

TOO MANY COOKS SPOIL THE BROTH: COMPETITION AND THE CORRUPTION OF INFORMATION BY DUAL-ROLE INTERMEDIARIES

Jiajun Jiang Shuo Liu Yu-Jane Liu Ruichang Lu*

Abstract

We develop a model of strategic information disclosure under competition among intermediaries that both rate and distribute financial products. Extending a multi-sender, multi-receiver Bayesian persuasion framework, the model predicts that intensified competition weakens each intermediary's incentive to maintain information quality relative to its incentive to exploit its own clientele, resulting in greater rating inflation and reduced informativeness. Using comprehensive data on seven accredited mutual fund rating agencies in China and a quasi-natural shock to rating coverage, we find strong empirical support for these mechanisms. Rating inflation increases with competition, and investor responses shift accordingly: sophisticated investors reduce their reliance on ratings, while retail investors remain largely unaffected. Together, the theory and evidence reveal how competitive pressure among conflicted information intermediaries can erode rating credibility, uncovering a novel channel through which competition distorts—rather than disciplines—information provision in financial markets.

Keywords: Mutual Fund Ratings, Financial Intermediates, Biased Recommendations, Investor Reactions.

JEL classification: *G30, G32, G34*

*Jiajun Jiang: School of Economics, Fudan University, jiangjj@fudan.edu.cn; Shuo Liu: Guanghua School of Management, Peking University, shuo.liu@gsm.pku.edu.cn; Yu-Jane Liu: Guanghua School of Management, Peking University, yjliu@gsm.pku.edu.cn; Ruichang Lu, Guanghua School of Management, Peking University, ruichanglu@gsm.pku.edu.cn. We thank Jidong Zhou and the conference and seminar participants at China Five-star Workshop at RUC, NCER-CCER China Economic Workshop for their helpful comments. Shuo Liu acknowledges financial support from the National Natural Science Foundation of China (grants 72322006 and 72192844).

1 Introduction

The adage “too many cooks spoil the broth” finds a troubling echo in modern financial markets. While competition among information intermediaries is widely presumed to enhance transparency, critical episodes suggest the opposite: more rating agencies have sometimes led to less reliable information. During the structured finance boom, AAA-rated mortgage tranches proved far riskier than their ratings implied. Empirical studies link this loss of quality to the very presence of multiple agencies, especially when issuers can shop for favorable ratings (Becker and Milbourn, 2011; Skreta and Veldkamp, 2009; Bolton *et al.*, 2012). These patterns reveal a paradox that challenges our theoretical understanding: under what conditions does competition among intermediaries *corrupt* rather than *cleanse* information?

The canonical framework of competitive persuasion offers an optimistic answer, suggesting that competition typically forces greater information revelation (Gentzkow and Kamenica, 2016). Yet this logic abstracts from a defining feature of many real-world intermediaries: they often serve a *dual role* as both evaluator and distributor of the products they rate. In financial product distribution platforms, investment advisory services, and even the “issuer-pays” rating agencies, revenue is tied to distribution outcomes, creating an inherent conflict of interest. Providing credible information sustains long-term trust, but inflating ratings boosts short-term sales. Prior research has examined related tensions, such as reputation concerns (Mathis *et al.*, 2009) or issuer-led rating shopping (Skreta and Veldkamp, 2009; Bolton *et al.*, 2012), but has not systematically analyzed how competition itself alters incentives when intermediaries wear these two hats simultaneously.

In this paper, we argue that the dual role reverses the classic logic of competition. We develop a model of strategic information disclosure among intermediaries who both rate and distribute the same financial product. The model captures a fundamental trade-off. A *demand-building* motive encourages accurate ratings to preserve the credibility of the system and attract sophisticated investors. An *exploitation* motive pushes toward rating inflation to

increase sales to less attentive, “naïve” investors. Crucially, the system’s overall credibility is a public good: each intermediary benefits from a trustworthy market but privately gains from inflating its own ratings. This sets up a free-riding problem.

To formalize this trade-off, our framework captures how competition reshapes intermediaries’ incentives to maintain informational accuracy and how investors, heterogeneous in their sophistication, respond to the resulting equilibrium level of rating inflation. A fraction of investors—whom we refer to as sophisticated—process information rationally and compare ratings across platforms before deciding whether to participate in the market. The remaining naïve investors, by contrast, follow the recommendations of their assigned intermediary mechanically. Because intermediaries derive revenue from product distribution, they are tempted to issue optimistic ratings to induce purchases by their captive clients. At the same time, they depend on sophisticated investors’ continued participation to sustain overall market credibility.

Two opposing motives that jointly determine equilibrium behavior. A demand-building motive encourages intermediaries to issue informative ratings to preserve the credibility of the rating system and attract sophisticated investors who value accuracy. An exploitation motive, by contrast, pushes them to inflate ratings to increase sales to less attentive investors. Crucially, the participation of sophisticated investors depends on the informativeness of the rating system as a whole. When one intermediary inflates, it slightly reduces the credibility of the entire system, thereby discouraging sophisticated investors from engaging with any intermediary. This creates a public-good problem in information provision: each intermediary benefits when the system remains trusted but has an incentive to free-ride on the credibility maintained by others.

As competition intensifies—whether through the entry of new intermediaries or greater investor mobility—the free-riding incentive becomes stronger. Each intermediary’s stake in the collective credibility of the market diminishes, while the temptation to boost short-term sales to its own clientele grows. The equilibrium consequence is greater rating inflation,

weaker information content, and a gradual withdrawal of sophisticated investors from the market. Put differently, when every intermediary shouts to be heard, the informational signal that ratings are meant to convey becomes drowned out by the collective noise.

The key intuition could be illustrate as follow. Consider a market with two competing platforms, A and B , that both *rate* and *distribute* the same mutual fund. The fund's true quality is unknown to investors. Each platform can either issue an accurate rating ($r_i = \text{"high"}$ only if quality is high) or inflate its rating ($r_i = \text{"high"}$ even if quality is low) to attract its own clientele. Investors are heterogeneous: a fraction λ are *sophisticated*, comparing ratings across platforms before deciding whether to invest, while the remaining fraction $1 - \lambda$ are *naïve* and automatically follow the recommendation of their assigned platform.

If both A and B issue truthful ratings, sophisticated investors participate, trusting the ratings, while naïve investors follow their assigned platform. However, if platform A inflates its rating, the naïve investors assigned to A are more likely to invest, boosting A 's short-term revenue. At the same time, sophisticated investors observe the conflicting or less informative ratings, reduce their participation, or switch to alternative investment channels.

As competition intensifies, each platform faces the same trade-off: inflating ratings increases short-term sales to naïve clients but erodes the collective credibility that sustains sophisticated investor participation. In equilibrium, rating inflation rises, sophisticated participation declines, and the informativeness of the rating system deteriorates. Put differently, when every platform shouts to attract clients, the signal about true fund quality is drowned out by the noise of inflated ratings.

Our mechanism is distinct from reputation concern framework with naive and sophisticated investors. In our setting, competition strengthens the incentive of each agency to inflate ratings to exploit its captive clientele while free-riding on this common credibility, even when individual market shares or continuation values are held fixed. In other words, agencies' decisions depend on within-market, across funds and over time in coverage, not just an

aggregate time-series market shares. Moreover, our model links competition not only to higher average ratings but also to a decline in the informativeness of ratings and in sophisticated investors’ participation and flow-rating sensitivity, predictions that are not implied by the simple shrinking-rents reputation story.

Our theoretical framework extends the Bayesian persuasion literature in several meaningful ways. Unlike the canonical single-sender models (Kamenica and Gentzkow, 2011) or even multi-sender settings with homogeneous receivers (Gentzkow and Kamenica, 2016), we study a market in which principals both rate and distribute financial products to a heterogeneous population of agents. While critics of the “Big Three” oligopoly argue that insufficient competition allows incumbents to pool risks and obscure quality (Lizzeri, 1999; Doherty *et al.*, 2012), our model demonstrates the opposite danger: intensified competition generates a free-riding systematic incentive to inflate. The dual role generates a novel conflict of interest absent from previous models, producing a mechanism through which competition systematically undermines the informativeness of ratings. Specifically, each principal optimally inflates ratings to exploit captive naive investors while simultaneously free-riding on the collective credibility of the industry to attract sophisticated investors. This interplay generates a strategic tension between exploitation and demand building, yielding sharp comparative statics and testable predictions.

Our model introduces heterogeneity in agent sophistication, allowing us to trace how the effects of competition vary with market composition. Prior theoretical work has shown that reputation is effective primarily when consumers can easily assess quality, but becomes doubtful in markets with naïve consumers or complex assets (Benabou and Laroque, 1992; Mathis *et al.*, 2009). Furthermore, Bolton *et al.* (2012) demonstrate that certifiers are more likely to inflate ratings when a larger fraction of consumers take ratings at face value. Prior studies largely focus on uniform receiver behavior; by contrast, we uncover a non-monotonic relationship between the share of naive agents and the adverse effect of competition on information quality—a pattern that, to our knowledge, does not appear in existing theoretical

accounts of ratings inflation or multi-sender Bayesian persuasion.

Together, these features generate both a novel theoretical mechanism and a set of empirically testable implications, bridging the gap between information design theory and observable behavior in real-world financial markets. Our work thus complements and extends the existing literature by highlighting how institutional features and heterogeneous agents interact with strategic information disclosure under competition, producing “upward bias” patterns frequently observed in empirical studies but often debated in theory.

We test the predictions of our model using a comprehensive panel of Chinese mutual funds from 2006 to 2023. The dataset combines quarterly fund ratings from the Asset Management Association of China (AMAC), fund returns from CSMAR, and fund characteristics from WIND. Importantly, the number of rating agencies covering each fund varies both cross-sectionally and over time, creating a naturally high-competition environment suitable for identifying the effects predicted by our theory. To further address endogeneity concerns—such as rating coverage being correlated with fund size, age, or performance—we exploit a quasi-natural experiment: in Q4 2021, Morningstar expanded its coverage to include the “Flexible Allocation” fund category, generating an exogenous increase in rating coverage for a subset of funds. This shock serves as a plausibly exogenous instrument for the number of ratings.

Consistent with our theoretical predictions, we find that intensified rating competition reduces fund flows. OLS estimates show that each additional rating agency covering a fund reduces quarterly net flows by 1.4 percentage points. Instrumental-variable estimates exploiting the Morningstar coverage shock yield an even larger effect: a one-standard-deviation increase in the number of ratings lowers quarterly net flows by roughly 8% of lagged total net assets. These results indicate that sophisticated investors respond to the dilution of informational content that accompanies greater competition among intermediaries.

Decomposing flows by investor type provides further support for our mechanism. While naive (retail) investors are largely unaffected, sophisticated (institutional) investors account for almost the entire reduction in fund flows. This asymmetry aligns with our model, which

predicts that sophisticated investors are more sensitive to rating inflation and discount the informational value of ratings as competition increases. Moreover, examining the ratings themselves, we document clear evidence of rating inflation: each additional rating agency covering a fund is associated with a higher mean rating, with IV estimates showing an increase of 0.28 stars per additional rater. This causal evidence confirms that intensified competition directly contributes to the upward bias in ratings, consistent with the free-riding mechanism highlighted in our theoretical framework.

Finally, we find that competition diminishes the sensitivity of institutional flows to ratings. Sophisticated investors interpret additional ratings as less informative, reducing the flow response to a one-star increase in mean rating by up to 2.6 percentage points around the Morningstar coverage shock. In contrast, retail investors' flow-rating sensitivity remains largely unchanged or slightly increases, consistent with our model's prediction that naive investors rely mechanically on available recommendations. Taken together, these empirical findings validate the core mechanism of our model: when every intermediary seeks to attract clients in a competitive environment, rating inflation rises, the informativeness of ratings declines, and sophisticated investors strategically reduce their exposure.

