# Hide in the herd: macroeconomic uncertainty and analyst forecasts dispersion*

Wen Chen[†1], Shen Zhao[‡2], and Guofu Zhou[§3]

[1]Texas Tech University
[2]The university of Macau
[3]Washington University in Saint Louis

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[†]Rawls College of Business, Texas Tech University, Lubbock TX, 79409 U.S.; e-mail: Wen.Chen@ttu.edu

[‡]Faculty of Finance and Business Economics, The University of Macau, Macau, China; email: shenzhao@um.edu.mo, Phone +853 8822 9094.

[§]Corresponding author: Guofu Zhou, Olin School of Business, Washington University in St. Louis, St. Louis, MO 63130, U.S. ; e-mail: zhou@wustl.edu; phone: 314-935-6384.

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## ABSTRACT

We uncover a negative correlation between macroeconomic uncertainty and analyst earning forecasts dispersion, and explain it via herding behavior. We find that the herding firms, whose analysts are subject to this behavior, have greater firm-level uncertainty than non-herding firms, and their stock prices are less informative about fundamentals. Moreover, the herding firms' stocks are also more likely to be overpriced and earn lower subsequent returns. Our study links the interaction between macro-uncertainty and micro-dispersion to the firms' characteristics, supporting the notion that greater uncertainty leaves more room for psychological biases that are associated with informational inefficiency.



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# I. Introduction

Macroeconomic uncertainty plays an important role in the economy. On the one hand, Ordonez (2011), Pastor and Veronesi (2012), and Bloom et al. (2016), among others, show that its shocks drive the aggregated economy to fluctuate over time. On the other hand, Diether et al. (2002), Christiano et al. (2014), and Kozeniauskas et al. (2019), for example, demonstrate that macroeconomic uncertainty affects each production unit in the economy and generates cross-section difference at the microeconomic level. However, little is known about how uncertainties at macro and micro levels relate to each other and what role they play in asset pricing.[1]

This paper studies the relationship between macroeconomic uncertainty and analyst earning forecasts dispersion and its implications for asset pricing. Security analysts are of our focus because they are important intermediaries of information that influence investors in making investment decisions, yet unlike investor expectations dispersion, analyst forecasts dispersion can be directly observed. Studying how analyst forecasts dispersions change with respect to the aggregate uncertainty can not only deepen our understanding about the relationship between macro and micro uncertainties but also help us to uncover hidden details about information transmission processes in the financial market.

The positive correlation between macroeconomic uncertainty and analyst forecasts dispersion is well documented in existing literature (e.g., Zarnowitz and Lambros (1987), Cujean and Hasler (2017), Kozeniauskas et al. (2019)). In this paper, however, we uncover a negative relationship between them. For certain type of firms, as macroeconomic uncertainty increases, security analysts tend to agree with each other more when they make forecasts of the firms' earnings. This novel finding can be analyzed through analysts' herding behavior. To facilitate the analysis, in this paper, we define this type of

[1]Our paper is also related to the linkage between Macroeconomics and Finance. There is a long list of studies on this front: Sharpe (1964), Merton (1973), Chen et al. (1986), Bernanke and Gertler (1989), Campbell and Hentschel (1992), Jagannathan and Wang (1996), Lettau and Ludvigson (2001), Jermann and Quadrini (2012), Shen et al. (2017), Watcher and Zhu (2022), to name but a few.

firms as herding firms whose analyst forecasts dispersions are negatively correlated with macroeconomic uncertainty.

Existing literature in economics and finance generally offers two primary explanations for why individuals engage in herding behavior.[2] One is information driven: individuals may take the same actions because they receive correlated information. For instance, the economy is booming and analysts may all revise their forecasts upward based on the promising information. The other is driven by agents' behavior: due to cognitive limits, the analysts may become conservative about incorporating their private information into their forecasts (e.g., Edwards, (1968), Keren (1997), Liberman and Tversky (1993)) ; or due to career or reputation concern, analysts strategically follow the herd (e.g., Scharfstein and Stein (1990), Trueman (1994), and Hong and Kubik (2003)). This strategic rationality can be traced back to Keynes (1936)' beauty contest argument: when analysts are concerned about how others assess their ability to make sound judgements, they devote their intelligences to anticipating the average opinion and follow it: " Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally."

