Social Media Livestreaming: Investor Information or Persuasion?

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Abstract

Regulators around the world endeavor to reduce search costs and enhance financial education among retail investors. In line with this goal, Chinese regulators recently began allowing mutual funds to use social media livestreams to deliver video presentations and interact with viewers. We analyze over 27,000 livestreams to investigate whether they accomplish regulators' intended goal of improving investment decisions. Our findings indicate that livestreams drive significant inflows, even within minutes of their start times. However, contrary to their educational objective, livestreams exacerbate retail investors' tendencies to chase past returns and predict sharp declines in subsequent fund performance. Investors who buy in response to livestreams would earn higher returns by investing in index funds or even holding cash. Further analyses using deep learning algorithms find that livestreams drive greater inflows when speakers are more physically attractive, use more positive language, and sound more excited. We conclude that livestreams primarily function as persuasive advertising and that regulators should be wary of educational efforts led by sellers of consumer financial products. We also conclude that prior findings about the benefits of firms' social media use in equity markets do not extend to financial product markets in our setting.

Keywords: social media, livestreaming, investor education, mutual funds, persuasion

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1. Introduction

Households around the world hold over $30 trillion in mutual funds, and the vast majority are confident that their funds will help them achieve financial goals (EFAMA 2024; ESMA 2024; ICI 2024; IFIC 2024; IIFA 2024). Despite this optimism, extensive research finds that retail investors struggle to make informed fund-buying choices (e.g., Bailey et al. 2011; Barber et al. 2016; Choi & Robertson 2020; deHaan et al. 2021; Ben-David et al. 2022; Cen 2024; Hong et al. 2025). Retail investors' difficulties in selecting funds persist despite decades of regulations attempting to mitigate information frictions.

We examine the effects of an innovation in the mutual fund market – social media livestreaming – which is sanctioned by Chinese regulators for the purposes of reducing search costs and improving investor education. The objective of our study is to examine whether mutual fund livestreaming helps retail investors to make better-informed buying decisions.

Livestreams in China began in 2020 to compensate for the restricted access to traditional information channels (e.g., advisors at bank branches) during the early days of COVID. Organized by fund families, a typical livestream consists of a host and fund representatives discussing a range of topics and answering viewer questions, and an on-screen icon allows viewers to buy featured funds. Strict rules limit what speakers can say on livestreams; for example, livestreams cannot speculate about future performance, are largely limited to what is already included in its prospectus when discussing fund-specific information, and must not be overly entertaining.[1] The effect of these rules is that livestreams tend to focus on broad topics such as market trends and general investing strategies. Despite these restrictions, livestreams are today ubiquitous and popular; 91% of fund families in our sample livestream at least once through 2024, attracting a total of 1.9 billion

[1] Section 2 further discusses livestream regulations. Much like in the U.S., all mutual fund communications are heavily regulated in China, which explains why advertisements for specific mutual fund are rare.

views.

The costs of livestreaming are considerable. The direct costs are significant because most livestreams are recorded in purpose-built facilities and require substantial time and effort from hosts, writers, and support staff. The indirect costs are potentially even higher, including that livestreaming exposes fund representatives to risks of poor on-screen performances, violating communication regulations, accidentally revealing proprietary information, pressure to commit to a strategy or opinion after publicly discussing it, and reputation damage if their funds subsequently underperform. Moreover, given extensive evidence that vocal and visual characteristics affect how market participants view speakers and those speakers' career outcomes, fund representatives likely spend significant time preparing for livestreams and risk consequences from factors that are largely beyond their control.[2,3]

Fund families and representatives are presumably only willing to incur these livestreaming costs because they expect that the benefits, which primarily arise from inflows, exceed the costs. We put forth two main hypotheses for why livestreams cause retail investors to buy featured funds. Our predictions are grounded in theory from the advertising literature, consistent with mutual funds being consumer products.

Our *information hypothesis* stems from the theory that sellers' communications mitigate search costs and increase demand elasticity (e.g., Chamberlin 1933; Nelson 1970; Grossman &

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[2] Anecdotally, some fund managers complain that participating in livestreaming takes time away from their research (https://36kr.com/p/2636500947664008), and an interview with the head of livestreaming of a large fund family reveals that fund managers often must be convinced to participate. Some fund families incorporate livestreaming in manager performance evaluations: www.stcn.com/article/detail/1114621.html. These Chinese language websites can be translated using: translate.google.com.

[3] Examples of verbal characteristics that affect perceptions and careers include pitch (Mayew et al. 2013), tone (Chen et al. 2018), foreign accents (Barcellos & Kadous 2022), affective state (Mayew & Venkatachalm 2012), vocal fry (Anderson et al. 2014), dissonance (Hobson et al. 2012), hyperbole (Bochkay et al. 2020), silence (Hollander et al. 2010), and obfuscation (Larcker & Zakolyukina 2012). Visual features include facial structure (He et al. 2019), body expansiveness (Dávila & Guasch 2022), and impressions taken from 30-second clips (Blankespoor et al. 2017).

Shapiro 1984; Bagwell 2007). Research shows that some funds persistently generate higher returns than other funds, so *informative* livestreams can potentially help investors differentiate between more and less skilled fund managers.[4] For example, although livestreams are restricted in what they can say about a fund, a fund manager's ability may still be gleaned from her presentation and responses to questions. A separating equilibrium can arise if strong on-screen portrayals are less costly for high-ability than low-ability fund management teams (e.g., Riley 2001; Cronqvist 2006; Huang et al. 2007; Roussanov et al. 2021; Chen et al. 2022). Also, livestreams often provide general investing advice that plausibly helps investors make wiser buying decisions, in which case high-type funds are more likely to livestream because they benefit from better-informed buying.

Additionally, signaling theory such as Nelson (1974) and Klein & Leffler (1981) predicts that a fund's willingness to appear in a livestream can signal the fund manager's ability, even if the livestream discussions are devoid of substance. Specifically, if a fund can only recuperate the cost of livestreaming after a buyer holds it for several months, and if the fund expects buyers to quickly divest when the fund does not out-perform, then funds will only livestream if managers are confident that they will out-perform for a sufficiently long time.

Together, the *information hypothesis* predicts that livestreams help viewers make better-informed purchasing decisions. Finding a beneficial effect of livestreams on fund investing decisions seems highly plausible given that equity market research generally finds that firms' social media usage mitigates information frictions (e.g., Blankespoor et al. 2014; Jung et al. 2018; Lee & Zhong 2022; Nekrasov et al. 2022; Choi et al. 2024; Crowley et al. 2024; Wong et al. 2024).

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[4] From a retail investor's perspective, a skilled manager is one who generates a higher net-of-fee returns than peers, by generating higher gross returns, charging lower fees, or both. While mutual funds are run by teams including a lead manager, analysts, and other employees, for expositional convenience we follow the literature's norm of referring to a "manager's" skill. We sometimes also use the term "fund" when referring to the management team. Studies finding evidence of persistent manager skill include Elton et al. (2004), Bhojraj et al. (2012), Berk & van Binsbergen (2015), Cornell et al. (2020), deHaan et al. (2021), Chi et al. (2022).

Our *persuasion hypothesis* is consistent with the advertising theory that sellers' communications create spurious product differentiation and extract rents from unsophisticated buyers (e.g., Braithwaite 1928; Leffler 1981; Hurwitz & Caves 1988; Carlin 2009; Bordalo et al. 2022). At the extreme, a *persuasive* livestream could contain entirely uninformative content yet still drive inflows through catching viewers' attention.[5] Buyers do not earn above-average future returns, and instead likely earn below-average returns if livestreaming managers do not have good investment ideas for inflows (e.g., Berk & Green 2004; Cai & Ku 2022; Cen 2024) or if flow volatility requires funds to trade holdings at inefficient prices (e.g., Coval & Stafford 2007; Song & Gao 2022). A persuasion strategy can persist because retail investors struggle to identify and learn from past mistakes or because new unsophisticated investors enter the market each period (e.g., Hortacsu & Syverson 2004; Barber & Odean 2013). Consistent with *persuasion*, Jain & Wu (2000) find that funds' print advertisements generate positive inflows followed by below-average performance.

In sum, our *information* and *persuasion* hypotheses both predict that livestreams drive inflows. The distinction is that *information* helps investors identify funds that will out-perform, while *persuasion* drives flows to funds with neutral or below-average future performance.

We investigate our hypotheses in a sample of 27,046 livestreams by Chinese active equity funds on the *Tiantian Fund* app from May 2020 through December 2024.[6] Our sample includes 3,970 funds, of which 56% livestream at least once. The typical livestream lasts an hour, includes

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[5] The accounting and finance literatures provide extensive evidence that retail investors are susceptible to attention-induced buying. In the marketing literature, *persuasive* advertising includes communications designed to capitalize on salience and attention. For example, an advertisement featuring Coke on the front of a convenience store refrigerator catches shoppers' attention and causes spurious product differentiation that drives sales of Coke over other beverages in the same refrigerator.

[6] Retail investors in China can buy mutual funds from issuers, commercial banks, brokers, or third-party platforms such as *Tiantian Fund*. *Tiantian Fund* is the third largest fund distribution outlet in China, and the largest is another third-party platform *Ant Financial* (AMAC 2024). Trades on apps such as *Tiantian* are self-directed, meaning that the investor decides and executes all trades.

a host and fund representative, and attracts 47,000 views. Textual analysis reveals a range of discussion topics, such as market conditions, investment strategies, and industry trends.

We first examine the determinants of the livestreaming decision. Funds livestream after bouts of strong returns, which is logical given that past performance is a primary driver of retail flows (e.g., Sirri & Tufano 1998; Jain & Wu 2000; Kaniel & Parham 2017; Hong et al. 2025). Livestreaming funds also have higher service fees but lower up-front loads, suggesting a high-service strategy while reducing purchasing frictions (Carlin 2009; Roussanov et al. 2021).

Next, we confirm that livestreaming drives fund purchases. As depicted in Figure 1, generalized difference-in-differences ("DiD") models find that funds that begin livestreaming have no difference in flows in the two trailing quarters, a 39% increase in flows in the livestream quarter, and a return to normal thereafter.[7] Because livestreams plausibly coincide with funds' marketing efforts or industry trends that drive quarterly flows, we supplement our main models with two better-identified tests. First, we exploit cases where funds have both "A" and "C" classes, but sometimes only one class, either A or C, is linked in the livestream's on-screen shopping cart. Classes A and C of a fund are nearly identical except for their fee structures, including that they have the same trailing gross returns. Thus, regressions including fund-year-quarter fixed effects hold constant prior returns and many other factors that could cause flows and correlate with livestreaming. We find that the class in the livestream cart has significantly greater inflows than the unincluded class.

Second, we perform intraday analysis using an alternative proxy: whether a fund-class appears on *Tiantian*'s "hot" list of funds that have the greatest intraday inflows. We perform DiD

[7] While most of our tests use monthly or intraday data, flows data are only available quarterly. Our main tests examine initial and ongoing livestreams because their determinants and effects plausibly differ, but our inferences do not materially differ between the two samples. The 39% increase in flows is calculated relative to the within-fixed-effect standard deviation of quarterly flows.

analyses with fund-day-time fixed effects to compare classes of the same fund within the same day, and we find that the class listed in a shopping cart is 55% more likely to become "hot" after the livestream starts. Finding a precise intraday effect isolates livestream-induced flows from the effects of other marketing efforts such as print advertisements.

We differentiate between our *information* and *persuasion* hypotheses using two sets of tests: one of *ex ante* fund choices, and a second of *ex post* investment outcomes. Research shows that, despite the required warnings that past performance is not indicative of future results, retail investors systematically under-perform by buying funds that report strong past returns.[8] Informative livestreams should help investors make better *ex ante* choices, yet we find that livestreams instead facilitate buyers' returns-chasing tendencies. Our second set of tests examines funds' post-livestreaming returns. Numerous specifications reveal a pattern of returns displayed in Figure 2: livestreaming funds' out-performance in the months before livestreaming quickly becomes negative afterwards. Investors would be better off buying index funds or non-livestreaming funds, or even just holding cash. These results are consistent with the *persuasion* hypothesis in which funds livestream to showcase strong recent returns but do not sustain their out-performance. Instead, livestream-induced inflows are followed by a rapid decline in performance.[9]

Next, we investigate whether the role of livestreams differs when a fund's lead manager

[8] Just a few of many examples include: Sirri & Tufano (1998); Coval & Stafford (2007); Frazzini & Lamont (2008); Lou (2012); Choi et al. (2016); Jiang (2020); Song (2020); Ben-David et al. (2022); Hong et al. (2025).

[9] Research provides several non-exclusive reasons why retail fund inflows predict or drive declines in returns; a phenomenon referred to as the "dumb money effect" (Frazzini & Lamont 2008). First, Berk & Green (2004) show that optimal fund size is an increasing function of the manager's skill, and that an out-performing manager will attract inflows until her skill is fully utilized and performance reverts to average. Second and relatedly, Song (2020) finds that unsophisticated investors continue to buy out-performing funds after they have reached their optimal size per Berk & Green (2004), which drives performance to below-average. Third, papers such as Wermers (1999; 2004) and Coval & Stafford (2007) find that retail inflows inflate the prices of the fund's underlying holdings, and so fund performance turns negative as the over-pricing unwinds. A final contributing factor is simple mean reversion.

attends. The manager is responsible for the fund's strategy and performance, and she likely has stronger incentives to protect her reputation and a higher opportunity cost of time than other fund representatives. Given the manager's unique risks and costs of appearing in a livestream, she plausibly only does so when she is confident that the fund will out-perform (livestreams are *informative*). At the same time, if the manager is more credible to viewers, then her participation could amplify *persuasion* effects. We find that livestreams with managers drive 47% greater fund inflows than those without managers but post-livestream returns remain negative, indicating that managers are *persuasive*.

Finally, we examine whether persuasive delivery moderates the effect of livestreaming on investor behaviors. Drawing on findings that investors are affected by salience (e.g., Hirshleifer & Teoh 2003; Barber & Odean 2008) and speakers' features (e.g., Breuer et al. 2023; Hu & Ma 2025), we construct persuasion measures based on the fund's position in the shopping cart and speakers' verbal, vocal, and visual characteristics. We find that livestreams with persuasive qualities indeed attract significantly higher inflows and tend to have greater declines in post-livestream returns.

In sum, our findings are consistent with livestreams being *persuasive* rather than *informative*. This conclusion is subject to four caveats. First, we do not observe what investors would have done in the absence of livestreams; possibly, they might have chosen even worse investments. Second, it is conceivable that livestreams have beneficial long-term effects on financial literacy or market participation that outweigh the initial under-performance. Third, while we believe that our collection of tests provides compelling evidence that livestreams drive flows, we cannot completely rule out selection effects or other endogeneity threats.

Our fourth caveat is that we cannot be sure whether our inferences from evidence in China would extend to the U.S., although we have little reason to believe they would not. At a high level, our paper tests hypotheses about outsourcing investor education to financial product sellers. Fund regulations and market designs are comparable in the U.S. and China (see Section 2.1), and the arguments supporting our hypotheses are based on research from both countries. Furthermore, over a quarter of the livestreaming fund issuers in our sample are joint ventures or subsidiaries of multinational companies (e.g., JP Morgan, Morgan Stanley, and UBS), and it is plausible that U.S. funds will expand their social media communications (Wall Street Journal 2012).

Our first contribution is to the accounting literature on information frictions and households' financial decision-making. Accounting has a long history of examining retail investing and has recently begun investigating consumer financial products.[10] A common finding is that households struggle to make informed decisions using complex financial information. Consistent with that finding, regulators in the U.S. and China pursue a two-pronged strategy of improving consumers' education and sellers' disclosures. Livestreaming plausibly accomplishes both objectives because it provides a dynamic platform for funds to educate and engage with investors, and theory provides compelling reasons why livestreaming can be informative about funds' future performance. Our results are not consistent with livestreams improving decision-making. Instead, livestreams exacerbate investors' returns-chasing tendencies and lead to below-average investment outcomes, indicating that they have similar directional effects as funds' print advertisements (Jain & Wu 2000; Solomon et al. 2014; Hong et al. 2025). Furthermore, livestreams have unique persuasive features (e.g., speakers' attractiveness) which we show amplify their detrimental effects on investors and

[10] Accounting studies on consumer financial products includes mutual funds (deHaan et al. 2021; Darendeli 2024), mortgages (Kielty et al. 2023; Nicoletti & Zhu 2023; Dou et al. 2024), banking (Hayes et al. 2021), peer-to-peer loans (Michels 2012), and savings plans (Li et al. 2023). The accounting literature on retail stock and bond choices includes: Cready (1988); Bhattacharya (2001); Bhattacharya et al. (2007); Hirshleifer et al. (2008); Miller (2010); Lawrence (2013); Kalay (2015); Blankespoor et al. (2018, 2019, 2020); Christensen et al. (2019); Cuny et al. (2021); Israeli et al. (2022); deHaan et al. (2023); deHaan & Glover (2024).

are likely much harder to regulate than print ads' contents.[11] Broadly, our findings indicate that regulators should be cautious when outsourcing investor education to financial product sellers.

Our second contribution is to the literature on firms' use of social media to communicate with investors. Research in equity markets tends to find that firms' social media usage mitigates information frictions and improves efficiency, despite incentives for bias. Most closely related to our study are Lee & Zhong (2022) and Wong et al. (2024), which find that a discussion platform for corporate managers and investors improves transparency and price discovery. We find that social media usage by mutual funds, a critical intermediary for retail investors, attracts flows without improving decision-making. Our study indicates that the generally beneficial effects of firm-investor social media interactions in equity markets do not always apply to consumer financial products. Our study also introduces livestreaming to the literature, which has features (e.g., long-form, interactive video) distinct from social media such as tweets that have been the focus of prior research, and thus is worth investigating in markets other than mutual funds.[12]

2. Institutional background and related literature

2.1 Mutual fund communications and livestream regulations

Chinese mutual fund communication regulations are similar to those in the U.S. For example, communications can only display long-window prior performance statistics that are

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[11] Given that the persuasive effects of livestreams are directionally similar to print advertisements, one might question our study's contribution over prior literature. As we detail in Section 2.2, livestreams are a fundamentally different communication mechanism compared to static advertisements and, *ex ante*, there are compelling reasons to think that livestreams are informative. Similar to the equity market literature, which examines a wide range of communication mechanisms (e.g., press releases, conference calls, social media, interactive investor platforms, press interviews, etc.), it is valuable for the literature on consumer financial products to examine plausible differences in the determinants and effects of different communication methods between agents and principals.

[12] To our knowledge, other research on social media and mutual funds includes a contemporaneous study by Gil-Bazo & Imbet (2022) that examines Tweets. The economics of Tweets and livestreams are dissimilar given that livestreaming can contain large amount of information and entails significantly higher costs and risks, and thus plausibly gives rise to a separating equilibrium in which livestreams are *informative*. Also, a contemporaneous paper on livestreaming by Liu et al. (2024) focuses on whether the visual and vocal characteristics of livestream speakers affect investor attention.

calculated in a standardized manner, and they must clearly warn investors to consider fund investment objectives, risks, and expenses before purchasing. Communications cannot omit material facts that could mislead investors about the fund's performance or risks, generally cannot include any fund-specific information that is not also contained in its prospectus, and cannot make any statements about hypothetical future performance. See Appendix A.1 for further discussion of mutual fund disclosure regulation in China.

Tiantian Fund and *Ant Financial*, which are two of the three largest fund distribution platforms in China, launched livestreaming in May of 2020 (AMAC 2024). The platforms wield significant power to influence investor decisions, shape market trends, and dictate terms for fund visibility.[13] The platforms rank fund families based on factors including average number of viewers, viewing times, inflows, and viewer interactions (e.g., comments, likes, and shares). Higher rank fund families are more likely to have their livestreams prominently featured by the platform.

China's regulators and mutual fund industry association permit livestreaming for the purpose of investor education and provide guidelines to promote investor protection and transparency (e.g., AMAC 2021a, 2021b, also see Appendix A.2). Guidelines from 2020 clarify that the existing rules regarding fund communications and advertising apply to livestreams (CSRC 2020a, 2020b). In 2021, the Asset Management Association of China (AMAC) further emphasized that livestreams should not be overly entertaining and that livestream participants must hold asset management certificates.[14] Section 3 further investigates the contents of livestreams.

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[13] New media such as livestreaming is the most popular form of investor education across all age ranges in China (AMAC 2021b). While funds can also post videos on other platforms, the critical feature of *Tiantian Fund* and *Ant Financial* is that they are licensed to sell funds, so viewers can immediately click and buy livestreaming funds.

[14] Fund families are also advised to carefully plan livestream contents in advance, and like other fund communications, scripted content must be approved by families' compliance departments. Compliance officers monitor livestreams in real-time in case corrections are needed. Livestreams cannot offer discounts tied to specific funds (AMAC 2021a).

Livestream channels are typically managed by fund families (i.e., issuers), often with a regular host and sometimes a regular time slot. The shopping cart icon in the lower left corner of the livestream allows viewers to purchase the featured funds (see Appendix B). Each livestream has one or more funds in the cart, often with those funds' managers or representatives speaking during the livestream. Speakers and topics are advertised up to a week in advance, and viewers can submit questions in advance or in real time. Although a recording is available after the livestream, analyses in Section 3.2 find that over 99% of views occur on the livestream day.

2.2 Related literature

Research and practitioners generally assume that retail mutual fund investors endeavor to maximize wealth and, accordingly, attempt to differentiate between high- and low-ability fund managers (e.g., ICI 2006; SEC 2012; Barber et al. 2016; deHaan et al. 2021).[15] That the livestreams in our sample attract an average of 47,000 views despite being (in our opinion) unentertaining is consistent with the notion that retail investors attempt to make informed decisions. Financial literacy tends to be low, though, and research generally finds that retail fund investors struggle to make wise trading decisions (e.g., Lusardi & Mitchell 2014; Barber et al. 2016; Ben-David et al. 2022; Tan et al. 2024). That said, studies find evidence that some retail flows predict positive returns or covary with risk-adjusted benchmarks, suggesting that at least some retail fund investors are relatively sophisticated (e.g., Lou 2012; Akbas et al. 2015; Barber et al. 2016; Fang et al. 2024).

As discussed in Section 1, the advertising literature generally categorizes communications as either informative or persuasive (Bagwell 2007), and existing studies tend to find that mutual fund marketing plays a persuasive role. For example, Jain & Wu (2000) and Gil-Bazo & Imbet

[15] Prior studies document that while active equity managers do not collectively generate positive risk-adjusted net returns, at least some managers do demonstrate consistent stock picking skills (e.g., Grinblatt & Titman 1989; Berk & van Binsbergen 2015; Cornell et al. 2020). Unlike corporate managers' abilities, mutual fund managers' abilities are not immediately reflected in market prices because funds trade at their net asset values.