Our study makes several key contributions to the literature. First, we advance the understanding of financial intermediation and rating competition by demonstrating how intensified competition among dual-role intermediaries—those that both rate and distribute financial products—can systematically erode information quality. While prior research emphasizes the disciplining role of competition through reputational mechanisms (e.g., Benabou and Laroque, 1992; Bolton *et al.*, 2012; Doherty *et al.*, 2012; Xia, 2014), we highlight a countervailing force: competition can incentivize rating inflation when intermediaries face conflicts of interest. This aligns with the "race to the bottom" hypothesis (Skreta and Veldkamp, 2009) and the empirical evidence in the corporate bond market (Becker and Milbourn, 2011; Bongaerts *et al.*, 2012; Jiang *et al.*, 2012) and MBS issuances (Ashcraft *et al.*, 2011; He *et al.*, 2012; Griffin and Tang, 2012). This mechanism is particularly relevant in

markets where intermediaries derive revenue from product distribution, such as mutual fund platforms and credit rating agencies. By identifying this trade-off, our findings extend the theoretical frameworks of Bayesian persuasion (Kamenica and Gentzkow, 2011; Gentzkow and Kamenica, 2016) and reputation-based incentives (Mathis *et al.*, 2009) to competitive dual-role environments.

Second, our paper contributes to the empirical literature on mutual fund flows and investor behavior (e.g., Keswani and Stolin 2008; Ivković and Weisbenner 2009; Barber *et al.* 2016). By combining a comprehensive panel of fund ratings, returns, and characteristics with institutional ownership data, we differentiate between sophisticated and naive investors. We show that the negative effect of rating competition on flows is almost entirely driven by sophisticated investors, who actively discount inflated ratings, whereas retail investors remain largely unresponsive. This validates the theoretical concern that reputation costs are lower—and thus inflation higher—when the market contains a significant proportion of trusting, naive investors (Bolton *et al.*, 2012). This evidence clarifies a long-standing puzzle regarding heterogeneous responses to rating signals and underscores the importance of investor sophistication in shaping the effectiveness of information intermediaries.

Third, our work bridges theoretical and empirical research on strategic information provision (Kamenica and Gentzkow, 2011; Gentzkow and Kamenica, 2016, 2017). We integrate a multi-sender Bayesian persuasion framework with high-quality fund-level data, leveraging a quasi-exogenous increase in rating coverage to identify causal effects. The analysis not only demonstrates the prevalence of rating inflation under competitive pressures but also shows how such inflation alters the sensitivity of fund flows to ratings. This link between theory and empirical evidence provides actionable insights for market participants and policymakers, highlighting that promoting competition without safeguards can unintentionally degrade informational quality and distort capital allocation.

2 Institutional Background

China’s public mutual fund industry has grown rapidly over the past three decades. As of September 2024, there are 163 fund management companies with combined net assets exceeding RMB 32 trillion, comparable in scale to insurance funds and larger than bank wealth management products. Individual investors hold roughly half of all mutual fund assets, highlighting the importance of intermediary-provided information. Mutual fund rating agencies play a crucial role in reducing search costs, increasing market transparency, and guiding capital allocation.

2.1 Mutual Fund Rating Agencies in China

Mutual fund rating agencies in China serve as key information intermediaries, primarily targeting retail investors who rely heavily on their evaluations. The industry was formalized under regulatory oversight in 2010, when the “Interim Measures for the Administration of Securities Investment Fund Evaluation Business” required agencies to be accredited by the Securities Association of China (under the supervision of the China Securities Regulatory Commission, CSRC). Initially, ten agencies were licensed, including three independent firms (Morningstar, Tian Xiang, Ji’an) and four securities companies (Galaxy, Haitong, CMSC, SHSC). This paper focuses on the seven agencies with consistent quarterly disclosures and regulatory accreditation, as media-based ratings are sporadic and less influential.

Rating agencies provide fund assessments that are publicly disclosed on the Asset Management Association of China (AMAC) website quarterly, though the data format is fragmented and not easily usable by investors. Distribution platforms typically display only selected ratings, often favoring the agency affiliated with the platform or the highest-rated funds. This selective presentation creates a curated information environment, directly relevant for our study of rating competition and investor responses.

2.2 Mutual Fund Sales Channels

The mutual fund market in China relies on a mix of direct and third-party distribution, with third-party channels—banks, independent agencies, and securities firms—accounting for over 60% of assets by end-2023. Distribution institutions collect substantial fees, including point-of-sale charges and ongoing asset-based compensation. These economic incentives create discretion in which fund ratings are displayed and emphasized, making the choice of ratings salient for investor behavior.

2.3 Fund Rating Usage

In China, the regulator mandates that mutual fund ratings be disclosed on the Asset Management Association of China (AMAC) website on a quarterly basis, typically with a one-quarter lag.¹ Although the information is publicly available, it is not user-friendly: each rating agency uploads a standalone file of its rated funds, with no cross-agency consolidation, historical series, or comparison tools. As a result, retail investors are unlikely to make routine use of these postings.

On the direct-sales side, fund management companies generally do not display third-party ratings on their own websites, partly because ratings from different agencies can be inconsistent and partly to avoid creating an explicit internal ranking of their products.² By contrast, U.S. mutual fund firms commonly present Morningstar ratings alongside product information.³

Across distribution channels, the presentation of ratings is highly discretionary. First, platforms affiliated with rating agencies (e.g., Tianxiang and Ji'an) or with securities firms that operate rating businesses (e.g., Galaxy, Haitong, CMSC, and SHSC) typically display only

¹AMAC fund rating portal: <https://www.amac.org.cn/fwdt/wyc/jjpjcx/>

²For example, see <https://www.jsfund.cn/main/fund/index.shtml>. Some firms instead highlight award-winning funds.

³For example, see Fidelity's fund screener: <https://fundresearch.fidelity.com/fund-screener/results/table/overview/averageAnnualReturnsYear3/desc?fidelityFundOnly=F&order=fidelityFundOnly>.

their own in-house ratings on product pages, omitting alternative assessments and preventing cross-agency comparisons. Second, commercial banks commonly maintain a whitelist of funds with high ratings from one or more agencies and preferentially offer those products to retail clients. Third, independent distribution agencies and other platforms also display ratings selectively: within the same platform (e.g., Ali Fund), funds with top-tier outcomes are prominently labeled with ratings, whereas no rating is shown for other funds—even when those funds are rated by one or more agencies on the AMAC portal. This pattern aligns with commercial incentives. Because distributors earn both point-of-sale charges and ongoing asset-based compensation, they have reason to highlight the most favorable ratings available, suppress less favorable ones, or withhold ratings for lower-rated products. Consequently, the ratings that investors encounter on sales platforms constitute a curated subset of the full information set.

3 Theory

Our model is closely related to the Bayesian persuasion literature with multiple senders (Gentzkow and Kamenica, 2016, 2017). Existing models also study receivers who differ in their priors, signal processing costs, or preferences (e.g., Bergemann and Morris, 2016; Kolotilin *et al.*, 2017) show that a sender’s optimal signal structure becomes a complex tool for market segmentation. However, these models largely retain a monopoly sender. Instead, we develop a model of strategic information disclosure tailored to our empirical setting: a market consisting of agencies that both rate financial products and distribute them.

The model serves two primary goals. First, it delivers new theoretical insights by studying an underexplored mechanism through which competition undermines the informativeness of ratings. Specifically, agencies are incentivized to inflate ratings to exploit their captive clientele while free-riding on the industry’s collective credibility to sustain the participation of more discerning investors, and competition amplifies this incentive. Second, it provides

sharp comparative statics that yield testable predictions to guide our subsequent empirical analysis.

3.1 Model Set-Up

We study a market for mutual funds, motivated by the institutional structure of the Chinese fund industry. The market consists of $n \geq 1$ principals, representing licensed fund rating agencies, and a unit continuum of agents, representing potential investors. For simplicity, we focus on their interactions concerning a single fund. The fund’s quality is modeled as a binary state $\omega \in \Omega \equiv \{0, 1\}$, with $\omega = 1$ denoting high quality (e.g., high expected return) and $\omega = 0$ denoting low quality. Initially, all parties are uninformed about the true state but share a common prior assigning probability $\mu \in (0, 0.5)$ to the fund being high quality.

Each principal $i \in \{1, \dots, n\}$ must choose a public rating policy, which specifies the probabilities of issuing a good rating ($s_i = 1$) or a bad rating ($s_i = 0$) conditional on the true fund quality. We are interested in how market competition affects the informativeness of principals’ ratings. To capture the potential scope of this effect, we follow the information design literature (Kamenica and Gentzkow, 2011; Bergemann and Morris, 2019) and assume that principals can commit to their chosen policies. Each principal disseminates her rating through a platform she controls, which also serves as a distribution channel for the fund. A principal’s payoff is proportional to the mass of agents who purchase the fund through her platform, possibly because she earns commission fees from sales. This institutional feature—financial intermediaries acting both as raters and distributors—mirrors our empirical setting and generates the conflict of interest central to our theoretical analysis.

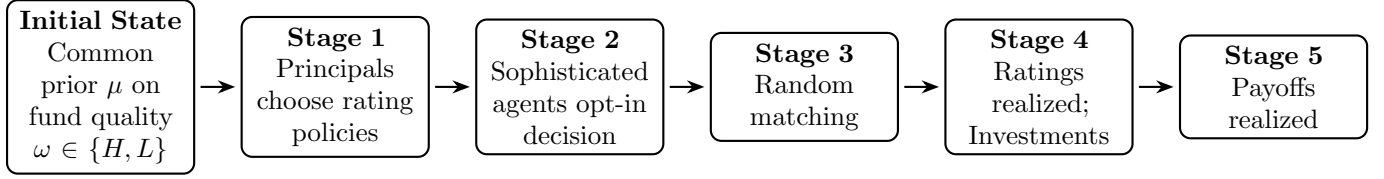
The agent population is heterogeneous, varying in the extent to which their investment decisions are susceptible to the principals’ rating policies. A fraction $\lambda \in (0, 1)$ of agents are *naive*. From the outset, each naive agent is captive to a principal to which he is randomly assigned with equal probability. He invests exclusively through that principal’s platform, purchasing the fund whenever it is rated favorably there. Such agents resemble investors

who do not consider alternative opportunities and instead follow salient or easily accessible recommendations blindly, either due to limited attention, cognitive constraints, or a strong preference for convenience.

The remaining fraction $1 - \lambda$ are *sophisticated* agents. Unlike their naive peers, these agents are rational Bayesians who draw on all available information and actively choose whether and how to engage with the principals' platforms. More specifically, a sophisticated agent first compares the expected value of using the principals' ratings to invest in the fund with an outside option that yields a privately known payoff θ , drawn uniformly from $[0, \bar{\theta}]$ with $\bar{\theta} > 0$. The outside option may represent investing through alternative channels without consulting the principals' ratings, or pursuing entirely different opportunities. If the agent forgoes his outside option, he is randomly matched with one of the principals with equal probability. Crucially, he does not follow the assigned principal's recommendation mechanically. Instead, he also takes into account the ratings issued by other principals (for instance, by checking their platform apps) and bases his investment decision on a careful assessment of expected returns. He recognizes that investing is risky: while a high-quality fund generates a net gain of 1, a low-quality fund incurs a loss of -1 . In contrast, abstaining from investment guarantees a safe payoff of 0. Hence, a sophisticated agent would invest through his assigned principal only when the ratings are sufficiently informative and favorable to suggest that the fund is of high quality.