The analyst herding behavior marked by the negative relationship between macroeconomic uncertainty and analyst forecasts dispersion is not likely to be driven by more correlated information as the overall information environment grows noisier with macroeconomic uncertainty (e.g., Kozeniauskas, Orlik and Veldkamp (2018), Zhang and Zhao (2023)). Instead, it should be mainly driven by analysts' cognitive limits or/and strategic rationality. To illustrate the mechanism and develop the related testable hypotheses, we choose strategic rationality as a motivation and build a model with the analyst's objective function inspired by Keynes' beauty contest argument (Keynes (1936)), in which analysts are concerned not only about forecast accuracy but also about the deviation of their forecasts from the average opinion (herding tendency). In equilibrium, this behavior causes

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

noisier information of fundamentals being conveyed to the financial market and thus results in informational inefficiency of the market. Based on the theoretical framework, we develop three testable Hypotheses and conduct related empirical tests.

We use the widely-cited daily U.S. Economic Policy Uncertainty (EPU) index constructed by Baker et al. (2016) as our macroeconomic uncertainty measure. We choose the EPU index for two reasons.[3] First, the news-based EPU index reflects a fairly complete assessment of investors' perceived macroeconomic uncertainty, which not only captures uncertainty in capital market but also uncertainty in the decision making process of the agents in the real economy (e.g., Nagar et al. (2019), Kaviani et al. (2020), and Zhang and Zhou (2023)). Second, the index has daily frequency that serves well for our purpose of measuring macroeconomic uncertainty between two adjacent reporting dates of analyst recommendations available from the Institutional Brokers' Estimate System (IBES), which is the database we use to calculate the analyst forecasts dispersion.

Empirically, we find that, both over time and in the cross-section, there exist frequently negative comovements between analyst forecasts dispersion and macroeconomic uncertainty. According to the theoretical framework, comparing with the positive relationship, the negative relationship between macro uncertainty and analyst forecasts dispersion indicates analysts' higher tendency to herd, which is associated with higher firm-level uncertainty. The intuition is that as macro uncertainty increases, forecast accuracy decreases across all the analysts who therefore have higher tendency to imitate others so that the whole group can share the ultimate blame on less accurate forecasts. This herding behavior is more severe for the firms with higher firm-level uncertainty as it is harder to forecast these firms' future earnings accurately. We hence intuitively develop the following hypothesis:

**Hypothesis I**: Herding firms, with analyst forecast dispersion negatively comoving with macroeconomic uncertainty, exhibit higher firm-level uncertainty than non-herding

[3]Our empirical results are robust for other well-known macro uncertainty measures, e.g., VIX. The main test results using VIX are reported in Table G2-G4 of Appendix.

firms, whose dispersion positively correlates with macroeconomic uncertainty.

Empirically, we conduct difference-in-mean tests and probit regressions to test the hypothesis based on eight proxies for firm-level information uncertainty, six of which are from Zhang (2006a) (which are firm size, age, analyst coverage, analyst dispersion, return volatility and cash flow volatility), plus the number of analyst forecasts, and a composite uncertainty measure based on the seven individual measures. The results strongly support *Hypothesis I*: the average firm-level uncertainty measures are significantly greater for the herding firms than for the non-herding firms. Moreover, all the firm-level uncertainty measures significantly predict the probability of being a herding firm. In short, the empirical evidence shows convincingly that the herding firms are the ones with greater firm-level uncertainty and their values are harder to estimate.

Furthermore, we develop a simple model to explain the above hypothesis as well as the two following hypotheses. The model identifies the theoretical conditions under which these hypotheses hold and demonstrates that herding behavior makes the consensus forecast a noisier signal of the firm's fundamental value, leading to informational inefficiency in the stock market. This analysis provides deeper economic insights into the issue. In reality, even though investors' information sets contain not only analysts' forecasts but also other sources of information, nosiness of various information sources is positively related: more severe herding behavior of the firm's analysts indicates a noisier information environment for the firm. Since herding firms' analysts have stronger tendency to herd and these firms also have noisier information environments, we expect that herding firms' stock prices exhibit more severe informational inefficiency. Therefore, we have following two related hypotheses.

