Hide in the Herd: Uncertainty and Informational Inefficiency

ABSTRACT

We document a negative correlation between macroeconomic uncertainty and analysts' earnings forecast dispersion, driven by herding behavior that favors consensus over accuracy. This convergence transmits noisier signals and contributes to informational inefficiencies. Controlling for firm characteristics, we find that "herding firms"—those whose forecast dispersion declines with rising uncertainty—exhibit higher firm-level uncertainty, less informative stock prices, greater overpricing, and lower subsequent returns. By linking macro-level uncertainty to micro-level forecast behavior, our study highlights a behavioral transmission channel through which uncertainty amplifies psychological biases and distorts information processing. These findings offer new insight into micro-foundations of how uncertainty impairs market efficiency, complementing traditional risk-based explanations.

JEL Classification: G12, G14, D8, G41

Keywords: Macroeconomics, Uncertainty, Dispersion, Herding behavior, Anomalies, Momentum

I. Introduction

Uncertainty plays a central role in financial markets. The literature has primarily interpreted its impact on asset pricing through the lens of *efficient risk compensation*. This mechanism is well-documented in models emphasizing delayed investment, precautionary behavior, and capital reallocation frictions (e.g., Bloom (2009), Basu and Bundick (2017), Bianchi et al. (2018), Alfaro et al. (2024)). These frameworks typically assume frictionless information aggregation, implying that prices adjust efficiently to reflect uncertainty.

However, the persistence of return anomalies—such as momentum, post-earnings-announcement drift, and broader return predictability—suggests some limitations to this perspective. As Grossman and Stiglitz (1980) argue, markets deviate from full informational efficiency because information is costly and imperfectly processed. Under heightened uncertainty, these inefficiencies are amplified through two main channels: a *learning channel*, where uncertainty slows the assimilation of information (e.g., Pastor and Veronesi (2012)), and a *behavioral channel*, where uncertainty heightens psychological biases and distorts attention, beliefs, and disclosure (e.g., Peng and Xiong (2006)). As Shleifer (2000) emphasizes, uncertainty can magnify behavioral biases that persist even in the presence of arbitrage, thereby contributing to systematic mispricing and persistent informational inefficiencies. Together, these mechanisms suggest that uncertainty not only delays learning but also alters how information is perceived, processed, and transmitted in financial markets.

Yet much of the existing literature either treats prices as efficient aggregators of uncertainty or models uncertainty as a generic friction—an undifferentiated obstacle that slows learning—without specifying the underlying mechanisms. As a result, the *microfoundations linking uncertainty shocks to the processing and dissemination of information in financial markets remain underexplored.*

We fill this gap by investigating the relationship between macroeconomic uncertainty and analysts' earnings forecast dispersion, and exploring its implications for asset pricing. We focus on financial analysts because they serve as key information intermediaries, shaping investor expectations and contributing to price discovery. Unlike investor expectation dispersion, which is unobservable, analyst forecast dispersion is directly measurable and offers a unique window into how information is processed and transmitted in the market.

Our analysis uncovers a *negative relationship between macroeconomic uncertainty and analysts' earnings forecast dispersion.*[1] In particular, We find that this negative relationship is associated with a specific type of firm, termed *"herding firm"* in this paper. These firms' analysts tend to agree with each other more as macroeconomic uncertainty increases—a pattern indicative of *herding behavior*. As we demonstrate below, the negative relation between macroeconomic uncertainty and analyst forecast dispersion has profound implications for asset pricing and market efficiency.

There are generally two major explanations for herding behavior among individuals.[2] The first explanation is information-driven: individuals act similarly because they receive correlated information (e.g., Bikhchandani et al. (1992), Bikhchandani and Sharma (2001)). The second explanation centers on behavioral factors. Cognitive limitations may lead analysts to conservatively underweight their private information (e.g., Edwards (1968), Liberman and Tversky (1993), Keren (1997)). Alternatively, career or reputational concerns can motivate analysts to deliberately align with the consensus (e.g., Scharfstein and Stein (1990); Trueman (1994); Hong and Kubik (2003)). This form of strategic behavior reflects Keynes (1936) "beauty contest" analogy, in which participants prioritize predicting the average opinion over expressing independent judgment.

We adopt the second explanation as the theoretical foundation to interpret our empirical findings for two reasons. First, since macroeconomic uncertainty amplifies noise in the

[1] In contrast, existing literature (e.g., Zarnowitz and Lambros (1987), Cujean and Hasler (2017), Kozeniauskas et al. (2018)) documents a positive relationship between uncertainty and dispersion in different contexts.

[2] See Devenow and Welch (1996), Bikhchandani and Sharma (2001), and Hirshleifer and Teoh (2003) for comprehensive surveys of the herding literature.

information environment (e.g.,Kozeniauskas et al. (2018), Zhang and Zhao (2023)), the reduced dispersion in analyst opinions with increasing uncertainty cannot be attributed to the information channel. Instead, macroeconomic uncertainty heightens psychological biases (e.g., Hirshleifer (2001)), likely driving analysts' herding behavior through behavior factors. Second, our empirical results indicate that the negative correlation between macroeconomic uncertainty and analyst forecast dispersion is linked to market inefficiencies that exceed what information-driven theories can account for (e.g., Shleifer (2000)). Incorporating behavioral biases into the model is therefore crucial to generate information friction and account for the observed market inefficiency.[3] Therefore, we construct an elucidative model that builds on Keynes (1936)'s beauty contest framework, where analysts trade off forecast accuracy against conformity with consensus. Following Morris and Shin (2002), we prove the existence and uniqueness of an equilibrium forecasting strategy, which transmits noisier signals to financial markets causing market inefficiency. From this framework, we derive three testable hypotheses.

Hypothesis I : Herding firms, where analyst forecast dispersion negatively correlates with macroeconomic uncertainty, exhibit higher firm-level uncertainty compared to non-herding firms, where dispersion positively correlates with macroeconomic uncertainty.

The intuition is that as macroeconomic uncertainty rises, forecast accuracy declines, prompting analysts to imitate others to share the blame for less accurate forecasts. This herding behavior is more pronounced for firms with greater uncertainty, where accurate earnings forecasts are more challenging.

Empirically, we use the U.S. Economic Policy Uncertainty (EPU) index, developed by Baker et al. (2016), as our measure of macroeconomic uncertainty. We select the EPU index for two key reasons. First, this index provides a comprehensive assessment

[3] If we model the negative correlation between macroeconomic uncertainty and analyst forecast dispersion via analysts assigning greater weight to public information and less to private signals—with the weight driven by macro uncertainty—the aggregated forecast remains optimal, without information loss. See detailed proof in Internet Appendix B

of investors' perceived macroeconomic uncertainty, capturing not only capital market fluctuations but also uncertainty in real economy decision-making processes (e.g., Gulen and Ion (2016), Nagar et al. (2019), Kaviani et al. (2020), Zhang and Zhou (2023)). Second, its daily frequency aligns well with the timing of analyst recommendations from the Institutional Brokers' Estimate System (IBES), which we use to calculate analyst forecast dispersion.[4]

To test *Hypothesis I*, we conduct difference-in-means tests and probit regressions to examine the relationship between firm-level information uncertainty and herding behavior. We use eight proxies for firm-level uncertainty, including six from Zhang (2006)—firm size, firm age, analyst coverage, analyst forecast dispersion, return volatility, and cash flow volatility—along with the number of analyst forecasts and a composite uncertainty index constructed from the seven individual measures. The results provide strong support for Hypothesis I: firms classified as herding (those firms whose analysts have herding behavior) exhibit significantly higher average levels of firm-level uncertainty compared to non-herding firms. Moreover, all eight uncertainty measures significantly predict the likelihood that a firm is identified as a herding firm. Taken together, the evidence indicates that herding behavior is more prevalent among firms with greater informational uncertainty, where valuations are inherently more difficult to estimate.

Hypothesis II: Herding firms' stock prices are less informative about the firms' fundamental values compared to those of non-herding firms.

The model demonstrates that herding behavior—where analysts prioritize conformity to consensus forecasts over independent judgment—introduces systematic noise into consensus estimates of a firm's fundamental value. This distortion amplifies informational inefficiencies in the market, as investors rely on imperfectly aggregated signals to make decisions. Consequently, we expect that herding firms, where analysts exhibit a greater propensity to conform, will experience greater informational inefficiency in their stock

[4]Our empirical results are robust to other well-known macroeconomic uncertainty measures, such as the VIX. Key findings using VIX are reported in Table H2-H4 of Internet Appendix H.

prices. This inefficiency is reflected in muted price responses to new information, indicating a delayed incorporation of fundamentals into market valuations.

To test *Hypothesis II*, we employ two different approaches. First, we examine one of the most well-known market anomalies—momentum—first documented by Jegadeesh and Titman (1993), who show that a strategy of buying past winners and shorting past losers yields abnormal profits.[5] Economically, momentum is often attributed to slow information diffusion (e.g., Chan et al. (1996), Hong and Stein (1999), Zhang (2006)). Our model predicts that stronger herding behavior should be associated with greater positive return autocorrelation. Consistent with this, we find that a standard momentum strategy—long past winners and short past losers—generates a significant average monthly return of 1.79% for herding firms, compared to just 0.34% for non-herding firms. Fama-MacBeth regressions further confirm that herding firms exhibit stronger momentum effects, even after controlling for firm-level uncertainty. These results support *Hypothesis II* by showing that herding behavior contributes to reduced price informativeness beyond the effects of firm-specific uncertainty.

Second, we test Hypothesis II by examining the market reaction to one of the most critical firm-level events: earnings announcements. Specifically, we analyze post-earnings-announcement drift (PEAD) to isolate the impact of herding. We construct long-short portfolios separately for herding and non-herding firms. Each month, stocks are sorted into deciles based on standardized unexpected earnings (SUE), and a portfolio is formed by going long on firms in the top decile (good news) and short on those in the bottom decile (bad news). Among non-herding firms, the strategy yields a modest monthly return of 0.08%, whereas for herding firms, it delivers a statistically significant 0.65% return (p-value < 0.01). This pronounced divergence indicates that herding firms' stock prices respond more sluggishly to earnings surprises. In line with our theoretical framework, this delayed adjustment reflects the noisier transmission of fundamental information caused

[5]This influential study has received numerous awards and over 17,000 citations on Google Scholar.

by analysts' strategic herding. The stronger PEAD observed among herding firms further corroborates *Hypothesis II*: herding behavior distorts the market's aggregation of fundamentals, thereby reducing price informativeness.

Hypothesis III: Compared to non-herding firms, herding firms' stock prices tend to be overpriced and earn lower subsequent returns.

The theoretical framework illustrates that, under the short-sale constraint,[6] analyst herding behavior amplifies overpricing and contributes to lower subsequent returns. The intuition is that more pronounced herding behavior leads to noisier signals about the firm's value. This, in turn, increases the risk premium associated with excess demand for the firm's stock due to the short-sale constraint.

To empirically test the hypothesis, we employ two complementary approaches. First, we construct a long-short portfolio where the short (long) leg consists of firms classified as herding (non-herding) in month t. The average monthly excess return of this strategy in month t+1 is 0.39% per month, with a statistically significant t-statistic of 3.29. Second, we conduct a Fama-MacBeth regression analysis, regressing the one-month-ahead stock return on a herding dummy variable while controlling for a set of well-established predictors (idiosyncratic volatility, analyst forecast dispersion, economic uncertainty beta, and various anomalies). The results reveal that the herding dummy retains a significant negative predictive power for future returns, even after accounting for these factors.

We make a primary contribution to the literature by establishing a unified, market-wide, and cross-sectional link between uncertainty and informational inefficiency. While prior research has separately examined how uncertainty affects investment and risk premia (e.g., Bloom (2009), Pastor and Veronesi (2012), Baker et al. (2016)), and how market inefficiencies manifest through price continuation patterns such as momentum and post-earnings-announcement drift (e.g., Jegadeesh and Titman (1993), Bernard and Thomas

[6]The short-sale constraint, assumed in our model, is well-established in the literature and supported by evidence of arbitrage limitations (e.g., Shleifer and Vishny (1997), Diether et al. (2002), Lamont and Thaler (2003)).

(1989), Hou and Moskowitz (2005)), our study bridges these strands by showing that macroeconomic uncertainty systematically induces analyst herding behavior. This herding distorts the transmission of information, leading to persistent mispricing and reduced price informativeness. Building on the Keynesian beauty contest framework and behavioral finance insights (e.g., Scharfstein and Stein (1990), Shleifer (2000), Hirshleifer (2001)), we demonstrate that uncertainty amplifies strategic conformity among analysts, creating a distinct behavioral channel through which uncertainty undermines market efficiency.

Second, we uncover a novel behavioral linkage between macro-level and firm-level uncertainty. While existing literature typically finds a positive comovement between macroeconomic and microeconomic uncertainty (e.g., Christiano et al. (2014), Kozeniauskas et al. (2018), Bloom et al. (2018)), we document a negative relationship driven by analysts' strategic rationality. Under heightened macro uncertainty, analysts reduce forecast dispersion to avoid reputational risk, thereby masking firm-level uncertainty. This insight challenges conventional interpretations and highlights the role of behavioral responses in shaping the information environment.

Third, we shift the focus of herding research from analyst characteristics (e.g., Graham (1999), Hong et al. (2000), Welch (2000), Clement and Tse (2005)) to firm-level determinants. Rather than identifying which analysts herd, we examine which firms attract herding behavior. We find that analysts are more likely to herd when forecasting firms with greater valuation uncertainty. This firm-level perspective allows us to directly link herding behavior to stock performance, revealing that herding firms experience weaker price discovery and lower subsequent returns.

Finally, we contribute to the growing literature on behavioral biases under uncertainty by demonstrating that herding behavior intensifies during periods of elevated macroeconomic uncertainty.[7] Analysts strategically suppress disagreement to avoid personal blame,

[7]Studies that investigate relations among uncertainty, behavioral biases and asset pricing include Heath and Tversky (1991), Hirshleifer et al. (1994), Fox and Tversky (1995), Caskey (2009), Roussanov (2010), Lin (2018), to name but a few.

leading to less dispersed forecasts and noisier consensus signals. This behavior not only distorts individual decision-making but also impairs the market's ability to aggregate information efficiently. Our findings underscore the importance of incorporating behavioral dynamics into models of asset pricing, especially in uncertain environments.

The rest of the paper is organized as follows. Section 2 lays out the theoretical framework and develops hypotheses. Section 3 describes the data and discusses the variables. Section 4 reports the main empirical results. Section 5 concludes.

II. Theoretical framework

In this section, we construct a model to illustrate the mechanism and develop hypotheses. The model assumes that analysts gather public and private information about the firm's future earnings to make forecasts, which investors then aggregate and use to form their trading decisions.

A. Model

We consider the stock of a firm, where each share has a liquidation value of $V + v$. Here, V represents the earnings disclosed in the firm's earnings announcement, and v is the undisclosed portion of the value.[8] We assume V and v are independent and normally distributed:

$$V \sim \mathcal{N}(\bar{V}, \tau_V^{-1}), \qquad v \sim \mathcal{N}(0, \tau_v^{-1}). \tag{1}$$

[8] The variance of v can be viewed as a measure of the quality of earning announcement. Higher variance indicates the announcement is less informative about the value of the firm.

To study macro uncertainty and firm-level uncertainty separately in the paper, we decompose variance of V into macro uncertainty σ_m^2 and idiosyncratic uncertainty σ^2,[9]

$$\tau_V^{-1} = \sigma_m^2 + \sigma^2. \tag{2}$$

We model a single firm to isolate the informational inefficiency channel driving the herding effect.[10] The economy also includes a risk-free bond, which has zero net return and zero net supply, and serves as the numéraire.

There are two trading dates: $t = 1, 2$. Before trading begins, at $t = 0$, each analyst reports their earnings forecast. Investors aggregate these forecasts and commence trading at $t = 1, 2$. At $t = 2$ the firm's earning per share V is announced. Finally, at $t = 3$, each share's liquidation value, $V + v$, is realized. The timeline is summarized in Figure 1.

Figure 1 here

A..1 Analysts

Before investors trade, analysts report forecasts of the firm's earnings V at $t = 0$. There is an unit mass of analysts, indexed by $i \in [0, 1]$. Analysts cannot observe V directly but receive a common signal,

$$c = V + \eta, \tag{3}$$

where $\eta \sim \mathcal{N}(0, \tau_\eta^{-1})$ is normally distributed, independent of V. Additionally, analyst i observes a private information s_i, which is noise signal about V,

$$s_i = V + \varepsilon_i, \tag{4}$$

[9]The difference between σ_m^2 and σ^2 can be understood through an economy with n firms. Firm j's output, $V_j = \bar{V}_j + \sigma_m \epsilon_j^s + \sigma_j \epsilon_j^{us}$, where ϵ_j^s is the systematic volatility and ϵ_j^{us} is the unsystematic volatility. Aggregating V_j across n firms to get the output of the economy: $V \sim \mathcal{N}(\bar{V}, \tau_V^{-1})$, where $\tau_V^{-1} = \sigma_m^2 + \frac{\bar{\sigma}^2}{n}$ with $\bar{\sigma}^2 = \frac{\sum \sigma_j^2}{n}$. As n becomes larger, $\lim_{n\to\infty} \tau_V^{-1} = \sigma_m^2$, which measures the macroeconomic uncertainty while σ_j measures firm j's idiosyncratic uncertainty.

[10]Our empirical evidence shows that the herding effect on stocks' prices cannot be explained by their different exposures to the systematic risk factors.

where $\varepsilon_i \sim \mathcal{N}(0, \tau_\varepsilon^{-1})$ is normally distributed, independent of V and η. Thus, analyst i's information set is $\{c, s_i\}$, with conditional expectation and variance denoted by

$$\mathrm{E}^i[\cdot] = \mathrm{E}[\cdot \mid c, s_i], \qquad \mathrm{Var}^i(\cdot) = \mathrm{Var}(\cdot \mid c, s_i). \tag{5}$$

We assume that all analysts simultaneously report their forecasts about V at $t = 0$. Analyst i reports a forecast f_i, which maximizes their utility function,

$$u_i(f_i) = -(1-\delta)\mathrm{E}^i[(f_i - V)^2] - \delta \mathrm{E}^i[(f_i - \bar{f})^2], \tag{6}$$

where $\bar{f}$ is the consensus, i.e., the average forecast of all the analysts,

$$\bar{f} = \int_0^1 f_i di. \tag{7}$$

Following Morris and Shin (2002), our model incorporates Keynes (1936) beauty contest theory, which suggests that professionals may "follow the herd" when concerned about others' perceptions of their judgment.[11] Hence, beyond forecast accuracy, analysts also seek to minimize deviations from the consensus, as captured by the second term in Eq (6). The parameter $\delta \in (0, 1)$ measures the strength of this herding incentive. We further assume that δ decreases with τ_V,

$$\frac{d\delta}{d\tau_V} < 0, \tag{8}$$

implying that herding intensifies under greater fundamental uncertainty.[12] This aligns with Hirshleifer (2001)'s insight that heightened uncertainty exacerbates psychological biases.