To summarize, the timing of the game unfolds in five steps. First, the principals simultaneously and independently select and publicly announce their rating policies. Second, sophisticated agents, having observed these policies, decide whether to opt into the principals' rating service or to exercise their outside option. Third, all agents who opt in—naive agents by default and sophisticated agents by choice—are randomly matched with a principal. Fourth, ratings are realized, and agents proceed with their investment decisions as described earlier. Finally, payoffs are realized.

We close this section by introducing two parametric assumptions that will be maintained

Agent Types:**Naive** (fraction λ): Captive to principal, invest if $s_i = 1$;**Sophisticated**: Bayesian, outside option $\theta \sim U[0, \bar{\theta}]$ 

Timeline of the Mutual Fund Rating Game

throughout the theoretical analysis. First, we assume $\lambda < \mu$, which rules out equilibria in which principals profit entirely from naive agents and inflate ratings without discipline. Second, because the principals' rating service yields at most an expected benefit of μ , we impose $\bar{\theta} \leq \mu$. This assumption confines our analysis to situations where agent participation is sensitive to the informativeness of ratings, a feature that aligns with observed behavior in our empirical setting.

3.2 Equilibrium Analysis

We analyze the perfect Bayesian equilibrium of the game (henceforth equilibrium). Because all parties' interests are aligned when the fund is of high quality, we can, without loss of generality, restrict attention to rating policies that truthfully disclose this state; that is, principals always send $s_i = 1$ when $\omega = 1$. Each principal's strategy can therefore be summarized by a single parameter $p_i \in [0, 1]$, the probability of issuing a favorable rating when the quality of the fund is actually low. A higher p_i corresponds to greater rating inflation, with the principal more frequently certifying a low-quality fund as good.

A sophisticated agent's strategy has two components. First, he makes a participation decision that specifies, for any policy profile $(p_1, \dots, p_n)$ and his type θ , whether to opt into the fund market using the principals' services ($d = 1$) or to exercise his outside option ($d = 0$). Second, conditional on opting in, he makes an investment decision that specifies, for each rating profile $(s_1, \dots, s_n)$, whether to purchase the fund through his assigned principal ($a = 1$) or abstain ($a = 0$). Naive agents, by contrast, behave mechanically as described earlier.

The equilibrium strategies of the agents can be pinned down via backward induction and an application of the Bayes' rule. To see this, fix a rating policy profile $(p_1, \dots, p_n) \in [0, 1]^n$ and consider the investment decision of a sophisticated agent who has opted in. Because a single unfavorable rating perfectly reveals that $\omega = 0$, the agent invests only if all ratings are favorable. In that event, his posterior belief is

$$\hat{\mu} = \frac{\mu}{\mu + (1 - \mu) \cdot \prod_{j=1}^n p_j},$$

and he purchases if and only if $\hat{\mu} \geq 0.5$, or equivalently, $\prod_{j=1}^n p_j \leq \mu/(1 - \mu)$. Anticipating this decision rule, the agent evaluates his ex-ante expected payoff from participation. When the policies are sufficiently informative to induce investment conditional on unanimous favorable ratings, the expected payoff is $\mu - (1 - \mu) \prod_{j=1}^n p_j$. He chooses to participate if and only if this payoff exceeds the value of his outside option.

The equilibrium behavior of the agents gives rise to a strategic trade-off for the principals. By increasing the probability of certifying a low-quality fund as good, a principal increases the likelihood that investors assigned to her platform—both naive agents and sophisticated agents with low outside options—will purchase the fund. Yet greater rating inflation diminishes the informativeness of the rating system as a whole, inducing a larger share of sophisticated agents to opt out. Principals therefore face two opposing incentives: an exploitation motive, which favors inflation to boost sales, and a demand-building motive, which favors restraint to sustain participation. Our main result establishes that the interplay of these forces yields a unique symmetric equilibrium.

Proposition 1. *There exists a unique symmetric equilibrium where all principals adopt the same rating policy, issuing a good rating with probability one if the fund is high quality and*

with probability

$$p^*(n) = \left(\frac{\lambda \bar{\theta}}{2(1-\lambda)(1-\mu)} \right)^{\frac{1}{2n-1}}$$

if the fund is low quality. In equilibrium, a sophisticated agent participates if and only if the value of his outside option satisfies $\theta \leq \theta^* \equiv \mu - (1-\mu)(p^*)^n$.

Proposition 1 fully characterizes both the extent of equilibrium rating inflation and the participation margin of sophisticated investors. We now turn to comparative statics, asking how competition among rating agencies alters the equilibrium outcomes.

Proposition 2. *As the number of competing principals grows, each principal inflates more, the rating system as a whole becomes less informative about fund quality, and a smaller share of sophisticated agents choose to rely on the principals' services for investment. Formally, both p^* and $(p^*)^n$ increase with n , while θ^* decreases.*

The mechanism behind Proposition 2 is a free-rider problem in the provision of information. The informativeness of the rating system is a public good: sophisticated agents participate only when ratings are sufficiently accurate, and their participation benefits all principals. Yet when a single principal inflates her ratings, she fully captures the incremental sales to her own assigned clients, both naive and participating sophisticated, while the cost of reduced informativeness is borne collectively by all rivals. As the ratings market becomes more crowded, each principal has less at stake in the sophisticated segment, weakening their incentives to contribute to the informational public good. Competition thus shifts the strategic calculus of principals, tilting policies from cultivating additional demand toward exploiting existing clientele. In equilibrium, ratings become more inflated, information quality deteriorates, and sophisticated agents increasingly turn to their outside options.

Finally, we examine how the severity of the free-riding problem depends on the composition

of the agent population. The analysis reveals a non-monotonic relationship that, to our knowledge, does not appear in competing theories that likewise stress the potential adverse effect of competition on the dissemination and utilization of information in markets.

Proposition 3. *As the share of naive agents λ increases, the marginal effect of competition on participation, $\partial\theta^*/\partial n$, first becomes more negative and then less negative.*

The intuition for Proposition 3 rests on why competition exerts relatively little influence on the demand for principals' services when the share of naive agents is either very low or very high. With few naive agents, principals are primarily motivated to sustain their user base within the sophisticated segment, and thus keep rating inflation restrained. As a result, the probability of unanimous favorable ratings for a low-quality fund remains low regardless of market size. The informativeness of the system, and hence the demand for principals' services, changes little with additional competition. In the opposite case, when naive agents make up a large fraction of the market, ratings are already heavily inflated and most sophisticated types have turned to their outside options, leaving little scope for further erosion. The force of competition is therefore greatest at intermediate levels, where rating inflation is moderate: the system retains enough credibility to sustain substantial demand from sophisticated agents, yet is fragile enough that additional competition significantly undermines it.

3.3 Testable Hypotheses

Building on the analysis of our theoretical model and the institutional features of China's mutual fund industry, we formulate three testable hypotheses to guide our empirical analysis. These hypotheses map the model's implications (Propositions 2 and 3) to observable measures of the ratings and flows of mutual funds in our data.

A key implication of the model is that intensified competition among rating agencies reduces the informativeness of the rating system and induces potential investors to reallocate capital away from the fund market toward alternative opportunities. Empirically, we interpret

ratings as less informative when funds are systematically assigned more favorable grades despite unchanged fundamentals, and we measure capital allocation through net flows into funds. This yields our first hypothesis:

H1: *Greater rating coverage leads to higher average ratings but lower net fund flows.*

Our model attributes the joint pattern of inflated ratings and reduced fund flows to that investors, especially the sophisticated ones, recognize the deterioration in the informativeness of the ratings system and, in response, curtail their reliance on it or exit the market altogether. Alternative explanations for this pattern are possible. For instance, as the number of ratings increases, naive investors—rather than sophisticated ones—might find it cognitively costly to process diverse assessments and thus opt out. In that case, inflated ratings could instead reflect agencies’ efforts to retain naive investors. To provide more direct evidence in favor of our proposed mechanism, we examine whether the responsiveness of flows to ratings varies with both competition and investor sophistication. In the context of the fund market, the sophistication of investors can be proxied by whether they are retail or institutional, with the institutional ones generally regarded as more sophisticated given their technical resources and professional expertise. If deteriorating information quality is indeed the operative channel behind the observed pattern, then competition among rating agencies should reduce the sensitivity of flows to ratings, with this effect concentrated among institutional investors. This motivates our second hypothesis.

H2: *The sensitivity of fund flows to average ratings declines as rating coverage increases, with a sharper reduction among institutional investors than retail investors.*

4 Data and Empirical Analysis

4.1 Sample Construction

Our study constructs a comprehensive panel dataset of Chinese mutual funds by integrating data from multiple sources. Fund ratings are manually collected from the Asset Management Association of China (AMAC), where they are disclosed quarterly. Monthly return data come from the CSMAR database, and quarterly fund characteristics—including Total Net Assets (TNA), fund type, and institutional ownership—are obtained from WIND.

Tables OA.1 and OA.2 summarize the landscape of fund rating coverage. As shown in Table OA.1, the number of funds rated by the seven major agencies increases sharply over the sample period, reflecting the rapid expansion of the industry. Table OA.2 further documents overlapping coverage, highlighting that while many funds receive at least one rating, far fewer are covered by multiple agencies. This cross-sectional and time-series variation in the number of ratings per fund is central to our empirical analysis.

Our sample construction proceeds in three steps to create a relevant dataset for analysis.

First, we define the initial universe of funds. Our focus is on actively managed funds investing in the domestic Chinese market. We therefore begin by selecting all equity funds and hybrid funds from the WIND database, while explicitly excluding all passive instruments such as index funds, Exchange-Traded Funds (ETFs), and Listed Open-Ended Funds (LOFs). Furthermore, we exclude Qualified Domestic Institutional Investor (QDII) funds to restrict our sample to products focused on the domestic market. Under Chinese regulations, equity funds must invest at least 80% of their assets in stocks, whereas hybrid funds have more flexible mandates regarding their equity allocation. To ensure our analysis remains centered on equity-driven investment decisions, we apply an additional screen, requiring that all hybrid funds in our sample maintain an equity portfolio of at least 50% of their total assets under management.

Second, we align our sample with the eligibility criteria used by rating agencies. Rating agencies in China, as a standard practice, only assign ratings to funds that have accumulated at least a three-year performance history. To ensure our sample consists of funds that are eligible for rating coverage, we impose the same requirement, excluding funds with fewer than three years of historical return data.

Third, we filter by fund size. We require all funds to have a minimum of 100 million CNY in Total Net Assets (TNA). This threshold is implemented to exclude micro-funds, for which flow data can be noisy and potentially distorted by the actions of a few large investors, making them less representative of general market trends.

The resulting dataset is a fund–quarter panel covering the period from 2010 to 2023.

4.2 Variables Construction

Our primary dependent variable is the quarterly fund flow, which captures the net new capital entering or exiting a fund. Following the literature (Chevalier and Ellison, 1999), we compute the net flow for fund p in quarter t as the growth in total net assets (TNA) not attributable to investment returns:

$$\text{Flow}_{p,t} = \frac{\text{TNA}_{p,t}}{\text{TNA}_{p,t-1}} - (1 + R_{p,t}), \quad (1)$$

where $\text{TNA}_{p,t}$ denotes the total net assets of fund p at the end of quarter t , and $R_{p,t}$ is the fund’s total return over the same period.

To differentiate the behavior of sophisticated versus naive investors, we decompose total flows into institutional and retail components. Information on the proportion of institutional and retail ownership is available at a semi-annual frequency. To align with our quarterly framework, we linearly interpolate these ownership ratios for the intervening quarters. Institutional flow is then defined as the change in the market value of institutional

holdings, net of investment returns, scaled by lagged TNA:

$$\text{InstFlow}_{p,t} = \frac{\text{TNA}_{p,t} \times \text{InstRatio}_{p,t} - \text{TNA}_{p,t-1} \times \text{InstRatio}_{p,t-1} \times (1 + R_{p,t})}{\text{TNA}_{p,t-1}}, \quad (2)$$

Retail flow is computed analogously. This decomposition provides a direct measure of the net allocation decisions of different investor types.