(2022) find that print communications attract flows but predict neutral to negative performance. Dolatabadi (2022) shows that demand becomes less sensitive to expense ratios and past returns when a fund family advertises, and Roussanov et al. (2021) show that eliminating marketing improves investor welfare. Koehler & Mercer (2009) find that investors fail to recognize that fund families selectively advertise their top-performing funds. Hong et al. (2025) find significant inflows to top-performing funds that are displayed on the front page of a retail trading platform, consistent with attention-related persuasion. One exception to evidence on persuasion comes from Chen et al. (2022), which finds that high-ability funds can signal their types by persistently marketing through periods of poor performance.

The contribution of our paper over the existing fund marketing literature is to examine a fundamentally different communication mechanism that, *ex ante*, is plausibly informative instead of persuasive. Appendix C summarizes differences between livestreams and print advertisements, which have been the primary focus of prior literature. Print ads consist of texts and static images, and contain little information beyond trailing returns and content found in a prospectus. In contrast, livestreams provide long-form video and audio contents, including discussions of investment principles, recent market conditions, and economic trends, and can respond in real time to current events and viewers' questions. Livestreams also often feature fund representatives, providing a level of personal engagement not present in traditional ads. Additionally, livestreams reach a much broader audience than the readers of *Money* or *Barron's*, which are the focus of prior research. Perhaps most importantly, livestreams are explicitly intended to be educational, and research from equity markets finds that firms' social media usage improves investment decisions (Blankespoor et al. 2014; Lee et al. 2015; Jung et al. 2018; Lee & Zhong 2022; Nekrasov et al. 2022; Choi et al. 2024; Crowley et al. 2024; Wong et al. 2024). These differences indicate that livestreams plausibly serve as a powerful investor education tool rather than merely persuasive advertising. Thus, investigating whether livestreams accomplish their intended educational purpose is valuable from both academic and regulatory perspectives.

3. Data and descriptive statistics

3.1 Sample selection

As shown in Table 1 Panel A, our sample selection begins with 9,116 classes of 5,599 predominantly equity mutual funds from the China Stock Market & Accounting Research (CSMAR) database from May 2020 (the start of livestreaming) through December 2024.[16] Most of our analyses aggregate classes to the fund level. Our final sample includes 3,970 actively managed equity funds in 138 fund families, corresponding to 147,151 fund-month observations.

We download livestreams from the mobile app of *Tiantian Fund*.[17] We identify the funds that are featured in each livestream as those that have a class included in the list of "related funds" that are in the shopping cart. Appendix B Panel B shows that clicking the shopping cart brings up links to purchase the included funds.

The 3,970 funds in our sample are featured in a total of 27,046 livestreams, with 2,243 funds (or 56%) appearing at least once. Table 1 Panel B shows that the fraction of fund families with at least one livestream during the quarter increases from 21% in 2020Q2 to 72% in 2024Q4 (column 2), and 91% of families livestream at least once by the end of the sample (column 3). That the majority of fund families livestream indicates that variation primarily exists at the fund instead of the family level. From 1% to 21% of funds are featured in livestreams in any given quarter

[16] Consistent with many prior studies, we exclude bond funds because they have dissimilar performance characteristics and managerial incentives. In addition, bond fund investors are primarily institutional investors. We define a predominantly equity fund as those holding at least 50% in equity securities at all report dates in the year.
[17] We do not use livestreaming data from the other major fund platform (*Ant Financial*) because it only lists the most recent 200 livestreams for each fund family and it employs anti-scraping measures. We have no reason to expect that livestreams on *Tiantian Fund* have systematically different determinants or effects than those on *Ant Financial.*

(column 4). Our conversations with livestreaming professionals indicate that the dip in 2024Q1 to 2024Q3 was because of the stock market's poor performance during the period.

Table 1 Panel C reports summary statistics. *First Stream* is an indicator for a fund's first month of livestreaming. *Livestream* is an indicator variable for a fund appearing in a livestream during the month and averages 13%. All variables are defined in Appendix D and are discussed when introduced in the following sections.

3.2 Livestream descriptive information

Table 2 provides descriptive information about livestream contents. Data on the livestream start time, end time, and viewership are downloaded from the *Tiantian Fund* app, as are recordings for 97% of the livestreams.[18,19] The mean livestream lasts 53 minutes, has 47,076 views, and features four sample funds. Virtually all (~99.4%) of livestreams are on trading days, and Figure 3 shows that around half start during trading hours.

We obtain speaker names and job titles by combining several sources. First, the *Tiantian* app lists some, but not all, of the speaker names. Second, we supplement the app's listed speakers using a machine learning facial-recognition algorithm to detect and count distinct speakers from livestream video. Third, we use a Chinese large language model (Kimi) to review transcripts to identify each speaker's name, employer, and job function.[20] If the number of speakers identified

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[18] Viewership data are as of 2024 and 2025 when we access *Tiantian* app, and it includes both viewers watching it live and those who watch the recording. Given the large number of livestreams available and that livestreams discuss timely topics, we expect that most viewers watch the livestream either live or shortly after. To verify this intuition, we track livestreams in November of 2024 for 30 days and confirm that only 0.1% of views are after the livestream day. We are unsure why 3% of livestreams in our sample do not provide a video link. Missing videos are roughly evenly distributed over time and do not appear to correlate with likely determinants.

[19] We create livestream transcripts by extracting audio using Python *MoviePy* and then use *Faster Whisper* package (github.com/SYSTRAN/faster-whisper) to transcribe the audio into text. We clean the transcripts by applying routine procedures in natural language processing.

[20] Specifically, for facial recognition we take screenshots every five minutes and use the *face_recognition* Python package to encode facial features, and then compare the features across images to identify unique speakers. We feed each transcript into Kimi three times, combine the resulting three lists of identified speakers, and remove duplicates. The prompt we use (translated) is as follows: "Read the names, companies, and job functions of participants, including

by the facial-recognition algorithm or language model exceeds the number reported by *Tiantian*, we manually review the videos to determine which is correct. Finally, we match the speakers' names and titles to CSMAR data to identify whether they are fund managers (CSMAR does not contain the names of other fund team members). Table 2 Panel A reports that the average livestream has 1.73 speakers. Figure 4 shows that 77% of livestreams have a host, 27% have a manager, 17% have an analyst, 8% have an investment advisor, and 10% have other speakers.

Although we cannot observe livestream viewer characteristics, we can gain insights from institutional research reports. According to ChinaFund (2024), in 2023, 78% of viewers are aged 30 and above, with those in the 30-39, 40-49, and over 50 age groups making up 29%, 19%, and 30%, respectively. 56% of viewers are female. Geographically, most viewers reside in economically developed provinces; Guangdong accounts for 31% of total viewers, followed by Beijing (13%), Shanghai (13%), Zhejiang (9%), and Jiangsu (7%).

3.3 Livestream discussion topics

We investigate livestream discussion topics using an unsupervised topic modeling algorithm, Latent Dirichlet Allocation (LDA). Specifically, we extract audio from the livestream videos, transcribe the audio into text, and cut each transcript into one-minute segments. We then set the number of topics to be ten, train an LDA model, and classify each segment into one of ten topics based on its highest probability (Huang et al. 2018). Table 2 Panel A shows that the average livestream discusses 7.07 topics. The largest topic consumes 44% of a livestream's time, with the second and third largest topics constituting 21% and 13%, respectively, suggesting that livestreams tend to focus on a few topics.

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hosts and guests, from the livestream transcript below. Use the following format for the output: 'Name||Company||Job Function'. If a host's name is not mentioned, replace it with 'Host||Host||Host'. If a guest's name is not mentioned, replace it with 'Guest||Guest||Guest'. Separate multiple individuals with commas."

Table 2 Panel B lists the most frequent 20 words for each topic, translated to English using ChatGPT. We also use ChatGPT to summarize each topic's economic meaning based on these keywords.[21] As shown, livestreams spend most of the time discussing market conditions, general fund investment strategies, global economic policies, and new technological trends.

3.4 Construct validity in identifying livestreaming funds

As discussed, we identify funds that are featured in a livestream as those with at least one class listed in the shopping cart. In practice, it seems unlikely that all the featured funds are given equal attention during a livestream. Consistent with that notion, manual review of the data indicates that a fund can be included in the shopping cart of a few episodes before or after the fund's representative appears on a livestream, possibly because the host mentions the fund when referring to an upcoming or past episode. From the perspective of our *information* hypothesis, in which investors learn about fund managers' types, livestreams that only briefly mention a fund may have weak treatment effects.

Defining *Livestream* at the fund-month level helps to mitigate concerns about livestreams that only briefly discuss a fund. As long as the fund management team meaningfully participates in at least one livestream during the month, then *Livestream = 1* is appropriately identified.

As a second approach to improving construct validity, we create an alternative and more stringent proxy for livestreaming funds as only when the fund's lead manager appears in the livestream, variable *Manager_On*. It seems safe to assume that a livestream meaningfully focuses on a fund when the manager participates. Table 1 Panel C shows that the manager is on a livestream in 9% of fund-quarters.[22] Section 7.1 investigates *Manager_On*.

[21] Prompt: "You are a fund manager. Please summarize the following words in 1~5 English words [20 keywords]. The provided words are from mutual fund livestreams, which are initiated by mutual fund families for retail investors."
[22] We are unable to identify the specific funds that other team members work for (see Figure 4).

4. Livestreaming determinants

We investigate determinants at the fund-month level using the following OLS regression:[23]

$$\textit{First Stream}_m \text{ or } \textit{Livestream}_m = \beta_1 \textit{Fund Characteristics} + \textit{Fund FE} + \textit{Yr-Mth FE} + \varepsilon \qquad (1)$$

First Stream is an indicator for the first month in which a fund livestreams, and *Livestream* is an indicator for all livestreaming months. We examine both because the decision to begin livestreaming is plausibly different from ongoing livestreaming decisions, and because the determinants in the *First Stream* regressions are unaffected by the existence of livestreams in the trailing months. Fund fixed effects restrict analysis to within-fund variation and year-month fixed effects control for common time trends. *Fund Characteristics* are measured at *m-1*, except for *Disclosure*, which is measured at *m*. Some determinants have minimal within-fund variation (see Table 1 Panel C), so we present results with and without fund fixed effects. All non-binary independent variables are standardized to facilitate interpretation, and standard errors are clustered by fund family.[24] Variables are further defined in Appendix D.

First, given that performance is among the most significant drivers of investors' buy/sell decisions, we expect that funds are more likely to livestream when they can report strong recent performance. We measure recent performance, *Recent Return*, as the fund's net-of-fee returns over the trailing six-months, which aligns with one of the performance measures commonly displayed in the *Tiantian Fund* app.[25] We also include an indicator, *Top 5 Return*, for the five funds within each family that have the highest returns in the previous six months. *Top 5 Return* is intended to better capture the ranking that families plausibly use to select which funds to include in livestreams.

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[23] We use OLS instead of logit to better accommodate high-frequency fixed effects.

[24] We cluster by fund family because livestream channels are run by families, so livestreaming decisions are jointly decided by the fund and family. Clustering by family should be more conservative than clustering by fund.

[25] We do not use risk-adjusted returns because: i) research finds that retail fund investors do not consider risk-adjusted returns (Ben-David et al. 2022); ii) *Tiantian Fund* does not display risk-adjusted returns; and iii) regulators prohibit platforms from ranking funds on measures not directly available from fund reports or prospectus (Hong et al. 2025).

Second, research finds that some funds appeal to sophisticated investors by charging low fees and providing minimal services such as investment advice, while other funds aim to attract less sophisticated investors via customer relations and marketing, and so charge higher fees to pay for those efforts (e.g., Barber et al. 2005; Carlin 2009; Kostovetsky 2016; deHaan et al. 2021). We expect that livestreaming funds likely fall into the latter category, and thus livestreaming is likely associated with high service fees. At the same time, we expect that livestreaming funds are less likely to charge loads (i.e., one-time buying/selling fees), which could deter viewers from buying the funds. Variables *Management Fee* and *Service Fees* capture ongoing fees, while *Loads* measures buying/selling charges.

We include regressors to capture fund assets under management (*Fund Size*) and age (*Fund Age*), although we do not have clear predictions for either. On the one hand, larger and more established funds plausibly have more resources to spend on livestreaming. On the other hand, smaller and younger funds may have more to gain from elevating their profiles. Finally, we control for the release of updated regulatory filings (*Disclosure*) to address the possibility that funds time livestreams to coincide with changes in fund fees or other fundamentals.

The results are presented in Table 3. Column (1) has *First Stream* as the dependent variable and excludes fund fixed effects. Column (2) is the same but includes fund fixed effects. Columns (3) and (4) repeat the same analyses but for all livestreams. All columns indicate that trailing returns captured by *Recent Return* and *Top 5 Return* are significant drivers of livestreaming, consistent with funds livestreaming when they have strong performance to report. For fees and loads, we focus on columns (1) and (3) given that these variables have little within-fixed-effect variation. Column (3), which has a higher explanatory power, indicates that livestreaming funds have higher service fees and lower loads, consistent with them following a high-service strategy but minimizing purchasing frictions. *Fund Size* is generally positively associated with livestreaming, and *Fund Age* is negative in the initial livestream tests but positive in the all-livestream tests. Thus, at least for the sample of all livestreams, livestreaming seems more common among larger and more established funds. *Disclosure* is insignificant, suggesting that livestreams do not tend to coincide with structural fund changes.

5. Livestreams and fund flows

We conduct most of our fund flow analyses at the quarterly level because funds only report assets under management, which is needed to calculate flows, on a quarterly basis.

5.1. Main analyses at the fund-quarter level

Following prior studies (e.g., Sirri & Tufano 1998; Barber et al. 2016; Ben-David et al. 2022), we calculate quarterly fund flow as follows:

$$Fund\ Flow_q = \frac{AUM_q - AUM_{q-1} \times \left(1 + Net\ Return_q\right)}{AUM_{q-1}}$$

where AUM_q is net assets under management at the end of calendar quarter q, calculated as the number of fund shares times AUM per share.

We examine fund flows using a generalized difference-in-differences ("DiD") model:[26]

$$Fund\ Flow_q = \beta_1 First\ Stream_q\ or\ Livestream_q + \beta_2 Controls + Fund\ FE + Yr\text{-}Qtr\ FE + \varepsilon \qquad (2)$$

Fund fixed effects restrict analysis to within-fund variation and year-quarter fixed effects control for common time trends. Thus, β_1 can be interpreted as the within-fund difference in flows in quarters when a given fund does versus does not livestream, all relative to the contemporaneous difference in flows for non-livestreaming funds. *Controls* include the regressors from our

[26] As discussed in Section 7.4, our tests are unlikely to be materially confounded by issues stemming from heterogeneous effects in staggered difference-in-differences models, and reperforming all DiD analyses using a stacked-cohort design produces unchanged inferences.

determinant tests.[27] For brevity, we only investigate regression (2) when including both fund and time fixed effects, given that our independent variables of interest have substantial within-fixed-effect variation (see Table 1 Panel C). However, we caution against drawing strong inferences from *Controls* that exhibit little within-fixed-effect variation. If livestreams drive fund flows, we expect to observe a positive β_1.

Column (1) of Table 4 Panel A presents results for funds' first livestream and, as expected, shows a highly significant β_1 coefficient. The coefficient of 11.332 is an economically meaningful 39% of the within-fixed-effect standard deviation of *Fund Flow*. Column (2) investigates flows around all livestreams and finds very similar results.

Figure 1 plots β_1 coefficient estimates in the five quarters surrounding initial livestreams.[28] The estimates in *q-2* and *q-1* are close to zero and provide no indication of a pre-treatment trend in fund flows before the initial livestream. Flows increase sharply in the quarter of the first livestream and revert to normal by quarter *q+2*.

5.2. Within-fund analysis of flows

Our main tests could be confounded by unobserved variables that influence both livestreaming and inflows. For example, industry trends or changes in a fund's management team could drive inflows and motivate funds to livestream. Furthermore, it is possible that *Controls* such as trailing returns have nonlinear effects that are incompletely isolated in Panel A.

We further mitigate potentially omitted variables by exploiting the fact that some livestreams include just one of two fund classes within the shopping cart. Classes "A" and "C" of

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[27] Except for *Disclosure*, all controls are measured as of the end of the prior quarter. We do not control for prior flows because controlling for lagged dependent variables is problematic in models with subject fixed effects (Breuer & deHaan 2024). Still, untabulated analyses show controlling for prior flows have very little impact on the β_1 estimate.

[28] We use lagged *Controls* from *q-3* and *q-2* in regressions of fund flows in *q-2* and *q-1*, respectively. We use lagged controls from *q-1* in regressions of fund flows in quarters *q* through *q+2*.

a fund are virtually identical; for example, they have the same portfolio, gross performance, managers, and disclosures, and they are equally affected by external events such as industry trends. The only difference is that class A charges front-end loads while class C charges service fees. In cases where either only class A or only class C is listed in the livestream shopping cart in a quarter, we can consider the listed class to be a "treatment" and non-featured class to be "control," and in doing so hold perfectly constant the trailing performance and many other unobserved characteristics. Thus, observing that flows increase more for the class that is in the cart than for the other fund class would provide compelling evidence that livestreaming drives flows. This is a conservative test given that livestreaming likely drives flows to both classes, even if only one class is in the shopping cart. Still, for investors who are largely indifferent between fund classes, we expect that they are marginally more likely to purchase the class that is in the cart instead of taking time to search for the fund's other class.

Column (1) of Table 4 Panel B examines the determinants of *Class in Cart* among the 2,490 funds that have both A and C classes. Observations are now at the class-period level, instead of the fund-period level, as in Panel A. *Class in Cart* is an indicator if the class is included in a livestream cart during the period, and fund-year-month fixed effects contrast the A and C classes of the same fund within the same period.[29] We exclude *Class Management Fee* and *Disclosure* because 98% and 100% of their variation are eliminated by the fixed effects. We also exclude returns-based variables because differences in returns for classes of the same fund are entirely

[29] Very few funds in China have classes other than A or C, so we limit these analyses to A and C classes. We also require that both classes are at least a year old and have non-missing controls. 10.98% of fund-quarters have both classes in the cart; 4.67% (6.74%) of fund-quarters have only A (C) class in the cart. *Class in Cart* does not have any within-fixed-effect variation in fund-periods where neither or both of classes A and C are in the cart (Breuer & deHaan 2024), and untabulated tests dropping these observations produce extremely similar results.

determined by loads and fees, which are included in the model.[30] Column (1) shows that the class featured in a cart tends to have higher fees and lower loads, and is larger and older.

Column (2) investigates class-level flows, *Class Flow*, among funds that are versus are not in a shopping cart, and include fund-year-quarter fixed effects to eliminate all characteristics that do not vary between two classes. The coefficient on *Class in Cart* in column (2) of 1.134 is a meaningful 13% of the within-fixed-effect standard deviation of *Class Flow*, corroborating that featuring a class in a livestream shopping cart drives significant incremental inflows.

5.3. Intraday flows analysis

We also examine changes in *intraday* flows around livestreams to further reduce concerns about biases from omitted variables or reverse causality. Flows are not observable by minute, so we proxy for flows using the *Tiantian* app's "hot fund" list. The list reports the 30 equity funds that have the largest cumulative net purchases during the day on *Tiantian* app. The list is updated every 10 minutes during trading hours and 10 minutes before the afternoon trading session.

These tests use a different sample from our other analyses. First, because the hot funds list is not available retroactively, the sample is limited to livestreams from December 2, 2024, through March 31, 2025. Second, we limit the sample to livestreams that occur during 9:30 am through 3:00 pm, during which the hot fund list is updated. Third, we improve identification by only including funds that have both A and C classes and only one of them is included in a livestream shopping cart. Our sample includes 4,455 days for fund-classes that appear in a livestream shopping cart, each of which is accompanied by a class of the same fund that is not included in a shopping cart. With 27 intraday time intervals, the sample includes 239,096 class-day-time

[30] Said differently, within-fixed-effects differences in returns are a linear combination of within-fixed-effects differences in service fees and loads. To be extremely precise, the linear combination is not quite perfect because *Class Management Fee* has non-zero within-fixed-effect variation, but untabulated results including *Class Management Fee* produce unchanged inferences.

observations, perfectly balanced between treatment and control groups.[31]

Our intraday analyses use the following OLS model:

$$Hot_{f,c,d,t} = \beta_1 Class\ in\ Cart_{f,c,d} \times Post_{f,d,t} + Controls_{f,c,d} \times Post_{f,d,t} + Fund\text{-}Day\text{-}Post\ FE_{f,d,t} + Class\text{-}Day\ FE_{f,c,d} + \varepsilon \quad (3)$$

This specification is a stacked DiD in which each fund-day (f,d) is a separate cohort. *Hot* = 1 if the fund-class (f,c) appears on the hot list on day d at the end of time interval t. *Class in Cart* = 1 if the fund-class appears in a livestream cart that day, and *Post* = 1 for both fund-classes for intraday time intervals after the beginning of the livestream.[32] A set of 8,910 *Fund-Day-Post* fixed effects remove the average intraday pre/post difference in *Hot* for both classes of the same fund, and in doing so hold constant any factors that would equally affect flows for both fund-classes during the day. Another set of 8,910 *Class-Day* fixed effects remove the average *Hot* for each fund-class-day. The main effects of *Controls* are eliminated by the class-day fixed effects.[33] We cluster standard errors by fund-day to adjust for within-cohort dependence.[34]

Because our determinants tests in Table 3 do not model intraday *Class in Cart*, we include a determinants model in column (1) of Table 4 Panel C. We relax the fixed effects to fund-day so that we can investigate class-level determinants.[35] Like before, these within-fund-period tests necessarily omit *Management Fee*, *Disclosure*, and returns-based variables. Classes with a higher

[31] 4,455 fund-days with dual classes and 27 intraday updates should generate (4,455 × 2 × 27 =) 240,570 fund-class-day-time observations. *Tiantian* failed to update the "hot" list for some intervals, resulting in 239,096 observations.
[32] If a fund is included in multiple livestream shopping carts during a day, we retain only the first one. We identify funds in the shopping cart before the trading day begins to avoid any concerns that funds are added to a livestream cart in response to high inflows (i.e., potential reverse causality).
[33] We interact *Controls* with *Post* to control for the possibility that certain types of classes (e.g., larger classes) are more likely to become *Hot* during the day.
[34] All our stacked-cohort DiD models are clustered by cohort or cohort-subject following Cengiz et al. (2019), Baker et al. (2022), and Roth et al. (2023). Clustering by cohort seems consistent with the advice in Abadie et al. (2023) to cluster at the level of the treatment assignment, but the most appropriate level of clustering is not obvious. Untabulated robustness tests cluster by: 1) fund and day; 2) fund-class-day; 3) fund-day-time; and 4) fund-class-day and fund-day-time. In all cases, the β_1 coefficient remains statistically significant at the 1% level.
[35] The adjusted R-squared in column (1) of Table 4 Panel C is -0.532 due to the inclusion of high-dimensional fixed effect at the fund-day level. Untabulated result shows an adjusted R-squared of 0.128 when no fixed effect is included.

service fee, a lower load, and a larger size are more likely to be in the shopping cart.