**Hypothesis II**: Comparing with the non-herding firms, the herding firms' stock prices are less informative about the firms' fundamental values.

To test the hypothesis, we consider first the momentum anomaly, which is one of the most important anomalies. Chan et al. (1996), Barberis et al. (1998) and Zhang (2006),

among others, argue that price momentum effect is due to slow information diffusion. Our theoretical framework also shows that the stronger herding effect is associated with higher possibility of the positive return correlation over time. If the hypothesis is correct, we expect to see stronger momentum pattern for the herding firms. Sorting the stocks into deciles based on the past 11-month accumulated returns, we construct the standard momentum strategy by going long the past winners (the highest decile) and short the losers (the lowest decile). While the long-short portfolio earns a modest 0.12% per month for non-herding firms, its performance is significant larger at 1.84% per month for herding firms. Moreover, the Fama and Mac Beth (1973) (Fama-MacBeth) regression analysis shows that the herding firms have stronger momentum patterns after controlling for various firm-level uncertainty variables, indicating that the herding effect further amplifies the return momentum in addition to the impact of firm-level uncertainty documented in existing literature. The result is consistent with the argument that stock return momentum is due to informational inefficiency. Since the herding firms' stock prices suffer more severe informational inefficiency (Barberis et al. (1998); Jegadeesh and Titman (1993); Hong et al. (2000)), the stock returns show more significant momentum patterns, supporting *Hypothesis II*.

In addition to examin stock prices' responses to the broad set of information in the momentum test, we also examine how herding firms' stock prices respond to specific information release: firms' earning announcements.

We compare the post-earnings-announcement drift (PEAD) between 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 construct the PEAD strategy by going long the good-news firms (the highest decile) and short the bad-news firms (the lowest decile). While the long-short portfolio earns 0.10% per month for the non-herding firms, its performance within the herding firms is 0.49% per month, indicating that the herding firms' stock prices are less responsive to the newly announced earnings, consistent with our theo-

retical reasoning that stronger tendency to herd is associated with the noisier signal of fundamentals, which leads to higher variation of the post-earning-announcement return.

These evidences of stock price contiguity all suggest that the stock prices of herding firms are less reflective of firm-value related information, further supporting *Hypothesis II*.

Moreover, the theoretical framework illustrates that with the short-sale constraint, analyst herding behavior amplifies overpricing and leads to a lower subsequent return. 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-sell constraint.[4] The last hypothesis follows:

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

To test it, we addopt two approaches. First, we construct a long-short portfolio with the short leg being the herding firms classified in month $t$. The average value-weighted monthly benchmark-adjusted return on the long-short strategy in month $t+1$ is 0.42% per month (t-sta=3.34). Second, we conduct a Fama-MacBeth regression, using the herding dummy as a predictor on the one-month ahead stock return after controlling a number of well documented predictors. We find that the herding dummy variable can still predict the future return with a significant and negative slope coefficient. The result suggests that the informational inefficiency associated with the herding behavior has a significant impact on asset pricing beyond the inefficiencies documented in the existing literature. This leaves room for us to explore the relationship of the herding effect with various anormalies in the future studies.

Our paper makes several contributions. First, it deepens our understanding of relationship between macro and micro uncertainties. The positive correlation between pairs of

[4]There are also other alternatives to explain overpricing for herding firms: more dispersed opinions among investors along with the short-sell constraint (e.g. Miller (1977), Diether et al. (2002)); or higher unpriced information risk (e.g., Johnson (2004)).

various types of uncertainties is well documented in literature (e.g., Diether et al.(2002), Christiano et al. (2014), and Kozeniauskas et al. (2019). It is mainly driven by the positive comovements of outputs at macro and micro levels of the economy. The negative relationship between macro and micro uncertainties, to our knowledge, is first studied by us. We show that the negative relationship between macroeconomic uncertainty and analyst forecasts dispersion is driven by analyst strategic rationality, which is related to information environment of the financial market. This linkage allows us to further contribute to the literature studying the impact of uncertainty and asset prices (e.g., Bansal and Shaliastovich (2010) and Pastor and Veronesi (2012)).