The key explanatory variables in our analysis are the number of ratings and their average level, which capture the breadth of rating coverage, respectively. *No. of Ratings* is defined as the total number of ratings a fund receives from the seven major agencies in a given quarter. *Mean Rating* is the simple average of these ratings, measured on a five-star scale.

In our regressions, we control for a set of standard fund characteristics known to influence flows. These include $\ln(\text{Fund size})$, the natural logarithm of TNA; $\ln(\text{Fund age})$, the natural logarithm of the fund’s age in years since inception; *Return*, the fund’s excess return in the current quarter; and *Lag Flow*, the fund’s total flow from the current quarter. We also include a dummy variable, *Tiered*, which equals one for structured funds.

To mitigate the influence of outliers, key continuous variables, including total flows, decomposed flows, and returns, are winsorized at the 1st and 99th percentiles within each quarter.

4.3 Quasi-natural Experiment: The Morningstar Coverage Shock

A major challenge in estimating the causal effect of rating coverage on fund flows is the potential endogeneity of rating coverage. Rating agencies may strategically choose to rate larger, older, or better-performing funds, making it difficult to disentangle the impact of rating coverage from these underlying characteristics. To address this concern, we employ an instrumental variables (IV) approach leveraging a quasi-natural experiment.

Our identification strategy exploits a methodological shift by Morningstar, a leading global rating agency, in Q4 2021. Prior to this date, Morningstar excluded funds classified

as “Flexible Allocation” from its coverage. Beginning in Q4 2021, Morningstar expanded its scope to include these funds, resulting in an exogenous increase in the number of ratings for this group. This coverage shock serves as a plausibly exogenous source of variation in rating coverage, unrelated to contemporaneous fund performance or flow dynamics.

We define the treatment group as funds that (i) are classified as “Flexible Allocation,” (ii) were not rated by Morningstar prior to Q4 2021, and (iii) received their first Morningstar rating in Q4 2021. The control group comprises all other funds whose rating coverage remained unaffected by this change. To exploit this quasi-natural experiment, we construct a difference-in-differences (DiD) style instrument using the interaction term, $Treated \times Post$, where $Treated$ is a time-invariant indicator equal to one for funds in the treatment group and $Post$ is a time-varying indicator equal to one from Q4 2021 onward and zero before. The interaction term captures the differential shift in rating coverage for treated funds in the post-period.

This DiD-style instrument isolates the effect of Morningstar’s policy change under the assumption of parallel trends: absent the coverage expansion, treated and control funds would have followed similar trajectories in rating coverage. We implement a two-stage least squares (2SLS) framework, using $Treated \times Post$ as an instrument for the number of ratings. This approach mitigates endogeneity concerns and allows us to estimate the causal impact of rating coverage on fund flows.

4.4 Descriptive Statistics

Before presenting the regression results, we briefly characterize the mutual fund rating landscape and our sample. Detailed statistics on the evolution of rating coverage are provided in Section 5.

Table OA.1 in the Appendix reports the proportion of funds covered by each of the seven primary rating agencies from 2010 to 2023. The data reveal a consistent expansion in rating coverage across domestic agencies, mirroring the development of the Chinese mutual

fund industry. Notably, Morningstar’s coverage trajectory exhibits a distinct structural break: following its methodology reform in late 2021, its coverage rate increased by almost 40% compared to the previous year. This sharp discontinuity serves as the basis for our identification strategy.

Complementing this view, Appendix Table OA.2 illustrates the evolution of coverage intensity. The key stylized fact is the dominance of a multi-rater environment. Over the sample period, the market has shifted such that the majority of funds are scrutinized by multiple intermediaries simultaneously. By the end of the sample, funds covered by fewer than five agencies have become a minority, while those covered by all seven agencies represent a significant share of the market. This intense overlap in coverage confirms that the Chinese mutual fund market is a highly competitive arena for information intermediaries, providing the necessary variation to test our theoretical predictions.

To motivate our formal analysis, we first present visual evidence on the relationship between rating competition and rating behavior. Figure 1 plots the distribution of fund ratings against the number of rating agencies covering the fund.

While the trend is not strictly monotonic—funds covered by only one or two agencies also exhibit high average ratings, likely reflecting a selection effect where agencies initially cover only top-performing funds or high variance due to smaller sample sizes—a distinct inflationary pattern emerges as coverage expands from 3 to 7 agencies. In the high-competition regime ($N = 7$), both the mean (circle) and median (cross) ratings reach their peak. Moreover, the 25th percentile (the bottom of the box) is significantly elevated compared to lower-coverage groups. This upward shift of the lower bound indicates that the rating distribution is heavily skewed toward the top end; in a crowded market, it becomes increasingly rare for a fund to receive a low rating, consistent with the hypothesis of systematic rating inflation.

Finally, Table 1 provides summary statistics for the variables used in our regression analysis. The average quarterly net flow is positive (3.3%), indicating that, on average, the funds in our sample experienced net inflows over the period. The average fund is covered

by approximately 6 rating agencies, with a median of 7, reinforcing the high-competition environment shown in Table OA.2. The mean rating is 3.005 on a five-point scale, suggesting no systematic positive or negative bias in aggregate ratings. The table also shows considerable variation in fund characteristics such as age and size. The average quarterly return was 1.6%, though with a high standard deviation, reflecting market volatility.

4.5 Empirical Results

4.5.1 The Effect of Rating Coverage on Fund Flows

We begin by examining the effect of rating coverage on fund flows. Our model predicts that as the number of rating agencies (*No. of Ratings*) increases, intensified competition among raters dilutes the informational content of ratings, leading investors to reduce allocations or withdraw capital.

Table 2 presents the results of our baseline regressions. Columns (1)–(5) report ordinary least squares (OLS) estimates with progressively richer sets of controls and fixed effects. In column (1), a simple specification shows a negative and statistically significant relationship ($p < 0.01$) between *No. of Ratings* and fund flows. Adding standard fund-level controls in column (2), including fund age, size, past returns, and lagged flows, confirms the robustness of this relationship. In column (3), we expand the sample to include unrated funds, adding a dummy variable, *Rated*, to account for the presence of rating coverage, and the result remains consistent. Incorporating quarter fixed effects in column (4) and fund fixed effects in column (5) yields similar findings. In our preferred specification (column 5), the coefficient on *No. of Ratings* is -0.014 ($p < 0.01$), implying that a one-standard-deviation increase in the number of ratings (approximately one and two-thirds agencies) predicts a 2.32 percentage point decrease in quarterly net flow, an effect that is equivalent to approximately 70% of the average fund flow in our sample (3.3%).

While OLS estimates provide compelling evidence, they may be subject to endogeneity

concerns: rating agencies may strategically select funds based on size, performance, or other characteristics. To address this issue, we employ an instrumental variables (IV) approach, leveraging the Morningstar coverage shock described in Section 4.3. Columns (6) and (7) of Table 2 present the first-stage and second-stage results from our 2SLS framework. The first-stage regression shows that the $Treated \times Post$ interaction significantly predicts increases in *No. of Ratings*, with Sanderson-Windmeijer and Cragg-Donald Wald F-statistics far exceeding conventional thresholds, confirming the strength of the instrument.

The second-stage IV regression in column (7) reveals a larger negative effect of rating coverage on fund flows. The coefficient on *No. of Ratings* is -0.048 ($p < 0.10$), indicating that an exogenous increase of one rating agency reduces quarterly net flows by approximately 4.8 percentage points. This causal estimate is larger in magnitude than the corresponding OLS coefficients, suggesting that the latter may understate the true effect due to endogeneity. Economically, this result implies that a one-standard-deviation increase in the number of ratings (approximately 1.66 agencies) reduces quarterly net flows by about 8% of lagged total net assets (TNA), a substantial effect relative to the average flows in our sample.

To further validate the exogeneity of this shock and the robustness of our IV estimates, we conduct a series of additional tests detailed in online appendix. These tests graphically confirm that the parallel trends assumption for our instrument’s first stage holds (see Figure OA.1). Furthermore, we re-estimate our main IV specifications on a propensity-score matched (PSM) sample (see Table OA.3). The results from this PSM-IV approach are consistent with our main findings, reinforcing the causal interpretation of our estimates.

4.5.2 Mechanism Test: Institutional vs. Retail Investors

Our theoretical framework predicts that the negative effect of rating coverage on fund flows is primarily driven by sophisticated investors, who are more likely to discern declines in informational quality, while naive investors remain relatively unaffected. To test this prediction, we decompose total flows into institutional (*InstFlow*) and retail (*RetailFlow*)

components, which serve as proxies for sophisticated and naive investors, respectively.

Table 3 reports the results of this decomposition. The findings provide a clear channel for our baseline results. While OLS estimates in columns (2) and (5) show negative coefficients for both investor types, the IV regressions—which isolate causal effects—reveal a striking divergence.

For institutional flows, the IV estimate in column (3) is -0.029 ($p < 0.05$), indicating that an exogenous increase of one rating agency covering a fund reduces quarterly net flows from institutional investors by 2.9 percentage points. By contrast, the IV coefficient for retail flows in column (6) is small and statistically insignificant.

Table 3 presents the results of this decomposition. Columns (1)–(3) focus on institutional flows, while columns (4)–(6) focus on retail flows. For institutional investors, the OLS estimates in columns (1) and (2) show a negative relationship between *No. of Ratings* and *InstFlow*, and the IV regression in column (3) confirms this effect. Specifically, the IV estimate in column (3) indicates that an additional rating agency reduces institutional net flows by 2.9 percentage points ($p < 0.05$). This result highlights that sophisticated investors, who are more likely to recognize the informational dilution caused by rating inflation, respond by reducing their capital allocations.

These findings provide strong evidence for the heterogeneous effects of rating competition on different investor types. The aggregate net outflows documented in Section 4.5.1 are primarily driven by institutional investors, who interpret increased competition as a signal of potential rating inflation and informational degradation. Retail investors, on the other hand, remain largely reliant on curated ratings and do not significantly alter their investment behavior in response to changes in rating coverage.

4.5.3 Mechanism Test: Rating Inflation

A central mechanism proposed by our theoretical model is that increased competition among rating agencies incentivizes them to issue more favorable ratings, leading to rating inflation.

As competition intensifies, agencies face stronger incentives to inflate ratings to attract funds, which collectively undermines the informational quality of the ratings ecosystem. We test this hypothesis by examining the relationship between the number of ratings a fund receives (*No. of Ratings*) and its average rating (*Mean Rating*).

Table 4 presents the results of this analysis. Across all OLS specifications in columns (1)–(4), the coefficient on *No. of Ratings* is positive and highly significant, even after including a full set of fund and quarter fixed effects. In the fully controlled specification (column 4), the coefficient on *No. of Ratings* is 0.126 ($p < 0.01$), indicating that an additional rating agency increases the average rating of a fund by 0.126 stars on a five-point scale. This substantial increase supports the hypothesis that competition fosters rating inflation.

To address potential endogeneity concerns, we turn to the IV approach using the Morningstar shock. Column (5) of Table 4 reports the IV estimate, which indicates a larger coefficient of 0.283 ($p < 0.01$). This result suggests that the OLS estimates may understate the true causal effect of competition on rating inflation. Economically, the IV estimate implies that a one-standard-deviation increase in *No. of Ratings* leads to an increase of approximately 0.283 stars in the fund’s average rating, which is a meaningful shift in ratings. This causal evidence strongly supports our model’s premise: intensified competition directly contributes to higher, and potentially inflated, fund ratings.