For analyst i, given the private and public information, the analyst's expected value of V is

$$\mathrm{E}^i[V] = \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon s_i}{\tau_V + \tau_\eta + \tau_\varepsilon}, \tag{9}$$

[11] Herding motivations, such as reputation and career concerns (as modeled by Scharfstein and Stein (1990)), are omitted to streamline the theoretical mechanism and maintain focus on how herding behavior generates information friction and cause market inefficiency.

[12] The functional form of δ is flexible. For instance, it could take the forms $\delta = \frac{1}{1+\kappa\tau_V}$, $\delta = e^{-\kappa\tau_V}$, or $\delta = \frac{2}{1+e^{\kappa\tau_V}}$, where $\kappa > 0$ governs δ's sensitivity to τ_V.

which is a weighted average of the prior $\bar{V}$, the common information c, and the private information s_i. However, due to the herding effect, analyst i's forecast of V will not reflect their true expectation of V. Instead, it will represent a weighted average of prior $\bar{V}$, common and private information, with weights that differ from the Bayesian estimation in Eq (9). This forecast is formalized in the following lemma.

Lemma 1. *There exists an unique linear forecast strategy for every analyst,*

$$f_i = \frac{\tau_V \bar{V} + \tau_\eta c + (1-\delta)\tau_\varepsilon s_i}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}. \tag{10}$$

Thus, analysts' consensus, i.e. the average forecast, is

$$\bar{f} = \frac{\tau_V \bar{V} + \tau_\eta c + (1-\delta)\tau_\varepsilon V}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}. \tag{11}$$

Proof. See Internet Appendix A. □

The dispersion of analysts' forecast D is defined as

$$D = \int_0^1 (f_i - \bar{f})^2 di = \frac{(1-\delta)^2 \tau_\varepsilon}{(\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon)^2}. \tag{12}$$

Macro uncertainty (σ_m^2) can influence the dispersion in two ways: it can either directly impact D via τ_V ($\tau_V^{-1} = \sigma_m^2 + \sigma^2$) or indirectly via its effect on δ ($\frac{d\delta}{d\tau_V} < 0$).

If there is no strategic herding in Keynes (1936) beauty contest theory ($\delta = 0$), each analyst truthfully reports his rational expectation of V:

$$f_i = \mathrm{E}^i[V] = \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon s_i}{\tau_V + \tau_\eta + \tau_\varepsilon}, \tag{13}$$

the forecast dispersion simplifies to:

$$D = \frac{\tau_\varepsilon}{(\tau_V + \tau_\eta + \tau_\varepsilon)^2} \quad \Rightarrow \quad \frac{dD}{d\sigma_m^2} > 0, \tag{14}$$

implying a positive relationship between macro uncertainty and forecast dispersion, consistent with the empirical evidence widely documented in the literature. The negative correlation, however, is uncovered by this paper and we show that it is associated with analyst tendency to strategically herd ($\delta > 0$), which is an increasing function of firm's idiosyncratic uncertainty.[13] The first proposition follows:

Proposition 1. *If δ is a decreasing function of τ_V, for sufficiently small τ_V, the dispersion D decreases as the macroeconomic uncertainty σ_m^2 increases.*

Proof. See Internet Appendix C. □

Corollary 1.1. *If δ is a decreasing convex function of τ_V, there exists a threshold value δ_c such that, holding all else equal,*

$$\delta > (<)\delta_c \iff \frac{dD}{d\sigma_m^2} < (>)0. \tag{15}$$

Similarly, there exists a threshold value σ_c for firm-level uncertainty σ such that, holding all else equal,

$$\sigma^2 > (<)\sigma_c^2 \iff \frac{dD}{d\sigma_m^2} < (>)0. \tag{16}$$

The negative relationship between analyst forecast dispersion and macroeconomic uncertainty ($\frac{dD}{d\sigma_m^2} < 0$) is driven by elevated firm-level uncertainty (σ) through analysts' increased propensity for herding behavior (δ). This Corollary implies that macro uncertainty and forecast dispersion are negatively correlated for firms with high firm-level uncertainty, but positively correlated for those with low firm-level uncertainty.

A..2 Investors

We assume there are Θ shares of stock outstanding, and the financial market opens at $t = 1, 2$ for an unit mass of investors to trade the firm's stock as Figure 1 shows. At $t = 1$,

[13]Alternative explanation for reduced forecast dispersion is that analysts place greater weight on the common signal c relative to their private signal s_i. In Internet Appendix B, we show that this mechanism requires very strong condition, and more importantly, it cannot generate information inefficiency observed in empirical evidence.

investors aggregate financial analysts' reports into the consensus $\bar{f}$, which can be rewritten as a weighted average of the prior $\bar{V}$ and the effective information $s_f = V + \frac{\tau_\eta}{\tau_\eta + (1-\delta)\tau_\varepsilon}\eta$,

$$\bar{f} = \omega\bar{V} + (1-\omega)s_f, \tag{17}$$

where $\omega = \frac{\tau_V}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}$, and $s_f \sim \mathcal{N}(\bar{V}, \tau_V^{-1} + \tau_f^{-1})$. The consensus $\bar{f}$ is informationally equivalent to s_f, whose precision $\tau_f = \frac{(\tau_\eta + (1-\delta)\tau_\varepsilon)^2}{\tau_\eta}$,

$$\frac{d\tau_f}{d\delta} < 0 \tag{18}$$

declines as the herding effect δ increases. At $t = 2$, earning announcement V is released, and at $t = 3$ the residual uncertainty v is realized. We assume that investors base on the consensus $\bar{f}$ to form their portfolios, and let P_t denote time t's equilibrium price. Thus, investors' time t information set $\mathcal{F}_t$ is given by:

$$\mathcal{F}_1 = \{\bar{f}, P_1\}, \quad \mathcal{F}_2 = \{\bar{f}, V, P_1, P_2\}, \quad \mathcal{F}_3 = \{\bar{f}, V, v, P_1, P_2, P_3\}. \tag{19}$$

At time 1 and 2, the investors choose their optimal position x_t to maximize their CARA expected utility over their final wealth,

$$\max_{x_t} \mathrm{E}_t[-e^{-\lambda W_3}], \tag{20}$$

where $\mathrm{E}_t[\cdot] = \mathrm{E}[\cdot \mid \mathcal{F}_t]$ and $\mathrm{Var}_t(\cdot) = \mathrm{Var}(\cdot \mid \mathcal{F}_t)$ denote investors' conditional expectation and variance at time t respectively, and W_3 is investor's final wealth at $t = 3$:

$$W_3 = (P_2 - P_1)x_1 + (P_3 - P_2)x_2. \tag{21}$$

To facilitate trading, we assume there exists another group of traders in the financial market: liquidity traders. Their position is assumed to follow a AR(1) process:

$$\theta_1 = z_1, \qquad \theta_2 = \beta\theta_1 + z_2, \tag{22}$$

where $0 \le \beta \le 1$, and z_1 and z_2 are independent normally distributed random variables, both with mean 0 and variance 1 for simplicity. Therefore, the market clearing conditions at $t = 1, 2$ are

$$x_t + \theta_t = \Theta. \tag{23}$$

To obtain the equilibrium prices for each period, we solve the model by backward induction (see Internet Appendix D):

$$P_2 = V + \lambda\tau_v^{-1}(\beta z_1 + z_2) - \lambda\tau_v^{-1}\Theta, \tag{24}$$

and

$$P_1 = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v}(1-\beta)\right)\right] z_1 - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta. \tag{25}$$

As shown in Eq (18), if the firm's analysts have stronger tendency of engaging in herding behavior, i.e., larger δ, their consensus contains less information about V, i.e., smaller τ_f, resulting in less informativeness of P_1 about V. It follows:

Proposition 2. *Given all else equal, analysts' stronger tendency of engaging in herding behavior, i.e., higher δ, causes the stock price to be less informative about the fundamental:*

$$\frac{d\mathrm{Var}(V \mid P_1)}{d\delta} > 0. \tag{26}$$

Proof. See Internet Appendix D. □

Price Continuity

Since the herding effect is associated with informational inefficiency of the stock price. We hypothesize that stronger herding amplifies price continuity, manifesting as return momentum and post-earnings-announcement drift (PEAD). It can be verified via Proposition 3 and Proposition 4.

Proposition 3. *There exists a critical value β_c such that the return momentum, i.e., a positive return autocorrelation* $\mathrm{Cov}(P_3 - P_2, P_2 - P_1) > 0$, *occurs if and only if $\beta > \beta_c$ and* $\mathrm{Var}(V \mid \bar{f}) > \mathrm{Var}(v)$.

$$\frac{d\beta_c}{d\delta} < 0, \qquad \frac{d\mathrm{Var}(V \mid \bar{f})}{d\delta} > 0, \tag{27}$$

implies that given all else equal, return momentum is more likely to occur when analysts have stronger tendency to engage in herding behavior.

Proof. See Internet Appendix E. □

We define earning surprise as ES $:= V - \bar{f}$ and post-earning return as PR $:= V + v - P_2$. In the base model of financial market, there is no post earning announcement drift, $\text{Cov}(\text{ES}, \text{PR}) = 0$, because at $t = 2$ when V is announced, information is completely incorporated in P_2. The herding effect is confined to P_1. However in reality, informational inefficiency persists over time. Still consistent with Hirshleifer (2001) insight that heightened uncertainty exacerbates psychological biases, we extend the base model and posit that under elevated macroeconomic uncertainty, a fraction of investors fail to update their beliefs with newly available information. Following prior literature (e.g., Hirshleifer et al. (2009), Hung et al. (2015)), we term these investors "inattentive" and denote their proportion as α. At time $t = 2$, the demand of inattentive investors is given by:

$$x_2^{in} = \frac{\text{E}_1[V + v] - P_2}{\lambda \text{Var}_1(V + v)}, \tag{28}$$

reflecting their reliance on time-1 information for time-2 demand. Consequently, the equilibrium market clearing condition is:

$$(1 - \alpha)x_2 + \alpha x_2^{in} + \theta_2 = \Theta, \tag{29}$$

which determines the equilibrium price.

Proposition 4. *If $\alpha > 0$, i.e., there is a group of inattentive investors in the market, the post-earning return is positively correlated with earning surprise,*

$$\text{Cov}(\text{ES}, \text{PR}) = \frac{\alpha}{\tau_V + \tau_f + \tau_v} > 0, \tag{30}$$

and the covariance increases with the herding tendency,

$$\frac{d\text{Cov}(\text{ES}, \text{PR})}{d\delta} > 0. \tag{31}$$

Proof. See Internet Appendix F. □

This is because a higher δ increases the variance of earnings surprises, which in turn raises the covariance between ES and PR. As a result, analysts' herding behavior amplifies the variation in post-earnings announcement drift (PEAD). Furthermore, if α is positively correlated with δ—a highly plausible assumption—this amplification effect becomes even stronger.

Overpricing

The existing literature suggests that informational inefficiency is linked to stock mispricing and return predictability. We demonstrate that, under the short-sale constraint—well-established in the literature and supported by evidence of arbitrage limitations (e.g., Shleifer and Vishny (1997), Diether et al. (2002), Lamont and Thaler (2003)—the herding effect further exacerbates stock overpricing and forecasts lower subsequent returns.

Now let's impose the short-sale constraint in the market, i.e., $x_t \geq 0$ and $\theta_t \geq 0$. We define the difference between the two prices as follows:

$$\Delta = \mathrm{E}[P_1^{ss}] - \mathrm{E}[P_1], \tag{32}$$

where P_t^{ss} is time-t price under short-sale constraint. In Internet Appendix G, we demonstrate that the expected price with a short-sale constraint is higher than without it, $\Delta > 0$, driven by excess demand due to the constraint. A greater tendency for analysts to herd amplifies this overpricing, as reduced informativeness increases the required risk premium. Consequently, herding firms exhibit lower subsequent returns compared to non-herding firms.

Proposition 5. *The analyst tendency to herd, δ is positively correlated to the expected magnitude of overpricing at $t = 1$: $\Delta = \mathrm{E}[P_1^{ss}] - \mathrm{E}[P_1]$*

$$\frac{d\Delta}{d\delta} > 0. \tag{33}$$

Proof. See Internet Appendix G. □

Corollary 5.1. *The analyst tendency to herd, δ is negatively correlated to the expected return at $t = 2$:* $\mathrm{E}[R^{ss}] = \mathrm{E}[P_2^{ss}] - \mathrm{E}[P_1^{ss}]$

$$\frac{d\mathrm{E}[R^{ss}]}{d\delta} < 0. \tag{34}$$

A..3 Discussion

The theoretical framework reveals that the negative relationship between macroeconomic uncertainty and analysts' forecast dispersion reflects stronger herding tendencies, contributing to greater informational inefficiency in financial markets. To focus on this dynamic, the model simplifies several aspects: 1.Herding motivations, such as reputation and career concerns, are omitted to streamline the theoretical mechanism and maintain focus; 2. Analysts possess homogeneous forecasting abilities, allowing us to examine herding at the firm level rather than through individual differences; 3. Investors rely solely on analysts' forecasts and historical stock prices, highlighting how herding of analysts degrades information quality in the market; 4. Investors share homogeneous beliefs, isolating the impact of analyst herding on overpricing under short-sale constraints. While alternative explanations may exist, this framework establishes a well-supported and economically significant channel through which analyst herding behavior generates market inefficiency.

B. Hypotheses development

We formulate testable hypotheses derived from the theoretical framework to steer the subsequent empirical analysis. As Proposition 1 and Corollary 1.1 outline, while a positive relationship exists, the negative relationship between macroeconomic uncertainty and analyst forecast dispersion suggests elevated firm-level uncertainty. To empirically assess this relationship, we regress analyst forecast dispersion for individual firms against macroeconomic uncertainty over a specific timeframe and compare the resulting slope coefficients across firms. The testable hypothesis is as follows:

Hypothesis I. *Herding firms, where analyst forecast dispersion negatively correlates with macroeconomic uncertainty, exhibit higher firm-level uncertainty compared to non-herding firms, where dispersion positively correlates with macroeconomic uncertainty.*

Drawing from Corollary 1.1, the negative relationship between macroeconomic uncertainty and analyst forecast dispersion reflects analysts' heightened tendency to herd. As demonstrated by Proposition 2, this contributes to informational inefficiency in the stock market. The corresponding hypothesis is as follows:

Hypothesis II. *Herding firms' stock prices are less informative about the firms' fundamental values compared to those of non-herding firms.*

To empirically evaluate stock price informativeness, we examine price continuation patterns, focusing on two key phenomena: return momentum and post-earnings-announcement drift (PEAD). When stock prices are less reflective of underlying fundamentals, they exhibit stronger return momentum and PEAD as they gradually adjust toward their intrinsic value. Proposition 3 and Proposition 4 link analysts' herding tendencies to these price continuation patterns.

Furthermore, Proposition 5 and Corollary 5.1 suggest that, under short-sale constraints, analyst herding behavior exacerbates overpricing, leading to lower subsequent returns. The final hypothesis is as follows:

Hypothesis III. *Comparing with non-herding firms, herding firms' stock prices tend to be overpriced and earn lower subsequent returns.*

III. Data

The macroeconomic uncertainty measure, U_t^m, is computed as the average daily news-based U.S. Economic Policy Uncertainty (EPU) index constructed by Baker et al. (2016) between each firm's two consecutive statistic dates (in month $t-1$ and t respectively) in the IBES summary file, which is updated monthly. Following Diether et al. (2002), analyst forecast dispersion, $disp_{i,t}$, is calculated as the cross-sectional standard deviation of analyst forecasts for annual EPS (for the current fiscal year end) of firm i in month t, scaled by the absolute value of the cross-sectional mean of the forecasts from the IBES summary file.

The firm-level uncertainty measures are: $mv_{i,t}$, the market capital for firm i by the end of month t; $age_{i,t}$, the number of years for firm i from the first month covered by CRSP to month t; $vol_{i,t}$, firm i's daily return standard deviation over 12-month ending in month t; $bm_{i,t}$, book value of firm i's equity divided by its market value by the end of last fiscal year; $cvol_{i,t}$, the 5-year (ending at the last fiscal year) standard deviation of firm i's cash flow, scaled by the average total assets;[14] $cov_{i,t}$, the number of analysts covering firm i at the last fiscal year end; $disp_{i,t}$, the analyst forecasts dispersion for firm i in month t; $num_{i,t}$, the number of earning estimations for firm i in month t from IBES summary file; and $u_{i,t}^{com}$ is the average of percentile ranks of firm i among all the firms in month t with respective of each firm-level uncertainty measures mentioned above.[15]

In addition, our empirical tests also involve standard unexpected earnings (SUE), idiosyncratic volatility, uncertainty beta and nine anomaly variables: 1. $\text{SUE}_{i,t}$ is defined as $\frac{E_{i,q}-E_{i,q-4}-c_{i,t}}{\sigma_{i,t}}$ in Sadka (2006); 2. $ivol_{i,t}$ is computed as the standard deviation of the daily residuals in month t from the Fama-French 3-factor regression; 3. $\beta_{i,t}^{U}$ is the estimated slope coefficient of the one-month-ahead economic uncertainty index developed by Jurado et al. (2015) from the monthly rolling regression of the Fama-French 3-factor model adding the economic uncertainty index as another risk factor over a 24-month

[14] We treat $cvol$ as missing if there are less than 2 years' data available. Cash flow equals earnings before extraordinary items minus total accruals, scaled by average total assets of last year and the current year, where total accruals are equal to changes in current assets minus changes in cash, changes in current liabilities, and depreciation expense plus changes in short-term debt. Using the balance sheet items instead of cash flow statement's is due to the fact that cash flow statements are not available until 1987. In the post-1987 period, the correlation between the cash flow numbers calculated using balance sheet and cash flow statement is as high as 0.93.