Second, the existing herding literature faces the challenge of differentiating the case that analysts make similar forecasts by receiving the correlated information from the one they herd due to cognitive limits or strategic rationalities (e.g., Devenow and Welch(1996), Bikhchandani and Sharma (2001), and Hirshleifer and Teoh (2003)). By examining the negative relationship between analyst forecasts dispersion and macroeconomic uncertainty, we can exlclude the information-driven channel because information tends to be noisier and less correlated as macro uncertainty increases.

Third, our paper provides a novel link between analysts herding and firm's valuation. When there is greater uncertainty regarding the firm's value, the analysts who cover the firm are more likely to herd. While the previous literature focuses on what kind of analysts tend to herd (e.g. Zwiebel (1995), Graham (1999), and Hong et al. (2000)), we focus on what kind of firms whose analysts tend to herd. It allows us to link the herding behavior with the firm's stock performance in the market.

Finally, this paper joins the effort of establishing the linkage between behavioral bias and uncertainty. When macroeconomic uncertainty is high, analysts tend to have less dispersed opinions due to their strategic rationing to avoid being blamed alone. We show that the high uncertainty firms' analysts are more likely to be subject to this herding behavior, consistent with Hirshleifer (2001)'s assertion that greater uncertainty leaves more

room for psychological biases.[5] Moreover, we show that the interaction of the behaviorial bias and uncertainty further hinders information transmission and causes market inefficiency.

The rest of the paper is organized as follows. Section 2 layouts 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 build a model and use it to further understand the hypothesis. In our model, we assume that analysts collect public and private information about the firm's future earning and make forecasts, which are aggregated by investors and trade upon.

## A. Setup

We consider an economy with one firm. Each share of the firm's stock liquidation value is $V + v$, where $V$ is the output/earning revealed by the firm's earning announcement and $v$ is the part of the value not revealed by the earning announcement.[6] We assume that $V$ and $v$ are independent normally distributed random variables

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

where the variance of $V$ has two components: $\sigma_m^2$ and $\sigma^2$, the macro and firm level uncertainties respectively,

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

[5]Other studies that investigate relations among uncertainty, behavioral biases and asset mispricing include Heath and Tversky (1991), Hirshleifer et al. (1994), Fox and Tversky (1995), Zhang (2006a), Epstein and Schneider (2008), Caskey (2009), and Lin (2018), to name but a few.

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

To study macro uncertainty and firm-level uncertainty separately in the paper, we decompose variance of $V$ into $\sigma_m^2$ and $\sigma^2$.[7] Moreover, simplifying the economy with one firm allows us to focus on the information inefficiency channel to explain the herding effect without involving in portfolio management problem.[8]

The economy features two assets: a risk-free bond and the stock of a firm. The bond has a zero net return and serves as the numéraire. There are two trading dates: $t = 1, 2$. Before trading begins at $t = 0$, each analyst reports his or her earning forecast. Investors aggregate these forecasts and commence trading at $t = 1, 2$. At $t = 2$ the firm's earning $V$ is revealed. Finally, at $t = 3$, each share of stock 's liquidation value $V + v$ is realized. The details of the timeline is summarized in Figure 1.

Figure 1 here

### A..1 Analysts

Before investors trade, analysts report forecasts about the firm's earning $V$ at t=0. There is a continuum of analysts, indexed by the unit interval $[0, 1]$. Analysts can't directly observe $V$, but they have access to a common signal,

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

where $\eta$ is normally distributed, independent of $V$,

$$\eta \sim \mathcal{N}(0, \tau_\eta^{-1}). \tag{4}$$

[7]The difference between $\sigma_m^2$ and $\sigma^2$ 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 $\epsilon_j^s$ is the systematic volatility and $\epsilon_j^{us}$ 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 aggregated or macroeconomic uncertainty while $\sigma_j$ measures firm j's idiosyncratic uncertainty (the subscript $j$ is dropped for the economy with one firm).

[8]Our empirical evidence shows that the herding effect on stocks' prices cannot be explained by their different exposures to the systematic risk factors. Including multiple firms in the economy cannot bring additional insights to explain our empirical findings.