However, higher average ratings do not necessarily imply a loss of quality; they could simply reflect better fund performance. The core prediction of our model is that competition leads to “rating inflation”—a debasement of informational quality. We test this directly by examining whether increased competition erodes the ability of ratings (*Mean Rating*) to predict future fund performance, proxied by the one-quarter-ahead CAPM alpha (Alpha_{t+1}).

Columns (6) and (7) of Table 4 present this test. The coefficient on *Mean Rating* is positive, suggesting that ratings, on average, do contain predictive power for future alpha. Crucially, the coefficient on the interaction term, $\text{No. of Ratings} \times \text{Mean Rating}$, is negative and statistically significant, particularly in our preferred IV specification (column 7), with a

coefficient of -0.015 ($p < 0.01$).

This finding provides direct evidence for our mechanism. The negative interaction term implies that as competition increases, the informational content of ratings deteriorates; the positive link between a fund’s rating and its future performance becomes significantly weaker. This confirms that the ”inflation” documented in columns (1)-(5) is not benign but represents a genuine loss of informational quality, providing the fundamental explanation for why sophisticated investors grow skeptical and withdraw from the market.

4.6 Rating Competition and Flow-Rating Sensitivity

Having established the negative overall effect of rating coverage on fund flows, we next examine a more nuanced prediction of our model: how competition among rating agencies affects the sensitivity of fund flows to the ratings themselves. Our model predicts that as the number of ratings increases, sophisticated investors become more skeptical of ratings due to inflation, resulting in a sharper reduction in their flow sensitivity compared to naive investors.

We first test this hypothesis using a sub-sample analysis in Table 5, splitting funds into those with low coverage (*No. of Ratings* < 4) and high coverage (*No. of Ratings* ≥ 4). Columns (1) and (2) focus on institutional flows (*InstFlow*), while columns (3) and (4) analyze retail flows (*RetailFlow*). The results reveal a stark divergence in flow-rating sensitivity between sophisticated and naive investors.

For institutional flows, columns (1) and (2) show that the flow-rating sensitivity is significantly lower in the high-coverage group (coefficient 0.021) than in the low-coverage group (0.038). Economically, this suggests that a one-star increase in Mean Rating generates a 1.7 percentage point larger inflow for funds with fewer ratings compared to those with extensive coverage. This result supports the prediction that sophisticated investors discount ratings more heavily in competitive environments, interpreting higher coverage as indicative of potential rating inflation and reduced informational content.

For retail flows, the results in columns (3) and (4) reveal the opposite pattern. Flow

sensitivity to Mean Rating is higher for funds with extensive coverage (coefficient 0.031, $p < 0.01$) compared to those with limited coverage (coefficient 0.020, statistically insignificant). This finding aligns with the view that naive investors interpret additional ratings as a stronger signal of quality, maintaining or even increasing their reliance on curated ratings in competitive environments.

To provide stronger causal evidence, Table 6 implements a dynamic difference-in-differences specification, analogous to a difference-in-differences-in-differences (DDD) framework, focusing on flow-rating sensitivity changes around the Morningstar coverage shock. The key variable is the triple interaction term $Treated \times D_t \times Mean\ Rating$, where D_t represents time dummies for quarters relative to the coverage shock (e.g., $t = 0$ corresponds to Q4 2021). The analysis focuses on a four-quarter window before and after the shock to minimize confounding factors.

Columns (1)–(3) of Table 6 report results for institutional flows. In column (1), the coefficient on $Treated \times D_0 \times Mean\ Rating$ is -0.026 ($p < 0.05$), indicating a significant reduction in institutional flow sensitivity immediately following the coverage expansion. This effect corresponds to a 2.6 percentage point decrease in institutional flow responsiveness to a one-star rating increase. The effect is even larger for funds with fewer ratings pre-treatment, as shown in columns (2) and (3). By contrast, columns (4)–(6) show that changes in retail flow sensitivity are statistically insignificant, indicating that retail investors remain largely unaffected by the shock.

These results provide robust causal evidence that rating competition erodes the informational content of ratings for sophisticated (institutional) investors, who respond by discounting ratings more heavily. In contrast, naive (retail) investors continue to rely on ratings as signals of quality, unaffected by the strategic dynamics of rating agencies. This divergence underscores the differential impact of rating inflation on investor behavior, consistent with the predictions of our theoretical model.

4.7 Summary of Empirical Findings

The empirical results presented in Section 4.5.1-Section 4.6 provide strong support for the theoretical predictions of our model. First, we show that intensified competition among rating agencies leads to rating inflation, reducing the credibility and informational content of ratings. Second, we demonstrate that sophisticated investors respond to this dynamic by withdrawing capital from funds with extensive coverage, driving aggregate net outflows. Retail investors, however, remain reliant on curated ratings and do not significantly adjust their allocations. Finally, we provide causal evidence that competition reduces flow-rating sensitivity for sophisticated investors while preserving or enhancing sensitivity for naive investors.

Together, these findings highlight the detrimental effects of rating competition on information quality and capital allocation in financial markets. They underscore the importance of understanding the dual role of rating agencies as both evaluators and distributors of financial products. The results suggest that while competition may appear beneficial in terms of increased coverage and accessibility, it can lead to unintended consequences, such as rating inflation and reduced trust among sophisticated investors. These dynamics ultimately undermine the allocative efficiency of capital markets, as funds with inflated ratings attract less discerning capital, potentially misallocating resources.

5 Conclusion

This paper investigates the impact of competition among financial intermediaries on the informativeness of ratings and investor behavior in dual-role environments, where intermediaries both evaluate and distribute financial products. Leveraging by the rapid growth of the Chinese mutual fund industry as a natural laboratory, we identify a critical trade-off in competitive settings: while competition can enhance market accessibility and reduce search costs, it also incentivizes rating inflation, reducing the credibility and quality of information available to

investors. By integrating a multi-sender Bayesian persuasion framework with rich fund-level data and a quasi-natural experiment, this study provides a comprehensive analysis of the mechanisms through which competition distorts information provision and reshapes investor behavior.

Theoretically, we model the tension intermediaries face between maintaining credibility to attract sophisticated investors and exploiting naïve investors who rely on curated ratings. Our framework highlights a free-riding mechanism: in competitive environments, intermediaries inflate ratings to gain a short-term advantage, relying on the broader credibility of the system to sustain investor trust. This dynamic systematically degrades the quality of information available in the market, particularly for sophisticated investors who rationally discount inflated ratings.

Empirically, using a comprehensive panel of Chinese mutual funds—including ratings, returns, fund characteristics, and ownership data—we provide robust evidence for the model’s predictions. Exploiting Morningstar’s expansion of coverage as a quasi-natural experiment, we establish that increased competition among rating agencies leads to higher average ratings, reduced flow sensitivity among sophisticated investors, and net capital outflows driven primarily by institutional investors. These findings confirm that rating inflation is a central channel linking competition to diminished information quality and inefficient capital allocation. Moreover, our decomposition of investor flows reveals heterogeneous responses, with sophisticated investors disengaging in response to rating inflation while naïve investors remain reliant on curated ratings.

Beyond its academic contributions, this study has significant policy implications that resonate with global regulatory discussions led by organizations such as the SEC and IOSCO. Both regulators have raised concerns about rating inflation, conflicts of interest, and the broader impact of intermediary competition on market efficiency. While the SEC has implemented stricter oversight of credit rating agencies under Dodd-Frank and IOSCO has issued global standards for transparency and accountability, our findings suggest that these

frameworks must be adapted to address challenges specific to dual-role intermediaries in mutual fund markets and similar asset classes. Our findings challenge the conventional view that competition among intermediaries always enhances market efficiency. Instead, we show that unregulated competition in dual-role environments can undermine the credibility of ratings, distort capital flows, and reduce overall welfare. Policymakers must weigh the benefits of competition against the risks of rating inflation and information degradation, such as enhanced transparency requirements, stricter oversight of rating practices, and measures to reduce conflicts of interest in dual-role intermediaries. Second, for investors, our results underscore the importance of exercising caution when relying on ratings in highly competitive environments, particularly when ratings are presented selectively by distribution platforms with commercial incentives.

This paper also opens several avenues for future research. First, while our analysis focuses on the mutual fund industry, the framework can be extended to other financial markets, such as corporate bond ratings, credit scoring, and ESG (environmental, social, and governance) evaluations, where dual-role intermediaries play a critical role. Second, future studies could explore dynamic interactions among intermediaries, examining how repeated competition shapes rating practices over time and whether reputational mechanisms can partially discipline inflationary tendencies. Finally, empirical work on potential remedies—such as centralized disclosure platforms, standardized rating methodologies, or alternative incentive structures for intermediaries—could offer valuable insights into designing market environments that preserve the integrity of information while fostering healthy competition.

References

- ASHCRAFT, A., GOLDSMITH-PINKHAM, P., HULL, P. and VICKERY, J. (2011). Credit ratings and security prices in the subprime mbs market. *American Economic Review*, **101** (3), 115–119.
- BARBER, B. M., HUANG, X. and ODEAN, T. (2016). Which factors matter to investors? evidence from mutual fund flows. *Review of Financial Studies*, **29** (10), 2600–2642.
- BECKER, B. and MILBOURN, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, **101** (3), 493–514.
- BENABOU, R. and LAROQUE, G. (1992). Using privileged information to manipulate markets: Insiders, gurus, and credibility. *Quarterly Journal of Economics*, **107** (3), 921–958.
- BERGEMANN, D. and MORRIS, S. (2016). Information design, bayesian persuasion, and bayes correlated equilibrium. *American Economic Review*, **106** (5), 586–591.
- and — (2019). Information design: A unified perspective. *Journal of Economic Literature*, **57** (1), 44–95.
- BOLTON, P., FREIXAS, X. and SHAPIRO, J. (2012). The credit ratings game. *Journal of Finance*, **67** (1), 85–111.
- BONGAERTS, D., CREMERS, K. M. and GOETZMANN, W. N. (2012). Tiebreaker: Certification and multiple credit ratings. *Journal of Finance*, **67** (1), 113–152.
- CHEVALIER, J. and ELLISON, G. (1999). Are some mutual fund managers better than others? cross-sectional patterns in behavior and performance. *Journal of Finance*, **54** (3), 875–899.
- DOHERTY, N. A., KARTASHEVA, A. V. and PHILLIPS, R. D. (2012). Information effect of entry into credit ratings market: The case of insurers’ ratings. *Journal of Financial Economics*, **106** (2), 308–330.
- GENTZKOW, M. and KAMENICA, E. (2016). Competition in persuasion. *Review of Economic Studies*, **84** (1), 300–322.
- and — (2017). Bayesian persuasion with multiple senders and rich signal spaces. *Games*

- and *Economic Behavior*, **104**, 411–429.
- GRIFFIN, J. M. and TANG, D. Y. (2012). Did subjectivity play a role in cdo credit ratings? *Journal of Finance*, **67** (4), 1293–1328.
- HE, J., QIAN, J. and STRAHAN, P. E. (2012). Are all ratings created equal? the impact of issuer size on the pricing of mortgage-backed securities. *Journal of Finance*, **67** (6), 2097–2137.
- IVKOVIĆ, Z. and WEISBENNER, S. (2009). Individual investor mutual fund flows. *Journal of Financial Economics*, **92** (2), 223–237.
- JIANG, J. X., STANFORD, M. H. and XIE, Y. (2012). Does it matter who pays for bond ratings? historical evidence. *Journal of Financial Economics*, **105** (3), 607–621.
- KAMENICA, E. and GENTZKOW, M. (2011). Bayesian persuasion. *American Economic Review*, **101** (6), 2590–2615.
- KESWANI, A. and STOLIN, D. (2008). Which money is smart? mutual fund buys and sells of individual and institutional investors. *Journal of Finance*, **63** (1), 85–118.
- KOLOTILIN, A., MYLOVANOV, T., ZAPECHELNYUK, A. and LI, M. (2017). Persuasion of a privately informed receiver. *Econometrica*, **85** (6), 1949–1964.
- LIPNOWSKI, E., RAVID, D. and SHISHKIN, D. (2025). Perfect Bayesian persuasion. *Journal of Political Economy Microeconomics*, forthcoming.
- LIZZERI, A. (1999). Information revelation and certification intermediaries. *RAND Journal of Economics*, pp. 214–231.
- MATHIS, J., MCANDREWS, J. and ROCHET, J.-C. (2009). Rating the raters: Are reputation concerns powerful enough to discipline rating agencies? *Journal of Monetary Economics*, **56** (5), 657–674.
- SKRETA, V. and VELDKAMP, L. (2009). Ratings shopping and asset complexity: A theory of ratings inflation. *Journal of Monetary Economics*, **56** (5), 678–695.
- XIA, H. (2014). Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies? *Journal of Financial Economics*, **111** (2), 450–468.