Column (2) of Table 4 Panel C presents results of model (3). Relative to the sample average of *Hot*, the interaction term of 0.011 indicates that the class in a livestream cart experiences a 55% increase in the probability of becoming *Hot* after the beginning of a livestream, as compared to the other class of the same fund over the same intraday intervals.

Given that livestreams are pre-scheduled and that classes of the same fund are largely identical, it is hard to think of an omitted event that could cause this intraday increase in flows. Still, placebo tests in Section S1 of the Supplementary Materials assess the probability of finding an intraday DiD change in *Hot* in the absence of a livestream. Specifically, we run 999 trials in which we re-run model (3) for randomly selected non-livestreaming dates of the funds in Table 4 Panel C. Table 4 Panel D plots the 999 placebo DiD coefficients, all of which are smaller than the actual coefficient of 0.011 (a non-parametric p-value of <0.001).

5.4. Other robustness tests

Analyses in our Supplementary Materials further demonstrate the robustness of our tests of quarterly flows in Table 4 Panel A. Sections S2 and S3 find similar results after propensity score matching and entropy balancing. Section S4 examines dynamic patterns in flows by regressing the change in flows (*ΔFund Flow*) on indicators for when the fund starts and stops livestreaming, and finds significant increases and decreases in flows, respectively.

5.5. Conclusions regarding livestreams and fund flows

Our analyses provide consistent evidence that livestreaming drives fund inflows. That we see an association between livestreaming and flows even when comparing classes of the same fund largely eliminates concerns that flows are driven by past returns or industry trends, and observing intraday increases in app-specific flows after the livestream begins mitigates concerns that flows are driven by contemporaneous actions. In short, it is hard to think of an alternative explanation that would drive the precise timing of inflows that we observe. We conclude that the evidence is consistent with funds engaging in costly livestreaming because it increases retail buying.

6. Are livestreams *informative* or *persuasive*?

6.1. Tests of ex ante investment decisions

Informative livestreams should help retail investors make *ex ante* better-informed purchasing decisions. Thus, our first tests examine whether livestreams help mitigate the systematic biases that have been documented in retail fund investing.

We specifically examine "returns-chasing" behavior, which is the widely documented tendency of retail investors to buy funds that have strong trailing performance but that under-perform in the months ahead. If livestreams improve investor education, then livestream-induced trading should be less returns-chasing. If livestreams are persuasive, and given that livestreams follow strong performance, then they plausibly facilitate returns-chasing.

We examine returns-chasing using equation (2) for fund flows while interacting *Recent Return* × *First Stream* in column (1) and *Recent Return* × *Livestream* in column (2) of Table 5.[36] Both columns show significant positive coefficients on *Recent Return*, consistent with returns-chasing in the absence of livestreams. The significantly positive interaction coefficients in columns (1) and (2) relative to the main effects on *Recent Return* indicate that post-livestream flows are 54% and 49% more responsive to past returns. These results indicate that livestreams facilitate returns-chasing tendencies, and are thus consistent with livestreams having a persuasive effect.

6.2. Tests of ex post investment performance

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[36] We include interactions between *Recent Return* × *Controls* because the effects of prior returns may differ with fund characteristics. We standardize all interacted controls so that the main effects can be interpreted at the sample average. Untabulated robustness tests show that replacing these interactions with *Livestream* × *Controls* does not change our main inferences.

The *information* hypothesis implies that livestreams predict sustained above-average future performance. The *persuasion* hypothesis indicates that livestreams capitalize on investor attention and unsophistication, and thus predict neutral to below-average performance. To be clear, neither the *information* nor *persuasion* hypothesis necessarily predicts that livestreams causally affect future fund performance. Instead, similar to the logic in Jain & Wu (2000), our earlier tests document that livestreams affect flows, and these tests use future returns to gauge whether the effect on flows is helpful (i.e., *informational*) or harmful (i.e., *persuasive*) to investors.[37]

We start by examining simple net-of-fee returns (*Return*) for just livestreaming funds. These results show the actual returns over months [-5, -1] that livestream viewers would observe before buying, and the returns over months [+1, +5] that buyers would receive. The top row of Table 6 Panel A presents average monthly returns with tests of differences from zero, and the same data are plotted in Figure 2. Consistent with our determinant tests, livestreaming funds have a run-up in returns in the pre-livestream months. Returns then drop to significantly below zero in the livestreaming month and beyond, with a cumulative return of -2.29% in the five subsequent months. These results indicate that a viewer would do better holding cash than to purchase a livestreaming fund in month *m*.

We also investigate whether a viewer would do better to buy a low-cost index fund instead of a livestreaming fund. Specifically, we calculate abnormal returns (*Return – Index Return*) as the livestreaming fund's net-of-fee returns minus the net-of-fee returns of broad index funds.[38] The bottom row of Table 6 Panel A tests whether the average abnormal returns are different from zero.

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[37] We also do not mean to imply that livestream-induced inflows *cannot* affect future returns. Footnote 9 discusses several reasons why retail inflows have been found to negatively affect future fund performance.

[38] Index funds are widely and cheaply available in China. We calculate a broad index fund returns as the size weighted-average of the CSI 300 index fund (which tracks the largest 300 stocks) and the CSI 500 index fund (the 301st to 800th largest stocks). Untabulated results show unchanged inferences if we just use one of the two index funds.

As depicted in Figure 2, livestreaming funds outperform index funds in the pre-livestream months, dip to neutral in month *m*, and then earn significantly negative abnormal returns in months *m+1* onwards. The five-month cumulatively abnormal returns of livestream funds are -1.37%, indicating that livestream viewers would earn higher returns by buying an index fund.

We next use DiD tests and more sophisticated returns adjustments to investigate livestreaming funds relative to other active equity funds. The literature on fund performance is deep, so we examine four measures of returns. The first is again net-of-fee returns (*Return*). Second, *DGTW Alpha* is the net-of-fee benchmark-adjusted returns based on Daniel et al. (1997). Third, *Carhart Alpha* is the net-of-fee risk-adjusted returns based on Carhart (1997). Finally, *China 3F Alpha* is the net-of-fee risk-adjusted returns using China-specific factors (Liu et al. 2019). All returns are in percentages and defined in Appendix D. The measures are correlated at 52% to 84%.

Our generalized DiD model is as follows:

$$Returns_{m+j} = \beta_1 First\ Stream_m\ or\ Livestream_m + Controls + Fund\ FE + Yr\text{-}Mth\ FE + \varepsilon \qquad (4)$$

where $Returns_{m+j}$ is one of our return measures over months $m+j$ ($-5 \leq j \leq 5$) and *Controls* are the same as in model (2).[39] Given the fund and year-month fixed effects, β_1 estimates the average within-fund difference in returns for livestreamers versus non-livestreamers in the same month.

Table 6 Panels B and C report results for first streams and all livestreams, respectively. We tabulate only the β_1 coefficients for brevity. Many of the β_1 estimates over months *m-5* through *m-1* are positive in both panels, and especially so in the full sample in Panel C, which is consistent with funds livestreaming after strong performance. In Panel B, returns begin to dip during the livestream month *m*, and are consistently and significantly negative by month *m+4*. The results

[39] For months *m-5* through *m*, all controls except for *Disclosure* are measured through the end of the prior month, which is necessary to ensure that controls like *Recent Return* are appropriately aligned in time. For months *m+1* through *m+5*, all controls except for *Disclosure* are fixed at *m-1*. *Disclosure* is fixed at *m* in all regressions.

are starker in the full sample in Panel C, where returns dip to neutral or significantly negative by month *m+1*, and are significantly negative across all specifications by month *m+2*. In terms of economic magnitude, the cumulative DiD returns over months (+1, +5) for first stream and all livestream funds range from -0.49% to -1.18%. Overall, inferences from DiD regressions are largely the same as those from examining univariate returns.

6.3. Conclusions regarding livestreams and performance

Our findings are consistent with the persuasion hypothesis. Specifically, there is no indication that livestreaming funds have strong subsequent performance. Rather, the investors who buy funds in response to livestreams earn negative returns in the months afterward, indicating that they would be better off buying index funds or non-livestreaming funds, or even holding cash.

7. Additional analyses

7.1. Manager on livestream

We examine fund managers on livestreams for two reasons. First, as motivated in Section 1, managers plausibly only appear on livestreams when they are particularly confident in future out-performance, in which case their livestreams may be informative even if the typical livestream is persuasive.[40] Second, as discussed in Section 3.4, empirically identifying livestreaming funds as when the managers attend mitigates concerns about construct validity.

Table 7 shows that livestreams with managers spend more time discussing topics that require higher financial literacy and that are more relevant to specific sectors and funds, including technological topics and sector growth (see the top two rows). In contrast, livestreams without managers spend more time on general topics such as overviews of market conditions, risk management, and investor engagement (see the bottom three rows). These content differences

[40] Huhmann & Bhattacharyya (2005) report that no funds use a spokesperson in printed advertisements, indicating that managers' presence in communications is unique to livestreams.

could enhance the informational value and credibility of livestreams when the manager attends.

We examine the determinants of manager-attended livestreams (variable *Manager_On*) including several manager characteristics that are plausibly relevant. First, because early-career managers have greater incentives to build reputation (Holmstrom 1999; Li et al. 2011; Dikolli et al. 2014), we include the manager's years of experience managing funds. Second, professional backgrounds can shape investment decisions and performance (e.g., Chevalier & Ellison 1999; Aslan 2022), so we include the manager's highest academic degree and an indicator for graduating from the top two Chinese universities. Finally, studies document gender differences in fund outcomes (Niessen-Ruenzi & Ruenzi 2019) and in viewership in other settings (Lu et al. 2021), so we include an indicator for female managers.

Table 8 Panel A examines livestream determinants in columns (1) and (2), without and with fund fixed effects. Managers are more likely to appear on livestreams following strong performance, when the fund has higher service fees, and when the fund is larger. Less experienced managers are also more likely to livestream. Column (3) examines flows. The coefficient on *Livestream* × *Manager_On* of 3.780 relative to the main *Livestream* effect indicates that flows increase by 47% when a manager is present.

We examine post-livestream returns using equation (4) and separating our treatment variable into livestreams with and without the manager. Results in Table 8 Panel B find no evidence that post-livestream returns are better when managers are present. In fact, they are marginally worse in some months. This pattern indicates that managers' attendance enhances persuasiveness without improving informativeness.

7.2. Livestream persuasive features

Given our findings that livestreams are persuasive, we next examine whether six contextual features moderate livestreams' effects on investor inflows. The first feature is whether a fund appears in the first half of the shopping cart (*First Half*), which should make the fund more salient and generate greater attention-induced buying (Hirshleifer & Teoh 2003; Elliott 2006; Barber & Odean 2008; Hong et al. 2025).[41] The remaining five features are based on the characteristics of livestream speakers, and are similar to the measures in Hu & Ma's (2025) investigation of speakers in start-up pitches. *Verbal Sentiment* is the tone of the speakers' words, derived from transcripts; three vocal features derived from sound files, namely *Vocal Valence* capturing positive effect in speakers' voices, *Vocal Arousal* capturing the level of excitement versus calmness, and *Vocal Sentiment* capturing positive or negative sounds; and *Attractiveness* is based on speakers' faces. For each feature, a *High* indicator identifies months (or quarters) with a livestream whose value is above the sample median.

Section S5 of the Supplementary Materials provides computational details and summary statistics of the persuasion variables. Tests in Section S6 show that persuasive features are more prevalent when funds have strong recent returns, higher service fees, and greater size and age.

Table 9 Panel A investigates persuasive features and flows using a regression similar to column (3) of Table 8 Panel A. The controls from Table 8 Panel A are included but untabulated, as are *Manager_On* and its interactions with the controls, and the persuasion variables interacted with controls. Columns (1) – (6) show that each persuasion variable is positively associated with inflows, consistent with persuasive features amplifying livestream-induced buying. Column (7) reports that several features have incrementally significant effects when included together, while column (8) uses a composite *Persuasion* variable, calculated as the sum of the six indicators

[41] The average shopping cart contains 3.88 sample funds and, depending on the screen size of the device used, the cart displays either 3 or 3.5 funds on its first page without scrolling further down. Thus, funds in the first half of the cart are both higher on the list and more likely to be seen without scrolling down. Alternatively, we define salient funds as those in the top 3 positions of the cart and find similar results (untabulated).

normalized between zero and one. The main effect of *Livestream* in column (8) is significantly positive, indicating that livestreams drive flows even when *Persuasion* is zero. Furthermore, the interaction of *Livestream* × *Persuasion* suggests that inflows are roughly six times larger for livestreams exhibiting all six features than those without any.[42]

Table 9 Panel B explores the relation between persuasive features and post-livestream returns. Similar to Table 8 Panel B, we divide the *Livestream* indicator from equation (4) into two groups: high versus low persuasion. The controls from Table 8 Panel A, as well as *Manager_On* and its interactions with the controls, are included but untabulated. For brevity, we only tabulate the cells showing the cumulative returns of each group in the post-livestream periods and their difference (i.e., same as the last column in Table 8 Panel B).

Consistent with prior evidence that more persuasive delivery is not informative of future performance (Breuer et al. 2023; Hu & Ma 2025), our results indicate that persuasive signals in livestreams do not predict higher future performance.[43] They instead generally predict lower returns; all cumulative DiDs are nominally negative for high-persuasion livestreams, and 21 out of the 28 differences are statistically significant.

7.3. Cross-sectional differences in search costs

Regardless of whether livestreams are persuasive or informative, they should have a lesser effect for funds with low search costs (Sirri & Tufano 1998; Huang et al. 2007; Clifford et al. 2021). We test this prediction by re-estimating equation (2) including interactions between

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[42] Robustness tests reported in Section S7 of the Supplementary Materials include fixed effects for the number of livestream appearances per fund during the period, which controls for the possibility that persuasive features are positively correlated with livestreaming frequency. Adding these fixed effects have two drawbacks: i) the main effect of *Livestream* becomes unobservable; and ii) controlling for livestream frequency may partially over-control the effect of interest. Despite these limitations, the inferences remain largely unchanged.

[43] Tests in Section S7 account for livestreaming frequency while examining persuasion-related differences in post-livestream returns. We again find no evidence that high-persuasion livestreams have higher future performance.

Livestream and proxies for visibility. More visible funds have star awards (*Star*), are larger (*Large*), or are older (*Old*) following Clifford et al. (2021), or have more experienced managers (*Experienced*). Table 10 reports statistically and economically significant negative coefficients on all four interactions, consistent with livestreams having a smaller effect on more visible funds.

7.4. Stacked cohort DiD models

Papers such as Baker et al. (2022) and Barrios (2022) summarize the biases that can stem from heterogeneous effects in staggered DiD models. Our DiD models involve a treatment (livestreaming) that can alternate back-and-forth within a fund over time, which is dissimilar to a staggered DiD in which cohorts of firms switch from being untreated to permanently treated. Section S8 of our Supplementary Materials discusses why our models are unlikely to be materially confounded by heterogenous treatment effects and, for good measure, repeats our main analyses using a stacked-cohort design that avoids potential confounds. Our inferences are unchanged.

8. Conclusion

Despite decades of regulations attempting to improve investor education and reduce information frictions, extensive research finds that retail investors struggle to make informed choices when buying mutual funds. Chinese regulators permit funds to use social media to give live video presentations and answer questions for the purpose of investor education. In effect, regulators partially outsource investor education to the sellers of consumer financial products.

We examine whether livestreams improve investors' fund buying decisions and, in brief, we find they do not. Rather, livestreams exacerbate investors' returns-chasing behaviors. Investors who buy livestreaming funds would earn higher returns by buying index funds or holding cash.

Our findings indicate that regulators and investors should be wary of the educational efforts by sellers of consumer financial products, and that the generally beneficial effects of firms' social media usage in equity markets do not always extend to financial product markets.

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Appendix A: Mutual fund industry in China

A.1 Mutual fund disclosure regulation

The legal cornerstone of China's public fund industry is the Securities Investment Fund Law of the People's Republic of China ("Fund Law"). This law sets a framework for the operation of fund managers and funds. The China Securities Regulatory Commission (CSRC) supervises and manages the activities of securities funds. AMAC is a self-regulatory organization of the fund industry, which is subject to the oversight of CSRC.

Many CSRC policies resemble mutual fund regulations in the United States. For example, funds must produce prospectuses and periodic reports, must report performance, risk, and fees in standardized ways, and may not speculate about future performance (CSRC 2019). Fund communications and advertisements must comply with extensive regulations and must be approved by funds' internal oversight groups before dissemination. Advertisements must include clear disclosures advising investors to consider the fund's investment objectives, risks, charges, and expenses before investing. Furthermore, advertisements must comply with antifraud provisions, meaning they cannot omit material facts that could mislead investors about the fund's performance or risks, including selectively disclosing information for short-term marketing purposes. Such regulations apply to both mutual fund issuers and sellers (e.g., *Tiantian*). Fund sellers are required to "enhance investor education" and "guide investors to fully understand the risk-return characteristics of fund products before investing" (Ministry of Justice of the People's Republic of China 2020).

A.2 Mutual fund investor and investor education

As of February 2025, the total AUM of Chinese mutual funds is USD 4.4 trillion and comprised of over 759 million individual investors (AMAC 2023). The popularity of mutual funds has increased over the years as households' assets have stopped holding such a large concentration of assets in bank deposits (Yi 2017). When selecting funds, individuals consider the historical performance of the fund, the fund family, and the fund manager, as the most important criteria (AMAC 2022).

The framework of mutual fund investor education in China has been shaped through legislative and regulatory measures, notably China Securities Investment Fund Law, and initiatives from CSRC, Stock Exchanges, and AMAC. These measures aim to protect investors by enhancing their understanding of the availability and risk-return characteristics of different fund products, encouraging informed trading practices, and fostering a habit of long-term investment.

Under the guidance of regulators and industry associations, fund families have produced an increasing amount of educational content over the years in diverse formats. An investor survey conducted by AMAC in 2021 finds that new media such as livestreaming and short video is the most popular form of investor education among investors across all age groups (AMAC 2021b). Additionally, the survey reveals that investors express a desire for more face-to-face communication opportunities with fund managers and more access to investment advisory services.

Livestreams are well aligned with this emphasis on digital platforms and communication with investment professionals in investor education.

There is some evidence that mutual fund investors in China benefit from this educational content. For example, investors pay increasingly more attention to fees relative to other factors (AMAC 2020, 2022). In addition, they have significantly increased their investment horizon, with two-thirds of them holding funds for at least one year on average, and a quarter holding for more than three years (AMAC 2020, 2022). While Chinese retail equity investors' average holding horizon is shorter (average of 43-251 days, Jones et al. 2025), recent evidence indicates that the majority of retail equity investors in the U.S. also have short holding period. For example, Armstrong et al. (2025) document that short-term speculation accounts for a large fraction of trading by individual investors, with stocks held for 30 days or fewer representing three-quarters of all stock sales.

Appendix B: Livestream screenshots

Panel A: Screenshot of a livestream on May 29th, 2023, 11:00 am - 12:10 pm

Livestream Title

Speakers' Name & Job Function

14 Funds in Shopping Cart

Here is the translation of text in the screenshot:

Header in Small Font:

(App name) *Tiantian Fund*

(Channel name) Nanfang Fund Family

(Orange icon on the top left) Follow the Channel

(Livestream viewership) 83,000 Participants

(Livestream speakers) Xiaoxi Zheng || Tang Tang

(Livestream title) Will Global Semiconductor Sector Hit the Bottom in the Second Half of the Year?

Header in Large Font:

(Fund name) Nanfang Information Innovation Fund

(Fund class & purchase code) Class A 007490 || Class C 007491

Text in the Middle:

(Female speaker on the left) Tang Tang, fund selector

(Female speaker on the right) Xiaoxi Zheng, fund manager of Nanfang Information Innovation Fund

Text at the Bottom:

- (User comment) [Muxin] 23456: 6
- (Disclaimer) [Notice: The content of the livestream does not constitute investment advice. It is for reference only. The content is suitable for users with high risk tolerance. Please make your own judgment. Past performance of the fund does not represent future performance. Please carefully read the fund contract and risk disclosure materials. Fund investment is risky and requires caution.]
- (Orange shopping cart icon on the bottom left) 14 funds ← "Check out the fund details"
- (Icon with arrow) Share the livestream

  (Icon with heart) Like the livestream || "57,000 likes"

Panel B: Screenshot of clicking the shopping cart from Panel A.

Here is the translation of text in the screenshot:

Related Funds

Fund Name: Nanfang Information Innovation Mixed Fund Class A

- **Risk Level**: Equity-Oriented Mixed Fund, Mid-to-High Risk
- **Performance Since Inception**: 59.03%
- **Orange Bar**: Purchase
- **Icon with Star**: Add to Favorite

Fund Name: Nanfang Information Innovation Mixed Fund Class C

- **Risk Level**: Equity-Oriented Mixed Fund, Mid-to-High Risk
- **Performance Since Inception**: 52.16%
- **Orange Bar**: Purchase
- **Icon with Star**: Add to Favorite

Fund Name: Nanfang Artificial Intelligence Mixed Fund

- **Risk Level**: Equity-Oriented Mixed Fund, Mid-to-High Risk
- **Performance Since Inception**: 111.37%

(More Funds on Scroll)

Appendix C: Characteristics of livestreams and magazine ads

	Social Media Livestreams (this paper)	**Magazine Advertisements** (e.g., Jain & Wu 2000)
Sample period	2020 – 2025	1994 – 1996
Sample size	>27,000 livestreams	294 advertisements
Format	Live Social Media Video	Magazine page
Length	Average 53 minutes of video and audio contents	One static image + short captions or paragraphs
Intended to be educational	Yes	No
Production cost	Highly significant. Direct costs include professional staff and facilities. Indirect costs include preparation efforts by fund representatives and risks from poor onscreen performances or misspeaking	Likely modest. Primarily involves designing an ad and buying magazine placements
Research from equity markets indicates they should be informative	Yes, numerous studies find that corporate social media improves investing decisions	No
Manager can personally appear	Yes	No
Involve persuasive features	Yes. Speakers' verbal, vocal, and physical characteristics plausibly affect investor reactions	Unlikely
Display prior returns	Rarely. Users see trailing returns after clicking the shopping cart	Yes
Other Contents	Detailed discussions of investing strategy, market trends, and other topics	Basic prospectus information
Contents Timeliness	Can respond to real-time events	Determined weeks in advance
Interactivity	Viewers can submit questions live or in advance	None
Audience	A broad range of retail investors	Readers of *Money* and *Barron's*

Appendix D: Variable definition

All variables are calculated at the fund-month level unless otherwise stated. Unless otherwise noted, funds with multiple classes are aggregated to the fund-level based on the size-weighted average across classes. Continuous variables other than returns-related measures are winsorized at 1% and 99%.