In addition to the common signal, analyst $i$ observes a private information $s_i$, which is noise signal about $V$,

$$s_i = V + \varepsilon_i, \tag{5}$$

where $\varepsilon_i$ is normally distributed, independent of $V$ and $\eta$,

$$\varepsilon_i \sim \mathcal{N}(0, \tau_\varepsilon^{-1}). \tag{6}$$

Thus, analyst $i$'s information set is $\{c, s_i\}$, and his expectation and variance are denoted by

$$\mathrm{E}^i[.] = \mathrm{E}[.|c, s_i], \quad \mathrm{Var}^i(.) = \mathrm{Var}(.|c, s_i). \tag{7}$$

We assume all the analysts report their forecast about $V$ simultaneously at $t = 0$. Let $f_i$ denote analyst $i$'s forecast. In this model, analyst $i$ choose a forecast $f_i$, which maximizes his or her utility function,

$$u_i(f_i) = -(1-\delta)\mathrm{E}^i[(f_i - V)^2] - \delta \mathrm{E}^i[(f_i - \bar{f})^2], \tag{8}$$

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

$$\bar{f} = \int_0^1 f_i di. \tag{9}$$

In addition to accuracy of the forecast (the first term), the analyst is also concerned about the deviation of his or her opinion from the average one (the second term). The model is in the spirit of Keynes (1936)'s beauty contest theory, which suggests that professionals will "follow the herd" if they are concerned about how others will assess their ability to make sound judgments. The parameter $\delta \in [0, 1]$ captures severity of beauty contest effect, or herding effect.

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

$$\mathrm{E}^i[V] = \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon s_i}{\tau_V + \tau_\eta + \tau_\varepsilon}, \tag{10}$$

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 in the objective function, 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 (10). This forecast is formalized in the following lemma.

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

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

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

$$\bar{f} = \frac{\tau_V \bar{V} + \tau_\eta c + (1-\delta)\tau_\varepsilon V}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}. \tag{12}$$

*Proof.* See Appendix A □

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

$$\bar{f} = \omega \bar{V} + (1-\omega) s_f, \tag{13}$$

where

$$\omega = \frac{\tau_V}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}, \quad s_f = V + \frac{\tau_\eta}{\tau_\eta + (1-\delta)\tau_\varepsilon}\eta \sim \mathcal{N}(\bar{V}, \tau_V^{-1} + \tau_f^{-1}), \tag{14}$$

and

$$\tau_f = \frac{(\tau_\eta + (1-\delta)\tau_\varepsilon)^2}{\tau_\eta}. \tag{15}$$

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., $\delta$ increases, less information about $V$ is revealed to the financial market by the forecasts,

$$\frac{d\mathrm{Var}(V \mid \bar{f})}{d\delta} > 0, \tag{16}$$

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

The dispersion of analysts' forecast $D$ is defined as

$$D = \int_0^1 (f_i - \bar{f})^2 di = \frac{(1-\delta)^2 \tau_\varepsilon}{(\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon)^2}. \tag{17}$$

Macro uncertainty ($\sigma_m^2$) can influence the dispersion in two ways: it can either directly impact $D$ via $\tau_V$ ($\tau_V^{-1} = \sigma_m^2 + \sigma^2$) or indirectly via its effect on $\delta$. In the model, analyst tendency to herd is determined by $\delta$, and $\delta$ is assumed to be an increasing function of the variance of $V$, $\tau_V^{-1}$. As macro uncertainty increases, so does the variance of $V$ and the difficulty of accurately forecasting $V$ increases for each analyst and thus they exhibit stronger tendency to imitate each other since any ultimate blame for poor forecasting would be shared by the group of analysts as a whole: $\frac{\partial \delta}{\partial \tau_V}\frac{\partial \tau_V}{\partial \sigma_m^2} > 0$. It is also consistent with Hirshleifer (2001) that greater uncertainty and a delayed feedback about the underlying fundamentals leave more room for psychological biases. Let's see how does the change of macro uncertainty $\sigma_m^2$ affect analysts' forecast dispersion, .

$$\frac{\partial D}{\partial \sigma_m^2} = \frac{\partial D}{\partial \tau_V}\frac{\partial \tau_V}{\partial \sigma_m^2} = \frac{2(1-\delta)\tau_\varepsilon \tau_V^2}{(\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon)^3}\left[\frac{d\delta}{d\tau_V}(\tau_V + \tau_\eta) + (1-\delta)\right]. \tag{18}$$