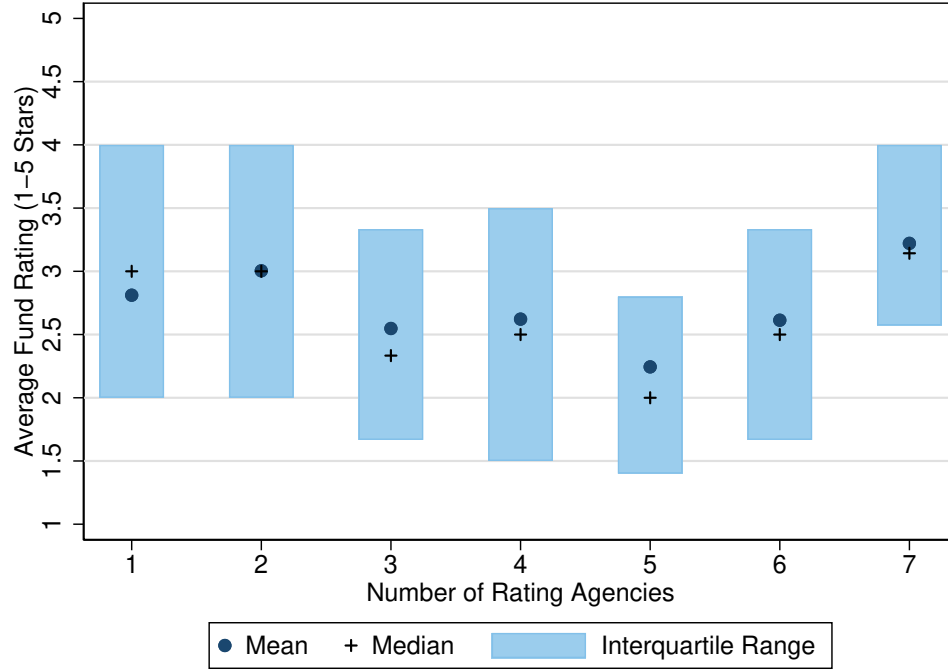


Figure 1: Rating Inflation: Rating Distribution by Coverage Intensity

Notes: This figure plots the distribution of average fund ratings for funds covered by different numbers of rating agencies ($N = 1$ to 7). The box represents the interquartile range (25^{th} – 75^{th} percentile), focusing on the core distribution. The median is marked by a cross (+), and the mean is marked by a solid circle (•).

Table 1: Summary Statistics

	N	mean	sd	min	p10	p25	p50	p75	p90	max
Flow	37692	0.033	0.560	-0.969	-0.204	-0.093	-0.030	0.017	0.186	25.981
InstFlow	37648	0.020	0.279	-0.774	-0.104	-0.025	0.000	0.010	0.109	9.428
RetailFlow	37687	0.006	0.324	-0.725	-0.140	-0.068	-0.022	0.015	0.103	13.324
No. of Ratings	37734	6.057	1.660	1.000	3.000	6.000	7.000	7.000	7.000	7.000
Mean Rating	37734	3.005	1.057	1.000	1.571	2.167	3.000	3.857	4.500	5.000
Ln(Fund age)	37734	2.034	0.432	0.000	1.507	1.689	1.995	2.355	2.650	3.109
Ln(Fund size)	37713	20.163	1.750	13.804	17.820	19.034	20.337	21.460	22.292	24.483
Return	37734	0.016	0.108	-0.390	-0.108	-0.046	0.006	0.068	0.155	0.656
Tiered	37734	0.580	0.494	0.000	0.000	0.000	1.000	1.000	1.000	1.000

Notes: This table reports summary statistics for the main variables used in the regression analyses. The sample consists of 37,734 fund-quarter observations covering the period from 2006 to 2023. All variables are defined in detail in Section 4.2. *Flow* is the total quarterly net fund flow, scaled by lagged Total Net Assets (TNA). *InstFlow* and *RetailFlow* are the institutional and retail components of the total flow, respectively, also scaled by lagged TNA. *No. of Ratings* is the count of ratings a fund receives in a quarter, ranging from 1 to 7. *Mean Rating* is the average star rating on a scale of one to five. *Ln(Fund age)* is the natural logarithm of the fund's age in years, and *Ln(Fund size)* is the natural logarithm of its TNA in CNY. *Return* is the fund's quarterly total return. *Tiered* is an indicator variable equal to one for structured funds.

Table 2: Response of fund flow to number of ratings—total flow

Model	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV
Dep. Var.	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	$Flow_{t+1}$	First Stage No. of Ratings	Second Stage $Flow_{t+1}$
No. of Ratings	-0.012*** (0.004)	-0.014*** (0.004)		-0.008** (0.003)	-0.014*** (0.005)		-0.048* (0.026)
Rated $\times$ No. of Ratings			-0.016*** (0.004)				
Rated $\times$ Mean Rating			0.038*** (0.007)				
Mean Rating	0.025*** (0.006)	0.036*** (0.006)		0.028*** (0.006)	0.054*** (0.008)	0.141*** (0.015)	0.059*** (0.009)
Ln(Fund age)		0.034*** (0.010)	0.054*** (0.015)	0.035*** (0.011)	0.229*** (0.054)	6.215*** (0.336)	0.453** (0.174)
Ln(Fund size)		-0.043*** (0.006)	-0.056*** (0.014)	-0.045*** (0.007)	-0.166*** (0.018)	0.009 (0.023)	-0.166*** (0.017)
Return		0.258*** (0.085)	0.513*** (0.093)	0.686*** (0.131)	0.630*** (0.120)	-0.034 (0.187)	0.627*** (0.119)
Lag Flow		0.050*** (0.014)	0.040*** (0.012)	0.040*** (0.014)	0.027 (0.017)	-0.060*** (0.012)	0.025 (0.017)
Tiered		0.015** (0.006)	0.017*** (0.006)	0.019*** (0.005)			
Rated			-0.091*** (0.033)				
Treated $\times$ Post						1.046*** (0.077)	
Constant	0.024 (0.032)	0.798*** (0.133)	1.109*** (0.293)	0.792*** (0.134)	2.832*** (0.346)	-7.292*** (0.656)	
Quarterly FE	N	N	N	Y	Y	Y	Y
Fund FE	N	N	N	N	Y	Y	Y
N	34667	34648	56682	34648	34422	34422	34422
R^2	0.004	0.030	0.028	0.054	0.141	0.762	0.052
adj. R^2	0.004	0.029	0.028	0.052	0.095	0.750	0.052
Cragg-Donald Wald F-stat						1468.81	
Sanderson-Windmeijer F-stat						182.4	

Notes: This table presents regression results on the relationship between the number of rating agencies covering a fund and its subsequent quarterly net flow. The dependent variable in all columns is quarterly fund flow ($Flow_{t+1}$). *No. of Ratings* is the count of ratings for a fund. Columns (1)-(5) report OLS estimates with an increasing set of controls and fixed effects. Columns (6) and (7) report two-stage least squares (2SLS) results where *No. of Ratings* is instrumented by *Treated $\times$ Post*, an interaction term capturing the exogenous coverage expansion by Morningstar in Q4 2021. Column (6) shows the first-stage regression, and Column (7) shows the second-stage results. Standard errors, reported in parentheses, are clustered by fund and quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Response of fund flow to number of ratings—flow decomposition

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	OLS	OLS	IV	OLS	OLS	IV
	$InstFlow_{t+1}$	$InstFlow_{t+1}$	$InstFlow_{t+1}$	$RetailFlow_{t+1}$	$RetailFlow_{t+1}$	$RetailFlow_{t+1}$
No. of Ratings	-0.003* (0.001)	-0.005* (0.002)	-0.029** (0.014)	-0.011*** (0.003)	-0.008** (0.003)	-0.011 (0.015)
Mean Rating	0.010*** (0.002)	0.020*** (0.003)	0.024*** (0.004)	0.024*** (0.004)	0.030*** (0.005)	0.030*** (0.006)
Ln(Fund age)	0.010*** (0.004)	0.090*** (0.026)	0.253** (0.096)	0.025*** (0.008)	0.130*** (0.034)	0.153 (0.101)
Ln(Fund size)	-0.017*** (0.003)	-0.068*** (0.008)	-0.068*** (0.008)	-0.021*** (0.004)	-0.083*** (0.011)	-0.083*** (0.011)
Return	0.127*** (0.032)	0.211*** (0.052)	0.209*** (0.052)	0.109* (0.063)	0.383*** (0.080)	0.383*** (0.080)
Lag Flow	0.032*** (0.007)	0.029*** (0.008)	0.027*** (0.009)	0.016 (0.011)	0.000 (0.012)	0.000 (0.012)
Tiered	0.008** (0.003)			0.006 (0.004)		
Constant	0.315*** (0.072)	1.180*** (0.148)		0.376*** (0.074)	1.376*** (0.222)	
Quarterly FE	N	Y	Y	N	Y	Y
Fund FE	N	Y	Y	N	Y	Y
N	34630	34409	34409	34648	34422	34422
R^2	0.021	0.107	0.029	0.021	0.160	0.044
adj. R^2	0.021	0.060	0.029	0.020	0.115	0.043

Notes: This table decomposes the baseline results from Table 2 by investor type. The dependent variable is institutional flow ($InstFlow_{t+1}$) in columns (1)-(3) and retail flow ($RetailFlow_{t+1}$) in columns (4)-(6). For each investor type, we present a baseline OLS regression, a full fixed effects OLS specification, and a 2SLS/IV specification where *No. of Ratings* is instrumented by the $Treated \times Post$ variable. Standard errors, reported in parentheses, are clustered by fund and quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Number of ratings and rating inflation