[15] To form the composite uncertainty measure, we use $\frac{1}{mv_{i,t}}$, $\frac{1}{age_{i,t}}$, $vol_{i,t}$, $\frac{1}{bm_{i,t}}$, $cvol_{i,t}$, $\frac{1}{cov_{i,t}}$, $disp_{i,t}$, $\frac{1}{num_{i,t}}$ to rank the firms so that a higher percentile rank corresponds to greater firm-level uncertainty.

fixed window; 4. $acret_{i,t}$, is firm i's accumulated return over month t-11 to month t; 5. $O\_score_{i,t}$, the Ohlson (1980) O-score measures the level of firm's financial distress. It is based on the accounting variables of the last fiscal year with respect of month t; 6. $g\_shares_{i,t}$, the growth of the split-adjusted shares outstanding of firm i in the last fiscal with respect of month t; 7. $\text{NOA}_{i,t}$, firm i's net operating asset is measured by the difference on the balance sheet between all operating assets and all operating liabilities scaled by total assets; 8. $gp_{i,t}$, firm i's gross profit of the last fiscal year; 9. $accruals_{i,t}$, firm i's total accruals calculated as changes in noncash working capital minus depreciation expense scaled by average total assets for the previous two fiscal years. 10. $g\_asset_{i,t}$, firm i's asset growth measured as the growth rate of total assets in the previous fiscal year; 11. $\text{ITA}_{i,t}$, firm i's investment-to-assets measured as the annual change in gross property, plant, and equipment plus the annual change in inventories scaled by the lagged book value of assets. 12. $\text{ROA}_{i,t}$, firm i's return on asset of the last fiscal year with respect of month t.

The sample period spans from Jan 1985 to Dec 2024 and the firms are the ones whose common stocks listed in NYSE, AMEX or NASDAQ covered by CRSP, COMPUSTAT and IBES. Returns are from CRSP Monthly or daily file, financial variables are from COMPUSTAT annual or quarterly file, the security analysts' forecast related variables are from IBES. Following Jegadeesh and Titman (2001), we exclude stocks with a share price below $5 at the portfolio formation date to make sure that the results are not driven by small, illiquid stocks or by the bid-ask bounce. Following Zhang (2006), we also exclude firms with less than 12 months of past return data on CRSP to avoid any potential confounding effect of recent IPOs. The economic uncertainty index developed by Jurado et al. (2015) is from Sydney Ludvigson's website. Fama and French three and five monthly factors are from Fama dataset.

Table 1 presents descriptive statistics of the macroeconomic uncertainty, analyst forecasts dispersion and other firm-level uncertainty variables, which can outline the main characteristics of the firms studied in our sample.[16] In order to compare U_t^m, the macroeconomic uncertainty, and the analysts' forecast dispersion, $disp_{i,t}$, at the similar scale, we divide the original EPU index by 100. The mean of $disp_{i,t}$ is 0.19 and the median is 0.04, indicating that unusually high dispersions are more likely to occur than the low ones. The statistics of the firm-level variables show that our sample has a wide range of coverage. The natural log of market value ranges from -1.24 to 15.04 corresponding to $288,562 to $3.39 billion. The firm age is from 1.9 to 99 years. The analysts coverage ranges from 2 to 65.

IV. Empirical Results

A. Herding and Uncertainty: *Hypothesis I*

To empirically test the hypothesis, we first identify the herding and non-herding firms by examining the comovement between the macroeconomic uncertainty and the analysts' forecast dispersion via the regression:

$$disp_{i,t} = a + b * U_t^m + \epsilon_{i,t}, \tag{35}$$

where $disp_{i,t}$ is the dispersion of analysts' forecasts on firm i's annual EPS in month t, and U_t^m is the macroeconomic uncertainty in month t.[17] Panel A of Table 2 presents the result of the pooled regression over the whole sample period from January 1985 to December 2024. The coefficient b is significantly positive, indicating that overall, the analysts' forecast dispersion increases with the macroeconomic uncertainty, consistent with the existing literature.

[16]The descriptive statistics for the additional variables used in the analysis are provided in Table H1 of Internet Appendix H.

[17]Equation (35) is designed to identify the comovement between macroeconomic uncertainty and analyst forecast dispersion. At this stage, other variables that may influence this comovement are intentionally omitted, as they will be analyzed in subsequent sections of the paper. In the first stage, we examine the distinct correlations observed between these two variables. In the second stage, we demonstrate that other factors—such as firm size, age, and analyst coverage—are associated with these correlations, and the observed relationships align with *Hypothesis I*.

To zoom in the relationship between the macroeconomic uncertainty and analyst forecast dispersion for each firm, we estimate regression (35) firm by firm over the entire sample period for each firm.[18] The means of the coefficient b and its corresponding t-statistic, averaged across all firms in our sample, are reported in Panel B. Among the total 13,154 firms, 7,020 firms exhibit positive coefficients b, while 6,134 firms exhibit negative ones. Focusing on observations with the statistically significant b ($|t| \geq 1.65$), we find that 1,852 out of 5,290 firms have negative coefficients.

In addition, we estimate regression (35) for each firm i in month t using a 24-month rolling window, spanning from month $t-23$ to t, with a minimum requirement of 10 observations per window. The results are also presented in Panel B. Among the 1,140,673 firm-month observations, 559,968 exhibit positive coefficients b, while 580,705 exhibit negative coefficients. For observations with statistically significant slope coefficients ($|t| \geq 1.65$), 137,244 out of 326,122 firm-month observations have negative coefficients. This evidence indicates that the negative correlation between macroeconomic uncertainty and analyst forecast dispersion is not rare but occurs frequently over time and across firms.

Table 2 here

We then construct a dummy variable $\text{herd}_{i,t}$, which equals one if the coefficient b is negative for firm i in month t over the corresponding sample period, and zero otherwise. We classify firm i as a herding firm in month t if $\text{herd}_{i,t}$ equals one. Figure 2 presents time series plots of U_t^m, the macroeconomic uncertainty, and $\text{Disp}_{herd,t}$ ($\text{Disp}_{non,t}$), the monthly aggregated analyst forecast dispersion for herding (non-herding) firms, estimated over firm i's past 24-month rolling window ending in month t.

Figure 2 here

[18] To ensure the regression analysis has sufficient statistical power, we exclude firms with a sample size smaller than 10.

The graph clearly illustrates the negative comovement between macroeconomic uncertainty (U_t^m) and the security analyst forecast dispersion ($\text{Disp}_{\text{herd},t}$) for herding firms. While both U_t^m and $\text{Disp}_{\text{non-herd},t}$ exhibit counter-cyclical behavior, $\text{Disp}_{\text{herd},t}$ is strikingly pro-cyclical.[19]

Next, to test *Hypothesis I*, which posits that firm-level uncertainty is higher for herding firms than for non-herding firms, we first conduct t-tests comparing the means of firm-level uncertainty variables between the two groups.[20] Panel A of Table 3 presents the results of independent samples t-tests, where the samples are classified based on the dummy variable $\text{herd}_{i,t}$. The value of $\text{herd}_{i,t}$ is determined by running regression (35) over each firm's entire sample period, with month t representing the end of the corresponding sample period for each firm.

The results reveal that the differences in means are statistically significant between herding and non-herding firms for seven out of eight individual firm-level uncertainty variables. The composite measure, $u_{i,t}^{\text{com}}$, is highly significant, with a t-value of 3.77. These findings indicate that herding firms are smaller and younger, exhibit greater volatility in stock returns and cash flows, have less analyst coverage, fewer earnings estimates and analysts' opinions for these firms are more dispersed. The evidence is largely consistent with the hypothesis that herding firms exhibit higher levels of firm-level uncertainty.

Table 3 here

Panel B of table 3 shows the results of the independent samples t-tests of the equal means of the firm-level uncertainty variables for the herding and non-herding firms, classified by $herd_{i,t}$ determined by running the regression (35) over firm i's past 24-month

[19] It also raises a cautionary note regarding the common practice of using aggregated analyst forecast dispersion as a proxy for macroeconomic uncertainty. A more appropriate measure should exclude the forecast dispersions of herding firms, as these negatively correlate with macroeconomic uncertainty.

[20] For the following empirical analysis, we present results for observations with statistically significant coefficients b (where $|t| \geq 1.65$), as this more rigorously defines herding firms. Main findings remain robust across all observations, which are detailed in Table H5-H7 of Internet Appendix H.

rolling window. The results are largely consistent with the ones of the whole-sample tests in Panel A except for $disp_{i,t}$ and $vol_{i,t}$, the analyst forecasts dispersion and the stock return volatility, of which the difference is statistically insignificant between the herding and non-herding firms. For the robustness check, we also conduct the dependent samples t-tests using the rolling window method. For each month t, we calculate the difference-in-means of the firm-level uncertainty variables for the herding and non-herding firms and report the time series means and t-statistics of the differences in Panel C. The results are consistent with the ones in Panel B.

Although the composite firm-level uncertainty measure, $u_{i,t}^{com}$, is significantly higher for herding firms than for non-herding firms across all tests, two individual uncertainty measures warrant further discussion.

First, analyst forecast dispersion is influenced not only by firm-level uncertainty but also by analyst behavior. High firm-level uncertainty tends to increase forecast dispersion, while herding behavior among analysts may reduce it. These opposing forces result in analyst forecast dispersion being a weak indicator of firm-level uncertainty.

Second, stock return volatility is similarly affected by mixed influences. For instance, the lower return volatility observed in herding firms could stem from their stock prices underreacting to news due to high uncertainty, thereby reducing the magnitude of stock price fluctuations over time. This mechanism coexists with the alternative explanation that high return volatility often accompanies elevated uncertainty about a firm. These opposing mechanisms together account for the mixed results observed in the individual measures.

To further test the hypothesis, we run the probit regression of firm-level uncertainty variables on a binary response variable, $herd_{i,t}$, which equals one if the coefficient b in the equation (35) is negative for firm i in month t over the 24-month rolling window sample, zero otherwise.[21]

[21] For the following empirical tests, firm i in month t is classified as a herding firm if the coefficient b

$$herd_{i,t} = c + d * u_{i,t} + \sigma_{i,t}, \tag{36}$$

where $u_{i,t}$ is a vector containing either one of the firm-level uncertainty variables or all the uncertainty variables for firm i in month t. Table 4 reports the results of the tests. Not surprisingly, the results of the univariate probit regressions are largely consistent with the ones reported in Table 3. The multivariate probit regression has the likelihood ratio with a p-value lower than 0.01%, indicating that these firm-level uncertainty variables as a whole can significantly explain the probability of being a herding firm.

Table 4 here

In summary, analysts exhibit a stronger tendency to herd when forecasting firms that operate in more opaque information environments and are associated with greater uncertainty regarding their values. The evidence presented in this subsection strongly supports *Hypothesis I*, which posits that herding firms are those with higher firm-level uncertainty.

B. Herding and Information Transmission: *Hypothesis II*

Security analysts, who collect, analyze, and convey value-relevant information to investors, play a critical role in the information transmission process within financial markets. In the theoretical framework, we demonstrate that analyst herding behavior reduces the efficiency of this process, making stock prices less reflective of firms' fundamental values. *Hypothesis II* states that herding firms' stock prices are less informative about the firms' fundamental values compared to those of non-herding firms. We test the hypothesis by examining stock price continuity.

First, we compare the momentum effect between herding and non-herding firms. In each month t, we sort stocks into deciles based on the accumulated return from month

in the equation (35) is negative for the firm over the past 24-month rolling window sample. Our findings remain robust across various rolling window sizes.

$t-11$ to $t-1$ and form ten value-weighted portfolios (M1 to M10) for both herding and non-herding firms. Table 5 presents the portfolio returns (Panel A) and Fama-French 3-factor model adjusted returns (Panel B) in month $t+1$. Profits of the momentum strategy, longing past winners (M10) and shorting past losers (M1), are compared between the herding firm group and non-herding firm group.

We observe a generally increasing pattern of returns from M1 to M10 for both herding and non-herding groups, confirming the presence of the momentum effect in our sample. Furthermore, we find that the trading strategy of longing M10 (past winners) and shorting M1 (past losers) generates significantly higher returns for herding firms compared to non-herding firms.

Previous literature attributes the momentum effect to a gradual stock price response to information (e.g., Chan et al. (1996), Barberis et al. (1998), Daniel et al. (1998)), and our theoretical framework clearly shows that the stronger analyst herding tendency is associated with noisier signal transmitted to the market and thus higher likelihood of the stock return momentum. The empirical results of the stronger momentum pattern for the herding firms well supports *Hypothesis II*.

Table 5 here

To show that herding behavior exacerbates informational inefficiency beyond the impact of firm-level uncertainty documented in the existing literature, we conduct Fama-MacBeth cross-sectional regressions on a monthly basis:

$$ret_{i,t+1} = e + f * acret_{i,t} + g * herd_{i,t} + h * acret_{i,t} * herd_{i,t} + i * u_{i,t} + j * acret_{i,t} * u_{i,t} + \epsilon_{i,t+1}, \quad (37)$$

where $ret_{i,t+1}$ is the return for firm i in month $t+1$, $acret_{i,t}$ is firm i's accumulated return over month t-11 to month t-1, $herd_{i,t}$ is the herding dummy, and $u_{i,t}$ is one of the firm-level uncertainty measures.

Table 6 presents the time-series averages of the slope coefficients from the monthly regressions (37). Notably, after accounting for the effects of firm-level uncertainty, the average slope coefficients of the interaction term between the past accumulated return ($acret_{i,t}$) and the herding dummy ($herd_{i,t}$) remain positive and statistically significant. This suggests that security analysts play a crucial role in the information transmission process, and the herding behavior of analysts further impedes market informational efficiency.

Table 6 here

Furthermore, we examine the post-earnings-announcement drift (PEAD) for both herding and non-herding firms. In each month t, we sort stocks into deciles based on standardized unexpected earnings ($\text{SUE}_{i,t}$), and form ten portfolios, labeled S1 (bad-news firms) to S10 (good-news firms). Table 7 presents the portfolio returns (Panel A) and Fama-French 3-factor model adjusted returns (Panel B) for S1 to S10 for both herding and non-herding firms.

Our findings indicate that, the trading strategy of longing S10 and shorting S1 yields significantly higher returns for herding firms compared to non-herding firms. These results provide further evidence supporting the hypothesis that stock prices of herding firms convey less information about the firms' fundamental values, resulting in stronger price continuity as they converge toward their intrinsic values.

Table 7 here

Similarly, to show that herding behavior exacerbates informational inefficiency beyond the impact of firm-level uncertainty documented in the existing literature, we conduct Fama-MacBeth cross-sectional regressions on a monthly basis:

$$ret_{i,t+1} = h + i * \text{SUE}_{i,t} + j * herd_{i,t} + k * \text{SUE}_{i,t} * herd_{i,t} + l * u_{i,t} + m * \text{SUE}_{i,t} * u_{i,t} + \epsilon_{i,t+1}, \quad (38)$$

where $ret_{i,t+1}$ is the return for firm i in month $t+1$, $\text{SUE}_{i,t}$ is firm i's standardized unexpected earnings in month t, $herd_{i,t}$ is the herding dummy, and $u_{i,t}$ is one of the firm-level uncertainty measures.

Table 8 presents the time-series averages of the slope coefficients from the monthly regressions (38). Notably, after accounting for the effects of firm-level uncertainty, the average slope coefficients of the interaction term between $\text{SUE}_{i,t}$ and the herding dummy ($herd_{i,t}$) remain positive and statistically significant.

Table 8 here

The empirical results reveal that the herding effect, evidenced by the negative correlation between macroeconomic uncertainty and analyst forecast dispersion, is linked to informational inefficiencies that surpass those documented in the existing literature.

C. Herding and Overpricing: *Hypothesis III*

Given that herding firms experience more severe informational inefficiency, our theoretical framework demonstrates that the short-sale constraint leads to these firms' stocks being more overpriced. The *Hypothesis III* posits that the stocks of herding firms are more overpriced and, as a result, tend to exhibit lower subsequent returns. To test this hypothesis, we first conduct a univariate —portfolio analysis. In each month t, based on the slope coefficient of U_t^m in equation (35), we classify firms as herding or non-herding and calculate the value-weighted portfolio returns for month $t + 1$ for both groups. The trading strategy involves longing the non-herding firm portfolio and shorting the herding firm portfolio.

The means and t-statistics of the excess return and the benchmark-adjusted returns are reported in Table 9. The excess return is defined as the portfolio return minus the risk-free rate, while benchmark-adjusted returns are calculated as the portfolio returns net of the returns attributable to exposures to: 1) the market factor (CAPM); 2) the market, size, and value factors (Fama-French 3-factor model); and 3) the market, size, value, profitability, and investment factors (Fama-French 5-factor model). Essentially, the benchmark-adjusted return reported here represents the estimated intercept, α_i, of the corresponding factor model.

Column (1)-(3) present the results in month $t+1$ with herding and non-herding firms, classified by the sign of the slope coefficient of equation (35): negative for the herding firms and the positive for the non-herding firms in month t; while column (4)-(6) present the results based on sorting stocks into deciles based on the slope coefficient of equation (35) in month t, where herding firms are classified as those in the lowest decile and non-herding firms as those in the highest decile. Across both classification methods, the long-short strategy generates significant positive average return spreads in terms of both excess returns and all benchmark-adjusted returns. These findings are consistent with the hypothesis that herding firms' stocks are overpriced and, consequently, earn lower future returns.

Table 9 here

C..1 Herding and Predictors

Existing literature identifies several predictors that exhibit statistically significant relationships with future stock returns. Idiosyncratic volatility, *ivol*, has been widely used in literature as a proxy for limits to arbitrage. Ang et al. (2006) document a negative relationship between idiosyncratic volatility and stock returns. In addition to the firm-level uncertainty measure, dispersion in analysts' earning forecasts is commonly used as a proxy for differences of opinion among investors (Diether et al., 2002). When combined with short-sale constraints, this divergence generates cross-sectional asset pricing predictions: greater disagreement between optimists and pessimists leads to higher equilibrium stock prices and, consequently, lower subsequent returns. Furthermore, Bali et al. (2017) find that exposure to an economic uncertainty index, referred to as the uncertainty beta ($\beta^U_{i,t}$), negatively predicts future returns.

To test the robustness of the herding effect's predictability, we conduct Fama-MacBeth regressions while controlling for the predictors documented in existing literature:

$$ret_{i,t+1} = n + o * herd_{i,t} + p * p_{i,t} + q * control_{i,t} + \epsilon_{i,t+1}, \quad (39)$$

where $ret_{i,t+1}$ is the return for firm i in month $t+1$, $herd_{i,t}$ equals one if the slope coefficient of equation (35) is negative for firm i in month t, zero otherwise, $p_{i,t}$ is one of the predictors: $ivol_{i,t}$, the idiosyncratic volatility for firm i in month t; $disp_{i,t}$, the analyst forecasts dispersion for firm i in month t, $\beta^U_{i,t}$, firm i stock's exposure to an economic uncertainty index in month t, and $control_{i,t}$ is a vector containing the firm characteristics related variables.[22] Table 10 presents the time-series averages of the coefficients of the cross-sectional regression in each month.