Obviously, if there is no herding effect, i.e., $\delta = 0$, analyst forecasts dispersion increases with macro uncertainty, $\frac{\partial D}{\partial \sigma_m^2} > 0$. This positive correlation between macro and micro uncertainties is well documented in existing literature. The negative correlation, however, is uncovered by this paper and we show in the model that it is associated with stronger analyst tendency to herd ($\delta > 0$), which is an increasing function of uncertainty. In this paper, we focus on discussing the necessary and sufficient conditions for the negative correlation. We deduce the first proposition:

**Proposition 1.** *Under the assumption that $\delta$ is a decreasing convex function of $\tau_V$*

$$\frac{d\delta}{d\tau_V} < 0, \quad \frac{d^2\delta}{d\tau_V^2} > 0,$$

*there exists a cutting-off value $\sigma_c$ for firm-level uncertainty $\sigma$ such that given all else equal,*

$$\sigma^2 > (<)\sigma_c^2 \iff \frac{\partial D}{\partial \sigma_m^2} < (>)0. \tag{19}$$

*Proof.* See Appendix B. □

Since $\frac{d\delta}{d\tau_V} < 0$, it follows that

**Corollary 1.1.** *There exists a cutting-off value $\delta_c = \delta(\tau_V^c)$. Given all else equal,*

$$\delta > (<)\delta_c \iff \frac{\partial D}{\partial \sigma_m^2} < (>)0. \tag{20}$$

The negative correlation between analyst forecasts dispersion and macro uncertainty ($\frac{\partial D}{\partial \sigma_m^2} < 0$) is associated with higher firm-level uncertainty ($\sigma$) and analysts' stronger tendency of engaging in herding behavior ($\delta$).

### A..2 Investors

We assume the financial market opens at $t = 1, 2$ for investors to trade the firm's stock as Figure 1 shows. At $t = 3$, the liquidation value of stock $V + v$ is realized, where $V \sim \mathcal{N}(\bar{V}, \tau_V^{-1})$ is the firm's earning and $v \sim \mathcal{N}(0, \tau_v^{-1})$ is the residual uncertainty, which is not resolved by earning announcement. Assume there are $\Theta$ shares of stock outstanding. At time 1 and 2, an unit mass of rational investors enter the market and load a position $x_t$ in the risky asset, i.e., the stock of firm. The unit mass of investors has CARA preferences (denote by $\lambda$ the coefficient of common risk aversion) and chooses the optimal position $x_t$ to maximize their expected utility over their final profit

$$\max_{x_t} \mathrm{E}_t[-e^{-\lambda W_3}], \tag{21}$$

where $W_3$ is investor's wealth at $t = 3$:

$$W_3 = (P_2 - P_1)x_1 + (P_3 - P_2)x_2. \tag{22}$$

$P_t$ is the equilibrium price of the stock at time $t$. $\mathrm{E}_t[.] = \mathrm{E}[.|\mathcal{F}_t]$ and $\mathrm{Var}_t(.) = \mathrm{Var}(.|\mathcal{F}_t)$ denote investors' conditional expectation and variance at time $t$ respectively, and investors' information set at $t$ is denoted by $\mathcal{F}_t$:

$$\mathcal{F}_1 = \{\{f_i\}, P_1\}, \quad \mathcal{F}_2 = \{\{f_i\}, V, P_1, P_2\}, \quad \mathcal{F}_3 = \{\{f_i\}, V, v, P_1, P_2, P_3\}. \tag{23}$$

At $t = 0$, analysts issue their earning forecasts to the market. At $t = 1$, although investors can't observe analysts' common or private information, they observe each analyst's forecast $\{f_i\}$. As investors start to trade at $t = 1$, they aggregate all the forecast $\{f_i\}$ to the equivalent signal $\bar{f}$, i.e., $s_f$. As shown in equation (15), if the firm's analysts have stronger tendency of engaging in herding behavior, i.e., larger $\delta$, their forecasts contain less information about $V$, i.e., smaller $\tau_f$.