Variables	Definition
Flow and Returns Variables (from CSMAR unless otherwise stated)	
Fund Flow	The fund size at the end of the quarter minus fund size at the beginning of the quarter times one plus the fund's quarterly net-of-fee returns, scaled by beginning fund size and expressed in percentage. For funds with multiple classes, fund size is the total size across all classes.
Class Flow	The class size at the end of the quarter minus class size at the beginning of the quarter times one plus the class's quarterly net-of-fee returns, scaled by beginning fund size and expressed in percentage.
Hot	An indicator for "hot" fund-classes on *Tiantian*, which include the 30 equity funds that have the largest cumulative net purchases during the day on *Tiantian* app. The "hot" list is updated 27 times during each trading day: every 10 minutes during trading hours (9:30 am – 11:30 am, and 1:00 pm – 3:00 pm) and at 12:50 pm, 10 minutes before the afternoon trading session. The variable is measured at the fund-class-day-time level (from *Tiantian Fund* App).
Return	The fund-month net-of-fee returns expressed in percentage. Calculated as the change in the fund's net asset value per share (with reinvested dividend).
(Return – Index Return)	The fund-month net-of-fee returns minus the size-weighted average of the net-of-fee returns of the CSI 300 index fund (ticker: 510300) and the CSI 500 index fund (ticker: 510500), expressed in percentage. Weights are based on each index fund's AUM at the beginning of the month.
DGTW Alpha	The DGTW-adjusted gross returns minus fund fees and loads, expressed in percentage. Fund DGTW-adjusted gross returns is weighted-average of the DGTW-adjusted stock returns using the fund's portfolio weights. Each DGTW-adjusted stock returns is calculated by subtracting the returns of a market cap-weighted portfolio that matches the stock's size, value, and momentum quintile from the stock's raw returns. Fund's complete portfolio weight is disclosed semi-annually.
Carhart Alpha	The risk-adjusted returns based on the Carhart (1997) factor model, minus fund fees and loads, expressed in percentage. *Carhart Alpha* in month m is the fund's net-of-fee returns plus fund fees and loads and in excess of the risk-free rate in month m minus returns of the Carhart factors in month m multiplied by factor loadings, where factor loadings are estimated using the 24-month estimation window ending in month $m-1$. We require a minimum of 18 months' trailing data in the past 24 months to calculate factor loadings.
China 3F Alpha	The risk-adjusted returns based on Liu et al. (2019)'s China three-factor model, minus fund fees and loads, expressed in percentage. *China 3F Alpha* in month m is the fund's net-of-fee returns plus fund fees and loads and in excess of the risk-free rate in month m minus returns of market, size, and value factors in month m multiplied by factor loadings, where factor loadings are estimated using the 24-month estimation window ending in $m-1$. We require a minimum of 18 months' trailing data in the past 24 months to calculate factor loadings. Source: Factors are from Stambaugh & Yuan's asset management database (https://en.mingshiim.com/database).
Livestreaming Characteristics (from *Tiantian Fund* App)	
First Stream	An indicator for the first month (or quarter) that a fund is featured in the shopping carts of livestreams.
Livestream	An indicator for all months (or quarters) that a fund is featured in the shopping carts of livestreams.
Class in Cart	An indicator for fund-classes featured in the shopping carts of livestreams. For the class level analyses, the variable is measured at the fund-class-quarter level. For the intraday analyses, it is defined as an indicator for fund-classes being livestreamed during trading hours and measured at the fund-class-day level.

Post	An indicator for intraday intervals which end after the start of a livestream.
Manager_On	An indicator for all months (or quarters) when a fund is featured in shopping carts and its fund manager attends at least one of the fund's livestreams in that month (or quarter).
First Half	An indicator for all months (or quarters) when a fund is featured in the first half of the shopping cart in at least one of the fund's livestreams during that month (or quarter). *First Half* is defined in consideration of all funds in the shopping cart, regardless of whether the fund satisfies our sample selection procedures.
High Verbal Sentiment	An indicator for all months (or quarters) when a fund is featured in at least one livestream whose *Verbal Sentiment* score exceeds the median of all livestreaming funds' top *Verbal Sentiment* score during that month (or quarter). A livestream's verbal sentiment is defined as the difference between the number of positive and negative sentences in a livestream, scaled by one plus the sum of these two numbers. Sentence sentiment is classified using the Chinese FinBERT model, based on the highest probability among positive, neutral, and negative categories. See Section S5.1 of the Supplementary Materials for more details.
High Vocal Valence	An indicator for all months (or quarters) when a fund is featured in at least one livestream whose *Vocal Valence* score exceeds the median of all livestreaming funds' top *Vocal Valence* score during that month (or quarter). Livestream's vocal valence is the average valence score among first sentences per minute. Sentence valence is predicted using *pyAudioAnalysis*. See Section S5.2 of the Supplementary Materials for more details.
High Vocal Arousal	An indicator for all months (or quarters) when a fund is featured in at least one livestream whose *Vocal Arousal* score exceeds the median of all livestreaming funds' top *Vocal Arousal* score during that month (or quarter). Livestream's vocal arousal is the average arousal score among first sentences per minute. Sentence arousal is predicted using *pyAudioAnalysis*. See Section S5.2 of the Supplementary Materials for more details.
High Vocal Sentiment	An indicator for all months (or quarters) when a fund is featured in at least one livestream whose *Vocal Sentiment* exceeds the median of all livestreaming funds' most vocally positive livestream during that month (or quarter). Livestream's vocal sentiment is defined as the difference between the number of *Vocal Happy* and *Vocal Sad* sentences in a livestream, scaled by one plus the sum of these two numbers. We only consider the first sentence per minute due to computational constraints. Sentence vocal sentiment is predicted using *speechemotionrecognition*, based on the highest probability among happy, sad, and other (neutral, angry) categories. See Section S5.2 of the Supplementary Materials for more details.
High Attractiveness	An indicator for all months (or quarters) when a fund is featured in at least one livestream whose visual *Attractiveness* exceeds the median of all livestreaming funds' most visually attractive livestream during that month (or quarter). Livestream's visual attractiveness is defined as the average facial attractiveness score of face images cropped from screenshots taken every five minutes in a livestream. Image attractiveness is predicted using ResNeXt-50 model trained on SCUT-FBP5500 dataset. See Section S5.3 of the Supplementary Materials for more details.
Persuasion	The sum of six persuasion-related indicators (*First Half*, *High Verbal Sentiment*, *High Vocal Valence*, *High Vocal Arousal*, *High Vocal Sentiment*, *High Attractiveness*), normalized between zero and one.
Other Fund Characteristics (from CSMAR)	
Recent Return	The fund net-of-fee returns in the prior six months, expressed in percentage.
Top 5 Return	An indicator for the five funds within a family that have the highest net-of-fee returns in the prior six months.
Management Fee	The fund management fee in a month (or quarter), calculated as CSMAR's annual management fee divided by 12 (or 4), expressed in percentage.
Service Fees	The fund custodian and sales service fees in a month (or quarter), calculated as CSMAR's annual custodian and sales service fees divided by 12 (or 4), expressed in percentage.
Loads	The fund front-end and back-end loads in each month (or quarter) and expressed in percentage, calculated by dividing the combined loads (front plus back) by the average holding period across active-equity funds with load charges (16.56 months for Class A and single-class funds and 8.16 months for Class C funds in our sample). Front loads are

	multiplied by 10% because *Tiantian Fund* offered a 90% discount on front load throughout our sample period. Back-end loads are considered as 0 when the fund's longest holding period to be charged with back-end loads is shorter than the average holding period calculated above.
Fund Size	The natural logarithm of total assets under the fund's management.
Fund Age	The natural logarithm of one plus the number of years since the fund was launched.
Disclosure	The number of fund regulatory disclosures (i.e., quarterly, semi-annual, and annual reports) filed during the month (or quarter).
Star	An indicator for funds awarded with one of Morningstar (China) Fund Award, Golden Bull Fund Award, China Fund Industry Star Fund Award, and China Golden Fund Award in the 12 months prior to the quarter. Source: Asset Management Association of China's website https://www.amac.org.cn/businessservices_2025/fundevaluationbusiness/.
Large	An indicator for funds in the top quintile of total assets in a quarter.
Old	An indicator for funds in the top quintile of years since launched in a quarter.
Manager Characteristics (from Easymoney.com)	
Manager Experience	The natural logarithm of one plus the average years of managing funds of all managers of a fund.
Highest Degree	The highest academic degree obtained by a fund manager: three for Ph.D., two for MBA/EMBA; one for other master's degrees; and zero for a bachelor's degree or lower. For funds with multiple managers, the variable is averaged across managers.
Top 2 University	An indicator for funds with at least one fund manager graduating from Peking University or Tsinghua University.
Female	An indicator for funds with at least one female fund manager.
Experienced	An indicator for funds whose average manager experience is in the top quintile of all funds in that quarter.

Figure 1: Quarterly flows around first livestreams

This figure plots β_l coefficient estimates of the generalized difference-in-differences model (2), which examines flows for livestreaming versus non-livestreaming funds. We present results for each of the five quarters surrounding funds' first livestreams. Blue dots represent coefficient estimates for β_l. Vertical lines represent 95% confidence intervals. Quarter 0, with the vertical dashed line, represents the first livestreaming quarter. See Appendix D for variable definitions.

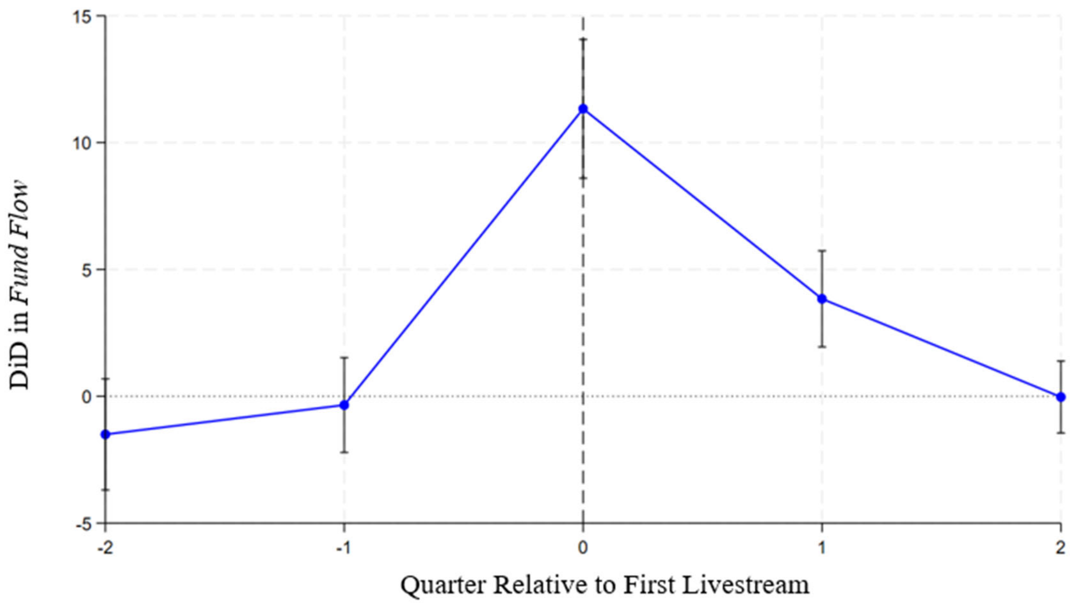

Figure 2: Monthly returns around livestreams

This figure plots the Table 6 Panel A net-of-fee returns (*Return*) and abnormal returns (*Return – Index Return*) in the eleven months around livestreams, without risk adjustment or controls. *Return* is the returns observed and received by investors. *Return – Index Return* is calculated as the difference between a fund's net-of-fee returns and the size-weighted average net-of-fee returns of the CSI 300 index fund and the CSI 500 index fund. The sample includes only livestreaming funds. Vertical lines represent 95% confidence intervals. Month 0, with the vertical dashed line, represents the livestream month.

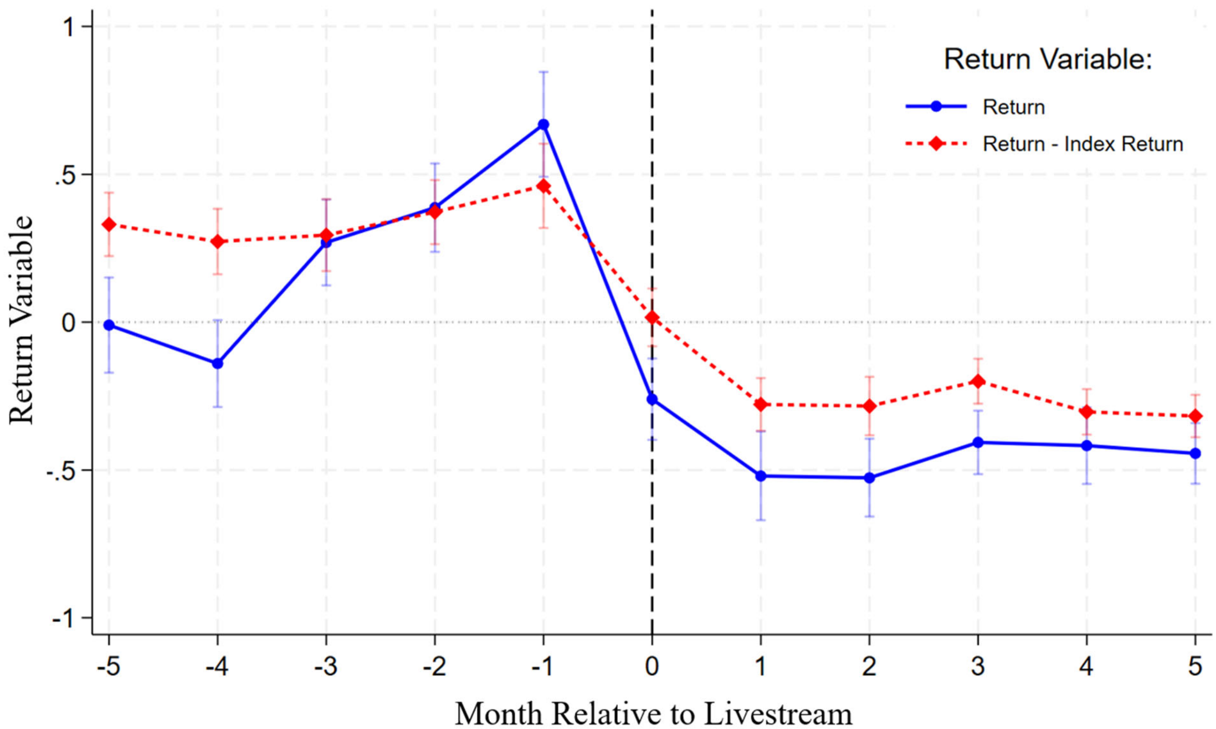

Figure 3: Livestream timing

This figure illustrates the count of livestreams that commence at each half-hour interval from 7:30 am till midnight. The bins in the boxes mark the trading hours in China, which span from 9:30 am to 11:30 am and 1:00 pm to 3:00 pm on trading days, i.e., Monday through Friday excluding public holidays. Blue bars represent livestreams on trading days; orange bars represent livestreams on non-trading days. 99.4% of livestreams occur on trading days.

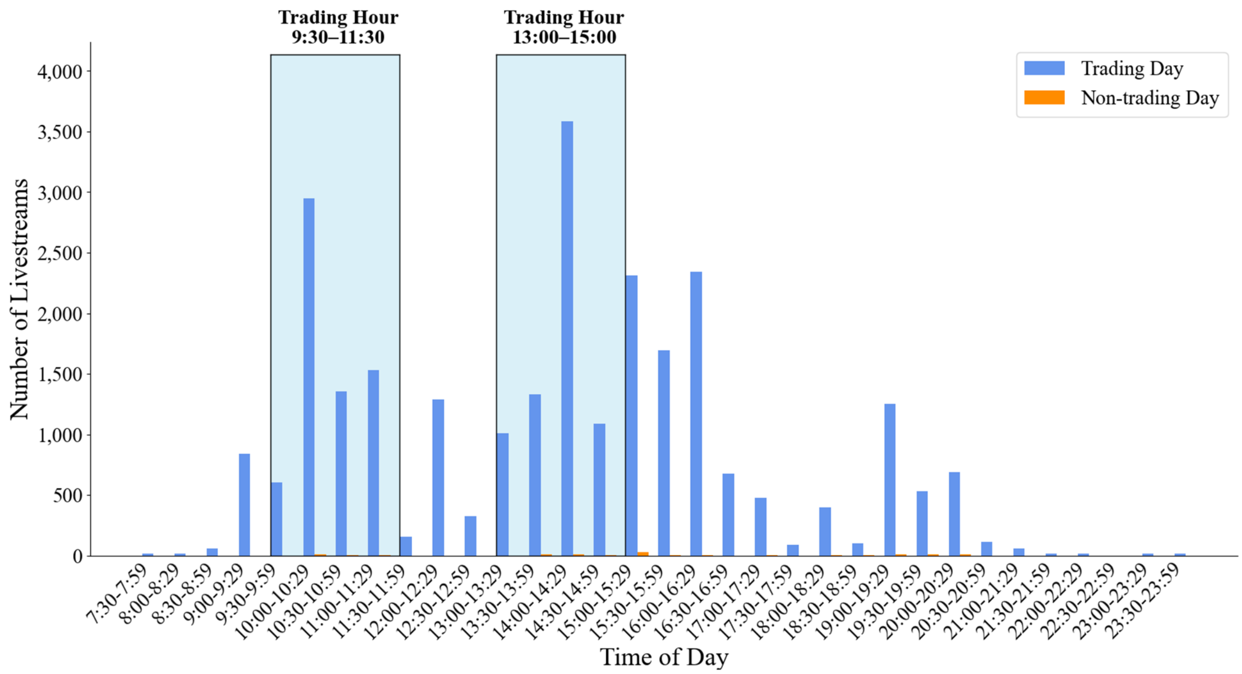

Figure 4: Speaker types in livestreams

This figure lists the types of speakers in livestreams. We obtain speaker names and job functions from the *Tiantian* app and supplement with names and job functions extracted from transcripts and via manual review of livestreams. See Section 3.2 for further discussion.

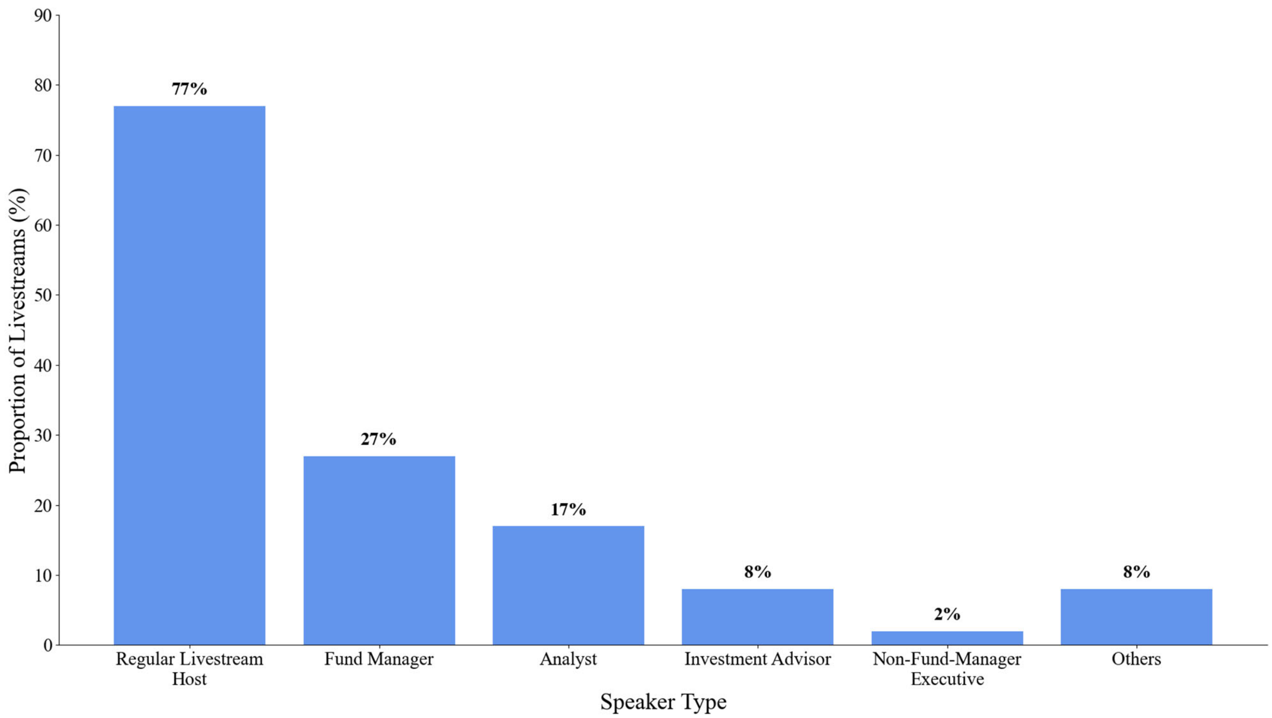

Table 1: Sample selection and summary statistics

Panel A details the sample selection process. Panel B tracks the quarterly and cumulative adoption rates of livestreaming from 2020Q2 to 2024Q4. Panel C provides summary statistics, with within fixed effects standard deviations (*Within FE S.D.*) consistent with the main fixed effect used in the specifications. Specifically, we calculate standard deviation within fund and year-month for fund-month, within fund-year-month for fund-class-month variables, within fund and year-quarter for fund-quarter variables, within fund-year-quarter for fund-class-quarter variables, and within fund-day-time and class-day for fund-class-day-time variables. All variables are defined in Appendix D.