Model Dep. Var.	(1) OLS Mean Rating	(2) OLS Mean Rating	(3) OLS Mean Rating	(4) OLS Mean Rating	(5) IV Mean Rating	(6) OLS $Alpha_{t+1}$	(7) IV $Alpha_{t+1}$
No. of Ratings	0.088*** (0.012)	0.149*** (0.010)	0.179*** (0.009)	0.126*** (0.014)	0.283*** (0.072)	0.002** (0.001)	0.039*** (0.012)
Mean Rating						0.003* (0.002)	0.091*** (0.023)
No. of Ratings×Mean Rating						-0.001** (0.000)	-0.015*** (0.004)
Ln(Fund age)		-0.500*** (0.028)	-0.583*** (0.035)	-1.001*** (0.209)	-2.034*** (0.518)	-0.019 (0.014)	0.029 (0.036)
Ln(Fund size)		0.166*** (0.009)	0.182*** (0.007)	0.336*** (0.021)	0.329*** (0.022)	-0.010*** (0.001)	-0.006*** (0.001)
Return		1.171*** (0.278)	3.903*** (0.390)	2.833*** (0.304)	2.772*** (0.301)	-0.051 (0.046)	-0.056 (0.046)
Lag Flow		0.104*** (0.027)	0.065*** (0.020)	0.011 (0.015)	0.020 (0.015)	0.003*** (0.001)	0.002** (0.001)
Tiered		0.163*** (0.014)	0.133*** (0.014)				
Constant	2.473*** (0.078)	-0.345** (0.166)	-0.701*** (0.132)	-2.553*** (0.519)		0.230*** (0.037)	
Quarterly FE	N	N	Y	Y	Y	Y	Y
Fund FE	N	N	N	Y	Y	Y	Y
N	37734	37692	37692	37584	37584	37520	37520
R^2	0.019	0.133	0.190	0.503	0.119	0.407	-0.170
adj. R^2	0.019	0.133	0.189	0.474	0.119	0.373	-0.171

Notes: This table tests for rating inflation and rating informativeness. The dependent variable is *Mean Rating* in columns (1)-(5) and the one-quarter-ahead CAPM alpha ($Alpha_{t+1}$) in columns (6)-(7). Columns (1)-(5) test whether competition (*No. of Ratings*) leads to higher average ratings (inflation). Columns (6)-(7) test whether competition erodes the predictive power of ratings for future fund performance (informativeness). OLS estimates are reported in columns (1)-(4) and (6). Columns (5) and (7) report 2SLS (IV) estimates. In column (5), *No. of Ratings* is instrumented by the *Treated* × *Post* variable derived from the Morningstar shock. In column (7), *No. of Ratings*, *Mean Rating*, and their interaction term are instrumented using *Treated* × *Post* and its interaction with *Mean Rating*. All specifications include control variables as listed in the table. Standard errors, reported in parentheses, are clustered by fund and quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: The number of ratings and flow-rating sensitivity — subgroup analysis

Model	(1)	(2)	(3)	(4)
Group	OLS	OLS	OLS	OLS
Dep. Var.	No. of Ratings<4 $InstFlow_{t+1}$	No. of Ratings $\geq$ 4 $InstFlow_{t+1}$	No. of Ratings<4 $RetailFlow_{t+1}$	No. of Ratings $\geq$ 4 $RetailFlow_{t+1}$
Mean Rating	0.038*** (0.012)	0.021*** (0.004)	0.020 (0.049)	0.031*** (0.005)
Ln(Fund age)	0.290 (0.244)	0.047** (0.020)	0.382 (0.256)	0.068* (0.037)
Ln(Fund size)	-0.151*** (0.026)	-0.072*** (0.009)	-0.418*** (0.094)	-0.078*** (0.011)
Return	0.025 (0.133)	0.207*** (0.055)	0.527 (0.321)	0.357*** (0.075)
Lag Flow	-0.006 (0.010)	0.034*** (0.010)	-0.054*** (0.018)	0.005 (0.014)
Constant	2.571*** (0.670)	1.300*** (0.178)	7.977*** (2.035)	1.333*** (0.233)
Quarterly FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
N	2788	30813	2793	30819
R^2	0.499	0.109	0.371	0.143
adj. R^2	0.295	0.061	0.116	0.097

Notes: This table examines how the sensitivity of fund flows to mean ratings varies with the number of ratings and investor type. The sample is split into funds with low coverage (*No. of Ratings* < 4) and high coverage (*No. of Ratings* $\geq$ 4). The dependent variable is institutional flow ($InstFlow_{t+1}$) in columns (1) and (2), and retail flow ($RetailFlow_{t+1}$) in columns (3) and (4). The key independent variable is *Mean Rating*. All models are estimated using OLS and include a full set of control variables as well as fund and quarter fixed effects. Standard errors, reported in parentheses, are clustered by fund and quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Response of fund flow to number of ratings—Morningstar coverage shock

No. of rating before treatment Dep. Var.	(1) < 7 <i>InstFlow_{t+1}</i>	(2) < 6 <i>InstFlow_{t+1}</i>	(3) < 5 <i>InstFlow_{t+1}</i>	(4) < 7 <i>RetailFlow_{t+1}</i>	(5) < 6 <i>RetailFlow_{t+1}</i>	(6) < 5 <i>RetailFlow_{t+1}</i>
Treated× D_0 ×Mean Rating	-0.026** (0.010)	-0.083** (0.026)	-0.096* (0.046)	-0.013 (0.012)	-0.011 (0.042)	-0.013 (0.064)
Treated× D_1 ×Mean Rating	-0.016 (0.013)	-0.077* (0.036)	-0.085 (0.059)	0.017 (0.013)	0.007 (0.039)	0.093 (0.074)
Treated× D_2 ×Mean Rating	-0.021 (0.017)	-0.061 (0.040)	-0.063 (0.060)	-0.028* (0.014)	-0.026 (0.039)	0.067 (0.065)
Treated× D_3 ×Mean Rating	-0.002 (0.025)	-0.002 (0.050)	-0.053 (0.066)	-0.015 (0.014)	0.004 (0.039)	0.075 (0.059)
Treated× D_{-2} ×Mean Rating	-0.009 (0.006)	0.048** (0.016)	0.005 (0.024)	-0.012 (0.025)	0.053** (0.018)	0.003 (0.023)
Treated× D_{-3} ×Mean Rating	-0.018 (0.013)	0.040 (0.026)	0.051 (0.060)	0.000 (0.024)	-0.015 (0.022)	0.054 (0.063)
Treated× D_{-4} ×Mean Rating	-0.037** (0.013)	-0.026 (0.027)	-0.030 (0.040)	-0.028 (0.032)	-0.193** (0.070)	-0.150 (0.084)
Mean Rating	0.046 (0.025)	0.018 (0.035)	0.030 (0.040)	0.008 (0.038)	-0.004 (0.047)	0.019 (0.069)
Constant	1.979** (0.761)	1.645 (1.157)	1.217 (1.639)	4.938*** (1.034)	3.718** (1.199)	4.386* (2.025)
Controls	Y	Y	Y	Y	Y	Y
Quarterly FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
N	3510	1116	567	3518	1124	573
R^2	0.323	0.377	0.442	0.343	0.344	0.385
adj. R^2	0.196	0.204	0.214	0.220	0.162	0.134

Notes: This table presents a dynamic difference-in-differences analysis of the impact of the Morningstar coverage shock on flow-rating sensitivity. The dependent variable is institutional flow in columns (1)-(3) and retail flow in columns (4)-(6). The key variables are the triple interaction terms, *Treated* × D_t × *Mean Rating*, where D_t are dummy variables for quarters relative to the shock in 2021:Q4 (the event quarter is $t = 0$, and the pre-event quarter $t = -1$ is the omitted baseline). The analysis is restricted to a window of four quarters before and after the event. Regressions are run on progressively smaller subsamples based on the fund's number of ratings in the quarter before the treatment. All specifications include fund and quarter fixed effects and a full set of control variables. Standard errors, reported in parentheses, are clustered by fund and quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A Proofs

A.1 Proof of Proposition 1

We solve for the unique symmetric Perfect Bayesian Equilibrium (PBE) of the game. The proof proceeds in four steps. First, we characterize the optimal strategy of a sophisticated agent, taking the principals' rating policies as given. Second, we set up the optimization problem for individual principals and derive the best-response function. Finally, we impose symmetry to solve for the equilibrium. Throughout the analysis, we impose the tie-breaking rule that agents' indifference is resolved in favor of the principals, which is without loss in our setting with binary state and action, as demonstrated by Lipnowski *et al.* (2025).

Step 1: Sophisticated Agent's Strategy. We solve the agent's problem via backward induction. A sophisticated agent who has chosen to participate observes the vector of ratings $(s_1, \dots, s_n)$. Given that the principals are truthful in the state $\omega = 1$, a bad rating from any principal i ($s_i = 0$) is a perfectly informative signal that the state is $\omega = 0$. In this case, it is clear that the agent would choose not to invest. Investment is only considered if all principals issue a good rating. Upon observing this event, the agent updates his posterior belief via Bayes' rule to:

$$\hat{\mu} = \Pr(\omega = 1 | s_1 = \dots = s_n = 1) = \frac{\mu}{\mu + (1 - \mu) \cdot \prod_{j=1}^n p_j}.$$

The agent would therefore choose to invest if and only if $\hat{\mu} \geq 0.5$, or, equivalently,

$$\prod_{j=1}^n p_j \leq \frac{\mu}{1 - \mu}. \tag{A.1}$$

Now consider the agent's decision on whether to participate in the fund market through the principals. If condition (A.1) is violated, the agent expects to never invest, yielding a

utility of 0, so he would not participate regardless of the value of his outside option (except perhaps when $\theta = 0$). If condition (A.1) holds, the agent anticipates that, should he decide to engage, he would invest in the fund if and only if he observes good ratings from all principals. Therefore, the agent's ex-ante expected utility from engaging with the principals is:

$$U(\mathbf{p}) = \mu - (1 - \mu) \prod_{j=1}^n p_j.$$

The agent chooses to engage if and only if $U(\mathbf{p}) \geq \theta$. Given that θ is drawn uniformly from $[0, \bar{\theta}]$, the total measure of participating sophisticated agents is $(1 - \lambda) \cdot \min\{U(\mathbf{p})/\bar{\theta}, 1\}$.

Step 2: Principal's Optimization Problem. We proceed to formulate the optimization problem of the principals by first ruling out two classes of non-equilibrium strategies. First, no equilibrium can have $U(\mathbf{p}) > \bar{\theta}$. If it did, all sophisticated agents would participate, and a principal could marginally increase p_i to boost revenue from naive agents without losing any sophisticated agents, a profitable deviation. Second, no equilibrium can violate the investment condition (A.1). If it did, sophisticated agents would not participate, and a principal could profitably deviate to full information ($p_i = 0$). This would satisfy (A.1), attract sophisticated agents, and increase payoffs (given that $\lambda < \mu$ is assumed).