Table 10 here

The coefficients of those previously documented predictors are statistically significant in most cases, consistent with the literature. Controlling for the predictors, however, we find that the herding dummy variable continues to negatively predict the one-month ahead return with high significance, strongly supporting *Hypothesis III*. This finding also indicates that the herding effect exerts an independent influence on future stock returns, beyond the effects of the predictors documented in existing literature.

C..2 Herding and Anomalies

Previous literature has documented that various anomaly variables can predict cross-sectional stock returns. The portfolio analysis presented earlier, which shows that stocks of herding firms tend to earn lower future returns, already suggests that the herding effect may represent another anomaly. In this subsection, we further examine the herding effect in conjunction with nine widely cited anomalies: 1. $acret_{i,t}$, the momentum effect (Jegadeesh and Titman, 1993), 2. $O\_score_{i,t}$, financial constraint (Ohlson, 1980), 3.

[22]The control variables include $acret_{i,t}$, $mv_{i,t}$, $age_{i,t}$, $vol_{i,t}$, $bm_{i,t}$, $cvol_{i,t}$ and $cov_{i,t}$.

$g\_share_{i,t}$, net stock issues (Stambaugh et al., 2012), 4. $\text{NOA}_{i,t}$, net operating asset (Hirshleifer et al., 2004), 5. $gp_{i,t}$, gross profitability (Novy-Marx, 2013), 6. $accrual_{i,t}$, total accruals (Sloan, 1996), 7. $g\_asset_{i,t}$, asset growth (Cooper et al., 2008), 8. $\text{ROA}_{i,t}$, return on assets (Fama and French, 2006), 9. $\text{ITA}_{i,t}$, investment-to-assets (Titman et al., 2004).

Panel A of Table 11 presents the results of difference-in-means tests comparing each anomaly variable between herding and non-herding firms. The t-values indicate that most anomaly variables exhibit statistically significant differences, with the exception of gross profitability. Overall, herding firms tend to have greater financial constraints, issue more shares in the past, possess higher net operating assets, exhibit higher levels of accruals, display greater asset growth rates, maintain higher investment-to-assets ratios, and achieve lower returns on assets. These findings suggest that firms in the short legs of long-short trading strategies based on these anomalies are likely to be herding firms.

Table 11 here

To compare the herding effect and these anomalies in predicting future stock returns, we conduct the Fama-MacBeth cross-sectional regression in each month:

$$ret_{i,t+1} = r + s * herd_{i,t} + t * anml_{i,t} + u * anml_{i,t} * herd_{i,t} + \epsilon_{i,t+1}, \tag{40}$$

where $ret_{i,t+1}$ represents the return for firm i in month $t+1$, and $anml_{i,t}$ denotes one of the nine anomaly variables. The regression model captures the relationship between future stock returns and the herding effect. Panel B presents the time-series averages of the slope coefficients. The slope coefficient of $herd_{i,t}$ is negative and statistically significant across all regressions, indicating that the herding effect significantly impacts future stock returns, independent of the influence of these anomalies. Additionally, the slope coefficient of the interaction term $anml_{i,t} * herd_{i,t}$ is significant for several anomalies, including momentum and investment-to-asset ratio, suggesting that the herding effect amplifies the predictive power of these anomalies for herding firms. These results reinforce *Hypothesis III*, as the herding effect contributes to overpricing and lower subsequent returns, distinct from the effects of established anomalies.

The findings highlight that the herding effect is not subsumed by other well-documented anomalies and represents a unique behavioral anomaly driven by analysts' strategic responses to macroeconomic uncertainty. This is consistent with our theoretical framework, which posits that herding behavior distorts information transmission, leading to persistent mispricing. The evidence suggests that herding firms are more likely to exhibit characteristics associated with the short legs of anomaly-based trading strategies, further underscoring the role of behavioral biases in asset pricing.

V. Conclusion

This paper provides new insights into how uncertainty affects the information environment of financial markets through the lens of analyst behavior. By documenting a robust negative relationship between macroeconomic uncertainty and analyst forecast dispersion, we highlight a strategic herding response among analysts that distorts the aggregation of information into prices. This behavioral mechanism, grounded in a beauty contest framework (Keynes (1936)), contributes to persistent mispricing and diminished price informativeness.

Our empirical findings demonstrate that herding behavior is concentrated in firms with greater valuation uncertainty and is associated with a range of inefficiency patterns, including momentum, post-earnings-announcement drift, and overpricing under short-selling constraints. These effects are not fully explained by traditional risk factors or known anomalies, underscoring the distinct role of this behavioral dynamic in shaping asset prices.

Beyond its implications for asset pricing, the paper also challenges the conventional wisdom that macro and micro uncertainties move in tandem. We show that strategic analyst behavior can invert this relationship, revealing a novel behavioral linkage between macroeconomic conditions and firm-level information quality.

Taken together, our results suggest that uncertainty not only influences market outcomes through risk channels but also through its impact on the behavior of information intermediaries. Future research could build on this framework by exploring how technological advances—such as AI-assisted forecasting or algorithmic trading—interact with behavioral herding under uncertainty, potentially amplifying or mitigating its effects on market efficiency.

References

Alfaro, I., Bloom, N., and Lin, X. (2024). The finance uncertainty multiplier. *Journal of Political Economy*, 132(2):577–615.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance*, 61:259–299.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131:1593–1636.

Bali, T. G., Brown, S. J., and Tang, Y. (2017). Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics*, 126:471–489.

Barberis, N., Shleifer, A., and Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49:307–343.

Basu, S. and Bundick, B. (2017). Uncertainty shocks in a model of effective demand. *Econometrica*, 85(3):937–958.

Bernard, V. L. and Thomas, J. K. (1989). Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research*, 27(1):1–36.

Bianchi, F., Ilut, C. L., and Schneider, M. (2018). Uncertainty shocks, asset supply, and pricing over the business cycle. *The Review of Economic Studies*, 85(2):810–854.

Bikhchandani, S., Hirshleifer, D., and Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100(5):992–1026.

Bikhchandani, S. and Sharma, S. (2001). Herd behavior in financial markets. *IMF Staff Papers*, 47:279–310.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77:623–685.

Bloom, N., Floetotto, M., Jaimovich, N., Sapora-Eksten, I., and Terry, S. (2018). Really uncertain business cycles. *Econometrica*, 86:1031–1065.

Caskey, J. A. (2009). Information in equity markets with ambiguity-averse investors. *Review of Financial Studies*, 22:3595–3627.

Chan, L. K. C., Jegadeesh, N., and Lakonishok, J. (1996). Momentum strategies. *Journal of Finance*, 51:1681–1713.

Christiano, L. J., Motto, R., and Rostagno, M. (2014). Risk shocks. *American Economic Review*, 104:27–65.

Clement, M. B. and Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *Journal of Finance*, 60:307–341.

Cooper, M. J., Gulen, H., and Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *Journal of Finance*, 63:1609–1652.

Cujean, J. and Hasler, M. (2017). Why does return predictability concentrate in bad times? *Journal of Finance*, 72:2717–2758.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor psychology and security market over- and under-reactions. *Journal of Finance*, 53:1839–1886.

Devenow, A. and Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, 40:603–615.

Diether, K. B., Malloy, C. J., and Scherbina, A. (2002). Difference of opinion and the cross section of stock returns. *Journal of Finance*, 57:2113–2141.

Edwards, W. (1968). Conservatism in human information processing. *Formal Representation of Human Judgment*, pages 17–52.

Fama, E. F. and French, K. R. (2006). Profitability, investment, and average returns. *Journal of Financial Economics*, 82:491–518.

Fox, C. R. and Tversky, A. (1995). Ambiguity aversion and comparative ignorance. *Quarterly Journal of Economics*, 110:585–603.

Graham, J. R. (1999). Herding among investment newsletters: Theory and evidence. *Journal of Finance*, 54:237–268.

Grossman, S. J. and Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American Economic Review*, 70(3):393–408.

Gulen, H. and Ion, M. (2016). Policy uncertainty and corporate investment. *Review of Financial Studies*, 29:523–564.

Heath, C. and Tversky, A. (1991). Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty*, 4:5–28.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance*, 56:1533–1597.

Hirshleifer, D., Hou, K., Teoh, S. H., and Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets. *Journal of Accounting and Economics*, 38:297–331.

Hirshleifer, D., Lim, S. S., and Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *Journal of Finance*, 64:2289–2325.

Hirshleifer, D., Subrahmanyam, A., and Titman, S. (1994). Security analysis and trading patterns when some investors receive information before others. *Journal of Finance*, 49:1665–1698.

Hirshleifer, D. and Teoh, S. H. (2003). Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management*, 9:25–66.

Hong, H. and Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance*, 58:313–351.

Hong, H., Lim, T., and Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, 55:265–295.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54:2143–2184.

Hou, K. and Moskowitz, T. J. (2005). Market frictions, price delay, and the cross-section of expected returns. *The Review of Financial Studies*, 18(3):981–1020.

Hung, M., Li, X., and Wang, G. (2015). Investor attention and stock market volatility. *Review of Financial Studies*, 28:33–72.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for market efficiency. *Journal of Finance*, 48:65–91.

Jegadeesh, N. and Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance*, 56:699–720.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105:1177–1216.

Kaviani, M. S., Kryzanowski, L., Maleki, H., and Savor, P. G. (2020). Policy uncertainty and corporate credit spreads. *Journal of Financial Economics*, 138:838–865.

Keren, G. (1997). On the calibration of probability judgments: Some critical comments and alternative perspectives. *Journal of Behavioral Decision Making*, 10:269–278.

Keynes, J. M. (1936). *The General Theory of Employment, Interest and Money*. Macmillan, London.

Kozeniauskas, N., Orlik, A., and Veldkamp, L. (2018). What are uncertainty shocks? *Journal of Monetary Economics*, 100:1–15.

Lamont, O. A. and Thaler, R. H. (2003). Can the market add and subtract? mispricing in tech stock carve-outs. *Journal of Political Economy*, 111(2):227–268.

Liberman, V. and Tversky, A. (1993). On the evaluation of probability judgments: Calibration, resolution, and monotonicity. *Psychological Bulletin*, 114:162–173.

Lin, M. (2018). The impact of aggregate uncertainty on herding in analysts' stock recommendations. *International Review of Financial Analysis*, 57:90–105.

Morris, S. and Shin, H. S. (2002). Social value of public information. *American Economic Review*, 92:1521–1534.

Nagar, V., Schoenfeld, J., and Wellman, L. (2019). The effect of economic policy uncertainty on investor information asymmetry and management. *Journal of Accounting and Economics*, 67:36–57.

Novy-Marx, R. (2013). The other side of value: Good growth and the gross profitability premium. *Journal of Financial Economics*, 108:1–28.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18:109–131.

Pastor, L. and Veronesi, P. (2012). Uncertainty about government policy and stock prices. *Journal of Finance*, 67:1219–1264.

Peng, L. and Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80(3):563–602.

Roussanov, N. (2010). Diversification and its discontents: Idiosyncratic and entrepreneurial risk in the quest for social status. *The Journal of Finance*, 65(5):1755–1788.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics*, 80:309–349.

Scharfstein, D. S. and Stein, J. C. (1990). Herd behavior and investment. *American Economic Review*, 80:465–479.

Shleifer, A. (2000). *Inefficient Markets: An Introduction to Behavioral Finance*. Oxford University Press.

Shleifer, A. and Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, 52(1):35–55.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review*, 71:289–315.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104:288–302.

Titman, S., Wei, K. C. J., and Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39:677–700.

Trueman, B. (1994). Analyst forecasts and herding behavior. *Review of Financial Studies*, 7:97–124.

Welch, I. (2000). Herding among security analysts. *Journal of Financial economics*, 58(3):369–396.

Zarnowitz, V. and Lambros, L. A. (1987). Consensus and uncertainty in economic prediction. *Journal of Political Economy*, 95:591–621.

Zhang, C. and Zhao, S. (2023). The macroeconomic announcement premium and information environment. *Journal of Monetary Economics*, 139:55–73.

Zhang, H. and Zhou, G. (2023). Uncertainty and the risk-return tradeoff. Technical report, Working paper.

Zhang, X. F. (2006). Information uncertainty and stock returns. *Journal of Finance*, 61:105–137.

Table 1: Descriptive statistics

Panel A shows the summary statistics of the macroeconomic uncertainty, analyst forecasts dispersion and other firm-level uncertainty measures: U_t^m, the U.S. EPU index constructed by Baker et al. (2016) (scaled by 100) in month t; $disp_{i,t}$, the cross-sectional standard deviation of analyst forecasts for firm i in month t scaled by the absolute value of the cross-sectional mean; $mv_{i,t}$, the natural log of market capital (in millions of dollars) for firm i by the end of month t; $age_{i,t}$, the number of years for firm i from the first month covered by CRSP to month t; $vol_{i,t}$ is firm i's daily return standard deviation over 12-month ending in month t; $bm_{i,t}$ is book value of firm i's equity divided by its market value by the end of last fiscal year; $cvol_{i,t}$ is the 5-year (ending at the last fiscal year) standard deviation of firm i's cash flow scaled by average total assets; $cov_{i,t}$ is the number of analysts covering firm i at the last fiscal year end; $num_{i,t}$ is the number of earning estimations for firm i in month t. $u_{i,t}^{com}$, the composite firm-level uncertainty measure based the seven individual measures above. Panel B shows the Pearson (below diagonal line) and Spearman (above diagonal line) correlations. The sample spans from Jan. 1985 to Dec. 2024.

A: Summary statistics

	N	Mean	Std	Min	P25	P50	P75	Max
U_t^m	1140673	1.08	0.57	0.37	0.72	0.94	1.29	5.56
$disp_{i,t}$	1140673	0.19	1.49	0.00	0.02	0.04	0.11	356.00
$mv_{i,t}$	1140673	7.06	1.79	-1.24	5.80	6.95	8.21	15.04
$age_{i,t}$	1140673	19.32	17.24	1.90	6.50	14.20	25.90	99.10
$vol_{i,t}$	1140673	0.03	0.01	0.00	0.02	0.02	0.03	0.34
$bm_{i,t}$	1096428	0.53	0.43	-40.77	0.27	0.46	0.71	16.75
$cvol_{i,t}$	862112	0.08	0.39	0.00	0.03	0.05	0.10	98.90
$cov_{i,t}$	1138118	11.43	8.69	2.00	5.00	9.00	16.00	65.00
$num_{i,t}$	1140673	9.43	7.34	2.00	4.00	7.00	13.00	61.00
$u_{i,t}^{com}$	1140673	0.51	0.16	0.05	0.39	0.51	0.62	0.98

B: Correlations

	U_t^m	$disp_{i,t}$	$mv_{i,t}$	$age_{i,t}$	$vol_{i,t}$	$bm_{i,t}$	$cvol_{i,t}$	$cov_{i,t}$	$num_{i,t}$	$u_{i,t}^{com}$
U_t^m	1.00	0.04	0.01	0.04	0.13	0.07	0.00	0.04	0.03	0.00
$disp_{i,t}$	0.02	1.00	-0.27	-0.14	0.31	0.22	0.17	-0.08	-0.11	0.41
$mv_{i,t}$	0.06	-0.05	1.00	0.32	-0.40	-0.33	-0.22	0.71	0.70	-0.72
$age_{i,t}$	0.04	-0.02	0.38	1.00	-0.40	0.09	-0.27	0.15	0.18	-0.54
$vol_{i,t}$	0.17	0.07	-0.34	-0.33	1.00	0.01	0.41	-0.20	-0.25	0.60
$bm_{i,t}$	0.02	0.05	-0.28	0.02	0.05	1.00	-0.15	-0.22	-0.22	-0.01
$cvol_{i,t}$	0.00	0.03	-0.15	-0.21	0.31	-0.12	1.00	-0.08	-0.11	0.54
$cov_{i,t}$	0.03	-0.01	0.69	0.18	-0.16	-0.16	-0.07	1.00	0.94	-0.66
$num_{i,t}$	0.02	-0.02	0.69	0.22	-0.21	-0.16	-0.09	0.95	1.00	-0.71
$u_{i,t}^{com}$	0.00	0.09	-0.71	-0.55	0.54	0.01	0.40	-0.61	-0.66	1.00

Table 2: Relationship between the macroeconomic uncertainty and the forecasts dispersion

The table reports the results of the regression:

$$disp_{i,t} = a + b * U_t^m + \epsilon_{i,t},$$

where U_t^m is the U.S. EPU index constructed by Baker et al. (2016) (scaled by 100); $disp_{i,t}$ is the cross-sectional standard deviation of analyst forecasts scaled by the absolute value of the cross-sectional mean. Panel A shows the result of the pooled regression over the whole sample period. Panel B reports the means of the slope coefficient, b, and its t-statistic of the regression run firm by firm over each firm's whole sample period; and the statistics of the regression for each firm i in month t over the firm's 24-month rolling window period from month $t-23$ to t. The results are reported for both all observations and the observations with t-statistic not less than 1.65 respectively. The sample spans from Jan. 1985 to Dec. 2024.