Panel A: Mutual fund sample selection

	# Fund-Classes	**# Fund-Class-Months**
All predominantly equity fund-classes during May 2020 – Dec 2024	9,116	328,083
	# Funds	**# Fund-Months**
Consolidate to the fund level	5,599	219,367
Remove index, closed-end, Qualified Domestic Institutional Investor, and umbrella funds	4,413	179,385
Remove funds launched within the past 12 months	4,130	156,908
Remove fund-months with missing key variables	**3,970**	**147,151**
Including:		
Mutual funds in livestreams in the month	**2,243**	**18,926**

Panel B: Livestreaming adoption over time

Period	**Families that livestream during quarter**	**Cumulative families that livestream through quarter**	**Funds that livestream during quarter**	**Cumulative funds that livestream through quarter**
(1)	(2)	(3)	(4)	(5)
2020Q2	29 (21%)	29 (21%)	44 (1%)	44 (1%)
2020Q3	59 (43%)	64 (46%)	182 (5%)	206 (5%)
2020Q4	61 (44%)	74 (54%)	227 (6%)	347 (9%)
2021Q1	71 (51%)	84 (61%)	319 (8%)	519 (13%)
2021Q2	63 (46%)	87 (63%)	308 (8%)	637 (16%)
2021Q3	84 (61%)	95 (69%)	509 (13%)	866 (22%)
2021Q4	83 (60%)	100 (72%)	542 (14%)	1,033 (26%)
2022Q1	86 (62%)	104 (75%)	566 (14%)	1,168 (30%)
2022Q2	90 (65%)	106 (77%)	615 (16%)	1,292 (33%)
2022Q3	90 (65%)	107 (78%)	671 (17%)	1,408 (36%)
2022Q4	94 (68%)	111 (80%)	687 (17%)	1,520 (38%)
2023Q1	103 (75%)	115 (83%)	816 (21%)	1,688 (43%)
2023Q2	104 (75%)	118 (86%)	799 (20%)	1,804 (46%)
2023Q3	97 (70%)	119 (86%)	765 (19%)	1,906 (48%)
2023Q4	100 (72%)	122 (88%)	707 (18%)	1,976 (50%)
2024Q1	90 (65%)	124 (90%)	651 (16%)	2,090 (53%)
2024Q2	90 (65%)	124 (90%)	598 (15%)	2,156 (54%)
2024Q3	86 (62%)	124 (90%)	487 (12%)	2,180 (55%)
2024Q4	100 (72%)	125 (91%)	625 (16%)	2,243 (56%)

Panel C: Summary statistics

	N	Mean	S.D.	Within FE S.D.	25%	Median	75%
Fund-Month Variables							
First Stream$_m$	147,151	0.02	0.12	0.12	0	0	0
Livestream$_m$	147,151	0.13	0.33	0.28	0	0	0
Recent Return$_{m-1}$	147,151	0.83	15.58	9.08	-9.14	-1.77	8.32
Top 5 Return$_{m-1}$	147,151	0.20	0.40	0.33	0	0	0
Management Fee$_{m-1}$	147,151	0.11	0.02	0.005	0.10	0.12	0.12
Service Fees$_{m-1}$	147,151	0.07	0.02	0.008	0.06	0.07	0.07
Loads$_{m-1}$	147,151	0.01	0.01	0.001	0.01	0.01	0.01
Fund Size$_{m-1}$	147,151	17.82	1.59	0.54	16.69	17.88	18.97
Fund Age$_{m-1}$	147,151	1.81	0.60	0.11	1.39	1.79	2.20
Disclosure$_m$	147,151	0.48	0.50	0.02	0	0	1
Return$_m$	147,151	0.21	6.50	3.96	-3.47	-0.44	3.14
DGTW Alpha$_m$	147,151	-1.39	3.86	3.53	-3.45	-1.35	0.60
Carhart Alpha$_m$	147,151	-0.12	4.52	4.28	-2.20	-0.23	1.80
China 3F Alpha$_m$	147,151	0.16	4.65	4.33	-1.94	0.01	2.12
Manager Experience$_{m-1}$	147,151	1.84	0.53	0.26	1.50	1.95	2.20
Highest Degree$_{m-1}$	147,151	1.26	0.64	0.26	1	1	1
Top2 University$_{m-1}$	147,151	0.19	0.39	0.16	0	0	0
Female$_{m-1}$	147,151	0.21	0.41	0.18	0	0	0
Fund-Class-Month Variables							
Class in Cart$_m$	121,748	0.10	0.30	0.15	0	0	0
Class Service Fees$_{m-1}$	121,748	0.09	0.05	0.04	0.05	0.06	0.13
Class Loads$_{m-1}$	121,748	0.00	0.01	0.006	0	0	0.01
Class Size$_{m-1}$	121,748	16.50	2.06	1.2	15.22	16.64	17.97
Class Age$_{m-1}$	121,748	1.43	0.49	0.28	1.1	1.39	1.79
Fund-Quarter Variables							
First Stream$_q$	50,867	0.04	0.21	0.20	0	0	0
Livestream$_q$	50,867	0.20	0.40	0.32	0	0	0
Fund Flow$_q$	50,867	1.43	31.1	28.73	-7.85	-2.77	1.00
Recent Return$_{q-1}$	50,867	1.11	15.31	8.73	-9.25	-1.67	8.37
Manager_On$_q$	50,867	0.09	0.29	0.25	0	0	0
First Half$_q$	50,867	0.15	0.36	0.29	0	0	0
High Verbal Sentiment$_q$	50,867	0.10	0.30	0.25	0	0	0
High Vocal Valence$_q$	50,867	0.10	0.30	0.25	0	0	0
High Vocal Arousal$_q$	50,867	0.10	0.30	0.25	0	0	0
High Vocal Sentiment$_q$	50,867	0.10	0.30	0.25	0	0	0
High Attractiveness$_q$	50,867	0.10	0.30	0.25	0	0	0
Persuasion$_q$	50,867	0.11	0.26	0.20	0	0	0
Star$_{q-1}$	50,867	0.02	0.16	0.12	0	0	0
Large$_{q-1}$	50,867	0.20	0.40	0.32	0	0	0
Old$_{q-1}$	50,867	0.18	0.39	0.16	0	0	0
Experienced$_{q-1}$	50,867	0.17	0.38	0.19	0	0	0
Fund-Class-Quarter Variables							
Class in Cart$_q$	43,028	0.17	0.37	0.17	0	0	0
Class Flow$_q$	43,028	0.40	17.59	8.86	-3.60	-0.94	0.14
Fund-Class-Day-Time Variables							
Hot$_{f,c,d,t}$	239,096	0.02	0.15	0.08	0	0	0
Class in Cart$_{f,c,d}$	239,096	0.50	0.50	0.00	0	0.5	1
Post$_{f,d,t}$	239,096	0.58	0.50	0.00	0	1	1

Table 2: Livestream contents

This table displays summary characteristics and topics of mutual fund livestreams. Panel A summarizes the characteristics of livestreams. Panel B tabulates livestream topics, the proportion of time discussing each topic, the most frequent 20 words in each topic, and each topic's economic intuition as interpreted by ChatGPT based on their most frequent words. The topic analyses are based on the 26,103 livestreams that *Tiantian Fund* app provides access to the videos.

Panel A: Descriptive statistics

Variables	**# of Livestreams**	**Mean**	**S.D.**	**25%**	**Median**	**75%**
Length (minutes)	27,046	53	32	39	56	60
# of Viewers	27,046	47,076	52,700	22,220	35,956	50,090
# of Sample Funds Featured	27,046	3.88	2.61	2	3	5
# of Speakers	26,103	1.73	0.91	1	2	2
# of Topics in Livestream	26,103	7.07	1.78	6	7	8
Largest Topic (% of Livestream)	26,103	44%	17%	32%	40%	53%
2^{nd} Largest Topic (% of Livestream)	26,103	21%	7%	16%	21%	25%
3^{rd} Largest Topic (% of Livestream)	26,103	13%	5%	10%	13%	17%

Panel B: Livestream topics

% of Time in Livestream	**Keywords (translated)**	**ChatGPT Summary**
18.93%	Market, Sector, Valuation, Market Trend, Industry, Situation, Opportunity, Performance, Attention, Position, Rebound, Adjustment, Rise, Decline, Overall, Investment, Especially, Performance, Short-Term, Investor	Market Conditions & Investment Performance
13.95%	Investment, Fund, Returns, Allocation, Market, Asset, Risk, Product, Strategy, Fluctuation, Investor, Selection, Long-Term, Stock, Portfolio, Equity, Hold, Quantitative, Hope, Suitable	Fund Investment Strategies & Portfolio Management
12.77%	Economy, Market, Policy, Expectation, Data, United States, Impact, Situation, Interest Rate Cut, Overall, Growth, Domestic, Federal Reserve, Global, Factor, China, Meeting, Overseas, Real Estate, Inflation	Global Economic & Market Expectations
12.28%	New Energy, Semiconductor, Industry, Automobile, Chip, Industry, Demand, Development, Photovoltaic, Industrial Chain, Field, Technology, Future, Robot, Domestic, Direction, Intelligent, Related, China, Energy	Emerging China Tech & Green Energy
8.89%	Consumption, Industry, Company, Medicine, Innovation, Enterprise, Sector, Liquor, Healthcare, Growth, Demand, Focus, Product, Future, Field, Track, Investment, Direction, Improvement, R&D	Consumer & Healthcare Sector Growth
8.18%	Fund, Product, Investment, Attention, Manager, Risk, Management, Investor, Performance, Performance, Related, This Fund, Viewpoint, Returns, Situation, Reminder, Risk Tolerance, China Asset Management, Content, Mixed	Fund Performance & Risk Management
8.13%	Meeting Minutes, Development, Investment, Artificial Intelligence, Company, Technology, Model, Research, Industry, Gaming, Future, Economy, Technology, Industry, Work, Digital, Data, China, Finance, Innovation	AI & Technology Investment Trends
6.85%	Follow, Hope, Interaction, Benefits, Communication, Content, Fans, Special, End, Topic, Assistant, Market, Event, Support, Wealth, Viewpoint, Related, Red Envelope, Interested, Discussion Forum	Investor Engagement & Support
5.55%	Index, Dividend, China Securities, Hong Kong Stocks, Industry, Company, Market, Technology, Market Capitalization, Stocks, Performance, Dividend Payout, Dividend, Growth, Style, Sci-Tech Innovation, Value, Valuation, Attention, Enhancement	Stock Performance & Dividend Growth
4.47%	Bonds, Interest Rate, Gold, Funds, Assets, Bank, Credit, Bond Market, Government Bonds, Yield, Risk, Trading, Price, Market, Liquidity, Bond Trading, Returns, Situation, US Dollar, Short-Term Bonds	Bond Market & Interest Rates

Table 3: Determinants of livestreaming

This table examines the determinants of livestreaming using regression model (1). Columns (1) and (2) display results when using *First Stream*$_m$ as the dependent variable, columns (3) and (4) display results when using *Livestream*$_m$ as the dependent variable. Fixed effects, clustering, and other model details are listed at the bottom of each column. All variables are defined in Appendix D. All non-binary regressors are standardized. *t*-statistics are presented in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Dependent Variables:	*First Stream*$_m$		*Livestream*$_m$	
Recent Return$_{m-1}$	0.008***	0.008***	0.025***	0.030***
	(10.31)	(9.55)	(4.93)	(7.39)
Top 5 Return$_{m-1}$	0.007***	0.007***	0.099***	0.032***
	(6.28)	(4.90)	(9.25)	(6.34)
Management Fee$_{m-1}$	0.001*	-0.000	-0.002	0.004
	(1.94)	(-0.03)	(-0.53)	(0.43)
Service Fees$_{m-1}$	0.001***	-0.001	0.040***	0.021***
	(3.04)	(-0.85)	(7.43)	(4.15)
Loads$_{m-1}$	0.000	0.005	-0.027***	0.027
	(0.33)	(1.51)	(-8.66)	(1.36)
Fund Size$_{m-1}$	0.000	-0.009***	0.046***	0.111***
	(0.40)	(-7.01)	(8.82)	(13.01)
Fund Age$_{m-1}$	-0.005***	-0.021***	0.014***	0.029***
	(-10.24)	(-7.68)	(2.68)	(3.15)
Disclosure$_m$	0.013	0.013	-0.011	0.010
	(0.69)	(0.66)	(-0.57)	(0.43)
Fund FE	No	Yes	No	Yes
Yr-Month FE	Yes	Yes	Yes	Yes
Cluster	Fund Family	Fund Family	Fund Family	Fund Family
Sample	Fund-Yr-Month	Fund-Yr-Month	Fund-Yr-Month	Fund-Yr-Month
# of Observations	147,151	147,151	147,151	147,151
Adjusted R-squared	0.012	0.002	0.072	0.325

Table 4: Livestreaming and fund flows

This table investigates the effects of livestreaming on fund flows. Panel A displays fund-year-quarter level tests using regression model (2). The dependent variable is quarterly flows. Panel B column (1) displays the fund-class-year-month level determinants test for *Class in Cart*$_{f,c,m}$ and column (2) investigates quarterly flows at the fund-class-year-quarter level. Panel C column (1) displays a fund-class-day level determinants test for *Class in Cart*$_{f,c,d}$ and column (2) is a fund-class-day-time level test of whether a fund-class appears as a "hot" fund after livestream. Panel D presents the results of 999 trials of intraday placebo tests, further discussed in Section 5.3. Fixed effects, clustering, and other model details are listed at the bottom of each column. All variables are defined in Appendix D. All non-binary regressors are standardized. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Generalized difference-in-differences regressions of quarterly fund flows

	(1)	(2)
Dependent Variable:	*Fund Flow*$_q$	
First Stream$_q$	11.332***	
	(8.12)	
Livestream$_q$		10.649***
		(14.45)
Recent Return$_{q-1}$	7.789***	7.561***
	(17.27)	(17.28)
Top 5 Return$_{q-1}$	4.739***	4.441***
	(7.18)	(6.80)
Management Fee$_{q-1}$	-1.915**	-1.997**
	(-2.46)	(-2.51)
Service Fees$_{q-1}$	2.384***	2.087***
	(4.79)	(4.13)
Loads$_{q-1}$	-3.675	-3.830*
	(-1.58)	(-1.66)
Fund Size$_{q-1}$	-27.409***	-29.078***
	(-27.21)	(-27.89)
Fund Age$_{q-1}$	-0.164	-1.204
	(-0.18)	(-1.34)
Disclosure$_q$	0.090	0.117
	(0.09)	(0.12)
Fund FE	Yes	Yes
Yr-Qtr FE	Yes	Yes
Cluster	Fund Family	Fund Family
Sample	Fund-Yr-Qtr	Fund-Yr-Qtr
# of Observations	50,867	50,867
Adjusted R-squared	0.164	0.171

Panel B: Class-level analysis of quarterly fund flows

	(1)	(2)
Dependent Variables:	*Class in Cart$_{f,c,m}$*	*Class Flow$_{f,c,q}$*
Class in Cart$_q$		1.134***
		(2.79)
Class Service Fees$_{t-1}$	0.018**	0.094
	(1.98)	(0.70)
Class Loads$_{t-1}$	-0.007**	0.182*
	(-2.04)	(1.81)
Class Size$_{t-1}$	0.016**	-2.982***
	(2.17)	(-14.15)
Class Age$_{t-1}$	0.020***	0.410***
	(3.90)	(2.80)
Fixed Effects	Fund-Year-Month	Fund-Year-Quarter
Cluster	Fund Family	Fund Family
Sample	Fund-Class-Year-Months of Dual Class Funds	Fund-Class-Year-Quarters of Dual Class Funds
# of Observations	121,748	43,028
Adjusted R-squared	0.533	0.510

Panel C: Class-level intraday analysis (10-minute intervals throughout trading hours)

	(1)	(2)
Dependent Variables:	*Class in Cart$_{f,c,d}$*	*Hot$_{f,c,d,t}$*
Class in Cart$_{f,c,d}$ × Post$_{f,d,t}$		0.011***
		(6.02)
Class Service Fees$_{m-1}$	0.149***	N/A
	(15.16)	
Class Loads$_{m-1}$	-0.098***	N/A
	(-11.31)	
Class Size$_{m-1}$	0.450***	N/A
	(19.68)	
Class Age$_{m-1}$	0.026	N/A
	(1.41)	
Controls × Post included	N/A	Yes
Fund-Day FE	Yes	No
Fund-Day-Post FE	No	Yes
Class-Day FE	No	Yes
Cluster	Fund-Day	Fund-Day
Sample	Fund-Class-Day of Dual Class Funds	Fund-Class-Day-Time of Dual Class Funds
# of Observations	8,910	239,096
Adjusted R-squared	-0.532	0.699

Panel D: Histogram of intraday placebo test coefficients

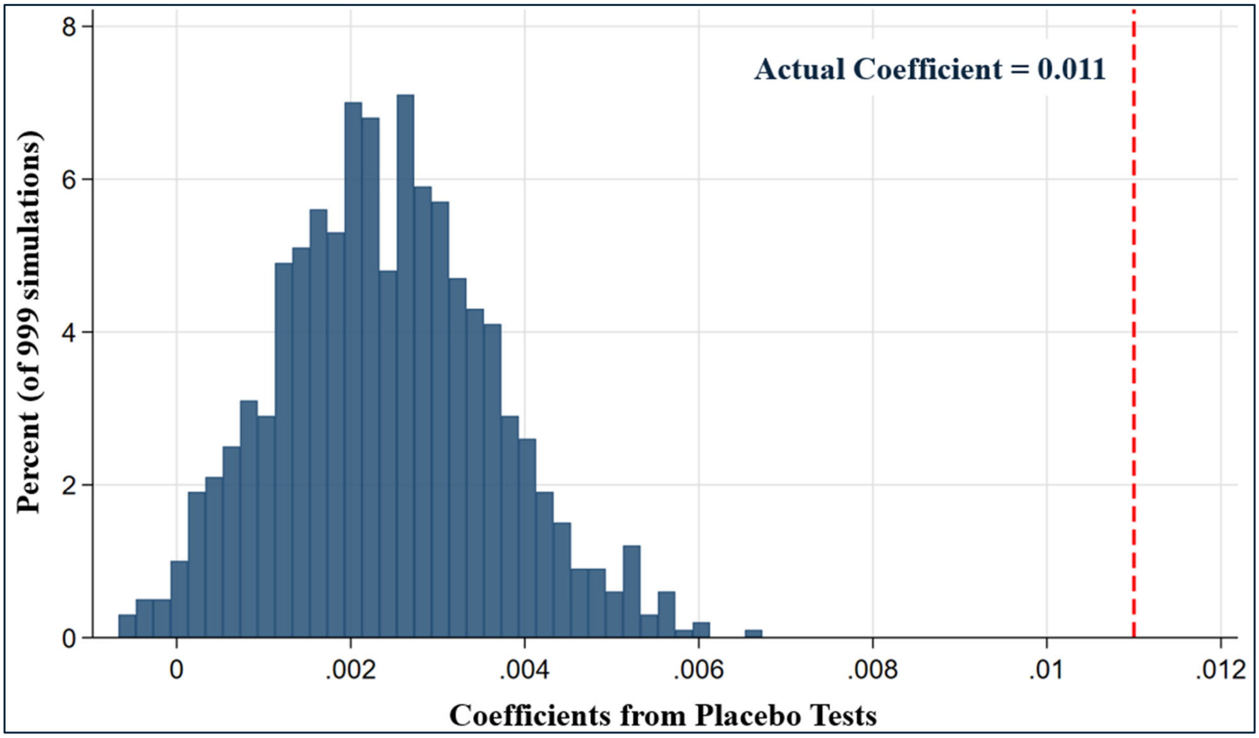

Table 5: Livestreaming and returns-chasing behavior

This table investigates whether livestreaming exacerbates retail investors' tendencies to chase strong trailing performance. Column (1) interacts *Recent Return*$_{q-1}$ with *First Stream*$_q$ and column (2) interacts *Recent Return*$_{q-1}$ with *Livestream*$_q$. The dependent variable is quarterly flows. Both columns include untabulated interaction terms of *Recent Return*$_{q-1}$ × *Controls*. Fixed effects, clustering, and other model details are listed at the bottom of each column. All variables are defined in Appendix D. All non-binary regressors are standardized. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)
Dependent Variable:	*Fund Flow*$_q$	
Recent Return$_{q-1}$	6.892***	5.991***
	(13.17)	(11.02)
Recent Return$_{q-1}$ × *First Stream*$_q$	3.703***	
	(3.50)	
Recent Return$_{q-1}$ × *Livestream*$_q$		2.919***
		(5.17)
First Stream$_q$	9.537***	
	(7.86)	
Livestream$_q$		10.433***
		(15.04)
Top 5 Return$_{q-1}$	4.006***	3.569***
	(6.03)	(5.43)
Management Fee$_{q-1}$	-1.692**	-1.776**
	(-2.15)	(-2.24)
Service Fees$_{q-1}$	2.447***	2.168***
	(4.85)	(4.25)
Loads$_{q-1}$	-3.518	-3.702
	(-1.45)	(-1.53)
Fund Size$_{q-1}$	-27.513***	-29.046***
	(-27.97)	(-28.83)
Fund Age$_{q-1}$	-0.620	-1.359
	(-0.71)	(-1.56)
Disclosure$_q$	0.026	0.017
	(0.03)	(0.02)
Recent Return$_{q-1}$ × *Controls* included	Yes	Yes
Fund FE	Yes	Yes
Yr-Qtr FE	Yes	Yes
Cluster	Fund Family	Fund Family
Sample	Fund-Yr-Qtr	Fund-Yr-Qtr
# of Observations	50,867	50,867
Adjusted R-squared	0.167	0.174

Table 6: Livestreaming and fund returns

Panel A presents the average monthly net-of-fee returns (*Return*) and abnormal returns (*Return – Index Return*) for livestreaming funds in the months around livestreams. Abnormal returns (*Return – Index Return*) are calculated as the difference between a fund's net-of-fee returns and the size-weighted average net-of-fee returns of the CSI 300 index fund and the CSI 500 index fund. The sample includes only livestreaming funds. Reported *t*-statistics in parentheses test whether these means differ from zero. Panels B and C report β_1 coefficient estimates from model (4), which are monthly generalized difference-in-difference regressions of: $Returns_{m+j} = \alpha + \beta_1 First\ Stream_m$ *or* $Livestream_m + \beta_2 Controls + Fund\ FE + Yr\text{-}Mth\ FE + \varepsilon$. *Returns* is one of four returns: *Return*, *DGTW Alpha*, *Carhart Alpha*, and *China 3F Alpha*. *Controls* include *Recent Return*, *Top 5 Return*, *Management Fee*, *Service Fees*, *Loads*, *Fund Size*, *Fund Age*, and *Disclosure*. Panel B displays results for initial livestreams and Panel C for all livestreams. For panels B and C, for months *m-5* through *m*, all controls except for *Disclosure* are measured through the end of the prior month, and *Disclosure* is contemporaneous. For months *m+1* through *m+5*, all controls except for *Disclosure* are fixed at *m-1*, and *Disclosure* is fixed at *m*. The last column presents accumulated *m+1* to *m+5* coefficients. All variables are defined in Appendix D. Standard errors are clustered by fund family. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%.