We can therefore focus on the relevant regime where $0 \leq U(\mathbf{p}) \leq \bar{\theta}$ and condition (A.1) holds. In this regime, principal i 's expected payoff from a given profile of rating policies can be expressed as follows:

$$\begin{aligned} \Pi_i(p_i, p_{-i}) &= \frac{1}{n} \cdot \left[\lambda (\mu + (1 - \mu)p_i) + \frac{1 - \lambda}{\bar{\theta}} \cdot \left(\mu - (1 - \mu) \cdot \prod_{j=1}^n p_j \right) \cdot \left(\mu + (1 - \mu) \cdot \prod_{j=1}^n p_j \right) \right] \\ &= \frac{1}{n} \cdot \left[\lambda (\mu + (1 - \mu)p_i) + \frac{1 - \lambda}{\bar{\theta}} \cdot \left(\mu^2 - (1 - \mu)^2 \cdot \prod_{j=1}^n p_j^2 \right) \right]. \end{aligned}$$

This objective function is concave in p_i , so the principal's payoff-maximization problem can

be solved via the following first-order condition:

$$\frac{\partial \Pi_i(p_i, p_{-i})}{\partial p_i} = 0 \quad \Longleftrightarrow \quad \lambda \bar{\theta} - 2(1 - \lambda)(1 - \mu) \cdot \prod_{j \neq i} p_j^2 \cdot p_i = 0.$$

As a result, principal i 's best response function is given by

$$p_i(p_{-i}) = \frac{\lambda \bar{\theta}}{2(1 - \lambda)(1 - \mu) \cdot \prod_{j \neq i} p_j^2}. \quad (\text{A.2})$$

Step 3: Equilibrium Rating and Participation. In a symmetric equilibrium, $p_i = p^*$ for all $i = 1, \dots, n$. Substituting this into the best-response function (A.2) gives:

$$p^* = \frac{\lambda \bar{\theta}}{2(1 - \lambda)(1 - \mu)(p^*)^{2(n-1)}}.$$

Solving for p^* yields the unique symmetric equilibrium level of rating inflation (as a function of the number of principals):

$$p^*(n) = \left(\frac{\lambda \bar{\theta}}{2(1 - \lambda)(1 - \mu)} \right)^{\frac{1}{2n-1}}.$$

Finally, substituting this equilibrium value back into the agent's utility function gives the participation threshold $\hat{\theta}(n) = \mu - (1 - \mu)(p^*(n))^n$ for sophisticated agents. ■

A.2 Proof of Proposition 2

Note that both $\frac{1}{2n-1}$ and $\frac{n}{2n-1}$ are strictly decreasing in n , and therefore, both p^* and $(p^*)^n$ are strictly increasing in n . ■

A.3 Proof of Proposition 3

First, note that

$$\frac{\partial(p^*)^n}{\partial n} = -\frac{1}{(2n-1)^2} \cdot \left(\frac{\lambda\bar{\theta}}{2(1-\lambda)(1-\mu)} \right)^{\frac{n}{2n-1}} \ln \left(\frac{\lambda\bar{\theta}}{2(1-\lambda)(1-\mu)} \right)$$

which is positive. In addition,

$$\frac{\partial^2(p^*)^n}{\partial \lambda \partial n} = -\frac{1}{(2n-1)^2} \cdot \frac{\bar{\theta}}{2(1-\mu)(1-\lambda)^2} \cdot \left(\frac{\lambda\bar{\theta}}{2(1-\lambda)(1-\mu)} \right)^{\frac{n}{2n-1}-1} \cdot \left[1 + \ln \left(\frac{\lambda\bar{\theta}}{2(1-\lambda)(1-\mu)} \right) \right],$$

which is positive when λ is small but negative when λ is large. ■

Online Appendix for

“Too Many Cooks Spoil the Broth: Competition and the Corruption of Information by Dual-Role Intermediaries”

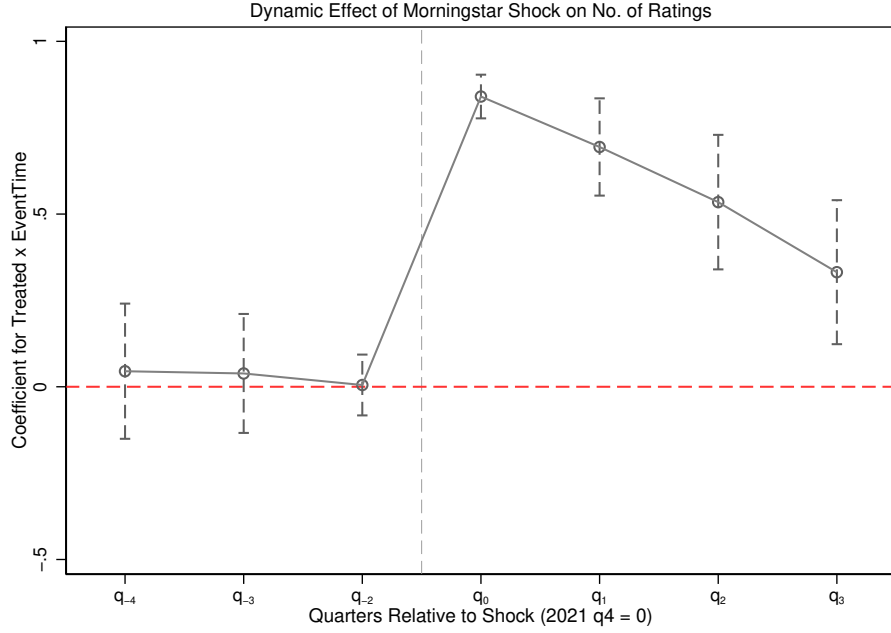


Figure OA.1: Dynamic Effect of Morningstar Shock on Rating Coverage

Notes: This figure plots the coefficients and 90% confidence intervals from the dynamic first-stage regression (corresponding to Table OA.3, column 1). The specification is: $Nall_{i,t} = \alpha_i + \gamma_t + \sum_{k \neq -1} \beta_k (\text{Treated}_i \times D_t^k) + \text{Controls} + \varepsilon_{i,t}$. The dependent variable is *No. of Ratings*. The omitted base category is $k = -1$ (2021:Q3), the quarter immediately preceding the shock. The coefficients for all pre-shock quarters ($k \leq -2$) are statistically insignificant from zero, supporting the parallel trends assumption for our instrument. The coefficients in the post-shock period ($k \geq 0$) are positive and significant, confirming the strong first-stage effect of the shock.

Table OA.1: Rating Coverage by Agency (Percentage of Total Sample)

Year	(1) GalaxySec	(2) HaitongSec	(3) ShanghaiSec	(4) ChinaMerchantsSec	(5) Tianxiang	(6) JiAn	(7) Morningstar	(8) Total Number of Funds
2010	92.6	37.1	85.7	74.3	88.6	96.0	93.7	175
2011	92.7	63.4	88.3	93.7	89.8	96.6	95.1	205
2012	90.0	68.0	84.0	88.8	85.1	96.7	95.5	269
2013	89.7	76.0	87.5	93.8	84.4	97.5	95.3	321
2014	91.8	83.2	89.1	94.4	90.7	97.1	94.4	376
2015	91.2	86.0	91.9	96.0	94.3	97.4	94.3	420
2016	88.7	85.7	91.6	94.9	94.0	97.6	93.1	467
2017	87.4	82.4	86.9	93.1	88.1	98.6	92.0	564
2018	85.9	72.7	87.0	93.8	88.5	96.7	78.3	807
2019	87.0	75.3	87.4	93.0	90.4	97.2	73.2	967
2020	87.7	71.0	84.2	84.5	88.2	97.6	68.1	1216
2021	91.9	74.7	89.1	83.5	91.9	98.9	92.7	1486
2022	93.8	76.7	86.7	83.9	94.5	97.9	96.5	1749
2023	84.6	72.2	77.5	75.3	84.9	91.0	88.7	2115

Notes: This table presents the evolution of rating coverage for the seven accredited mutual fund rating agencies in China from 2010 to 2023. Columns (1) to (7) report the proportion of funds covered by each respective agency in a given year. The proportion is calculated as the number of unique funds rated by the agency divided by the total number of funds in our sample (Column 8) for that year. A fund is considered "covered" by an agency in a year if it receives a rating from that agency in at least one quarter. Column (8) reports the total number of unique funds in our final sample for each year, including both rated and unrated funds. The sample consists of actively managed equity and hybrid funds that meet our screening criteria (e.g., non-indexed, age requirements).

Table OA.2: Proportion of fund covered by multiple agencies

Year	(1) 0 Ratings	(2) 1 Rating	(3) 2 Ratings	(4) 3 Ratings	(5) 4 Ratings	(6) 5 Ratings	(7) 6 Ratings	(8) 7 Ratings	(9) Total Number of Funds
2010	1.1	2.9	29.1	62.9	4.0	0.0	0.0	0.0	175
2011	1.0	0.0	3.9	2.9	3.4	11.2	34.1	43.4	205
2012	1.1	0.4	5.6	3.7	7.1	8.6	22.3	51.3	269
2013	0.6	0.6	5.3	4.0	6.9	2.8	19.3	60.4	321
2014	1.1	1.6	2.7	1.3	3.5	7.7	14.9	67.3	376
2015	0.7	1.4	1.7	1.9	3.3	5.2	12.6	73.1	420
2016	0.6	1.9	3.2	1.1	2.8	4.9	12.0	73.4	467
2017	0.2	2.0	5.5	3.4	3.5	5.9	14.0	65.6	564
2018	1.0	3.1	4.2	8.8	7.8	8.4	13.5	53.2	807
2019	0.4	4.3	3.1	3.6	4.4	12.4	19.4	52.2	967
2020	0.7	3.0	7.6	5.6	5.8	9.0	22.4	46.0	1216
2021	0.5	1.4	4.7	5.5	7.1	9.1	24.3	47.3	1486
2022	0.3	1.0	4.6	3.9	5.6	6.6	10.5	67.5	1749
2023	7.8	0.9	5.8	3.4	3.2	5.5	9.9	63.6	2115

Notes: This table presents the percentage distribution of rating coverage intensity for mutual funds in our sample from 2010 to 2023. Columns (1) to (8) report the proportion of funds that are covered by exactly N rating agencies in a given year, where N ranges from 0 to 7. For example, Column (1) shows the percentage of funds covered by 0 agencies (unrated), and Column (8) shows the percentage of funds covered by all 7 agencies. A fund is considered to have a coverage intensity of N if the average number of ratings it receives across all quarters in that year (rounded to the nearest integer) is N . Column (9) reports the total number of unique funds in our final sample for each year, which serves as the denominator for the proportions in Columns (1)-(8). The sample consists of actively managed equity and hybrid funds.

Table OA.3: IV Results using a PSM-Matched Sample

	(1) Column (6) in Table 2 No. of Ratings	(2) Column (7) in Table 2 $Flow_{t+1}$	(3) Column (3) in Table 3 $InstFlow_{t+1}$	(4) Column (6) in Table 3 $RetailFlow_{t+1}$	(5) Column (5) in Table 4 Mean Rating	(6) Column (7) in Table 4 $Alpha_{t+1}$
Treated $\times$ Post	1.002*** (0.123)					
No. of Ratings		-0.078** (0.036)	-0.050** (0.020)	-0.020 (0.019)	0.140 (0.104)	0.027** (0.010)
Mean Rating	0.129*** (0.022)	0.072*** (0.014)	0.031*** (0.007)	0.034*** (0.008)		0.074*** (0.018)
No. of Ratings $\times$ Mean Rating						-0.013*** (0.003)
Ln(Fund age)	7.337*** (0.563)	0.843*** (0.303)	0.481*** (0.173)	0.281* (0.154)	-1.080 (0.895)	0.080* (0.047)
Ln(Fund size)	0.041 (0.035)	-0.187*** (0.024)	-0.077*** (0.011)	-0.094*** (0.015)	0.315*** (0.032)	-0.004*** (0.002)
Return	0.085 (0.202)	0.708*** (0.153)	0.250*** (0.075)	0.446*** (0.095)	2.672*** (0.305)	-0.060 (0.051)
Lag Flow	-0.070*** (0.023)	0.023 (0.024)	0.025** (0.012)	0.001 (0.016)	-0.014 (0.018)	0.002 (0.002)
Quarterly FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
N	10527	10,527	10,521	10,527	11,237	11,214
R^2	0.725	0.048	0.017	0.053	0.147	-0.122
adj. R^2	0.709	0.048	0.016	0.052	0.147	-0.123

Notes: This table reports the robustness of our main IV specifications using a sample restricted by Propensity Score Matching (PSM). We use a 1:1 nearest-neighbor match (with a caliper of 0.01) based on fund characteristics in 2021:Q3 (the quarter prior to the shock). Covariates for matching include $Ln(Fund\ age)$, $Ln(Fund\ size)$, $Return$, $Lag\ Flow$, and $Institutional\ Investor\ Ratio$. Column (1) reports the first-stage regression for the instrument ($Treated \times Post$) on the endogenous variable ($No. of Ratings$). Columns (2)-(6) report the 2SLS (IV) second-stage results for the same dependent variables as in our main tables. $No. of Ratings$ and its interaction terms are instrumented by $Treated \times Post$ and its interactions. All regressions include fund and quarter fixed effects. Standard errors, reported in parentheses, are clustered by fund and quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.