	0.292	0.333	0.290

Appendix

Figure A1: Propensity Score Matching: Common Support and Balancing Tests

This figure presents tests for the common support and balancing assumptions of the propensity score matching (PSM) procedure. Panel A shows the distribution of propensity scores for the treated (livestreaming) and control (non-livestreaming) groups. Panel B compares the standardized percentage bias of key covariates before and after matching.

Panel A: Common Support Assumption



Panel B: Balancing Assumption

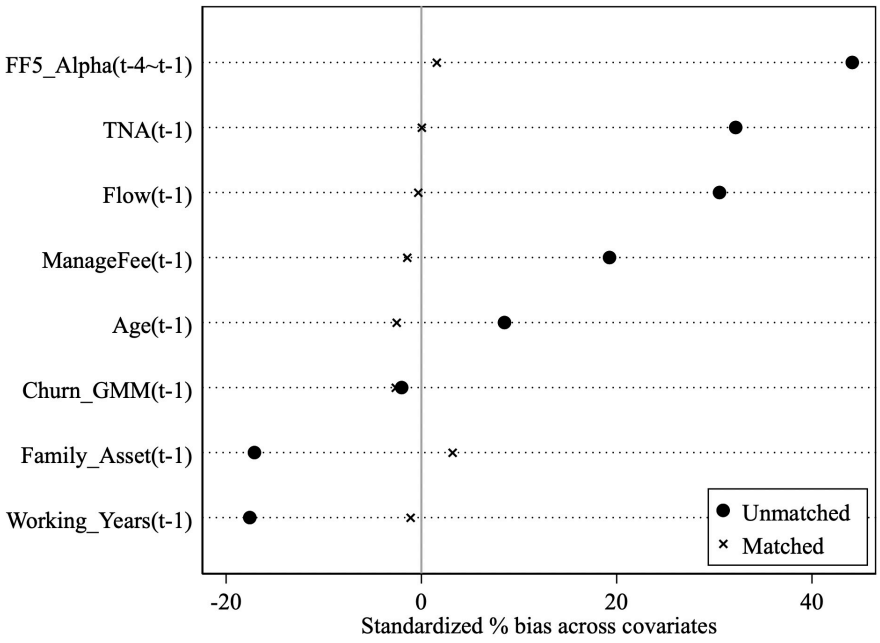


Table A1: Variables Description

	Description
Fund variables	
$Return_{i,t}$	Net asset value growth rate of fund i in quarter t, calculated as: $Return_{i,t}=(adjNPVS_{i,t} - adjNPVS_{i,t-1}) / adjNPVS_{i,t-1}$ where $adjNPVS_{i,t}$ denotes the adjusted net asset value per share of fund i on the last trading day of quarter t (adjusted for fund dividends, share splits, and dividend reinvestment).
$Exc_Return_{i,t}$	Return of fund i in quarter t over the risk-free rate.
$FF5_Alpha_{i,t}$	Fama-French five-factor alpha of fund i in quarter t.
$D(Live)_{i,t}$	Livestream dummy variable that equals 1 if fund i conducted manager livestream activities in quarter t, and 0 otherwise.
$Live_day_{i,t}$	Number of days fund i conducted manager livestreaming activities in quarter t.
$Size_{i,t}$	Natural logarithm of the total net assets of fund i in quarter t.
$\Delta Size_{i,t}$	Flow-induced change in size of fund i in quarter t, calculated as: $\Delta Size_{i,t}=TNA_{i,t}-TNA_{i,t-1}\times(1+Return_{i,t})$.
$Flow_{i,t}$	Net fund flow of fund i in quarter t, calculated as: $Flow_{i,t} = (TNA_{i,t} - TNA_{i,t-1}\times(1+Return_{i,t}))/TNA_{i,t-1}$
$Age_{i,t}$	Natural logarithm of the number of quarters since fund i's inception as of quarter t.
$Manage_fee_{i,t}$	Management fee rate of fund i in quarter t.
$Load_{i,t}$	Up-front load rate of fund i in quarter t.
$Size_family_{i,j,t}$	Natural logarithm of the total net assets of fund family j (to which fund i belongs) in quarter t.
$FF5_Alpha_SD_{i,t}$	Standard deviation of daily Fama-French five-factor alpha for fund i over the preceding year as of quarter t.
$D(Upgrade)_{i,t}$	Dummy variable that equals 1 if fund i experienced a Morningstar rating upgrade in quarter t, and 0 otherwise.
$Churn_GMM$	Churn rate of fund i in quarter t, calculated as: $Churn_GMM_{i,t}=(\sum_{s\in K}\left\|N_{s,i,t}P_{s,t} - N_{s,i,t-1}P_{s,t-1} - N_{s,i,t-1}\Delta P_{s,t}\right\| / \sum_{s\in K}(N_{s,i,t}P_{s,t} + N_{s,i,t-1}P_{s,t-1})/2$, where K is the number of firms held in the portfolio of fund i, $P_{s,t}$ and $N_{s,i,t}$ are the price and number of shares of firm s held by fund i in quarter t.
$Pumping_{i,t}$	Performance pumping measure for fund i in quarter t, calculated as: $Blip_FF5_Alpha_{i,t}= FF5_Alpha_lastday_{i,t} - FF5_Alpha_firstday_{i,t+1}$, where $FF5_Alpha_lastday_{i,t}$ and $FF5_Alpha_firstday_{i,t+1}$ denote the Fama-French five-factor alpha on the last trading day of quarter t and the first trading day of quarter t+1, respectively.
Manager variables	
$D(Phd)_{i,t}$	Fund manager education dummy variable that equals 1 if any of fund i's managers held a Ph.D. degree in quarter t, and 0 otherwise.
$D(Male)_{i,t}$	Fund manager gender dummy variable that equals 1 if any of fund i's managers is male in quarter t, and 0 otherwise.
$Num_Site_visit_{i,t}$	Number of site visits conducted by fund i's managers in quarter t.
$D(Star_promoting)_{i,t}$	Dummy variable that equals 1 if fund i's livestream guest introduction contained "star-promoting" descriptions in quarter t, and 0 otherwise.
$D(Education)_{i,t}$	Dummy variable that equals 1 if fund i's livestream guest introduction included educational background in quarter t, and 0 otherwise.
$D(Personality)_{i,t}$	Dummy variable that equals 1 if fund i's livestream guest introduction described personality in quarter t, and 0 otherwise.
$D(Awards)_{i,t}$	Dummy variable that equals 1 if fund i's livestream guest introduction included award achievements in quarter t, and 0 otherwise.