Panel A: Summary of net-of-fee returns (Return) and abnormal returns (Return – Index Return) of livestreaming funds around livestreams, without risk adjustment or controls

	m-5	m-4	m-3	m-2	m-1	m	m+1	m+2	m+3	m+4	m+5	m(+1, +5)
Return	-0.010	-0.140*	0.269***	0.387***	0.669***	-0.260***	-0.520***	-0.526***	-0.407***	-0.417***	-0.444***	-2.293***
	(-0.12)	(-1.88)	(3.68)	(5.13)	(7.47)	(-3.75)	(-6.83)	(-7.87)	(-7.49)	(-6.38)	(-8.57)	(-10.15)
(Return – Index Return)	0.331***	0.273***	0.294***	0.372***	0.461***	0.016	-0.278***	-0.284***	-0.200***	-0.303***	-0.317***	-1.374***
	(6.11)	(4.88)	(4.79)	(6.79)	(6.41)	(0.33)	(-6.17)	(-5.68)	(-5.21)	(-7.80)	(-8.76)	(-8.22)

Panel B: Summary of monthly generalized DiD regression results, first livestream, with controls, with fund and year-month FE

	m-5	m-4	m-3	m-2	m-1	m	m+1	m+2	m+3	m+4	m+5	m(+1, +5)
Return												
First Stream$_m$	0.014	0.066	0.429***	0.602***	1.474***	0.869***	0.120	-0.179*	-0.060	-0.232*	-0.334***	-0.683***
	(0.10)	(0.46)	(3.57)	(5.15)	(10.40)	(6.49)	(0.99)	(-1.70)	(-0.61)	(-1.95)	(-2.75)	(-3.08)
DGTW Alpha												
First Stream$_m$	-0.146	0.100	0.321***	0.417***	0.982***	0.697***	0.123	-0.045	-0.034	-0.188**	-0.346***	-0.491**
	(-1.17)	(0.79)	(3.45)	(4.44)	(8.30)	(5.90)	(1.18)	(-0.43)	(-0.38)	(-2.03)	(-2.81)	(-2.26)
Carhart Alpha												
First Stream$_m$	-0.150	0.003	0.140	0.591***	1.150***	0.740***	0.244**	-0.127	-0.117	-0.316***	-0.245**	-0.562**
	(-1.25)	(0.02)	(1.20)	(5.47)	(8.94)	(5.71)	(2.41)	(-1.03)	(-1.19)	(-2.77)	(-2.51)	(-2.24)
China 3F Alpha												
First Stream$_m$	0.087	0.160	0.346***	0.636***	1.183***	0.829***	0.325***	-0.147	-0.170*	-0.312***	-0.354***	-0.659***
	(0.76)	(1.20)	(2.71)	(5.57)	(10.62)	(6.24)	(3.18)	(-1.44)	(-1.75)	(-2.73)	(-3.67)	(-3.14)

Panel C: Summary of monthly generalized DiD regression results, all livestreams, with controls, with fund and year-month FE

	m-5	m-4	m-3	m-2	m-1	m	m+1	m+2	m+3	m+4	m+5	m(+1, +5)
Return												
Livestream$_m$	0.544***	0.619***	0.669***	0.791***	1.008***	0.356***	-0.179***	-0.308***	-0.174***	-0.233***	-0.290***	-1.179***
	(9.10)	(11.02)	(10.88)	(13.09)	(12.35)	(6.08)	(-3.41)	(-6.55)	(-3.78)	(-4.53)	(-6.39)	(-7.56)
DGTW Alpha												
Livestream$_m$	0.322***	0.428***	0.479***	0.483***	0.646***	0.247***	-0.116**	-0.231***	-0.183***	-0.227***	-0.235***	-0.988***
	(6.25)	(8.52)	(8.02)	(10.10)	(10.26)	(5.40)	(-2.60)	(-5.74)	(-4.06)	(-5.52)	(-5.14)	(-7.61)
Carhart Alpha												
Livestream$_m$	0.457***	0.514***	0.630***	0.735***	0.803***	0.402***	-0.024	-0.192***	-0.136***	-0.259***	-0.255***	-0.863***
	(7.87)	(9.28)	(10.42)	(12.57)	(10.99)	(7.07)	(-0.48)	(-4.19)	(-2.75)	(-4.92)	(-5.99)	(-5.50)
China 3F Alpha												
Livestream$_m$	0.521***	0.550***	0.601***	0.716***	0.795***	0.420***	0.027	-0.148***	-0.139***	-0.207***	-0.209***	-0.674***
	(8.64)	(10.16)	(9.98)	(11.59)	(10.96)	(6.86)	(0.55)	(-3.32)	(-2.84)	(-3.89)	(-4.63)	(-4.09)

Table 7: Manager on livestream – topics

This table tabulates the topics of mutual fund livestreams separately for livestreams with and without manager attendance. ***, **, * indicates statistical significance at 1%, 5%, and 10%.

	% of Time in Livestream		
ChatGPT Summary of Topics	**Manager-Attending (a)**	**Manager-not-Attending (b)**	**Diff: (a)-(b)**
Emerging China Tech & Green Energy	14.44%	10.13%	4.31%***
Consumer & Healthcare Sector Growth	10.55%	7.00%	3.55%***
AI & Technology Investment Trends	10.18%	7.92%	2.26%***
Fund Investment Strategies & Portfolio Management	14.54%	13.29%	1.25%***
Stock Performance & Dividend Growth	6.62%	5.53%	1.09%***
Global Economic & Market Expectations	12.30%	13.07%	-0.77%***
Bond Market & Interest Rates	3.45%	5.45%	-2.00%***
Market Conditions & Investment Performance	16.61%	18.65%	-2.04%***
Fund Performance & Risk Management	6.85%	10.10%	-3.25%***
Investor Engagement & Support	4.47%	8.85%	-4.38%***

Table 8: Manager on livestream

This table examines the determinants and consequences of fund managers attending livestreams. Panel A displays the determinants of fund managers attending livestreams and its effect on fund flows. Columns (1) and (2) display the determinants of fund managers attending livestreams. Column (3) examines the effect of fund managers attending livestreams on fund flow. Column (3) also includes untabulated interaction terms of $Manager\_On_q \times Controls$. Period *t-1* controls are *m-1* for columns (1) and (2) and are *q-1* for column (3). Fixed effects, clustering, and other model details are listed at the bottom of each column. Panel B tabulates β_l coefficient estimates from model (4), which are generalized difference-in-difference regressions for all livestreams, similar to those in Table 6 Panel C, but including additional fund manager characteristics and the interaction terms of $Manager\_On_q \times Controls$. Controls are included but untabulated. The last column presents accumulated *m+1* to *m+5* coefficients. All variables are defined in Appendix D. All non-binary regressors are standardized. Standard errors are clustered by fund family. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Determinants of Manager_On and its effect on quarterly fund flows

	(1)	(2)	(3)
Dependent Variables:	$Manager\_On_m$		$Fund\ Flow_q$
$Livestream_q \times Manager\_On_q$			3.780**
			(2.31)
$Livestream_q$			7.999***
			(8.96)
$Recent\ Return_{t-1}$	0.021***	0.021***	7.001***
	(8.36)	(9.75)	(14.69)
$Top\ 5\ Return_{t-1}$	0.015***	0.011***	3.976***
	(4.23)	(4.15)	(5.59)
$Management\ Fee_{t-1}$	0.001	-0.004	-1.939**
	(0.40)	(-0.92)	(-2.49)
$Service\ Fees_{t-1}$	0.011***	0.006***	1.953***
	(4.12)	(2.97)	(4.05)
$Loads_{t-1}$	-0.006***	-0.001	-3.731
	(-5.90)	(-0.37)	(-1.62)
$Fund\ Size_{t-1}$	0.010***	0.012***	-27.780***
	(4.71)	(5.04)	(-27.65)
$Fund\ Age_{t-1}$	0.000	0.008**	-1.457*
	(0.14)	(2.31)	(-1.68)
$Disclosure_t$	0.013	0.014	-0.028
	(0.71)	(0.68)	(-0.03)
$Manager\ Experience_{t-1}$	-0.008***	-0.008***	-2.048***
	(-4.52)	(-5.03)	(-4.05)
$Highest\ Degree_{t-1}$	0.001	-0.003*	0.207
	(0.48)	(-1.89)	(0.41)
$Top\ 2\ University_{t-1}$	0.010***	0.006	1.123
	(2.93)	(1.33)	(0.98)
$Female_{t-1}$	-0.002	-0.001	-2.416**
	(-0.63)	(-0.21)	(-2.31)
$Manager\_On_q \times Controls$	N/A	N/A	Yes
Fund FE	No	Yes	Yes
Time FE	Yr-Month	Yr-Month	Yr-Qtr
Cluster	Fund Family	Fund Family	Fund Family
Sample	Fund-Yr-Month	Fund-Yr-Month	Fund-Yr-Quarter
# of Observations	147,151	147,151	50,867
Adjusted R-squared	0.024	0.101	0.178

Panel B: Summary of monthly generalized DiD regressions, all livestreams, with controls, with fund and year-month FE (same specification as Table 6 Panel C)

	m-5	m-4	m-3	m-2	m-1	m	m+1	m+2	m+3	m+4	m+5	m(+1, +5)
Return												
With Manager$_m$	0.489***	0.603***	0.612***	0.953***	1.676***	0.800***	-0.080	-0.354***	-0.339***	-0.299***	-0.298**	-1.363***
	(3.46)	(4.77)	(5.22)	(8.77)	(11.56)	(4.95)	(-0.68)	(-3.17)	(-2.64)	(-2.77)	(-2.05)	(-4.54)
Without Manager$_m$	0.538***	0.615***	0.635***	0.713***	0.731***	0.167***	-0.208***	-0.286***	-0.135***	-0.198***	-0.237***	-1.059***
	(7.70)	(9.45)	(7.90)	(10.09)	(8.41)	(2.79)	(-3.06)	(-5.48)	(-2.73)	(-3.19)	(-4.52)	(-5.65)
Difference							0.128	-0.068	-0.204	-0.101	-0.062	-0.304
							(0.98)	(-0.57)	(-1.51)	(-0.81)	(-0.39)	(-0.97)
DGTW Alpha												
With Manager$_m$	0.319**	0.456***	0.598***	0.654***	1.090***	0.552***	0.012	-0.236**	-0.281**	-0.224**	-0.184	-0.910***
	(2.58)	(3.90)	(5.92)	(6.19)	(8.94)	(4.50)	(0.12)	(-2.18)	(-2.25)	(-2.06)	(-1.42)	(-3.33)
Without Manager$_m$	0.279***	0.417***	0.374***	0.413***	0.472***	0.127**	-0.164***	-0.247***	-0.171***	-0.183***	-0.199***	-0.959***
	(4.63)	(7.20)	(5.07)	(7.37)	(7.13)	(2.50)	(-2.89)	(-5.63)	(-3.79)	(-3.67)	(-3.94)	(-6.17)
Difference							0.176	0.011	-0.110	-0.042	0.015	0.049
							(1.57)	(0.09)	(-0.86)	(-0.34)	(0.11)	(0.17)
Carhart Alpha												
With Manager$_m$	0.389***	0.559***	0.551***	0.946***	1.362***	0.732***	0.136	-0.172	-0.353***	-0.352***	-0.298**	-1.036***
	(2.87)	(4.30)	(4.68)	(7.86)	(10.28)	(4.95)	(1.11)	(-1.38)	(-2.62)	(-2.74)	(-2.38)	(-3.21)
Without Manager$_m$	0.460***	0.494***	0.576***	0.659***	0.589***	0.252***	-0.050	-0.186***	-0.071	-0.220***	-0.203***	-0.727***
	(6.82)	(7.63)	(7.86)	(9.64)	(7.48)	(4.46)	(-0.72)	(-3.58)	(-1.37)	(-4.06)	(-3.75)	(-3.89)
Difference							0.186	0.014	**-0.282***	-0.132	-0.095	-0.308
							(1.32)	(0.10)	**(-1.96)**	(-0.97)	(-0.68)	(-0.88)
China 3F Alpha												
With Manager$_m$	0.447***	0.637***	0.479***	0.888***	1.293***	0.745***	0.155	-0.155	-0.324***	-0.314**	-0.304**	-0.939***
	(3.58)	(5.67)	(4.27)	(7.56)	(10.95)	(4.95)	(1.23)	(-1.28)	(-2.89)	(-2.43)	(-2.48)	(-3.29)
Without Manager$_m$	0.493***	0.514***	0.570***	0.647***	0.597***	0.273***	-0.029	-0.164***	-0.069	-0.150**	-0.150***	-0.560***
	(6.78)	(7.69)	(7.42)	(8.97)	(7.12)	(4.76)	(-0.47)	(-2.94)	(-1.31)	(-2.58)	(-3.01)	(-2.88)
Difference							0.183	0.009	**-0.255****	-0.164	-0.153	-0.378
							(1.29)	(0.07)	**(-2.17)**	(-1.19)	(-1.24)	(-1.27)

Table 9: Persuasive features in livestreams

This table examines the effect of livestreams' persuasion features on fund flows and subsequent returns: *FirstHalf*, *High Verbal Sentiment*, *High Vocal Valence*, *High Vocal Arousal*, *High Vocal Sentiment*, *High Attractiveness*, and the aggregate *Persuasion* measure. Panel A displays the effect of persuasion on fund flows. All specifications include the same set of controls as in Table 8 Panel A column (3), as well as *Manager_On* and its interaction with controls, and the persuasive features' interactions with controls. Panel B tabulates accumulated returns in months [*m+1*, *m+5*] of livestreaming fund-months with high and low persuasion, and their differences, by using generalized DiD regressions similar to those in Table 8 Panel B, including *Manager_On* indicator and the interaction terms of $Manager\_On_q$ × *Controls* from Table 8 Panel A. All variables are defined in Appendix D. All non-binary regressors are standardized. Standard errors are clustered by fund family. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Effect on quarterly fund flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variables:	$Fund\ Flow_q$							
$Livestream_q$ × $First\ Half_q$	8.590***						6.544***	
	(7.48)						(6.23)	
$Livestream_q$ × $High\ Verbal\ Sentiment_q$		5.199***					2.599**	
		(4.12)					(2.12)	
$Livestream_q$ × $High\ Vocal\ Valence_q$			4.801***				0.750	
			(3.58)				(0.48)	
$Livestream_q$ × $High\ Vocal\ Arousal_q$				6.122***			2.091	
				(4.88)			(1.41)	
$Livestream_q$ × $High\ Vocal\ Sentiment_q$					6.233***		3.171**	
					(4.69)		(2.23)	
$Livestream_q$ × $High\ Attractiveness_q$						5.284***	2.504*	
						(3.67)	(1.83)	
$Livestream_q$ × $Persuasion_q$								15.619***
								(7.05)
$Livestream_q$	3.594***	6.438***	6.103***	6.654***	6.281***	6.589***	0.735	2.466***
	(3.96)	(7.38)	(6.97)	(7.60)	(7.45)	(7.49)	(0.81)	(2.89)
Controls from Table 8 Panel A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Manager\_On_q$ × *Controls*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PersuasionVar_q$ × *Controls*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family
Sample	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr
# of Observations	50,867	50,867	50,867	50,867	50,867	50,867	50,867	50,867
Adjusted R-squared	0.184	0.182	0.180	0.181	0.181	0.181	0.187	0.185

Panel B: Post-livestream accumulated returns (from m+1 to m+5) of high- and low- persuasion groups and their differences

Persuasion Variables:	*First Half*	*Verbal Sentiment*	*Vocal Valence*	*Vocal Arousal*	*Vocal Sentiment*	*Attractiveness*	*Persuasion*
Return							
High Persuasion$_m$	-1.326***	-1.299***	-1.233***	-1.313***	-1.369***	-1.349***	-1.535***
	(-6.14)	(-6.10)	(-5.38)	(-5.51)	(-5.78)	(-5.85)	(-5.96)
Low Persuasion$_m$	-0.673***	-0.859***	-0.908***	-0.854***	-0.809***	-0.802***	-0.769***
	(-3.17)	(-4.17)	(-4.46)	(-4.00)	(-4.22)	(-4.15)	(-4.07)
Difference	**-0.653*****	**-0.440****	-0.326	**-0.459***	**-0.560*****	**-0.546*****	**-0.766*****
	(-3.14)	**(-2.43)**	(-1.54)	**(-1.85)**	**(-2.78)**	**(-2.73)**	**(-3.48)**
DGTW Alpha							
High Persuasion$_m$	-1.101***	-1.131***	-1.105***	-1.214***	-1.179***	-1.278***	-1.332***
	(-6.09)	(-6.22)	(-5.61)	(-5.95)	(-6.12)	(-6.31)	(-6.16)
Low Persuasion$_m$	-0.758***	-0.819***	-0.836***	-0.755***	-0.786***	-0.678***	-0.735***
	(-4.33)	(-4.92)	(-5.22)	(-4.43)	(-4.73)	(-4.37)	(-4.90)
Difference	**-0.344***	**-0.312****	-0.269	**-0.458****	**-0.392****	**-0.600*****	**-0.597*****
	(-1.93)	**(-2.06)**	(-1.54)	**(-2.21)**	**(-2.22)**	**(-3.25)**	**(-3.34)**
Carhart Alpha							
High Persuasion$_m$	-0.979***	-0.965***	-0.944***	-0.990***	-1.035***	-1.005***	-1.212***
	(-4.63)	(-4.64)	(-4.10)	(-4.01)	(-4.35)	(-4.41)	(-4.58)
Low Persuasion$_m$	-0.352*	-0.521**	-0.530***	-0.507**	-0.472**	-0.473**	-0.425**
	(-1.70)	(-2.48)	(-2.59)	(-2.48)	(-2.36)	(-2.50)	(-2.23)
Difference	**-0.626*****	**-0.444****	**-0.414***	**-0.483***	**-0.563****	**-0.531*****	**-0.788*****
	(-3.24)	**(-2.40)**	**(-1.89)**	**(-1.91)**	**(-2.49)**	**(-2.86)**	**(-3.23)**
China 3F Alpha							
High Persuasion$_m$	-0.679***	-0.715***	-0.702***	-0.738***	-0.750***	-0.816***	-0.844***
	(-3.15)	(-3.21)	(-2.96)	(-2.84)	(-3.06)	(-3.51)	(-3.15)
Low Persuasion$_m$	-0.380*	-0.424*	-0.430**	-0.409*	-0.401*	-0.324	-0.381*
	(-1.78)	(-1.90)	(-2.01)	(-1.89)	(-1.91)	(-1.55)	(-1.90)
Difference	-0.299	-0.291	-0.272	-0.329	-0.349	**-0.492****	**-0.463***
	(-1.64)	(-1.34)	(-1.21)	(-1.22)	(-1.50)	**(-2.37)**	**(-1.90)**

Table 10: Livestreaming and cross-sectional differences in search costs

This table investigates the effect of livestreaming on fund flows conditional on search costs. The dependent variable is quarterly fund flow. Proxies for search costs include *Star, Large, Old,* and *Experienced.* All columns include untabulated interaction terms of *Search Cost Proxies*$_{q-1}$ × *Controls*. Fixed effects, clustering, and other model details are listed at the bottom of each column. All variables are defined in Appendix D. All non-binary regressors are standardized. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	*Fund Flow*$_q$			
Livestream$_q$	11.008***	13.008***	11.438***	11.563***
	(14.83)	(14.82)	(13.84)	(14.67)
Livestream$_q$ × *Star*$_{q-1}$	-9.149***			
	(-5.85)			
Livestream$_q$ × *Large*$_{q-1}$		-9.110***		
		(-8.12)		
Livestream$_q$ × *Old*$_{q-1}$			-4.536***	
			(-3.81)	
Livestream$_q$ × *Experienced*$_{q-1}$				-6.590***
				(-4.49)
Star$_{q-1}$	6.464**			
	(2.27)			
Large$_{q-1}$		9.362***		
		(4.17)		
Old$_{q-1}$			17.039***	
			(3.44)	
Experienced$_{q-1}$				1.445
				(0.52)
Recent Return$_{q-1}$	7.510***	7.540***	7.586***	7.554***
	(17.14)	(15.58)	(17.48)	(16.92)
Top 5 Return$_{q-1}$	4.423***	4.824***	4.907***	4.387***
	(6.69)	(6.39)	(6.78)	(6.73)
Management Fee$_{q-1}$	-2.017**	-2.048**	-2.011**	-1.802**
	(-2.53)	(-2.58)	(-2.55)	(-2.23)
Service Fees$_{q-1}$	2.069***	2.199***	2.013***	1.871***
	(4.09)	(4.19)	(3.73)	(3.64)
Loads$_{q-1}$	-3.852*	-4.268*	-3.114	-3.565
	(-1.68)	(-1.77)	(-1.25)	(-1.51)
Fund Size$_{q-1}$	-29.077***	-27.681***	-29.204***	-29.189***
	(-27.75)	(-23.35)	(-27.01)	(-27.44)
Fund Age$_{q-1}$	-1.295	-0.945	-2.475**	-1.133
	(-1.44)	(-0.99)	(-2.53)	(-1.23)
Disclosure$_q$	0.116	0.213	0.369	0.086
	(0.12)	(0.22)	(0.38)	(0.09)
Manager Experience$_{q-1}$				-1.980***
				(-3.76)
Search Cost Proxies$_{q-1}$ × *Controls*	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Yr-Qtr FE	Yes	Yes	Yes	Yes
Cluster	Fund Family	Fund Family	Fund Family	Fund Family
Sample	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr
# of Observations	50,867	50,867	50,867	50,867
Adjusted R-squared	0.172	0.174	0.172	0.173

Supplementary Materials to

Social Media Livestreaming: Investor Information or Persuasion?

These Supplementary Materials contain additional discussion and analyses referenced in the main paper.

S1. Intraday placebo test

Our intraday DiD analyses in Table 4 Panel C find that livestreaming fund-classes are significantly more likely to become *Hot* after a livestream starts, relative to the contemporaneous change in *Hot* for the non-livestreaming class of the same fund. It is conceivable that differences between the livestreaming and non-livestreaming classes could cause intraday differences in *Hot* even in the absence of a livestream, in which case the parallel trends assumption would be violated.