A: Pooled Regression

	Parameter	Std. Err.	t Value	P Value
Intercept	0.110	0.015	7.370	< 0.0001
U^m	0.078	0.015	5.220	< 0.0001
N	1,140,673			

B: Regressions by firms

	Whole sample				Rolling window			
	All obs.		Significant obs.		All obs.		Significant obs.	
	N	Mean	N	Mean	N	Mean	N	Mean
Coefficient b	13,154	0.00	5,290	0.11	1,140,673	0.01	326,122	0.13
t-stat		0.71		1.89		0.21		0.97
Positive b	7,020	0.29	3,438	0.40	559,968	0.24	188,878	0.41
t-stat		2.48		4.28		1.63		3.41
Negative b	6,134	-0.33	1,852	-0.42	580,705	-0.21	137,244	-0.25
t-stat		-1.32		-2.55		-1.14		-2.37

Table 3: Herding and firm-level uncertainty: t-test

Panel A presents t-test results of equal means of the firm-level uncertainty variables for the herding and non-herding firms, classified by the regression (refequ1) over each firm's corresponding whole sample period. Panel B shows t-test results of equal means of the firm-level uncertainty variables for the herding and the non-herding firms, classified over the past 24-month rolling window up to month t. Panel C presents the results of the paired dependent samples t-tests using the same herding classification as in Panel B. The time series means and t-statistics of the difference-in-means of the firm-level uncertainty variables for the herding and non-herding firms in each month t are reported. The uncertainty variables are: $mv_{i,t}$ is the natural log of market capital (in millions of dollars); $age_{i,t}$ is the number of years for the firm since the first month covered by CRSP; $vol_{i,t}$ is firm's daily return standard deviation over 12-month ending in month t; $bm_{i,t}$ is book value of firm's equity divided by its market value by the end of last fiscal year; $cvol_{i,t}$ is the 5-year (ending at the last fiscal year) standard deviation of the firm's cash flow scaled by average total assets; $cov_{i,t}$ is the number of analysts covering the firm at the last fiscal year end; $disp_{i,t}$ is the cross-sectional standard deviation of analyst forecasts scaled by the absolute value of the cross-sectional mean; $num_{i,t}$ is the number of earning estimations; $u^{com}_{i,t}$ is the composite firm-level uncertainty measure for firm i in month t. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

A: Whole sample by the firm	$mv_{i,t}$	$age_{i,t}$	$vol_{i,t}$	$bm_{i,t}$	$cvol_{i,t}$	$cov_{i,t}$	$disp_{i,t}$	$num_{i,t}$	$u^{com}_{i,t}$
Herd	5.41	13.32	0.04	0.66	0.14	5.73	0.41	4.81	0.55
N	1,852	1,852	1,852	788	646	1,733	1,852	1,852	1,852
Non-Herd	6.45	18.62	0.04	0.72	0.11	7.59	0.34	6.29	0.50
N	3,438	3,438	3,438	1,885	1,315	3,330	3,438	3,438	3,438
Diff	-1.04	-5.30	0.01	-0.06	0.03	-1.86	0.07	-1.49	0.05
t-stat	(-3.13)	(-4.54)	(2.36)	(-0.77)	(2.62)	(-2.34)	(1.80)	(-2.25)	(5.55)
B: Rolling window_independent									
Herd	6.94	18.40	0.03	0.53	0.09	11.23	0.19	9.21	0.51
Non-Herd	7.05	20.02	0.03	0.56	0.08	11.66	0.19	9.65	0.50
Diff	-0.11	-1.62	0.00	-0.03	0.01	-0.43	0.00	-0.44	0.02
t-stat	(-2.22)	(-6.03)	(1.20)	(-3.67)	(5.03)	(-2.92)	(1.27)	(-3.84)	(6.05)
C: Rolling window_dependent									
Diff	-0.11	-1.61	0.00	-0.03	0.01	-0.43	0.00	-0.43	0.01
t-stat	(-3.21)	(-9.06)	(1.40)	(-6.67)	(5.37)	(-3.39)	(1.32)	(-3.47)	(4.92)
N	469	469	469	469	469	469	469	469	469

Table 4: Herding and firm-level uncertainty: probit regression

The table presents the results of the probit regression:

$$herd_{i,t} = c + d * u_{i,t} + \sigma_{i,t},$$

where $herd_{i,t}$ is the herding dummy, which equals one (zero) if the slope coefficient of the equation (refequ1) over the past 24-month rolling window sample is negative (positive); $u_{i,t}$ is a vector containing either one of the firm-level uncertainty variables or all the uncertainty variables for firm i in month t. The firm-level uncertainty variables are: $mv_{i,t}$ is the natural log of market capital (in millions of dollars); $age_{i,t}$ is the number of years for the firm since the first month covered by CRSP; $vol_{i,t}$ is firm's daily return standard deviation over 12-month ending in month t; $bm_{i,t}$ is book value of firm's equity divided by its market value by the end of last fiscal year; $cvol_{i,t}$ is the 5-year (ending at the last fiscal year) standard deviation of the firm's cash flow scaled by average total assets; $cov_{i,t}$ is the number of analysts covering the firm at the last fiscal year end; $num_{i,t}$ is the number of earning estimations; $u^{com}_{i,t}$ is the composite firm-level uncertainty measure for firm i in month t. The sample spans from Jan. 1985 to Dec. 2024.

Intercept	0.275	-0.108	0.064	-0.189	-0.198	-0.194	-0.189	-0.394	1.111	0.659
p-value	(< .0001)	(< .0001)	(< .0001)	(< .0001)	(< .0001)	(< .0001)	(< .0001)	(< .0001)	(< .0001)	(< .0001)
$mv_{i,t}$	-0.067								-0.132	0.117
p-value	(< .0001)								(< .0001)	(< .0001)
$age_{i,t}$		-0.005							-0.004	-0.002
p-value		(< .0001)							(< .0001)	(< .0001)
$vol_{i,t}$			-9.924						-18.277	-20.080
p-value			(< .0001)						(< .0001)	(< .0001)
$bm_{i,t}$				-0.027					-0.017	0.008
p-value				(< .0001)					(0.013)	(0.234)
$cvol_{i,t}$					0.311				0.684	0.475
p-value					(< .0001)				(< .0001)	(< .0001)
$cov_{i,t}$						-0.001			0.018	0.018
p-value						(< .0001)			(< .0001)	(< .0001)
$num_{i,t}$							-0.001		-0.003	0.003
p-value							(< .0001)		(0.009)	(0.009)
$u^{com}_{i,t}$								0.388		0.638
p-value								(< .0001)		(< .0001)
N	326,122	326,122	326,122	313,945	246,015	325,297	253,613	253,613	244,641	244,641

Table 5: Herding and momentum: portfolio analysis

The table reports the average returns (Panel A) and the Fama-Frech 3-factor model adjusted returns (Panel B) in month $t+1$ (in percentage) of portfolio M1 to M10 and the trading spread of longing M10 and shorting M1 for herding and non-herding firms. In each month t, we sort stocks into deciles based on the accumulated returns from month $t-11$ to $t-1$, and form ten value-weighted portfolios M1 (the lowest accumulated returns) to M10 (the highest accumulated returns) for herding and non-herding firms, which are classified by the slope coefficient of the equation (refequ1) over the past 24-month rolling window. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

Panel A: Portfolio returns											
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M10-M1
Herd	0.08	0.47	0.39	0.78	0.71	0.65	1.01	1.06	0.99	1.87	1.79
t-stat											(3.83)
Non-herd	0.93	0.83	1.21	1.06	0.70	0.82	1.02	1.10	1.01	1.27	0.34
t-stat											(0.75)
Diff.	-0.85	-0.36	-0.82	-0.28	0.00	-0.17	-0.01	-0.04	-0.02	0.60	1.44
t-stat											(3.09)
Panel B: FF 3-factor adjusted portfolio returns											
Herd	-1.28	-0.77	-0.64	-0.21	-0.25	-0.26	0.11	0.20	-0.02	0.94	2.22
t-stat											(4.88)
Non-Herd	-0.57	-0.48	0.08	0.02	-0.31	-0.14	0.04	0.07	0.10	0.23	0.80
t-stat											(1.68)
Diff.	-0.70	-0.29	-0.72	-0.23	0.06	-0.12	0.07	0.12	-0.12	0.71	1.41
t-stat											(3.19)

Table 6: Herding and momentum: Fama-MacBeth regression analysis

The table reports the time-series averages of the coefficients obtained from the monthly cross-section regressions:

$$ret_{i,t+1} = e + f * acret_{i,t} + g * herd_{i,t} + h * acret_{i,t} * herd_{i,t} + i * u_{i,t} + j * acret_{i,t} * u_{i,t} + \epsilon_{i,t},$$

where $ret_{i,t+1}$ is the return for firm i in month $t+1$, $acret_{i,t}$ is firm i's accumulated return over month t-11 to month t-1, $herd_{i,t}$ is the herding dummy equal to one (zero) if the slope coefficient of equation (refequ1) over the past 24-month rolling window is negative (positive), and $u_{i,t}$ is one of the firm-level uncertainty measures: $mv_{i,t}$ is the natural log of market capital (in millions of dollars); $age_{i,t}$ is the number of years for the firm since the first month covered by CRSP; $vol_{i,t}$ is firm's daily return standard deviation over 12-month ending in month t; $bm_{i,t}$ is book value of firm's equity divided by its market value by the end of last fiscal year; $cvol_{i,t}$ is the 5-year (ending at the last fiscal year) standard deviation of the firm's cash flow scaled by average total assets; $cov_{i,t}$ is the number of analysts covering the firm at the last fiscal year end; $disp_{i,t}$ is the cross-sectional standard deviation of analyst forecasts scaled by the absolute value of the cross-sectional mean; $num_{i,t}$ is the number of earning estimations; $u^{com}_{i,t}$ is the composite firm-level uncertainty measure for firm i in month t.. Newey-West t-statistics are given in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

	$mv_{i,t}$	$age_{i,t}$	$vol_{i,t}$	$bm_{i,t}$	$cvol_{i,t}$	$cov_{i,t}$	$disp_{i,t}$	$num_{i,t}$	$u^{com}_{i,t}$
Intercept	1.12	0.83	1.04	0.76	1.02	0.93	0.94	0.95	1.13
t-stat	(2.80)	(3.09)	(5.02)	(3.03)	(4.48)	(3.81)	(4.02)	(3.82)	(4.93)
$acret_{i,t}$	0.58	0.61	0.52	0.14	-0.07	0.12	0.21	0.27	-0.24
t-stat	(1.03)	(2.34)	(1.38)	(0.55)	(-0.25)	(0.44)	(0.82)	(1.04)	(-0.47)
$herd_{i,t}$	-0.31	-0.30	-0.26	-0.34	-0.36	-0.30	-0.29	-0.32	-0.27
t-stat	(-3.74)	(-3.59)	(-3.42)	(-3.93)	(-3.80)	(-3.57)	(-3.39)	(-3.72)	(-3.33)
$acret\_herd_{i,t}$	**0.51**	**0.54**	**0.52**	**0.62**	**0.78**	**0.56**	**0.59**	**0.57**	**0.55**
t-stat	**(2.29)**	**(2.49)**	**(2.41)**	**(2.81)**	**(3.13)**	**(2.55)**	**(2.65)**	**(2.61)**	**(2.52)**
$u_{i,t}$	-0.03	0.00	-9.48	0.16	-1.76	0.00	-0.23	-0.01	-0.48
t-stat	(-0.77)	(1.62)	(-1.00)	(1.09)	(-2.22)	(-0.44)	(-1.50)	(-0.84)	(-1.12)
$acret\_u_{i,t}$	-0.05	-0.02	-5.41	0.00	1.50	0.02	0.13	0.00	0.96
t-stat	(-0.64)	(-3.36)	(-0.52)	(0.02)	(1.26)	(1.23)	(0.32)	(0.29)	(1.32)
N	687	687	687	664	519	686	687	687	687
Adj R^2	3.58%	3.03%	5.61%	3.68%	4.37%	3.24%	3.00%	3.19%	3.92%

Table 7: Herding and Post Earning Announcement Drift

The table reports the average returns (Panel A) and the Fama-Frech 3-factor model adjusted returns (Panel B) in month $t+1$ (in percentage) of portfolio S1 to S10 and the trading strategy of longing S10 and shorting S1 for the herding and non-herding firms. In each month t, we sort stocks into deciles based on standardized unexpected earnings ($\text{SUE}_{i,t}$), and form ten value-weighted portfolios S1 (the lowest $\text{SUE}_{i,t}$) to S10 (the highest $\text{SUE}_{i,t}$) for herding and non-herding firms, which are classified by the slope coefficient of the equation (refequ1) over the past 24-month rolling window. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S10-S1
Panel A: Portfolio returns											
Herd	0.42	0.50	0.59	0.80	0.70	0.87	1.05	0.90	1.32	1.07	0.65
t-stat											(2.86)
Non-herd	1.27	0.93	1.08	1.02	1.18	0.96	1.11	1.06	1.21	1.36	0.08
t-stat											(0.45)
Diff.	-0.85	-0.43	-0.49	-0.22	-0.49	-0.08	-0.06	-0.16	0.12	-0.29	0.57
t-stat											(1.80)
Panel B: FF 3-factor adjusted portfolio returns											
Herd	-0.61	-0.48	-0.43	-0.23	-0.27	-0.10	0.03	-0.10	0.26	0.02	0.63
t-stat											(2.73)
Non-herd	0.13	-0.19	0.00	-0.07	0.09	-0.11	0.06	-0.02	0.11	0.30	0.17
t-stat											(0.94)
Diff.	-0.74	-0.29	-0.42	-0.16	-0.36	0.01	-0.02	-0.07	0.15	-0.28	0.46
t-stat											(1.78)

Table 8: Herding and PEAD: Fama-MacBeth regression analysis

The table reports the time-series averages of the coefficients obtained from the monthly cross-section regressions:

$$ret_{i,t+1} = h + i * \text{SUE}_{i,t} + j * herd_{i,t} + k * \text{SUE}_{i,t} * herd_{i,t} + l * u_{i,t} + m * \text{SUE}_{i,t} * u_{i,t} + \epsilon_{i,t+1},$$

where $ret_{i,t+1}$ is the return for firm i in month $t+1$, $\text{SUE}_{i,t}$ is firm i's standardized unexpected earnings in month t, $herd_{i,t}$ is the herding dummy equal to one (zero) if the slope coefficient of equation (refequ1) over the past 24-month rolling window is negative (positive), and $u_{i,t}$ is one of the firm-level uncertainty measures: $mv_{i,t}$ is the natural log of market capital (in millions of dollars); $age_{i,t}$ is the number of years for the firm since the first month covered by CRSP; $vol_{i,t}$ is firm's daily return standard deviation over 12-month ending in month t; $bm_{i,t}$ is book value of firm's equity divided by its market value by the end of last fiscal year; $cvol_{i,t}$ is the 5-year (ending at the last fiscal year) standard deviation of the firm's cash flow scaled by average total assets; $cov_{i,t}$ is the number of analysts covering the firm at the last fiscal year end; $disp_{i,t}$ is the cross-sectional standard deviation of analyst forecasts scaled by the absolute value of the cross-sectional mean; $num_{i,t}$ is the number of earning estimations; $u_{i,t}^{com}$ is the composite firm-level uncertainty measure for firm i in month t.. Newey-West t-statistics are given in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

	$mv_{i,t}$	$age_{i,t}$	$vol_{i,t}$	$bm_{i,t}$	$cvol_{i,t}$	$cov_{i,t}$	$disp_{i,t}$	$num_{i,t}$	$u_{i,t}^{com}$
Intercept	1.17	1.09	1.26	1.06	1.19	1.07	1.14	1.08	1.28
t-stat	(2.77)	(3.88)	(5.90)	(4.07)	(5.07)	(4.16)	(4.65)	(4.12)	(5.74)
$\text{SUE}_{i,t}$	0.08	0.02	-0.04	0.00	-0.05	0.01	0.01	0.01	-0.07
t-stat	(1.13)	(0.72)	(-0.91)	(-0.06)	(-1.63)	(0.33)	(0.50)	(0.30)	(-1.38)
$herd_{i,t}$	-0.26	-0.28	-0.22	-0.29	-0.30	-0.26	-0.26	-0.27	-0.25
t-stat	(-3.14)	(-3.39)	(-2.90)	(-3.54)	(-3.38)	(-3.17)	(-3.18)	(-3.26)	(-3.15)
$\text{SUE\_}herd_{i,t}$	**0.09**	**0.09**	**0.06**	**0.10**	**0.12**	**0.10**	**0.09**	**0.09**	**0.09**
t-stat	**(2.49)**	**(2.33)**	**(1.53)**	**(2.87)**	**(2.76)**	**(2.62)**	**(2.47)**	**(2.49)**	**(2.33)**
$u_{i,t}$	-0.01	0.00	-11.27	-0.08	-1.64	0.00	-0.29	0.00	-0.39
t-stat	(-0.30)	(0.29)	(-1.15)	(-0.50)	(-1.95)	(0.50)	(-1.59)	(0.24)	(-0.84)
$\text{SUE\_}u_{i,t}$	-0.01	0.00	2.06	-0.02	0.47	0.00	-0.13	0.00	0.15
t-stat	(-1.42)	(-1.12)	(1.02)	(-0.34)	(1.88)	(-0.25)	(-1.09)	(0.03)	(1.51)
N	565	565	565	549	434	564	565	565	565
Adj R^2	1.50%	1.03%	4.05%	1.44%	2.15%	1.08%	1.23%	1.01%	2.02%

Table 9: Herding and predictability: portfolio analysis

The table presents the means and t-statistics of the excess returns (in percentage) and the benchmark-adjusted returns of the long leg, the short leg and the long-short strategy spread (in percentage). In each month t, we identify the herding and non-herding firms and calculate the equally weighted portfolio returns. The long-short trading strategy is to long the non-herding firm portfolio and short the herding firm portfolio. In column (1)-(3), herding (non-herding) firms are the ones with the negative (positive) slope coefficients of equation (refequ1) over the past 24-month rolling window. In column (4)-(6), the firms are grouped by sorting the slope coefficients into deciles. The herding (non-herding) firms are the ones with the lowest (highest) coefficients. The excess return is the portfolio return minus the one-month T-bill rate. The benchmark-adjusted returns are defined here as the portfolio returns net of what is attributable to exposures to 1). the market factor (CAPM); 2). the market, size and value factors (Fama-Frech 3-factor model); 3). the market, size, value, profitability and investment factors (Fama-French 5-factor model). Newey-West adjusted t-statistics are reported in parentheses The sample spans from Jan. 1985 to Dec. 2024.