Table A2: Livestreaming, Inflows and Performance Decline

This table examines whether the performance decline associated with livestreaming is attributable to the inflows it generates. *Pos_Flow* is a dummy variable that equals 1 if a fund's quarterly flow is positive, and 0 otherwise. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)
	$FF5_Alpha_{t+1}$	
$Pos_Flow_t \times D(live)_t$	0.230	
	(0.332)	
$Pos_Flow_t \times Live_day_t$		0.109*
		(0.056)
Pos_Flow_t	0.431***	0.420***
	(0.112)	(0.105)
$D(live)_t$	-0.734***	
	(0.216)	
$Live_day_t$		-0.154***
		(0.053)
Controls	Yes	Yes
Fund FE	Yes	Yes
Quarter FE	Yes	Yes
Cluster	Family	Family
Observations	31957	31957
R^2	0.227	0.227

Table A3: Propensity Score Matching Robustness: Tradeoff between Flow-Performance Sensitivity and Fund Performance

This table presents robustness checks for the tradeoff resulting from fund manager livestreaming, estimated using a propensity-score-matched (PSM) sample. The PSM is implemented via one-to-one nearest-neighbor matching with a caliper, based on the following lagged characteristics: (1) Family: total net assets of fund family ($Family_Asset_{t-1}$); (2) Fund: total net assets (TNA_{t-1}}), fund age (Age_{t-1}}), net flow ($Flow_{t-1}$), management fee ratio ($ManageFee_{t-1}$}), average FF5 alpha from t-4 to t-1 ($FF5_Alpha_{t-4\sim t-1}$), and turnover rate ($Churn_GMM_{t-1}$); (3) Manager: the average years of experience since first becoming a fund manager ($Working_Years_{t-1}$). This procedure aims to mitigate potential selection bias by constructing a counterfactual sample of non-livestreaming funds that are observably similar to livestreaming funds. Columns (1) – (4) examine the impact of manager livestreaming activities on FPS, while columns (5) – (8) analyze their effect on fund performance. In columns (1) – (4), the coefficient on the interaction term captures the marginal effect of livestreaming on FPS. Fund performance is measured using two alternative approaches; detailed variable definitions are provided in Table A1. The odd-numbered columns examine the effect of the livestreaming indicator (a dummy variable) on FPS or performance, whereas the even-numbered columns examine the effect of the intensity of livestreaming (measured by the number of managers livestreaming days) on FPS or performance. Controls for column (1) – (4) are $Size_{t-1}$, $Manage_fee_{t-1}$, $Load_{t-1}$, $FF5_Alpha_sd_{t-4\sim t-1}$, $Size_family_{t-1}$, Age_{t-1}, $D(phd)_{t-1}$, $D(Male)_{t-1}$. Controls for column (5) – (8) are *corresponding performance variable of t*, $Flow_t$, $Size_t$, $Manage_fee_t$, $Load_t$, Age_t, $D(phd)_t$, $D(Male)_t$. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	$Flow_t$				Exc_Return_{t+1}		$FF5_Alpha_{t+1}$	
$D(Live)_t \times Exc_Return_{t-4\sim t-1}$	0.118**							
	(0.047)							
$Live_day_t \times Exc_Return_{t-4\sim t-1}$		0.085**						
		(0.033)						
$D(Live)_t \times FF5_Alpha_{t-4\sim t-1}$			0.218***					
			(0.079)					
$Live_day_t \times FF5_Alpha_{t-4\sim t-1}$				0.135***				
				(0.043)				
$D(Live)_t$	0.042***		0.041***		-1.399***		-1.005***	
	(0.011)		(0.011)		(0.304)		(0.274)	
$Live_day_t$		0.006***		0.004***		-0.141***		-0.122***
		(0.002)		(0.001)		(0.046)		(0.037)
$Exc_Return_{t-4\sim t-1}$	0.517***	0.515***						
	(0.055)	(0.054)						
$FF5_Alpha_{t-4\sim t-1}$			0.506***	0.508***				
			(0.054)	(0.055)				

Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5851	5851	5851	5851	5851	5851	5851	5851
R^2	0.401	0.398	0.408	0.406	0.402	0.400	0.696	0.695

Table A4: Livestreaming and Flow Volatility

This table examines whether the documented negative effect of livestreaming on fund performance operates through attracting more volatile fund flows. The dependent variable in columns (1) and (2) is the absolute value of fund flow at time t+1, while in columns (3) and (4) it is the standard deviation of fund flows from t+1 to t+4. The set of control variables is consistent with that used in the prior regressions where fund flow serves as the dependent variable. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	Abs_Flow_{t+1}		$SD_Flow_{t+1\sim t+4}$	
$D(Live)_t$	0.001		-0.011**	
	(0.007)		(0.005)	
$Live_day_t$		-0.002		-0.003**
		(0.001)		(0.001)
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	26442	26442	17296	17296
R^2	0.259	0.259	0.549	0.549

Table A5: Long-Term Flow and Fund Horizon—Live Day

This table examines the intertemporal flow dynamics resulting from livestreaming and identifies the types of funds that engage in livestreaming under such flow patterns. This table differs from Table 6 in that the dummy variable indicating whether a fund conducted livestreaming ($D(Live)_t$) is replaced with the number of livestreaming days ($Live_day_t$). In column (6), $Churn_GMM_{t\text{-}4\sim t\text{-}1}$ represents the fund's turnover rate over the past four quarters, constructed following the methodology of Gaspar et al. (2005). In column (7), $D(Pumping_{t\text{-}4\sim t\text{-}1})$ is derived by first measuring quarterly pumping intensity based on Ben-David et al. (2013), computed as the difference between the FF5 alpha on the last day of the quarter and the FF5 alpha on the first day of the next quarter. The average pumping intensity over the past four quarters is then calculated. This dummy variable takes a value of 1 if the average pumping intensity falls within the top tercile among all funds in that quarter, and 0 otherwise. All regressions include fund and year-quarter fixed effects. Standard errors are clustered at the fund family level and shown in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	$Flow_t$	$Flow_{t+1}$	$Flow_{t+2}$	$Flow_{t+3}$	$Flow_{t+4}$	$Live_day_t$	
$Live_day_t$	0.010***	-0.000	-0.002**	-0.002**	-0.002*		
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)		
$Churn_GMM_{t\text{-}4\sim t\text{-}1}$						0.131**	
						(0.053)	
$D(Pumping_{t\text{-}4\sim t\text{-}1})$							0.032
							(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Family	Family	Family	Family	Family	Family	Family
Observations	26442	26442	25705	24950	24164	31949	26445
R^2	0.225	0.223	0.234	0.236	0.231	0.262	0.270

Table A6: Keywords of Star-Promoting

This table presents the keywords used to identify star-promoting tendencies in guest tags of manager livestreams, covering three categories: Education, Personality, and Awards. Although the original keywords are in Chinese, they can be translated to English using: translate.google.com.

Category	Key words
Education	CFA、北大、本硕、博士、常青藤、复旦、复合背景、高学历、海归、科班、清华、上财、少年班、硕士、学霸、学神、学士、研究生、浙大、直博、中科大、状元
Personality	肤白、精致、可爱、梨涡、貌美、美女、男神、女神、欧巴、甜、仙女、鲜肉、小王子、颜值、氧气、风趣、搞笑、活力、开心果、暖男、暖心、亲和力、淘气、犀利、小棉袄、有趣、元气、知心、知性、直男、治愈系、博学多才、才华、才女、成熟、厚积薄发、匠人、锦鲤、理性、良心、呕心沥血、勤奋、上进、稳妥、信任、正能量、智慧、走心、咖啡、马拉松、阅读
Awards	百佳、晨星、大满贯、第一名、冠军、金基金、金牛、明星基金、明星团队、殊荣、五星、优秀研究员、最佳策略分析师、最佳分析师、最佳基金经理