The analyses in this section assess the probability that the DiD estimate in Table 4 Panel C could exist even in the absence of a livestream. We do so by constructing the null distribution of DiD estimates on non-livestreaming days, and then examine where our actual DiD estimate falls within the null distribution. Our procedures are as follows:

(1) We start with a sample including all non-livestreaming fund-days during Dec 2, 2024 – Mar 31, 2025 for funds in our intraday analysis in Table 4 Panel C. These are our "placebo" days on which neither class of a fund has a livestream. The dependent variable, *Hot*, is each fund-class's actual values on the placebo day. For each placebo day, we then assign the *Class in Cart* and *Post* variables using the date and time of the fund's next actual livestream day. For example, if the placebo date is December 2 and the next livestream occurs on December 4, then the *Hot* values are from December 2 and the *Class in Cart* and *Post* variables are from December 4. If no later livestream day exists, we use the most recent one. Following these procedures produces a placebo sample of 25,506 fund-days, resulting in 25,506 × 2 = 51,012 fund-class-days and 1,369,768 total observations.

(2) From the placebo sample in step (1), we randomly select approximately the same number of observations as in the actual livestream sample. This selection is done at the fund-day level to ensure that all corresponding class-level observations are retained. We select 4,455 fund-days, resulting in 4,455 × 2 = 8,910 fund-class-days, same as the actual sample. Fund-day selection is done without replacement.

(3) We run regression (3) using the placebo data and save the coefficient on *Class in Cart* × *Post* as $\beta_{1\_placebo}$.

(4) Steps (2) and (3) are repeated a total of 999 times, drawing new random placebo sample each iteration.

(5) We calculate the exact *p*-value as the proportion of simulations for which $\beta_{1\_placebo} \geq \beta_{1\_actual}$.

Table 4 Panel D plots the distribution of $\beta_{1\_placebo}$ from the 999 simulations. The coefficients center around 0.002, compared to the actual coefficient of 0.011. Table S1 reports that all placebo coefficients are smaller than the actual estimate ($p < 0.001$). These results indicate that there is a less than 1 in 1,000 chances of observing the intraday DiD increase in flows in Table 4 Panel C on days that a livestream does not occur.

S2. Fund flows: propensity-score matching

This section investigates the robustness of our quarterly fund flow regressions, presented in Table 4 Panel A in the paper.

To further address concerns about selection bias and improve covariate balance between treated and control funds, we implement a propensity score matched (PSM) DiD design. This approach allows us to construct a more comparable control group by matching treated and control funds based on observable fund characteristics prior to the first livestream event. Treated funds are defined as those that ever livestream during the sample period. Using a one-to-one propensity score matching procedure (with replacement and a caliper of 0.01), we match each treated fund in the quarter immediately preceding its first livestream to a control fund based on all fund controls (measured at the beginning of that quarter, except for *Disclosure* which is contemporaneous). If no suitable control is found in that exact quarter, we match to the closest earlier quarter with available data.

Table S2 Panel A presents post-matching covariate balance statistics at the matched fund-quarter level, confirming that most covariates are well balanced. Panel B reports the results of a generalized DiD regression of quarterly fund flows using the matched sample. We find extremely similar results as our main specification. For example, our main test of whether livestreams increase fund flows finds a coefficient of 10.649 (t = 14.45) in Table 4 Panel A column (2) and 11.362 (t = 13.81) in our PSM-DiD.

S3. Fund flows: entropy-balancing

This section investigates the robustness of our quarterly fund flow regressions, presented in Table 4 Panel A in the paper.

To further address potential concerns about selection bias and covariate imbalance, we implement entropy balancing as an additional test. Although Section S2 employs PSM to construct a comparable control group, recent studies suggest that entropy balancing may offer a more precise approach to achieving covariate balance (e.g., Hainmueller 2012; Boland & Godsell 2020; Cazier et al. 2020; McMullin & Schonberger 2020; Baik et al. 2024).

We present the results in Table S3. Panel A reports covariate balance after applying entropy balancing on the first two moments of the covariate distributions. The results confirm that the procedure achieves a successful balance between the treatment and control groups. Panel B presents the results of a generalized DiD regression of quarterly fund flows using the entropy-balanced sample. The estimates are highly consistent with our main specification: our primary test of whether livestreaming increases fund flows yields a coefficient of 10.649 (t = 14.45) in Table 4 Panel A column (2), and 11.112 (t = 14.62) in the entropy-balanced DiD specification.

S4. First differences regression of livestream on fund flows

This section investigates the robustness of our quarterly fund flow regressions, presented in Table 4 Panel A in the paper.

We examine the dynamic patterns in flows by regressing the change in flows (Δ*Fund Flow*) on indicators for whether the fund starts or stops livestreaming (Δ*Livestream* = +1 and −1). First-differences eliminate all fund characteristics that are unchanged between two consecutive quarters. Results in Table S4 show a sharp increase in flows when funds start livestreaming (coefficient = 9.929; t = 10.54) and a decline in flows in the first quarter that they stop livestreaming (coefficient = -1.670; t = -2.12).

S5. Construction of verbal, vocal, and visual persuasion measures

S5.1. Verbal sentiment

We calculate the verbal sentiment of livestreams by aggregating sentence-level sentiment. Each livestream transcript is segmented into sentences, which are then analyzed using Chinese FinBERT, a large language model specialized in classifying sentiment of financial discourse in Chinese (Huang, Wang, & Yang 2023).[44] This model is built upon Google's Chinese BERT base model and fine-tuned on a dataset of approximately 8,000 Chinese analyst report sentences with researcher-labeled sentiment.

The model outputs the probabilities of the sentence being positive, negative, and neutral. We classify each sentence into the one with the highest probability. As shown in Table S5 Panel A of the Supplementary Materials, 6% of the 21,734,488 sentences in our sample are classified as positive, while 3% are classified as negative.

We define the livestream-level sentiment, *Verbal Sentiment*, as the difference between the number of positive and negative sentences, scaled by one plus the sum of these two counts. Table S5 Panel A provides the summary statistics of verbal sentiment at the livestream level. This measure, bounded between -1 and 1, has a mean value of 0.36, indicating that livestreams are generally positive.

S5.2. Vocal persuasiveness

We assess the vocal persuasiveness of livestreams across three dimensions: valence, arousal, and vocal sentiment. Valence captures vocal emotional positivity, ranging from negative emotions (e.g., sadness, anger) to positive emotions (e.g., happiness, contentment). Arousal represents the intensity of emotions, spanning calm or low arousal states (e.g., relaxed, subdued) to excited or high arousal states (e.g., energetic, agitated). Vocal sentiment measures emotional positivity, from sadness to happiness (Frijda, 1986; Goudbeek & Scherer, 2010). Following Hu & Ma (2025), we use two python packages to predict vocal traits. First, we employ the pre-trained models in

[44] Available at https://huggingface.co/yiyanghkust/finbert-tone-chinese

pyAudioAnalysis to estimate valence and arousal scores for individual audio segments.[45] Second, we utilize the pre-trained models in *speechemotionrecognition* to predict the probabilities of vocal happiness and sadness for each audio segments.[46]

Because vocal analysis algorithms are trained using short audio segments, we follow the *pyAudioAnalysis* developer's recommendation to split livestream audios by sentence and retain only the first ten seconds of each sentence (Giannakopoulos 2015). For each livestream, the audio is segmented based on the start and end timestamps of sentences transcribed by *Faster Whisper* (as discussed in footnote 19 of the main paper). Due to computational constraints, we analyze one sentence per minute, selecting only the first sentence after each minute mark.[47] *pyAudioAnalysis* predicts valence and arousal scores for each sentence, which we average across the entire livestream to create livestream-level *Vocal Valence* and *Vocal Arousal* measures.

We further label a sentence as *Vocal Happy* if its happiness probability exceeds that of sadness and other emotions (including neutral and angry), and as *Vocal Sad* if its sadness probability exceeds that of happiness and other emotions, with all probabilities generated by *speechemotionrecognition*. Livestream-level *Vocal Sentiment* is defined similarly to *Verbal Sentiment*: the difference between its number of *Vocal Happy* and *Vocal Sad* sentences, scaled by one plus the sum of the two counts.

Table S5 Panel A summarizes vocal traits at sentence level. Among the sentences, 32% are classified as *Vocal Happy*, while only 7% are labeled as *Vocal Sad*. On average, sentences last 5.21 seconds. At the livestream level, the average *Vocal Valence* and *Vocal Arousal* scores are positive but lower than those reported in Hu & Ma (2025)'s start-up pitch sample, suggesting that livestreams are generally pleasant and desirable but less positive and passionate than fundraisers' energetic pitches.

S5.3. Facial attractiveness

We measure the facial attractiveness of a livestream's participants by capturing screenshots every five minutes, detecting faces from the screenshots, predicting their attractiveness, and then calculating the average attractiveness across all faces in all screenshots.

Specifically, we first use the *cv2* package in Python to take screenshots of the livestream based on their URL. Next, we use the *dlib* package in Python to detect and crop face images from each screenshot, resulting in 437,706 face images from 275,155 screenshots in 26,103 livestreams in our sample. On average, each livestream contains 17 faces.

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[45] *pyAudioAnalysis* predicts valence and arousal using 34 basic audio features extracted from audio segments, including short-term energy, zero-crossing rate, and spectral features (Giannakopoulos 2015). The package is available at https://github.com/tyiannak/pyAudioAnalysis.

[46] *speechemotionrecognition* predicts vocal emotions using Mel Frequency Cepstral Coefficients extracted from audio segments. The package is available at https://github.com/hkveeranki/speech-emotion-recognition.

[47] Using 500 randomly selected livestreams, we verify that our sampling technique produces measures that are highly correlated with the livestream-level vocal measures using all sentences (correlations of 0.995, 0.997, 0.977 & 0.959 for *Valence*, *Arousal*, *Happy* & *Sad* respectively).

To predict facial attractiveness for each photo, we use a deep-learning model trained based on the SCUT-FBP5500 dataset constructed by Liang et al. (2018).[48] The dataset includes 5,500 frontal face images, comprising 2,000 Asian females, 2,000 Asian males, 750 Caucasian females and 750 Caucasian males, with ages ranging from 15 to 60. Each image is rated for attractiveness on a scale from one to five by 60 raters aged 18-27, with five indicating the highest attractiveness. We select this dataset because it contains a large number of Asian faces and the attractiveness is rated by Asians, aligning closely with our livestream setting.

We compare the performance of three deep learning models used in Liang et al. (2018), including AlexNet, ResNet-18, and ResNeXt-50, on SCUT-FBP5500 dataset using 10-fold cross-validation. The dataset is split evenly into ten subsets, with nine used for training and the remaining one for testing, repeated 10 times with different testing sets. The best-performing model is ResNeXt-50, a convolutional neural network developed by Xie et al. (2017) that uses grouped convolutions and cardinality to enhance accuracy and efficiency. The model achieves strong predictive performance in the testing sample, with an average Pearson correlation coefficient of 0.91, an average maximum absolute error of 0.22, and an average root mean squared error of 0.29.

Next, we apply the trained ResNeXt-50 model to our livestream sample. To ensure consistency with the SCUT-FBP5500 training dataset, we standardize the cropping of face images. Specifically, for each image, the vertical direction is divided as follows: the middle region, spanning from the eye landmarks to the mouth landmark center, accounts for 35% of the vertical height; the bottom region represents 35%; and the top region covers the remaining 30%. Table S5 Panel A presents the attractiveness score distribution of images in our sample. Finally, we calculate a livestream-level *Attractiveness* measure by averaging the attractiveness scores of all detected faces within each livestream.

Table S5 Panel B shows that *Vocal Valence*, *Vocal Arousal*, and *Vocal Sentiment* are strongly and positively correlated at the livestream level. *Attractiveness* exhibits modest positive correlation with *Vocal Valence*, *Vocal Arousal*, and *Vocal Sentiment*, suggesting that higher facial attractiveness may be associated with more positive and intense vocal expressions during livestreams. In contrast, *Verbal Sentiment* demonstrates weak positive correlations with *Vocal Valence* and *Vocal Arousal*, and insignificant correlations with *Vocal Sentiment* and *Attractiveness*, suggesting that lexical sentiment and vocal/facial expressions capture distinct emotional dimensions in livestreams.

S6. Determinants of persuasion

We examine the determinants of persuasion to understand which fund and manager characteristics predict more persuasive livestream content. Livestreams often employ persuasive tactics as a form of impression management to influence investor perception, especially when advertised funds compete for flows in retail-oriented channels. Prior studies show that investors respond to persuasive cues, even when such cues fail to predict superior performance (Breuer et al. 2023; Hu

[48] The SCUT-FBP5500 dataset is available at https://github.com/HCIILAB/SCUT-FBP5500-Database-Release.

& Ma 2025). For instance, Breuer et al. (2023) find that charismatic delivery enhances analyst recommendations and market reactions but does not correlate with future firm performance. Similarly, Hu & Ma (2025) demonstrate that persuasive delivery across visual, vocal, and verbal dimensions increases the likelihood of funding, although these firms do not subsequently perform better.

We examine six binary indicators capturing different dimensions of persuasion (*First Half*, *High Verbal Sentiment*, *High Vocal Valence*, *High Vocal Arousal*, *High Vocal Sentiment*, and *High Attractiveness*), as well as a composite measure, *Persuasion*, that aggregates these elements. Table S6 presents the results, which are largely consistent across all columns. We find that funds with stronger recent performance (*Recent Return* and *Top 5 Return*) are more likely to employ persuasive tactics, supporting the idea that good news is expressed more positively due to increased confidence. For example, Baik et al. (2024) show that vocal delivery quality improves when conveying positive news but deteriorates for negative news.

Funds with higher service fees (*Service Fees*) are also more likely to use persuasive techniques, aligning with the notion that high-service funds invest more heavily in marketing. Additionally, we find that fund size (*Fund Size*) and age (*Fund Age*) are positively associated with persuasion, likely reflecting greater resources for speaker preparation, more experience in communicating with investors, or deliberate efforts to enhance presentation quality. At the manager level, there is some evidence that managers from more prestigious universities (*Top2 University*) are less reliant on persuasive tactics, potentially emphasizing their credibility over delivery. Overall, our results suggest that both fund-level characteristics and manager attributes shape the extent to which persuasion is used in livestreams.

S7. Robustness of persuasion-related flow and return tests

This section evaluates the robustness of our persuasion-related flow and return tests, as shown in Table 9 Panels A and B in the paper. Persuasive features are correlated with livestreaming frequency, which aligns with the expectation that a fund's *persuasive* strategy includes hosting both more frequent and more persuasive livestreams. To isolate the incremental effect of persuasive features, these tests control for livestreaming frequency. However, this approach is conservative, as it likely over-controls for the effect of interest. The results of these robustness tests are presented in Table S7.

The robustness flows tests include fixed effects for the number of livestreams in the fund-quarter. The *Livestream* indicator in Table 9 Panel A is omitted due to collinearity, but all other controls and interaction terms remain unchanged. Results in columns (1) - (6) of Table S7 Panel A show that four of the six persuasion measures continue to have a significantly positive effect on fund flows when tested individually. Column (7) shows that when all six variables are included in the same specification, only the coefficient for *First Half* remains significant. However, an untabulated test confirms that the six measures are jointly significant at the 1% level. When combined into a single *Persuasion* measure, column (8) finds a positive and significant coefficient. These results indicate that the frequency of livestreaming does not drive the effect of persuasion on fund flows.

The robustness returns tests mirror those in Table 9 Panel B, with an added control for *Log*(*1 + NumLivestreams*).[49] Consistent with our main findings, Table S7 Panel B shows that post-livestream returns are not higher for livestreams with persuasive features. Instead, post-livestream returns are nominally negative in almost all specifications. For the combined *Persuasion* measure, post-livestream returns are significantly more negative in one of the four specifications.

S8. Stacked-cohort difference-in-differences regressions

Baker et al. (2022) and Barrios (2022) summarize the literature on concerns about heterogeneous effects in DiD models. An important consideration in our setting is that we do not have a standard staggered DiD, in which cohorts of firms switch from untreated to permanently treated on different dates. Instead, a given fund in our setting can switch back-and-forth between livestreaming and not livestreaming each month.

From the perspective of biases in staggered DiD models, the fact that funds switch back-and-forth between treated and untreated conditions has two advantages. First, one of the main concerns in staggered DiD models is that treatment effects for a given firm can continue to increase over time (so called "dynamic" effects). If so, when an early treatment cohort serves as a control for a later treatment cohort, it is a "bad control" and can flip the estimated treatment effect for the later treatment cohort. In our setting, funds do not stay treated forever and there are not compelling reasons to think that livestream treatment effects increase in future months when livestreams do not occur, so dynamic effects are unlikely to be a major confound. Second, the other main concern in staggered DiD is that different cohorts have different treatment effect sizes, but the single DiD estimator is the variance-weighted average of the cohorts' 2×2 DiD estimates. Thus, the single DiD estimator can be biased towards certain cohorts, especially when some cohorts are bigger than others or have greater treatment variance. In our setting, funds frequently switch between livestreaming and not livestreaming, creating some amount of quasi-randomness across treatment cohorts that should mitigate concerns about especially influential cohorts.

Nevertheless, to validate the robustness of our main flow and returns results, we first re-estimate the effects of livestreaming using a stacked-cohort difference-in-differences (DiD) design. This approach allows us to isolate treatment effects across multiple event cohorts while controlling for cohort-specific unit and time heterogeneity. Table S8 Panel A presents the stacked DiD model corresponding to Table 4 Panel A column (2). For each treatment cohort, we define two event windows: [-1,0] in column (1) and [-2,0] in column (2). In column (1), treated funds are those that livestream in quarter *q* but did not livestream in quarter *q-1*, while control funds are those that did not livestream in either quarter *q-1* or *q*. In column (2), treated funds are those that livestream in quarter *q* and did not livestream in quarters *q-2* or *q-1*, while controls are funds with no livestreams in quarters *q-2* through *q*. Both specifications include fund-cohort and year-quarter-cohort fixed effects. We find extremely similar results as our main specification. For example, our main test of

[49] Fixed effects for the frequency of livestream would absorb the *Livestream* × *Low* groups in the returns test, preventing the testing of coefficient differences. Therefore, we control for the logged number of livestreams instead of using fixed effects.

whether livestreams increase fund flows finds a coefficient of 10.649 (t = 14.45) in our generalized DiD model and 11.933 (t = 14.07) in a stacked-cohort DiD.

Table S8 Panel B implements a stacked-cohort DiD for fund returns, corresponding to Table 6 Panel C. The event window spans months [-5,5], with treated funds defined as those that livestream in month *m* without any livestreams in *m-5* to *m-1*. Control funds are those that do not livestream at any point in the event window. The specification includes fund-cohort and year-month-cohort fixed effects. We again find very similar results as our main specification. In fact, our stacked-cohort DiD results show more consistently negative and significant coefficients across all post-livestream months in all four returns measures, compared to the results in Table 6 Panel C. In addition, our results are robust to using event windows of months [-3,3] and months [-1,1]. Importantly, all flow and returns results remain robust when we cluster standard errors at the fund family level, rather than at the fund-family-cohort level used in the specifications in Table S8.

Table S1: Intraday placebo tests

This table presents 999 simulations for non-livestreaming placebo dates for the intraday flow test, presented in column (2) of Table 4 Panel C in the paper. Specifically, for each fund in the intraday test sample, we assemble a dataset of all of its non-livestreaming dates to be used as placebo dates. The *Hot* variable is defined as the hot fund status of that placebo date, and *Class in Cart* and *Post* variables are defined based on the fund's next actual livestream date and time. If there are no later livestream day, we use the most recent prior one. Then from all non-livestreaming placebo fund-days, we randomly select 4,455 fund-days, the same number of fund-days as in the actual livestream sample. We run the specification in column (2) of Table 4 Panel C and save the coefficient on *Class in Cart* × *Post.* The procedure is repeated 999 times. Below presents distributional statistics of the placebo test coefficients and results of a non-parametric Fisher *p*-value, calculated as the ratio of more extreme occurrences to number of tests. *** indicates statistical significance at 1%.

	N	**Mean**	**Median**	**75%**	**95%**	**99%**	**Fisher *p*-value**
Coefficients from Placebo Tests	999	0.002	0.002	0.003	0.005	0.006	<0.001***

Table S2: Fund flows – propensity-score matched (PSM) DiD results

This table presents a propensity-score matched generalized difference-in-differences results for Table 4 Panel A column (2) to investigate the effects of livestreaming on fund flows. Treated funds are identified as those that ever livestream in our sample. Using the propensity-score matching procedure, for each treated fund in the quarter before its first livestream, we match one control fund based on all fund controls as of the beginning of that quarter, with replacement and using a caliper of 0.01. If we cannot find a suitable control fund in that quarter, we match a control fund in the closest available quarter before that. Panel A displays the post-PSM balance statistics at the matched fund-quarter level. Panel B displays the propensity-score matched generalized difference-in-difference regression of quarterly fund flows. Fixed effects, clustering, and other model details are listed at the bottom of each column. All variables are defined in Appendix D of the main paper. All non-binary regressors are standardized. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Covariate balance after propensity score matching (Matched sample, with replacement)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	N (Total)	N (Treated)	N (Control)	Mean (Treated)	Mean (Control)	(5) – (6) Difference	*t*-Test Difference *p*-value
Recent Return$_{q-1}$	3,744	1,872	1,872	8.710	7.910	0.800	0.177
Top 5 Return$_{q-1}$	3,744	1,872	1,872	0.270	0.245	0.025**	0.048
Management Fee$_{q-1}$	3,744	1,872	1,872	0.348	0.346	0.002	0.382
Service Fees$_{q-1}$	3,744	1,872	1,872	0.202	0.198	0.004**	0.018
Loads$_{q-1}$	3,744	1,872	1,872	0.028	0.030	-0.002*	0.082
Fund Size$_{q-1}$	3,744	1,872	1,872	17.728	17.798	-0.070	0.181
Fund Age$_{q-1}$	3,744	1,872	1,872	1.672	1.706	-0.034	0.105
Disclosure$_{q}$	3,744	1,872	1,872	1.512	1.511	0.001	0.948

Panel B: Propensity-score matched generalized difference-in-differences regression of quarterly fund flows

	(1)
Dependent Variable:	*Fund Flow*$_q$
Livestream$_q$	11.362***
	(13.81)
Recent Return$_{q-1}$	7.703***
	(13.50)
Top 5 Return$_{q-1}$	3.663***
	(3.55)
Management Fee$_{q-1}$	-1.581
	(-1.49)
Service Fees$_{q-1}$	1.477***
	(2.75)
Loads$_{q-1}$	-4.521*
	(-1.73)
Fund Size$_{q-1}$	-27.576***
	(-20.48)
Fund Age$_{q-1}$	-1.795*
	(-1.93)
Disclosure$_q$	-1.273
	(-0.80)
Fund FE	Yes
Yr-Qtr FE	Yes
Cluster	Fund Family
Sample	Fund-Yr-Qtr
# of Observations	57,721
Adjusted R-squared	0.181

Table S3: Fund flows – entropy-balanced DiD regression

This table presents an entropy-balanced generalized difference-in-differences results for Table 4 Panel A column (2) to investigate the effects of livestreaming on fund flows. Covariate balance is enforced using two moments, ensuring exact balance across all fund control variables. Panel A reports the post-entropy balancing statistics. Panel B presents the entropy-balanced generalized difference-in-differences regression of quarterly fund flows. Fixed effects, clustering, and other model details are listed at the bottom of each column. All variables are defined in Appendix D of the main paper. All non-binary regressors are standardized. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Covariate balance after entropy balancing (2 moments)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	N (Total)	N (Treated)	N (Control)	Mean (Treated)	Mean (Control)	(5) – (6) Difference	*t*-Test Difference *p*-value
Recent Return$_{q-1}$	50,867	34,538	16,329	2.010	2.009	0.001	0.992
Top 5 Return$_{q-1}$	50,867	34,538	16,329	0.224	0.224	0.000	0.998
Management Fee$_{q-1}$	50,867	34,538	16,329	0.336	0.336	0.000	0.998
Service Fees$_{q-1}$	50,867	34,538	16,329	0.202	0.202	0.000	0.973
Loads$_{q-1}$	50,867	34,538	16,329	0.027	0.027	0.000	0.999
Fund Size$_{q-1}$	50,867	34,538	16,329	17.962	17.962	0.000	0.999
Fund Age$_{q-1}$	50,867	34,538	16,329	1.855	1.855	0.000	0.962
Disclosure$_{q}$	50,867	34,538	16,329	1.502	1.502	0.000	0.999

Panel B: Entropy-balanced generalized difference-in-differences regression of quarterly fund flows

	(1)
Dependent Variable:	*Fund Flow$_q$*
Livestream$_q$	11.112***
	(14.62)
Recent Return$_{q-1}$	7.175***
	(13.92)
Top 5 Return$_{q-1}$	3.063***
	(4.37)
Management Fee$_{q-1}$	-1.786**
	(-2.07)
Service Fees$_{q-1}$	1.667***
	(3.27)
Loads$_{q-1}$	-4.262*
	(-1.78)
Fund Size$_{q-1}$	-29.115***
	(-24.07)
Fund Age$_{q-1}$	-1.168
	(-1.20)
Disclosure$_q$	-0.168
	(-0.17)
Fund FE	Yes
Yr-Qtr FE	Yes
Cluster	Fund Family
Sample	Fund-Yr-Qtr
# of Observations	50,867
Adjusted R-squared	0.176

Table S4: Fund flows – first differences

This table investigates the effects of starting and stopping livestreaming, on fund flows. $\Delta Livestream_q = +1$ measures when the fund livestreams in the current quarter and did not livestream in the previous quarter. $\Delta Livestream_q = -1$ measures when the fund does not livestream in the current quarter and livestreamed in the previous quarter. Fixed effects, clustering, and other model details are listed at the bottom of each column. All variables are defined in Appendix D and Appendix SA. All non-binary regressors are standardized. ***, ** indicates statistical significance at 1% and 5%, respectively.