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-herd	Herd	Long - Short	Non-herd	Herd	Long - Short
Excess return	0.83	0.55	0.28	0.80	0.41	0.39
t-stat	(3.28)	(2.30)	(3.10)	(2.49)	(1.38)	(3.29)
CAPM adj return	0.01	-0.21	0.22	-0.19	-0.52	0.33
t-stat	(0.12)	(-1.94)	(2.44)	(-1.23)	(-3.65)	(3.02)
FF 3-factor adj return	0.00	-0.20	0.20	-0.17	-0.47	0.30
t-stat	(-0.05)	(-2.63)	(2.21)	(-1.76)	(-5.21)	(2.76)
FF 5-factor adj return	-0.01	-0.26	0.25	-0.09	-0.41	0.32
t-stat	(-0.18)	(-3.36)	(2.70)	(-0.90)	(-4.57)	(2.85)

Table 10: Herding and predictability: Fama-MacBeth regression analysis

The table presents the time-series averages of coefficients obtained from the monthly cross-section regressions:

$$ret_{i,t+1} = k + l * herd_{i,t} + m * p_{i,t} + n * control_{i,t} + \epsilon_{i,t},$$

where $ret_{i,t+1}$ is the return for firm i in month $t+1$, $p_{i,t}$ is one of the predictors: $ivol_{i,t}$ is the monthly idiosyncratic volatility of stock i computed as the standard deviation of the daily residuals (in percentage) in month t from the Fama-Frech 3-factor model, $disp_{i,t}$ is the analysts' forecast dispersion for firm i in month t, $\beta^U_{i,t}$ is the coefficient of the economic uncertainty index of Jurado, Ludvigson, and Ng (2015) in the model with the Fama-French three factors plus the uncertainty index as the explanatory variables, and $herd_{i,t}$ equals one (zero) with the negative (positive) slope coefficient of equation (refequ1 over the past 24-month rolling window, and $control_{i,t}$ is a vector containing the firm characteristics related variables. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

		$ivol_{i,t}$		$disp_{i,t}$		$\beta^U_{i,t}$	
Intercept	1.26	1.32	1.56	1.15	1.25	1.96	2.06
t-stat	(5.11)	(4.86)	(5.12)	(4.65)	(5.06)	(4.04)	(4.22)
$herd_{i,t}$	**-0.25**		**-0.22**		**-0.21**		**-0.24**
t-stat	**(-2.74)**		**(-2.94)**		**(-2.33)**		**(-2.57)**
$p_{i,t}$		-0.23	-0.28	-0.33	-0.31	0.00	0.00
t-stat		(-3.90)	(-3.43)	(-2.33)	(-2.16)	(0.68)	(0.63)
control		Y	Y	Y	Y	Y	Y
N	561	459	459	561	560	548	548
R	6.59%	5.40%	10.15%	6.65%	7.03%	6.19%	6.37%

Table 11: Herding and anomalies: Fama-MacBeth regression analysis

Panel A presents t-test of equal means of the anomaly variables for the herding and non-herding firms. The anomaly variables are: (1).$acret_{i,t}$, firm i's accumulated return over month t-11 to month t; (2). $O\_score_{i,t}$, the Ohlson(1980) O-score measures; (3). $g\_shares_{i,t}$, the growth of the split-adjusted shares outstanding of firm i in the last fiscal with respect of month t; (4). $\text{NOA}_{i,t}$, firm i's net operating asset; (5). $gp_{i,t}$, firm i's gross profit of the last fiscal year; (6). $acruals_{i,t}$, firm i's total accruals; (7). $g\_asset_{i,t}$, firm i's asset growth measured as the growth rate of total assets in the previous fiscal year; (8). $\text{ITA}_{i,t}$, firm i's investment-to-assets measured as the annual change in gross property, plant, and equipment plus the annual change in inventories scaled by the lagged book value of assets. (9). $\text{ROA}_{i,t}$, firm i's return on asset of the last fiscal year with respect of month t. Panel B reports the time-series averages of coefficients obtained from the monthly cross-section regression:

$$ret_{i,t+1} = o + p * herd_{i,t} + q * anml_{i,t} + r * anml_{i,t} * herd_{i,t} + \epsilon_{i,t},$$

where $ret_{i,t+1}$ is the return for firm i in month $t+1$, $herd_{i,t}$ equals one (zero) with the negative (positive) slope coefficient of equation (refequ1) over the past 24-month rolling window, and $anml_{i,t}$ is one of the nine anomaly variables. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

A: Anomalies									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Herd	0.15	-2,490.70	0.14	0.64	0.29	0.07	0.21	0.09	0.01
Non_herd	0.15	-3,310.70	0.10	0.61	0.29	0.06	0.17	0.08	0.01
Diff	0.00	820.00	0.04	0.03	0.00	0.00	0.03	0.01	0.00
t-stat	(0.10)	(4.27)	(2.42)	(5.89)	(1.45)	(1.75)	(4.93)	(3.49)	(-2.86)
B: Herding and anomalies									
intercept	0.93	1.03	1.04	1.29	0.81	1.07	1.07	1.08	0.90
t-stat	(3.91)	(3.80)	(4.15)	(4.89)	(3.19)	(4.18)	(4.33)	(4.24)	(3.50)
$herd_{i,t}$	**-0.34**	**-0.36**	**-0.28**	**-0.34**	**-0.21**	**-0.35**	**-0.28**	**-0.26**	**-0.26**
t-stat	**(-4.13)**	**(-3.89)**	**(-3.38)**	**(-2.38)**	**(-1.83)**	**(-3.68)**	**(-3.34)**	**(-2.95)**	**(-2.98)**
$anml_{i,t}$	0.25	0.00	-0.19	-0.39	0.72	-0.26	-0.37	-0.70	11.18
t-stat	(1.02)	(-0.82)	(-0.95)	(-2.92)	(2.93)	(-0.48)	(-2.52)	(-2.32)	(5.62)
$anml\_herd_{i,t}$	0.65	0.00	-0.19	0.06	-0.28	-0.04	0.03	-1.09	1.40
t_stat	(3.07)	(0.19)	(-0.60)	(0.35)	(-0.97)	(-0.04)	(0.15)	(-2.51)	(0.57)
N	635	484	612	564	613	468	612	518	608
Adj R^2	2.29%	0.48%	0.53%	0.87%	1.12%	0.70%	0.88%	0.66%	1.50%

Figure 1: Timeline of the model

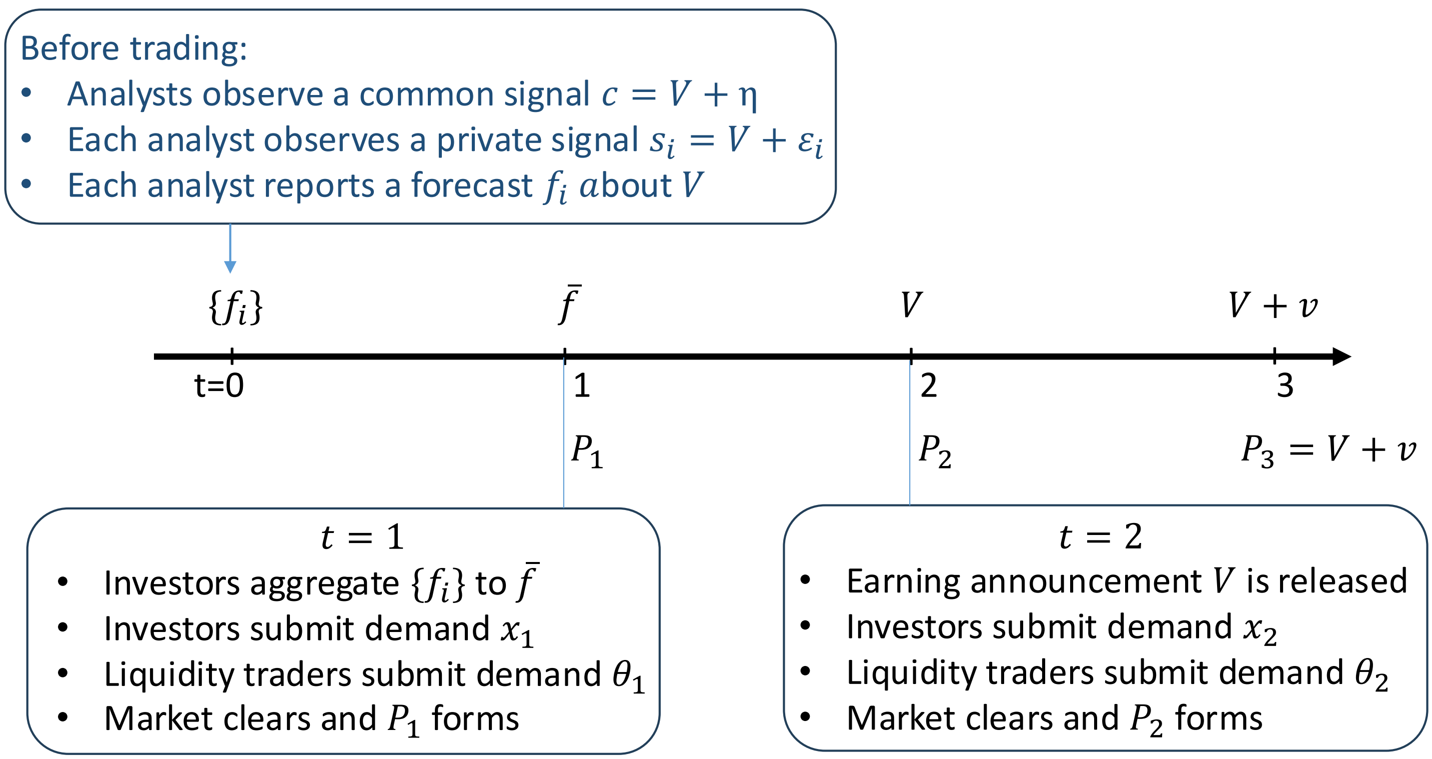
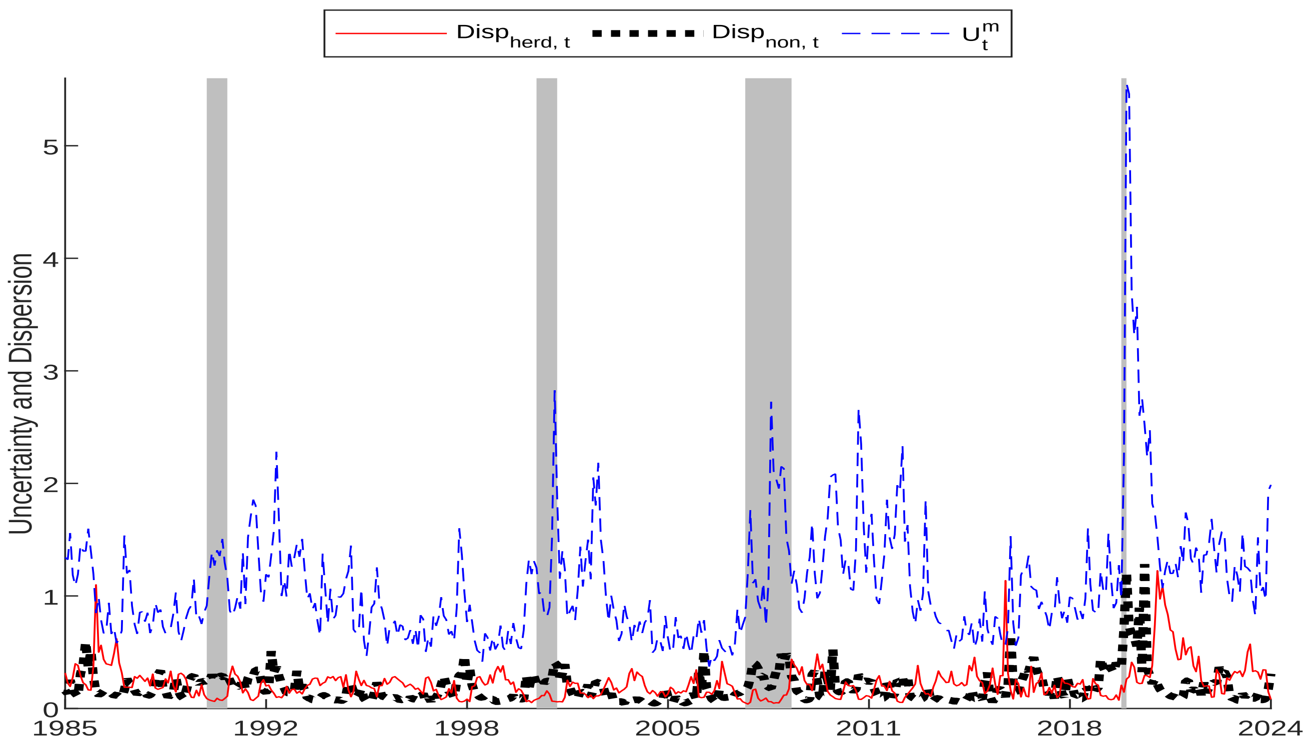


Figure 2: Macroeconomic Uncertainty and Analyst Forecasts Dispersion

The figure presents time series plots of U_t^m, the U.S. EPU index constructed by Baker et al. (2016) (scaled by 100), and $Disp_{herd,t}$ ($Disp_{non,t}$), the monthly aggregated $disp_{i,t}$, which is the cross-sectional standard deviation of analyst forecasts scaled by the absolute value of the cross-sectional mean for herding (non-herding) firms classified by the negative (positive) slope coefficient of regressing $disp_{i,t}$ on U_t^m over firm i's past 24-month rolling window ending in month t. The shaded areas are recessions defined according to NBER business cycle dating committee. The sample spans from Jan. 1985 to Dec. 2024.



Internet Appendix

A Proof of lemma 1

Proof. We will now show the existence and uniqueness of analysts' equilibrium forecast strategy. Following Morris and Shin (2002), we do this in two steps. We first solve for a linear equilibrium in which forecasts are a linear function of common and private signals. We will follow this with a demonstration that this linear equilibrium is the unique equilibrium. Thus, as the first step, suppose that all the analysts are following strategy of the form

$$f_i = (1 - \kappa_1 - \kappa_2)\bar{V} + \kappa_1 s_i + \kappa_2 c. \tag{41}$$

Then analyst i's conditional estimate of the average expected forecast across all analysts is

$$\mathrm{E}^i[\bar{f}] = (1 - \kappa_1 - \kappa_2)\bar{V} + \kappa_1 \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon s_i}{\tau_V + \tau_\eta + \tau_\varepsilon} + \kappa_2 c. \tag{42}$$

Note that in order to maximize the utility function Eq (6), analyst i best response is

$$f_i = (1 - \delta)\mathrm{E}^i[V] + \delta \mathrm{E}^i[\bar{f}]. \tag{43}$$

By substituting Eq (42) into above equation, we have

$$\begin{aligned} f_i = &\left(\delta(1 - \kappa_1 - \kappa_2) + (1 - \delta + \delta\kappa_1)\frac{\tau_V}{\tau_V + \tau_\eta + \tau_\varepsilon} \right) \bar{V} \\ &+(1 - \delta + \delta\kappa_1)\frac{\tau_\varepsilon}{\tau_V + \tau_\eta + \tau_\varepsilon} s_i + (1 - \delta + \delta\kappa_1)\frac{\tau_\eta}{\tau_V + \tau_\eta + \tau_\varepsilon} c. \end{aligned} \tag{44}$$

Comparing coefficients in Eq (41) and Eq (44), we therefore have

$$\kappa_1 = \frac{(1 - \delta)\tau_\varepsilon}{\tau_V + \tau_\eta + (1 - \delta)\tau_\varepsilon}, \tag{45}$$

$$\kappa_2 = \frac{\tau_\eta}{\tau_V + \tau_\eta + (1 - \delta)\tau_\varepsilon}. \tag{46}$$

Thus, the equilibrium forecast f_i is given by

$$f_i = \frac{\tau_V \bar{V} + \tau_\eta c + (1 - \delta)\tau_\varepsilon s_i}{\tau_V + \tau_\eta + (1 - \delta)\tau_\varepsilon}. \tag{47}$$

The argument presented above establish the existence of a linear equilibrium. We will follow this by showing that the linear equilibrium we have identified is the unique equilibrium. In doing so, we establish the role of higher-order expectations in the model. Recall that analyst i's expected value of V is

$$\mathrm{E}^i[V] = \frac{\tau_V \bar{V} + \tau_\varepsilon s_i + \tau_\eta c}{\tau_V + \tau_\varepsilon + \tau_\eta}. \tag{48}$$

Thus, the average expectation of V across all analysts is

$$\bar{\mathrm{E}}[V] = \int_0^1 \mathrm{E}^i[V] di = \frac{\tau_V \bar{V} + \tau_\varepsilon V + \tau_\eta c}{\tau_V + \tau_\varepsilon + \tau_\eta}. \tag{49}$$

We use $\bar{\mathrm{E}}^{\mathrm{n}}[V]$ to denote the nth order expectation of average expectation of V. We conjecture that for any n,

$$\begin{aligned}
\bar{\mathrm{E}}^{\mathrm{n}}[V] &= \frac{\tau_V \bar{V}}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n} \mu^{k-1} + \frac{\tau_\eta c}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n} \mu^{k-1} + \mu^n V, \\
\mathrm{E}^i[\bar{\mathrm{E}}^{\mathrm{n}}[V]] &= \frac{\tau_V \bar{V}}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n+1} \mu^{k-1} + \frac{\tau_\eta c}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n+1} \mu^{k-1} + \mu^{n+1} s_i,
\end{aligned} \tag{50}$$

where

$$\mu = \frac{\tau_\varepsilon}{\tau_V + \tau_\eta + \tau_\varepsilon}, \tag{51}$$

It is easy to verify that Eq (50) holds for $n = 1$, then the proof is by induction on n.

Recall that analyst i's best response is to report forecast

$$f_i = (1-\delta)\mathrm{E}^i[V] + \delta \mathrm{E}^i[\bar{f}]. \tag{52}$$

Substituting the average expectation of V, i.e., $\bar{\mathrm{E}}[V]$, we have

$$\begin{aligned}
f_i &= (1-\delta)\mathrm{E}^i[V] + (1-\delta)\delta \mathrm{E}^i[\bar{\mathrm{E}}[V]] + (1-\delta)\delta^2 \mathrm{E}^i[\bar{\mathrm{E}}^2[V]] + ... \\
&= (1-\delta) \sum_{n=0}^{\infty} \delta^n \mathrm{E}^i[\bar{\mathrm{E}}^{\mathrm{n}}[V]] \\
&= \frac{\tau_V \bar{V}}{\tau_V + \tau_\eta + \tau_\varepsilon} \frac{1}{1-\delta\mu} + \frac{\tau_\eta c}{\tau_V + \tau_\eta + \tau_\varepsilon} \frac{1}{1-\delta\mu} + \frac{(1-\delta)\mu}{1-\delta\mu} s_i \\
&= \frac{\tau_V \bar{V} + \tau_\eta c + (1-\delta)\tau_\varepsilon s_i}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}.
\end{aligned}$$

This is exactly the unique linear equilibrium we identified earlier.

We rewrite $\bar{f}$ as a weighted average of $\bar{V}$ and s_f

$$\bar{f} = \omega \bar{V} + (1-\omega) s_f, \tag{53}$$

where

$$\omega = \frac{\tau_V}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}, \quad s_f = V + \frac{\tau_\eta}{\tau_\eta + (1-\delta)\tau_\varepsilon}\eta \sim \mathcal{N}(\bar{V}, \tau_V^{-1} + \tau_f^{-1}), \tag{54}$$

and

$$\tau_f = \frac{(\tau_\eta + (1-\delta)\tau_\varepsilon)^2}{\tau_\eta}. \tag{55}$$

If there is no herding tendency, i.e, $\delta = 0$, analysts' average forecast $\bar{f}$ reveals a more precise signal about V. As stronger herding tendency presents, i.e., δ increases, less information about V is revealed to the financial market by the forecasts,

$$\frac{d\text{Var}(V \mid \bar{f})}{d\delta} > 0, \tag{56}$$

analysts' herding behavior leads to information inefficiency in the financial market.