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:

$$\theta_1 = z_1, \quad \theta_2 = \beta\theta_1 + z_2, \tag{24}$$

where $0 \leq \beta \leq 1$, 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

$$x_t + \theta_t = \Theta. \tag{25}$$

Since there is no information asymmetry among the investors, the price $P_t$ reveals $\theta_t$ to the investors.

To obtain the equilibrium prices for each period, we solve the model by backward induction in Appendix C:

$$P_2 = V + \lambda\tau_v^{-1}\left(\beta z_1 + z_2\right) - \lambda\tau_v^{-1}\Theta, \tag{26}$$

and

$$P_1 = \frac{\tau_V\bar{V} + \tau_f s_f}{\tau_V + \tau_f} + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v}(1 - \beta)\right)\right] z_1 - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta. \tag{27}$$

Obviously, the stronger the herding effect, the noisier the forecast and the less informative of $P_1$ with respective of $V$. It follows:

**Proposition 2.** *Given all else equal, higher $\delta$, analysts' stronger tendency of engaging in herding behavior, causes the stock price less informative about the fundamentals:*

$$\frac{d\mathrm{Var}(V \mid P_1)}{d\delta} > 0. \tag{28}$$

*Proof.* See Appendix C □

***Price Continuity***

Since the herding effect is associated with informational inefficiency of the stock price. We conjecture that analysts' stronger tendency to herd may cause stronger price continuity: return momentum and post-earning-announcement-drift (PEAD). It can be verified via Proposition 3 and Proposition 4.

**Proposition 3.** *The return momentum, i.e., a positive return autocorrelation,*

$$\mathrm{Cov}\left(P_3 - P_2, P_2 - P_1\right) > 0, \tag{29}$$

*occurs if and only if* $\mathrm{Var}(v) < \mathrm{Var}(V \mid \bar{f})$ *and* $\beta_c < \beta \leq 1$.

$$\frac{d\mathrm{Var}(V \mid \bar{f})}{d\delta} > 0, \quad \frac{d\beta_c}{d\delta} < 0, \tag{30}$$

*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 Appendix D. □

We define earning surprise as $\mathrm{ES} := V - \bar{f}$ and post-earning return as $\mathrm{PR} := V + v - P_2$. In the base model of financial market, there is no post earning announcement drift, $\mathrm{Cov}(\mathrm{ES}, \mathrm{PR}) = 0$, because at t=2 when $V$ is announced, it is completely reflected in $P_2$. The herding effect is confined to $P_1$. In reality, however, informational inefficiency is persistent over time. It is reasonable to believe that investors detect noisier information environment from analysts' herding behavior and cast doubt on the quality of earning announcement. As a result, certain portion of investors don't update their beliefs based on newly released information. Following the existing literature (Hirshleifer et al., 2009; Hung et al., 2015), we call them inattentive investors and denote the portion of this group

of investors as $\alpha$, which is positively correlated with analysts' tendency to herd, $\delta$. At $t = 2$, inattentive investors' demand is denoted by $x_2^{in}$,

$$x_2^{in} = \frac{\mathrm{E}_1[V + v] - P_2}{\lambda \mathrm{Var}_1(V + v)}, \tag{31}$$

indicating that these investors are still using time-1 information when submitting time-2 demand. Hence, in equilibrium, the market clearing condition

$$(1 - \alpha)x_2 + \alpha x_2^{in} + \theta_2 = \Theta \tag{32}$$

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,*

$$\mathrm{Cov}(\mathrm{ES}, \mathrm{PR}) = \frac{\alpha}{\tau_V + \tau_f + \tau_v} > 0, \tag{33}$$

*and the covariance increases with the herding tendency,*

$$\frac{d\mathrm{Cov}(\mathrm{ES}, \mathrm{PR})}{d\delta} > 0. \tag{34}$$

*Proof.* See Appendix E. □

This is because a higher $\delta$ leads to a larger variance of earning surprise, which results in a larger covariance between ES and PR. Moreover, high $\alpha$ can be directly associated with high $\delta$. Therefore, analysts' tendency to herd amplifies the variation of post-earning return or PEAD.

***Overpricing***

Existing literature argue that informational inefficiency is associated with stock mispricing and return predictability. We show that with the short-sale constraint, the herding effect amplifies stock overpricing and predicts the lower subsequent return.