	(1)
Dependent Variable:	$\Delta Fund\ Flow_q$
$\Delta Livestream_q = +1$	9.929***
	(10.54)
$\Delta Livestream_q = -1$	-1.670**
	(-2.12)
$Recent\ Return_{q-1}$	-4.965***
	(-10.07)
$Top\ 5\ Return_{q-1}$	-1.824***
	(-3.06)
$Management\ Fee_{q-1}$	0.990***
	(5.71)
$Service\ Fees_{q-1}$	-2.120***
	(-13.01)
$Loads_{q-1}$	0.727***
	(4.46)
$Fund\ Size_{q-1}$	-5.636***
	(-20.50)
$Fund\ Age_{q-1}$	0.280**
	(2.18)
$Disclosure_q$	4.272**
	(2.21)
Fund FE	No
Yr-Qtr FE	Yes
Cluster	Fund Family
Sample	Fund-Yr-Qtr
# of Observations	46,764
Adjusted R-squared	0.045

Table S5: Summary of verbal, vocal, and visual statistics

This table presents statistics of verbal, vocal, and visual traits for 26,103 livestreams in our sample from 2020Q2 to 2024Q4. Panel A summarizes the statistics of traits measured at sentence level, image level, and livestream level. Verbal sentiment elements (*Positive*, *Negative*) are identified at the sentence level across all sentences in livestreams. Vocal traits (*Length*, *Vocal Valence*, *Vocal Arousal, Vocal Happy, Vocal Sad*) are measured for the first sentence per minute due to computational constraints. Visual trait (*Attractiveness*) is predicted for images cropped from screenshots taken every five minutes during livestreams. Verbal, vocal, and visual traits (*Verbal Sentiment*, *Vocal Valence*, *Vocal Arousal*, *Vocal Sentiment*, *Attractiveness*) are then aggregated at the livestream level. Panel B shows the correlations among livestream-level variables. All variables are defined in Appendix SA. ***, ** indicates statistical significance at 1% and 5%, respectively.

Panel A: Summary of statistics

Variables	**N**	**Mean**	**SD**	**25%**	**Median**	**75%**
Verbal sentiment, measured at sentence level (for all sentences)						
Positive	21,734,488	0.06	0.24	0	0	0
Negative	21,734,488	0.03	0.17	0	0	0
Vocal traits, measured at sentence level (for the first sentence per minute)						
Length (seconds)	1,367,082	5.21	3.70	2.00	3.16	10.00
Vocal Valence	1,367,082	0.19	0.60	-0.14	0.21	0.54
Vocal Arousal	1,367,082	0.35	0.32	0.16	0.37	0.57
Vocal Happy	1,367,082	0.32	0.47	0	0	1
Vocal Sad	1,367,082	0.07	0.26	0	0	0
Visual trait, measured at image level						
Attractiveness	437,706	3.34	0.35	1.60	3.37	3.59
Verbal, vocal, & visual traits, measured at livestream level						
Verbal Sentiment	26,103	0.36	0.27	0.19	0.38	0.55
Vocal Valence	26,103	0.19	0.33	0.00	0.21	0.41
Vocal Arousal	26,103	0.35	0.24	0.20	0.36	0.51
Vocal Sentiment	26,103	0.55	0.47	0.31	0.74	0.91
Attractiveness	26,103	3.34	0.26	3.18	3.36	3.51

Panel B: Correlation table (livestream level)

	Verbal Sentiment	*Vocal Valence*	*Vocal Arousal*	*Vocal Sentiment*	*Attractiveness*
Verbal Sentiment	1				
Vocal Valence	0.071***	1			
Vocal Arousal	0.014**	0.640***	1		
Vocal Sentiment	0.008	0.490***	0.635***	1	
Attractiveness	-0.005	0.131***	0.133***	0.142***	1

Table S6: Determinants of livestream persuasive features

This table presents the determinants of persuasive features in livestreams. Columns (1) – (6) present the determinants of the individual binary persuasion measures. Column (7) presents the determinants of the combined *Persuasion* measure, which is scaled to be between zero and one. Fixed effects, clustering, and other model details are listed at the bottom of each column. All variables are defined in Appendix D. All non-binary regressors are standardized. *t*-statistics are presented in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variables:	*First Half$_m$*	*High Verbal Sentiment$_m$*	*High Vocal Valence$_m$*	*High Vocal Arousal$_m$*	*High Vocal Sentiment$_m$*	*High Attractiveness$_m$*	*Persuasion$_m$*
Recent Return$_{m-1}$	0.025***	0.019***	0.015***	0.014***	0.013***	0.017***	0.017***
	(7.74)	(6.56)	(4.47)	(4.61)	(4.18)	(4.71)	(5.93)
Top 5 Return$_{m-1}$	0.031***	0.015***	0.017***	0.015***	0.015***	0.015***	0.018***
	(7.05)	(3.79)	(4.40)	(3.67)	(4.48)	(3.72)	(5.22)
Management Fee$_{m-1}$	0.004	0.004	0.005	-0.001	0.006	0.003	0.004
	(0.57)	(0.59)	(0.63)	(-0.11)	(0.79)	(0.39)	(0.53)
Service Fees$_{m-1}$	0.015***	0.014***	0.009**	0.012***	0.011***	0.010**	0.012***
	(3.71)	(3.62)	(2.12)	(3.14)	(2.66)	(2.38)	(3.43)
Loads$_{m-1}$	0.015	0.015	0.003	0.008	0.009	0.021	0.012
	(0.91)	(1.04)	(0.17)	(0.59)	(0.64)	(1.41)	(0.94)
Fund Size$_{m-1}$	0.086***	0.059***	0.064***	0.057***	0.062***	0.059***	0.065***
	(11.13)	(9.77)	(8.64)	(7.92)	(8.02)	(8.33)	(10.12)
Fund Age$_{m-1}$	0.021***	0.015**	0.016***	0.023***	0.016***	0.015*	0.018***
	(2.98)	(2.36)	(2.92)	(3.83)	(3.11)	(1.89)	(3.33)
Disclosure$_m$	0.007	-0.002	-0.007	-0.005	0.004	0.032	0.005
	(0.38)	(-0.16)	(-0.79)	(-0.66)	(0.35)	(1.48)	(0.47)
Manager Experience$_{m-1}$	-0.007**	-0.003	-0.002	-0.002	-0.001	0.000	-0.003
	(-2.27)	(-1.22)	(-0.60)	(-0.67)	(-0.37)	(0.01)	(-0.98)
Highest Degree$_{m-1}$	-0.006*	-0.007*	-0.002	-0.003	-0.002	-0.006	-0.004
	(-1.69)	(-1.98)	(-0.70)	(-0.72)	(-0.62)	(-1.55)	(-1.37)
Top2 University$_{m-1}$	-0.019**	-0.011*	-0.014**	-0.015*	-0.016**	-0.014	-0.015**
	(-2.21)	(-1.77)	(-2.12)	(-1.94)	(-2.34)	(-1.58)	(-2.18)
Female$_{m-1}$	-0.003	0.000	-0.002	-0.011*	-0.006	-0.007	-0.005
	(-0.33)	(0.01)	(-0.26)	(-1.68)	(-0.96)	(-1.02)	(-0.84)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family
Sample	Fund-Yr-Month	Fund-Yr-Month	Fund-Yr-Month	Fund-Yr-Month	Fund-Yr-Month	Fund-Yr-Month	Fund-Yr-Month
# of Observations	147,151	147,151	147,151	147,151	147,151	147,151	147,151
Adjusted R-squared	0.272	0.225	0.238	0.268	0.255	0.251	0.348

Table S7. Persuasive features in livestreams - Robustness

This table examines the robustness results of livestream persuasion on fund flows and subsequent returns, presented in Table 9 Panels A and B, by controlling for the number of livestreams. Panel A displays the effect of persuasion on fund flows, by including the number of livestreams (*NumLivestreams*) as a fixed effect to the specifications used in Table 9 Panel A. Consequently, *Livestream* indicator is dropped due to collinearity. Panel B tabulates accumulated returns in months [*m+1*, *m+5*] of livestreaming fund-months with high and low persuasion, and their differences, based on generalized DiD regressions similar to those in Table 9 Panel B, while additionally controlling for *Log*(*1 + NumLivestreams*) in the specifications. Panel B also includes *Manager_On* indicator and the interaction terms of $Manager\_On_q$ × *Controls* from Table 9 Panel B. All variables are defined in Appendix D and Appendix SA. All non-binary regressors are standardized. Standard errors are clustered by fund family. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Effect on quarterly fund flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variables:	*Fund Flow$_q$*							
$Livestream_q$ × $First\ Half_q$	6.736***						5.583***	
	(5.83)						(5.17)	
$Livestream_q$ × $High\ Verbal\ Sentiment_q$		2.088*					1.117	
		(1.67)					(0.89)	
$Livestream_q$ × $High\ Vocal\ Valence_q$			1.686				-0.169	
			(1.23)				(-0.11)	
$Livestream_q$ × $High\ Vocal\ Arousal_q$				3.476***			1.474	
				(2.74)			(0.99)	
$Livestream_q$ × $High\ Vocal\ Sentiment_q$					3.298**		2.135	
					(2.32)		(1.47)	
$Livestream_q$ × $High\ Attractiveness_q$						2.038	1.279	
						(1.40)	(0.92)	
$Livestream_q$ × $Persuasion_q$								9.847***
								(3.96)
Controls from Table 9 Panel A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Manager\_On_q$ × *Controls*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PersuasionVar_q$ × *Controls*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NumLivestreams FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family
Sample	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr	Fund-Yr-Qtr
# of Observations	50,867	50,867	50,867	50,867	50,867	50,867	50,867	50,867
Adjusted R-squared	0.187	0.185	0.184	0.184	0.184	0.184	0.189	0.187

Panel B: Post-livestream accumulated returns (from m+1 to m+5) of high- and low- persuasion groups and their differences

Persuasion Variables:	*First Half*	*Verbal Sentiment*	*Vocal Valence*	*Vocal Arousal*	*Vocal Sentiment*	*Attractiveness*	*Persuasion*
Return							
High Persuasion$_m$	-0.204	0.024	0.144	-0.034	-0.111	-0.083	-0.241
	(-0.71)	(0.08)	(0.45)	(-0.09)	(-0.32)	(-0.26)	(-0.62)
Low Persuasion$_m$	0.210	0.049	0.035	0.058	0.063	0.062	0.021
	(0.72)	(0.18)	(0.13)	(0.21)	(0.24)	(0.23)	(0.08)
Difference	**-0.415****	-0.025	0.110	-0.092	-0.174	-0.145	-0.262
	(-2.00)	(-0.14)	(0.52)	(-0.35)	(-0.82)	(-0.75)	(-1.09)
DGTW Alpha							
High Persuasion$_m$	-0.316	-0.240	-0.194	-0.409	-0.329	-0.536*	-0.516
	(-1.35)	(-0.85)	(-0.66)	(-1.56)	(-1.18)	(-1.80)	(-1.63)
Low Persuasion$_m$	-0.142	-0.208	-0.213	-0.179	-0.198	-0.170	-0.237
	(-0.56)	(-0.90)	(-0.92)	(-0.75)	(-0.85)	(-0.74)	(-1.02)
Difference	-0.174	-0.031	0.019	-0.229	-0.131	**-0.366***	-0.279
	(-1.02)	(-0.20)	(0.10)	(-1.16)	(-0.74)	**(-1.93)**	(-1.54)
Carhart Alpha							
High Persuasion$_m$	-0.221	-0.097	-0.062	-0.150	-0.225	-0.181	-0.500
	(-0.72)	(-0.28)	(-0.19)	(-0.44)	(-0.72)	(-0.50)	(-1.43)
Low Persuasion$_m$	0.244	0.075	0.074	0.092	0.090	0.089	0.010
	(0.77)	(0.25)	(0.24)	(0.30)	(0.30)	(0.30)	(0.04)
Difference	**-0.465****	-0.172	-0.136	-0.242	-0.315	-0.270	**-0.510****
	(-2.53)	(-0.90)	(-0.66)	(-0.98)	(-1.53)	(-1.44)	**(-2.31)**
China 3F Alpha							
High Persuasion$_m$	-0.173	-0.167	-0.145	-0.213	-0.230	-0.371	-0.357
	(-0.48)	(-0.44)	(-0.38)	(-0.57)	(-0.60)	(-0.93)	(-0.88)
Low Persuasion$_m$	0.017	-0.048	-0.048	-0.034	-0.041	-0.020	-0.084
	(0.05)	(-0.14)	(-0.15)	(-0.10)	(-0.12)	(-0.06)	(-0.25)
Difference	-0.190	-0.119	-0.096	-0.179	-0.190	-0.351	-0.273
	(-1.03)	(-0.54)	(-0.43)	(-0.69)	(-0.83)	(-1.61)	(-1.19)

Table S8: Stacked-cohort DiD results

This table presents stacked-cohort difference-in-differences results for the main flow and returns results. Panel A runs a stacked DiD model of Table 4 Panel A column (2) to investigate the effects of livestreaming on fund flows. For each cohort, we define an event window [-1, 0] in column (1) and event window [-2, 0] in column (2). In column (1), treated funds are identified as ones that livestream in quarter 0 and did not in quarter *-1*, and control funds are identified as ones that did not livestream in quarters [-1, 0]. In column (2), treated funds are identified as ones that livestream in quarter 0 and did not livestream in quarters [-2, -1], and control funds are identified as ones that did not livestream in quarters [-2, 0]. Fixed effects, clustering, and other model details are listed at the bottom of each column. Panel B runs a stacked DiD model of Table 6 Panel C to investigate the effect of livestreaming on fund returns. The event window is defined as months [-5, 5] with treatment funds identified as ones that livestream in month 0 but did not livestream in months [-5, -1]. Control funds are identified as ones that did not livestream in months [-5, 5]. Panel B includes fund-cohort and year-month-cohort fixed effects. The dependent variable is one of four returns: *Return*, *DGTW Alpha*, *Carhart Alpha*, and *China 3F Alpha*. *Controls* include *Recent Return*, *Top 5 Return*, *Management Fee*, *Service Fees*, *Loads*, *Fund Size*, *Fund Age*, and *Disclosure*. For months *m-5* through *m*, all controls except for *Disclosure* are measured through the end of the prior month, and *Disclosure* is contemporaneous. For months *m+1* through *m+5*, all controls except for *Disclosure* are fixed at *m-1*, and *Disclosure* is fixed at *m*. All variables are defined in Appendix D of the main paper. All non-binary regressors are standardized. Standard errors are clustered by fund-family-cohort. *t*-statistics are in parentheses. ***, **, * indicates statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Stacked difference-in-differences regressions of quarterly fund flows

	(1)	(2)
Event Window	**Quarters[-1, 0]**	**Quarters[-2, 0]**
Dependent Variable:	*Fund Flow$_q$*	
Livestream$_q$	11.933***	13.466***
	(14.07)	(12.86)
Recent Return$_{q-1}$	8.202***	7.482***
	(18.30)	(20.54)
Top 5 Return$_{q-1}$	1.851***	2.104***
	(3.24)	(4.43)
Management Fee$_{q-1}$	1.047	0.362
	(0.90)	(0.42)
Service Fees$_{q-1}$	-0.020	0.132
	(-0.04)	(0.36)
Loads$_{q-1}$	7.270	6.070
	(1.38)	(1.59)
Fund Size$_{q-1}$	-116.524***	-86.620***
	(-43.94)	(-48.41)
Fund Age$_{q-1}$	-0.491	-1.756**
	(-0.49)	(-2.48)
Disclosure$_q$	-1.411	-0.692
	(-0.99)	(-0.61)
Fund-Cohort FE	Yes	Yes
Yr-Qtr-Cohort FE	Yes	Yes
# of Cohorts	18	17
Cluster	Fund-Family-Cohort	Fund-Family-Cohort
Sample	Fund-Yr-Qtr-Cohort	Fund-Yr-Qtr-Cohort
# of Observations	74,200	90,345
Adjusted R-squared	0.437	0.358

Panel B: Summary of stacked DiD regression results, all livestreams, with controls, with fund-cohort and year-month-cohort FE

	m-5	m-4	m-3	m-2	m-1	m	m+1	m+2	m+3	m+4	m+5	m(+1, +5)
Return												
Livestream$_m$	0.291***	0.396***	0.520***	0.791***	1.258***	0.298***	-0.434***	-0.566***	-0.464***	-0.542***	-0.415***	-2.398***
	(3.22)	(4.53)	(5.60)	(7.95)	(11.74)	(3.02)	(-5.26)	(-7.60)	(-6.66)	(-6.95)	(-5.64)	(12.38)
DGTW Alpha												
Livestream$_m$	0.109	0.312***	0.375***	0.467***	0.769***	0.170**	-0.317***	-0.357***	-0.333***	-0.400***	-0.272***	-1.667***
	(1.39)	(4.13)	(4.68)	(5.46)	(8.66)	(2.11)	(-4.14)	(-5.42)	(-5.12)	(-5.67)	(-3.91)	(-9.61)
Carhart Alpha												
Livestream$_m$	0.258***	0.303***	0.512***	0.796***	0.998***	0.340***	-0.211***	-0.497***	-0.464***	-0.597***	-0.413***	-2.163***
	(2.90)	(3.28)	(5.69)	(8.57)	(9.65)	(3.62)	(-2.63)	(-6.70)	(-6.00)	(-7.55)	(-5.43)	(-10.35)
China 3F Alpha												
Livestream$_m$	0.344***	0.355***	0.491***	0.707***	1.000***	0.319***	-0.188**	-0.466***	-0.504***	-0.532***	-0.369***	-2.042***
	(4.01)	(4.09)	(5.75)	(7.88)	(10.25)	(3.42)	(-2.44)	(-6.51)	(-6.87)	(-7.04)	(-5.12)	(-10.31)

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Appendix SA: Variable definitions – those not in the paper

Variables	Definition
Fund-Month/Quarter-Level Variables	
Δ*Livestream* = +1	An indicator variable for when the fund livestreams in the current quarter and did not livestream in the previous quarter.
Δ*Livestream* = −1	An indicator variable for when the fund does not livestream in the current quarter and livestreamed in the previous quarter.
Log(*1 + NumLivestreams*)	The logarithm of one plus the number of times a fund livestreams in the current month.
Sentence/Image-Level Variables	
Positive/Negative (Verbal)	An indicator for sentences classified as positive/negative by the Chinese FinBERT model, based on the highest probability among positive, negative, and neutral categories.
Length (Vocal)	The duration in seconds of an audio clip segmented from a full livestream audio, based on the start and end timestamps of sentences transcribed by *Faster Whister*. Due to computational constraints, we analyze the first sentence after each minute mark. Following Giannakopoulos (2015), we retain the first ten seconds of each sentence.
Vocal Valence/Vocal Arousal	Degree of vocal valence/arousal of the sentence, generated by *pyAudioAnalysis*.
Vocal Happy/Vocal Sad	An indicator for sentences for which the happiness/sadness probability exceeds that of all other emotions. The probability of happiness, sadness, and other emotions of the sentence is generated by *speechemotionrecognition*.
Attractiveness (Visual)	Attractiveness score of each face image predicted by a ResNeXt-50 model trained on the SCUT-FBP5500 dataset. Each face image is cropped using *dlib* from screenshots taken every five minutes during each livestream.
Livestream-Level Variables	
Verbal Sentiment	The difference between the number of positive and negative sentences in a livestream, scaled by one plus the sum of these two numbers.
Vocal Valence	The average valence score of first sentences per minute in a livestream.
Vocal Arousal	The average arousal score of first sentences per minute in a livestream.
Vocal Sentiment	The difference between the number of vocally happy and sad sentences in a livestream, scaled by one plus the sum of these two numbers.
Attractiveness	The average facial attractiveness score of face images cropped from screenshots taken every five minutes in a livestream.