□

B Explanation without strategic herding

One could argue that the mechanism behind the negative correlation between macro uncertainty and analyst forecast dispersion is that higher fundamental uncertainty, τ_V^{-1}, makes it more challenging for analysts to gather precise private information, resulting in a smaller τ_ε. Consequently, as macro uncertainty increases, analysts place greater weight on the common signal c relative to their private signal s_i, leading to reduced forecast dispersion. However, the following Lemma shows that this mechanism operates only under a strong condition—namely, that the common signal precision τ_η must far exceed the precision of private information even when the fundamental is extremely noisy.

Lemma 2. *In the absence of herding ($\delta = 0$), suppose analysts' private information precision τ_ε is an increasing function of τ_V, i.e. $\tau_\varepsilon = h(\tau_V)$, and h' is continuous with $h(0) > 0$. Then there exists a threshold $\tau_V^c > 0$ such that*

$$\frac{dD}{d\sigma_m^2} < 0 \quad \text{for } \tau_V < \tau_V^c, \tag{57}$$

if and only if

$$\tau_\eta > h(0)\left(1 + \frac{2}{h'(0)}\right). \tag{58}$$

Proof. Since analysts report their forecasts truthfully, $D = \frac{\tau_\varepsilon}{(\tau_V+\tau_\eta+\tau_\varepsilon)^2}$, and $\tau_\varepsilon = h(\tau_V)$,

$$\frac{dD}{d\sigma_m^2} = \frac{h' \frac{d\tau_V}{d\sigma_m^2}}{(\tau_V + \tau_\eta + \tau_\varepsilon)^2} - \frac{2\tau_\varepsilon(1 + h')\frac{d\tau_V}{d\sigma_m^2}}{(\tau_V + \tau_\eta + \tau_\varepsilon)^3}, \tag{59}$$

where $\frac{d\tau_V}{d\sigma_m^2} < 0$. Hence, $\frac{dD}{d\sigma_m^2} < 0$ is equivalent to

$$f(\tau_V) := h'(\tau_V + \tau_\eta - h) - 2h > 0. \tag{60}$$

Since h' is continuous near 0, f is also continuous near 0. Thus,

$$f(0) > 0 \qquad \Leftrightarrow \qquad h'(0)(\tau_\eta - h(0)) - 2h(0) > 0, \tag{61}$$

which is equivalent to

$$\tau_\eta > h(0)\left(1 + \frac{2}{h'(0)}\right). \tag{62}$$

By continuity, $f(0) > 0$ implies $f(\tau_V) > 0$ for some interval $[0, \tau_V^c)$. Conversely, if $f(\tau_V) > 0$ on $[0, \tau_V^c)$, taking $\tau_V \to 0^+$ gives $f(0) \geq 0$, and in fact > 0 unless the inequality fails right at 0.

□

Even though such a condition can generate the negative correlation, without behavior bias ($\delta = 0$), analysts will continue to report their forecasts truthfully :

$$f_i = \mathrm{E}^i[V] = \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon s_i}{\tau_V + \tau_\eta + \tau_\varepsilon}, \tag{63}$$

the aggregated consensus forecast is:

$$\bar{f} = \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon V}{\tau_V + \tau_\eta + \tau_\varepsilon}. \tag{64}$$

There is no information loss impeding financial market efficiency, inconsistent with our empirical findings.

C Proof of Proposition 1

Proof. The total derivative of dispersion D with respect to macro uncertainty σ_m^2 is

$$\frac{dD}{d\sigma_m^2} = \frac{dD}{d\tau_V}\frac{d\tau_V}{d\sigma_m^2} = \frac{2(1-\delta)\tau_\varepsilon \tau_V^2}{(\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon)^3}\left[\delta'(\tau_V)(\tau_V + \tau_\eta) + (1-\delta)\right]. \tag{65}$$

Let $g(\tau_V) := \delta'(\tau_V)(\tau_V + \tau_\eta) + (1-\delta)$. The necessary and sufficient condition for dispersion to decrease as macroeconomic uncertainty increases is that there exist values of τ_V such that

$$g(\tau_V) < 0. \tag{66}$$

Note that

$$g(0) = \delta'(0)\tau_\eta < 0, \tag{67}$$

thus, for sufficiently small τ_V, the dispersion D decreases as the macroeconomic uncertainty σ_m^2 increases.

Let τ_V^c denote the solution for $g(\tau_V) = 0$. One sufficient condition for the existence of τ_V^c is $g'(\tau_V) > 0$, i.e.,

$$\delta''(\tau_V)(\tau_V + \tau_\eta) > 0 \qquad \Leftrightarrow \qquad \delta''(\tau_V) > 0. \tag{68}$$

It follows:

$$for \quad \tau_V < (>)\tau_V^c, \quad g(\tau_V) < (>)0 \quad and \quad \frac{dD}{d\sigma_m^2} < (>)0. \tag{69}$$

As $\tau_V^{-1} = \sigma_m^2 + \sigma^2$, $\frac{d\tau_V}{d\sigma^2} < 0$. Holding σ_m^2 constant, there exists σ_c^2, so that

$$\delta > (<)\delta_c \iff \frac{dD}{d\sigma_m^2} < (>)0. \tag{70}$$

□

D Proof of Proposition 2

Proof. To derive the optimal holdings and price, we use the following lemma.

Lemma 3. *Let u be an $n \times 1$ normal vector with mean $\bar{u}$ and covariance matrix Σ, A a scalar, B an $n \times 1$ vector, C an $n \times n$ symmetric matrix, I the $n \times n$ identity matrix, and $|M|$ the determinant of a matrix M. Then,*

$$\mathrm{E}_u \exp\{-\rho[A + B^\top u + \frac{1}{2}u^\top C u]\} = \frac{1}{\sqrt{|I + \rho C\Sigma|}} \exp\big\{ -\rho[A + B^\top \bar{u} + \frac{1}{2}\bar{u}^\top C\bar{u} \\ -\frac{1}{2}\rho(B + C\bar{u})^\top (\Sigma^{-1} + \rho C)^{-1}(B + C\bar{u})]\big\}.$$

To obtain the equilibrium prices for each period, we solve the model by backward induction. In the last trading period $t = 2$, investors' optimal position is

$$x_2 = \frac{\mathrm{E}_2[V + v] - P_2}{\lambda \mathrm{Var}_2(V + v)} = \frac{V - P_2}{\lambda \tau_v^{-1}}. \tag{71}$$

By market clearing condition, the equilibrium price is

$$P_2 = V + \lambda \tau_v^{-1} (\beta z_1 + z_2) - \lambda \tau_v^{-1} \Theta. \tag{72}$$

Thus investor's value function at $t = 2$ is

$$J_2 = -e^{-\lambda\left[\left(V + \frac{\lambda}{\tau_v}(\theta_2 - \Theta) - P_1\right)x_1 + \frac{1}{2}\frac{\lambda}{\tau_v}(\theta_2 - \Theta)^2\right]}. \tag{73}$$

By Lemma 3, we solve

$$\max_{x_1} \mathrm{E}_1[J_2], \tag{74}$$

the optimal position at $t = 1$ is obtained as

$$x_1 = \left(\lambda \mathrm{Var}_1(V) + \frac{\lambda}{\tau_v}\frac{\lambda^2}{\lambda^2 + \tau_v}\right)^{-1} \left[\mathrm{E}_1[V] - P_1 + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v}\right)(\beta z_1 - \Theta)\right], \tag{75}$$

where

$$\mathrm{E}_1[V] = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f}, \quad \text{and} \quad \mathrm{Var}_1(V) = \frac{1}{\tau_V + \tau_f}. \tag{76}$$

By market clearing condition, the equilibrium price at $t = 1$ is

$$P_1 = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v}(1-\beta)\right)\right] z_1 - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta. \tag{77}$$

Hence, P_1 is informationally equivalent to the following signal

$$s_p = s_f + \lambda\left(b + \frac{b\tau_V + 1}{\tau_f}\right) z_1, \tag{78}$$

where

$$b = \frac{1}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v}(1-\beta)\right). \tag{79}$$

Therefore,

$$\mathrm{Var}(V \mid P_1) = \mathrm{Var}(V \mid s_p) = \frac{1}{\tau_V + \tau_f + \lambda^{-2}\left(b + \frac{b\tau_V + 1}{\tau_f}\right)^{-2}}. \tag{80}$$

As δ increases, τ_f decreases, leading to an increase in $\mathrm{Var}(V \mid P_1)$,

$$\frac{d\mathrm{Var}(V \mid P_1)}{d\delta} > 0, \tag{81}$$

which means that beauty contest makes the price more noisy and less informative.

□

E Proof of Proposition 3

Proof. The return covariance before and after earning announcement can be computed

$$\mathrm{Cov}\left(P_3 - P_2, P_2 - P_1\right) = \frac{\lambda^2}{\tau_v^2}\left[\beta\left(\frac{\tau_v}{\tau_V + \tau_f} + \frac{\lambda^2}{\lambda^2 + \tau_v}(1-\beta)\right) - 1\right]. \tag{82}$$

Thus, the necessary and sufficient condition for a positive return correlation is

$$f(\beta) := \beta\left(\frac{\tau_v}{\tau_V + \tau_f} + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z}(1-\beta)\right) - 1 > 0, \tag{83}$$

the left hand side of which is denoted as a function of β. $f(\beta)$ is a quadratic function of β. For simplicity, we denote

$$a = \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z} \in (0,1), \quad x = \frac{\tau_v}{\tau_V + \tau_f} \in (0, +\infty). \tag{84}$$

Thus, $f(\beta)$ can be rewritten as

$$f(\beta) = -a\beta^2 + (x+a)\beta - 1. \tag{85}$$

The necessary condition of $f(\beta) > 0$ is

$$(x+a)^2 - 4a > 0 \Longleftrightarrow x > 2\sqrt{a} - a, \tag{86}$$

under which $f(\beta) = 0$ has two positive roots:

$$\beta_c = \frac{x + a - \sqrt{(x+a)^2 - 4a}}{2a}, \quad \beta_d = \frac{x + a + \sqrt{(x+a)^2 - 4a}}{2a}. \tag{87}$$

Therefore, the sufficient condition for $f(\beta > 0)$ is

$$\beta_c < \beta < \beta_d. \tag{88}$$

Note $0 \leq \beta \leq 1$, however, under the condition of Eq.(86),

$$\beta_d > 1. \tag{89}$$

Thus, to guarantee $f\beta > 0$, we need

$$\beta_c < 1 \Longleftrightarrow x > 1. \tag{90}$$

Since $0 < a < 1$, we have $2\sqrt{a} - a < 1$. Therefore, the necessary and sufficient condition for $f(\beta) > 0$ is

$$x > 1, \quad \text{and} \quad \beta > \beta_c, \tag{91}$$

where

$$x > 1 \Longleftrightarrow \mathrm{Var}(v) < \mathrm{Var}(V \mid \bar{f}), \tag{92}$$

and

$$\frac{d\beta_c}{d\delta} = \underbrace{\frac{d\beta_c}{dx}}_{<0} \underbrace{\frac{dx}{d\delta}}_{>0} < 0. \tag{93}$$

□

F Proof of Proposition 4

Proof. This appendix proves Proposition 4, showing that the presence of inattentive investors ($\alpha > 0$) leads to a positive covariance between earnings surprise (ES) and post-earnings return (PR). By market clearing condition (29), we have time-2 equilibrium price

$$P_2 = \frac{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} V + \frac{\frac{\alpha}{\tau_v}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} - \frac{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\lambda}{\tau_v} (\Theta - \theta_2). \tag{94}$$

Thus, the post-earning return

$$\text{PR} = v + \frac{\frac{\alpha}{\tau_v}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\tau_V (V - \bar{V}) - \tau_f \varepsilon_f}{\tau_V + \tau_f} + \frac{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\lambda}{\tau_v} (\Theta - \theta_2). \tag{95}$$

Then the variance of the post-earning return is

$$\text{Var(PR)} = \frac{1}{\tau_v} + \frac{w_\alpha^2}{\tau_V + \tau_f} + (1 - w_\alpha)^2 \frac{\lambda^2}{\tau_v^2} (1 + \beta^2), \tag{96}$$

where

$$w_\alpha = \frac{\frac{\alpha}{\tau_v}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}. \tag{97}$$

The earning surprise is

$$\text{ES} = \frac{\tau_V (V - \bar{V}) - \tau_\eta \eta}{\tau_V + \tau_\eta + \tau_\varepsilon (1 - \delta)}, \tag{98}$$

and its variance is

$$\text{Var(ES)} = \frac{\tau_V + \tau_\eta}{\left(\tau_V + \tau_\eta + \tau_\varepsilon (1 - \delta)\right)^2}. \tag{99}$$

The covariance between the two is positive,

$$\text{Cov(ES, PR)} = \frac{w_\alpha}{\tau_V + \tau_f} = \frac{\alpha}{\tau_V + \tau_f + \tau_v} > 0. \tag{100}$$

Hence,

$$\frac{d\text{Var(ES)}}{d\delta} = \frac{2\tau_\varepsilon (\tau_V + \tau_\eta) \left(\tau_V + \tau_\eta + \tau_\varepsilon (1 - \delta)\right)}{\left(\tau_V + \tau_\eta + \tau_\varepsilon (1 - \delta)\right)^4} > 0. \tag{101}$$

$$\frac{d\text{Cov(ES, PR)}}{d\delta} = -\frac{\alpha}{\left(\tau_V + \tau_f + \tau_v\right)^2} \frac{d\tau_f}{d\delta} > 0. \tag{102}$$

□

G Proof of Proposition 5

Proof. Under short-sale constraint, i.e., $x_t \geq 0$ and $\theta_t \geq 0$, we have

$$0 \leq \theta_2 \leq \Theta, \quad 0 \leq \theta_1 \leq \Theta. \tag{103}$$

Since $\theta_2 = \beta\theta_1 + z_2$ and $\theta_1 = z_1$,

$$0 \leq z_1 \leq \Theta, \tag{104}$$

and given z_1, the range for z_2 should be

$$-\beta z_1 \leq z_2 \leq \Theta - \beta z_1. \tag{105}$$

Thus, under short-sale constraint,

$$\mathrm{E}_0^{ss}[\theta_1] = \Delta_1, \tag{106}$$

$$\mathrm{E}_1^{ss}[\theta_2] = \beta z_1 + \Delta_2, \tag{107}$$

where superscript $.^{ss}$ stands for short-sale constraint. Δ_t in the above expression are

$$\Delta_1 = \mathrm{E}[z_1 \mid 0 \leq z_1 \leq \Theta] = \frac{\phi(0) - \phi(\Theta)}{\Phi(\Theta) - \Phi(0)}, \tag{108}$$

$$\Delta_2 = \mathrm{E}[z_2 \mid -\beta z_1 \leq z_2 \leq \Theta - \beta z_1] = \frac{\phi(\beta z_1) - \phi(\Theta - \beta z_1)}{\Phi(\Theta - \beta z_1) - \Phi(-\beta z_1)}, \tag{109}$$

where ϕ and Φ denote probability density function and cumulative distribution function of standard normal respectively. Obviously,

$$\Delta_1 > 0, \quad \frac{\partial \Delta_2}{\partial \beta} < 0. \tag{110}$$

Under short-sale constraint, the condition variance of θ_2 is

$$\mathrm{Var}_2^{ss}(\theta_2) < \mathrm{Var}_2(\theta_2) = 1, \tag{111}$$

and obviously

$$\tau_z^{ss} := \frac{1}{\mathrm{Var}_2^{ss}(\theta_2)} > 1. \tag{112}$$

Under the short-sale constraint, by solving

$$\max_{x_1} \mathrm{E}_1^{ss}[J_2], \tag{113}$$

the optimal position under short-sale constraint at $t = 1$ is obtained as

$$x_1^{ss} = \left(\lambda \mathrm{Var}_1^{ss}(V) + \frac{\lambda}{\tau_v}\frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)^{-1} \left[\mathrm{E}_1^{ss}[V] - P_1 + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)(\beta z_1 - \Theta + \Delta_2)\right], \tag{114}$$

where

$$\mathrm{E}_1^{ss}[V] = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f}, \quad \text{and} \quad \mathrm{Var}_1^{ss}(V) = \frac{1}{\tau_V + \tau_f}, \tag{115}$$

i.e., short-sale constraint has no impact on the estimations about fundamentals since there is no information asymmetry in the model. By market clearing condition, the equilibrium price with short-sale constraint at $t = 1$ is

$$\begin{aligned} P_1^{ss} = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)\Delta_2 \\ + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}(1 - \beta)\right)\right] z_1, \end{aligned} \tag{116}$$

noting that Δ_2 is a function of βz_1. Therefore, the expected equilibrium price with short-sale constraint is

$$\begin{aligned} \mathrm{E}[P_1^{ss}] = \bar{V} - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)\mathrm{E}[\Delta_2 \mid 0 \leq z_1 \leq \Theta] \\ + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}(1 - \beta)\right)\right]\Delta_1, \end{aligned} \tag{117}$$

where by symmetry,

$$\mathrm{E}[\Delta_2 \mid 0 \leq z_1 \leq \Theta] = 0. \tag{118}$$

Hence, the difference between the expected price with and without short-sale constraint is

$$\Delta = \mathrm{E}[P_1^{ss}] - \mathrm{E}[P_1] = \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}(1 - \beta)\right)\right]\Delta_1 > 0, \tag{119}$$

which indicates that even there is no information asymmetry the short-sale constraint leads to a higher expected price. Furthermore, since $\frac{d\tau_f}{d\delta} < 0$,

$$\frac{d\Delta}{d\delta} = -\frac{\lambda\Delta_1}{(\tau_V + \tau_f)^2}\frac{d\tau_f}{d\delta} > 0, \tag{120}$$

Without short-sale constraints, the expected equilibrium price at $t = 2$ is

$$\mathrm{E}[P_2] = \bar{V} - \frac{\lambda}{\tau_v}\Theta. \tag{121}$$

With the short-sale constraints, the expected equilibrium price at $t = 2$ is

$$\mathrm{E}[P_2^{ss}] = \bar{V} + \frac{\lambda}{\tau_v}(\Delta_1 - \Theta), \tag{122}$$

which is also greater than $\mathrm{E}[P_1]$. However, since at time 2 fundamental V is publicly announced, the herding effect has no impact on overpricing. Therefore, the expected return with short-sale constraint is

$$\mathrm{E}[R^{ss}] = \mathrm{E}[P_2^{ss}] - \mathrm{E}[P_1^{ss}] = \frac{\lambda}{\tau_V + \tau_f}(\Theta - \Delta_1) + \frac{\lambda(1-\beta)\tau_z^{ss}}{\lambda^2 + \tau_v\tau_z^{ss}}\Delta_1. \tag{123}$$

Since $\frac{d\tau_f}{d\delta} < 0$, the expected return changes with δ negatively

$$\frac{d\mathrm{E}[R^{ss}]}{d\delta} = \frac{\lambda(\Theta - \Delta_1)}{(\tau_V + \tau_f)^2}\frac{d\tau_f}{d\delta} < 0. \tag{124}$$

□

H Supplementary Empirical Results

In this section, we present supplementary empirical results that further support the paper's hypotheses. Table H1 provides descriptive statistics for variables used in the empirical tests, omitted from Table 1 in the main body due to space constraints.

Tables H2, H3, and H4 report results of tests analogous to those in Tables 3, 5, and 9, respectively, which support Hypotheses I, II, and III, but use the VIX as an alternative measure of macroeconomic uncertainty.

Table H5 through H7 present results parallel to those in Tables 3, 5, and 9, with herding and non-herding firms classified based on the sign of the slope coefficient from regression (35), without the requirement that the t-statistic exceeds 1.65 in absolute value.

Table H1: Descriptive statistics

The table shows the summary statistics of the variables: (1). $\mathrm{MV}_{i,t}$, the market capital (in millions of dollars) for firm i by the end of month t. (2). $ret_{i,t}$, firm i's return (in percentage) in month t; (3). $\mathrm{SUE}_{i,t}$, the standardized unexpected earning for firm i in month t; (4). $ivol_{i,t}$, the monthly idiosyncratic volatility of stock i computed as the standard deviation of the daily residuals (in percentage) in month t from the Fama-Frech 3-factor model; (5). $\beta^U_{i,t}$, the slope coefficient of the economic uncertainty index of Jurado et al. (2015) in the model with the Fama-French three factors plus the uncertainty index as the explanatory variables; (6). $O\_score_{i,t}$, the Ohlson(1980) O-score measures; (7). $g\_shares_{i,t}$, the growth of the split-adjusted shares outstanding of firm i in the last fiscal with respect of month t; (8). $\mathrm{NOA}_{i,t}$, firm i's net operating asset; (9). $gp_{i,t}$, firm i's gross profit of the last fiscal year; (10). $accruals_{i,t}$, firm i's total accruals; (11). $g\_asset_{i,t}$, firm i's asset growth measured as the growth rate of total assets in the previous fiscal year; (12). $\mathrm{ITA}_{i,t}$, firm i's investment-to-assets measured as the annual change in gross property, plant, and equipment plus the annual change in inventories scaled by the lagged book value of assets. (13). $\mathrm{ROA}_{i,t}$, firm i's return on asset of the last fiscal year with respect of month t. The sample spans from Jan. 1985 to Dec. 2024.

	N	Mean	Std	Min	P25	P50	P75	Max
$\mathrm{MV}_{i,t}$	1,140,673	7,114	36,769	0.29	329	1,047.65	3,689	3,385,742
$ret_{i,t}$	1,134,075	0.97	12.49	-98.13	-5.21	0.76	6.80	1,625.05
$\mathrm{SUE}_{i,t}$	937,538	-0.12	1.66	-7.53	-0.73	0.00	0.68	4.11
$ivol_{i,t}$	1,096,428	0.02	0.01	0.00	0.01	0.01	0.02	0.72
$\beta^U_{i,t}$	1,181,769	3.49	118.01	-4,230.17	-31.86	1.83	38.63	10,565.8
$O\_score_{i,t}$	715,063	-2,114	7,095	-224,526	-1,225	-341	-105	41
$g\_shares_{i,t}$	856,108	0.14	5.97	-1.69	0.00	0.01	0.05	1,591.90
$\mathrm{NOA}_{i,t}$	766,240	0.62	0.71	-9.06	0.39	0.63	0.79	166.12
$gp_{i,t}$	855,747	0.32	0.27	-6.28	0.13	0.28	0.46	3.68
$accruals_{i,t}$	688,780	0.06	0.14	-4.58	0.02	0.05	0.10	17.69
$g\_asset_{i,t}$	854,749	0.19	0.89	-1.04	0.01	0.09	0.21	229.53
$ITA_{i,t}$	750,819	0.09	0.48	-2.57	0.01	0.05	0.11	150.51
$ROA_{i,t}$	854,512	0.01	0.06	-4.04	0.00	0.01	0.02	10.58

Table H2: Herding and firm-level uncertainty: t-test

Panel A presents t-test results of equal means of the firm-level uncertainty variables for the herding and non-herding firms, classified by the regression (refequ1) using VIX as the macroeconomic uncertainty measure over each firm's corresponding whole sample period. Panel B shows t-test results of equal means of the firm-level uncertainty variables for the herding and the non-herding firms, classified over the past 24-month rolling window up to month t. Panel C presents the results of the paired dependent samples t-tests using the same herding classification as in Panel B. The time series means and t-statistics of the difference-in-means of the firm-level uncertainty variables for the herding and non-herding firms in each month t are reported. The uncertainty variables are: $mv_{i,t}$ is the natural log of market capital (in millions of dollars); $age_{i,t}$ is the number of years for the firm since the first month covered by CRSP; $vol_{i,t}$ is firm's daily return standard deviation over 12-month ending in month t; $bm_{i,t}$ is book value of firm's equity divided by its market value by the end of last fiscal year; $cvol_{i,t}$ is the 5-year (ending at the last fiscal year) standard deviation of the firm's cash flow scaled by average total assets; $cov_{i,t}$ is the number of analysts covering the firm at the last fiscal year end; $disp_{i,t}$ is the cross-sectional standard deviation of analyst forecasts scaled by the absolute value of the cross-sectional mean; $num_{i,t}$ is the number of earning estimations; $u_{i,t}^{com}$ is the composite firm-level uncertainty measure for firm i in month t. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

A: Whole sample by the firm									
	$mv_{i,t}$	$age_{i,t}$	$vol_{i,t}$	$bm_{i,t}$	$cvol_{i,t}$	$cov_{i,t}$	$disp_{i,t}$	$num_{i,t}$	$u_{i,t}^{com}$
Herd	6.12	14.70	0.03	0.58	0.16	6.56	0.32	5.59	0.62
N	1,697	1,697	1,697	807	619	1,623	1,697	1,697	1,697
Non-Herd	6.92	18.87	0.03	0.60	0.11	8.32	0.23	6.96	0.58
N	3,325	3,325	3,325	2,056	1,487	3,232	3,325	3,325	3,325
Diff	-0.81	-4.18	0.00	-0.02	0.05	-1.76	0.10	-1.37	0.05
t-stat	(-2.71)	(-1.99)	(1.62)	(-0.54)	(3.51)	(-1.77)	(1.65)	(-1.89)	(2.23)
B: Rolling window_independent									
Herd	7.09	19.09	0.03	0.53	0.09	11.11	0.22	9.14	0.49
Non-Herd	7.23	19.86	0.03	0.52	0.08	11.52	0.17	9.55	0.48
Diff	-0.14	-0.77	0.00	0.01	0.01	-0.41	0.05	-0.41	0.01
t-stat	(-2.84)	(-4.08)	(0.84)	(1.42)	(4.49)	(-4.64)	(4.13)	(-4.85)	(6.98)
C: Rolling window_dependent									
Diff	-0.14	-0.77	0.00	0.01	0.01	-0.41	0.05	-0.41	0.01
t-stat	(-3.21)	(-4.84)	(2.54)	(-2.14)	(3.67)	(-5.36)	(3.15)	(-5.56)	(4.80)
N	409	409	409	409	409	409	409	409	409

Table H3: Herding and momentum: portfolio analysis

The table reports the average returns and the Fama-Frech 3-factor model adjusted returns in month $t+1$ (in percentage) of portfolio M1 to M10 and the trading spread of longing M10 and shorting M1 for herding and non-herding firms classified using VIX as the macroeconomic uncertainty measure. In each month t, we sort stocks into deciles based on the accumulated returns from month $t-11$ to $t-1$, and form ten value-weighted portfolios M1 (the lowest accumulated returns) to M10 (the highest accumulated returns) for herding and non-herding firms, which are classified by the slope coefficient of the equation (refequ1) over the past 24-month rolling window: the ones with the negative (positive) coefficients are herding (non-herding) firms in Panel A; sorting the slope coefficients into deciles, the ones in the most negative (positive) coefficient decile are herding (non-herding) firms in Panel B. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

Panel A: Portfolio returns

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M10-M1
Herd	0.14	0.74	0.76	0.99	0.77	0.81	0.82	1.23	0.85	1.58	1.44
t-stat											(3.49)
Non-herd	0.59	0.80	0.87	0.94	0.81	0.95	1.00	0.93	0.91	1.50	0.91
t-stat											(1.71)
Diff.	-0.45	-0.06	-0.11	0.05	-0.04	-0.15	-0.18	0.30	-0.05	0.08	0.53
t-stat											(2.14)

Panel B:FF 3-factor adjusted portfolio returns

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M10-M1
Herd	-1.25	-0.45	-0.35	0.01	-0.18	-0.10	-0.05	0.35	-0.07	0.65	1.90
t-stat											(4.77)
Non-Herd	-0.94	-0.48	-0.32	-0.11	-0.19	0.04	0.10	-0.02	-0.05	0.48	1.42
t-stat											(1.68)
Diff.	-0.32	0.02	-0.03	0.12	0.00	-0.14	-0.15	0.37	-0.02	0.17	0.48
t-stat											(3.19)

Table H4: Herding and predictability: portfolio analysis

Panel A presents the means and t-statistics of the excess returns (in percentage) and the benchmark-adjusted returns of the long leg, the short leg and the long-short strategy spread (in percentage). In each month t, we identify the herding and non-herding firms using VIX as the macroeconomic uncertainty measure and calculate the equally weighted portfolio returns. The long-short trading strategy is to long the non-herding firm portfolio and short the herding firm portfolio. In column (1)-(3), herding (non-herding) firms are the ones with the negative (positive) slope coefficients of equation (refequ1) over the past 24-month rolling window. In column (4)-(6), the firms are grouped by sorting the slope coefficients into deciles. The herding (non-herding) firms are the ones with the lowest (highest) coefficients. The excess return is the portfolio return minus the one-month T-bill rate. The benchmark-adjusted returns are defined here as the portfolio returns net of what is attributable to exposures to 1). the market factor (CAPM); 2). the market, size and value factors (Fama-Frech 3-factor model); 3). the market, size, value, profitability and investment factors (Fama-French 5-factor model). Panel B shows the time-series averages of the slope coefficients obtained from regressing the long-short spread on the risk factors of the factor models. Newey-West adjusted t-statistics are reported in parentheses The sample spans from Jan. 1985 to Dec. 2024.

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-herd	Herd	Long - Short	Non-herd	Herd	Long - Short
Excess return	0.91	0.70	0.21	0.91	0.59	0.33
t-stat	(3.37)	(2.78)	(2.26)	(2.72)	(1.86)	(3.18)
CAPM adj return	0.03	-0.11	0.14	-0.86	-0.42	-0.44
t-stat	(0.26)	(-0.92)	(1.98)	(0.39)	(-2.76)	(2.66)
FF 3-factor adj return	-0.03	-0.12	0.08	-0.19	-0.44	0.25
t-stat	(-0.64)	(-2.11)	(1.65)	(-1.86)	(-4.76)	(2.42)
FF 5-factor adj return	-0.06	-0.15	0.10	-0.06	-0.34	0.28
t-stat	(-1.00)	(-2.70)	(1.83)	(-0.60)	(-3.78)	(2.70)

Table H5: Herding and firm-level uncertainty: t-test

Panel A presents t-test results of equal means of the firm-level uncertainty variables for the herding and non-herding firms, classified by the regression (refequ1) over each firm's corresponding whole sample period. Panel B shows t-test results of equal means of the firm-level uncertainty variables for the herding and the non-herding firms, classified over the past 24-month rolling window up to month t. Panel C presents the results of the paired dependent samples t-tests using the same herding classification as in Panel B. The time series means and t-statistics of the difference-in-means of the firm-level uncertainty variables for the herding and non-herding firms in each month t are reported. The uncertainty variables are: $mv_{i,t}$ is the natural log of market capital (in millions of dollars); $age_{i,t}$ is the number of years for the firm since the first month covered by CRSP; $vol_{i,t}$ is firm's daily return standard deviation over 12-month ending in month t; $bm_{i,t}$ is book value of firm's equity divided by its market value by the end of last fiscal year; $cvol_{i,t}$ is the 5-year (ending at the last fiscal year) standard deviation of the firm's cash flow scaled by average total assets; $cov_{i,t}$ is the number of analysts covering the firm at the last fiscal year end; $disp_{i,t}$ is the cross-sectional standard deviation of analyst forecasts scaled by the absolute value of the cross-sectional mean; $num_{i,t}$ is the number of earning estimations; $u^{com}_{i,t}$ is the composite firm-level uncertainty measure for firm i in month t. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

A: Whole sample by the firm	$mv_{i,t}$	$age_{i,t}$	$vol_{i,t}$	$bm_{i,t}$	$cvol_{i,t}$	$cov_{i,t}$	$disp_{i,t}$	$num_{i,t}$	$u^{com}_{i,t}$
Herd	5.37	12.62	0.04	0.67	0.16	5.69	0.48	4.69	0.56
N	6,134	6,134	6,134	2,739	2,123	5,785	6,134	6,134	6,134
Non-Herd	6.08	16.59	0.04	0.67	0.14	6.91	0.41	5.73	0.52
N	7,020	7,020	7,020	3,504	2,545	6,767	7,020	7,020	7,020
Diff	-0.71	-3.96	0.01	0.01	0.02	-1.22	0.07	-1.04	0.04
t-stat	(-3.42)	(-3.71)	(3.30)	(0.15)	(1.94)	(-2.48)	(1.45)	(-2.47)	(5.84)
B: Rolling window_independent									
Herd	6.93	18.81	0.03	0.54	0.09	11.34	0.22	9.30	0.51
Non-Herd	7.02	19.65	0.03	0.54	0.08	11.54	0.18	9.54	0.50
Diff	-0.09	-0.84	0.00	-0.01	0.01	-0.20	0.04	-0.24	0.01
t-stat	(-1.76)	(-3.59)	(1.29)	(-1.29)	(6.62)	(-2.27)	(3.26)	(-2.84)	(8.35)
C: Rolling window_dependent									
Diff	-0.09	-0.84	0.00	-0.01	0.01	-0.20	0.04	-0.24	0.01
t-stat	(-5.41)	(-7.51)	(4.70)	(-2.83)	(8.63)	(-3.61)	(2.92)	(-4.06)	(6.39)
N	469	469	469	469	469	469	469	469	469

Table H6: Herding and momentum: portfolio analysis

The table reports the average returns and the Fama-Frech 3-factor model adjusted returns in month $t+1$ (in percentage) of portfolio M1 to M10 and the trading spread of longing M10 and shorting M1 for herding and non-herding firms. In each month t, we sort stocks into deciles based on the accumulated returns from month $t-11$ to $t-1$, and form ten value-weighted portfolios M1 (the lowest accumulated returns) to M10 (the highest accumulated returns) for herding and non-herding firms, which are classified by the slope coefficient of the equation (refequ1) over the past 24-month rolling window: the ones with the negative (positive) coefficients are herding (non-herding) firms in Panel A; sorting the slope coefficients into deciles, the ones in the most negative (positive) coefficient decile are herding (non-herding) firms in Panel B. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2024.

Panel A: Portfolio returns

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M10-M1
Herd	-0.02	0.57	0.36	0.37	0.73	0.88	0.82	0.92	1.10	2.01	2.03
t-stat											(2.64)
Non-herd	0.34	0.35	0.74	0.68	0.95	0.78	1.22	0.67	1.14	1.40	1.06
t-stat											(2.43)
Diff.	-0.35	0.22	-0.38	-0.30	-0.21	0.11	-0.40	0.25	-0.04	0.61	0.97
t-stat											(2.42)

Panel B:FF 3-factor adjusted portfolio returns

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M10-M1
Herd	-1.41	-0.74	-0.81	-0.78	-0.38	-0.18	-0.18	-0.13	0.04	0.89	2.31
t-stat											(2.28)
Non-Herd	-1.18	-0.99	-0.64	-0.42	-0.18	-0.34	0.10	-0.40	0.07	0.26	1.44
t-stat											(1.32)
Diff.	-0.23	0.25	-0.16	-0.36	-0.21	0.17	-0.28	0.27	-0.03	0.64	0.86
t-stat											(2.14)

Table H7: Herding and predictability: portfolio analysis

Panel A presents the means and t-statistics of the excess returns (in percentage) and the benchmark-adjusted returns of the long leg, the short leg and the long-short strategy spread (in percentage). In each month t, we identify the herding and non-herding firms and calculate the equally weighted portfolio returns. The long-short trading strategy is to long the non-herding firm portfolio and short the herding firm portfolio. In column (1)-(3), herding (non-herding) firms are the ones with the negative (positive) slope coefficients of equation (refequ1) over the past 24-month rolling window. In column (4)-(6), the firms are grouped by sorting the slope coefficients into deciles. The herding (non-herding) firms are the ones with the lowest (highest) coefficients. The excess return is the portfolio return minus the one-month T-bill rate. The benchmark-adjusted returns are defined here as the portfolio returns net of what is attributable to exposures to 1). the market factor (CAPM); 2). the market, size and value factors (Fama-Frech 3-factor model); 3). the market, size, value, profitability and investment factors (Fama-French 5-factor model). Panel B shows the time-series averages of the slope coefficients obtained from regressing the long-short spread on the risk factors of the factor models. Newey-West adjusted t-statistics are reported in parentheses The sample spans from Jan. 1985 to Dec. 2024.

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-herd	Herd	Long - Short	Non-herd	Herd	Long - Short
Excess return	0.81	0.68	0.13	0.80	0.41	0.39
t-stat	(3.25)	(2.81)	(2.76)	(2.49)	(1.38)	(3.29)
CAPM adj return	-0.07	-0.11	0.04	-0.19	-0.52	0.33
t-stat	(0.94)	(-1.17)	(2.16)	(-1.23)	(-3.65)	(3.02)
FF 3-factor adj return	-0.02	-0.10	0.09	-0.17	-0.47	0.30
t-stat	(-0.35)	(-2.03)	(1.82)	(-1.76)	(-5.21)	(2.76)
FF 5-factor adj return	-0.04	-0.14	0.10	-0.09	-0.41	0.32
t-stat	(-0.85)	(-2.77)	(2.09)	(-0.90)	(-4.57)	(2.85)