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:

$$\Delta = \mathrm{E}[P_1^{ss}] - \mathrm{E}[P_1], \tag{35}$$

where the superscript $.^{ss}$ denotes the short-sale constraint. In Appendix F, we demonstrate that the expected price with a short-sale constraint is higher than without it, 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, the forecasts of herding firms are followed by lower subsequent returns compared to those of non-herding firms.

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

$$\frac{\partial \Delta}{\partial \delta} > 0. \tag{36}$$

*Proof.* See Appendix F. □

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

$$\frac{\partial \mathrm{E}[R^{ss}]}{\partial \delta} < 0. \tag{37}$$

*Proof.* See Appendix F. □

### A..3 Discussion

The theoretical framework demonstrates that the negative relationship between macroeconomic uncertainty and analysts' forecast dispersion reflects stronger herding tendencies, leading to greater informational inefficiency in financial markets. To focus on this, the

model simplifies several aspects: analysts are assumed to have identical forecasting capabilities, allowing us to study herding from the firm's perspective rather than individual analysts; investors are assumed to have homogeneous beliefs to isolate the impact of analyst herding on overpricing under short-sell constraints; and investors' information is limited to analysts' forecasts and historical stock prices, emphasizing the role of herding in creating noisier information environments. While not the sole explanation for the empirical findings, this framework provides a significant and supported channel to link analyst herding behavior to market inefficiency.

## B. Hypotheses development

In this section, we will develop testable hypotheses based on the theoretical framework to guide the following empirical tests. According to Proposition 1, comparing with the positive relationship, the negative relationship between macro uncertainty and analyst forecasts dispersion indicates higher firm-level uncertainty. Empirically, we can identify the relationship by regressing analyst forecasts dispersion for individual firm on macro uncertainty over certain period of time and compare the slope coefficients across different firms. The testable hypothesis is:

**Hypothesis I**: Herding firms, with analyst forecast dispersion negatively comoving with macroeconomic uncertainty, exhibit higher firm-level uncertainty than non-herding firms, whose dispersion positively correlates with macroeconomic uncertainty.

To empirically test Hypothesis I, we compare various firm-level uncertainty proxies between herding and non-herding firms. The statistically significant higher firm-level uncertainty of herding firms than the one of non-herding firms support the hypothesis.

Based on Corollary 1.1, the negative relationship between macro uncertainty and analyst forecasts dispersion is associated with analysts' stronger tendency of herding, which is shown by Proposition 2 to cause informational inefficiency in the stock market. The related hypothesis follows:

**Hypothesis II**: Comparing with the non-herding firms, the herding firms' stock prices are less informative about the firms' fundamental values.

Empirically, we test stock price informativeness through stock price continuation, i.e., return momentum and post-earning-announcement drift. If stock prices are less informative about the fundamentals, in the process of converging to its intrinsic value, the stock exhibits stronger return momentum and post-earning-announcement drift. Proposition 3 and Proposition 4 link analyst tendency to herd with the stock price continuation. To empirically support Hypothesis II, we form the momentum trading strategy and PEAD trading strategy to compare the trading profits between herding and non-herding firms. Higher trading profits for herding firms than the ones for non-herding firms support the hypothesis.

In addition, Propsition 5 and Corollary 5.1 indicate that with the short-sale constraint, analyst herding behavior amplifies overpricing and leads to a lower subsequent return. The last hypothesis follows:

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

The main test for this hypothesis is regressing the one-month ahead stock return on the herding firm's dummy variable in the current month and the statistically significant and negative slope coefficient supports the hypothesis.

# 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 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 computed as the cross-sectional standard deviation of analyst fore-

casts on 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;[9] $cov_{i,t}$, 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. [10]

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 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;

[9]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 low numbers calculated using balance sheet and cash flow statement is as high as 0.93.

[10]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 the higher the percentile rank the higher the firm-level uncertainty.

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 2021 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 (2006a), 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 macro uncertainty, analyst forecasts dispersion and other firm-level uncertainty variables, which can outline the main characteristics of the firms studied in our sample.[11] In order to compare $U_t^m$, the macroeconomic uncertainty, and the analysts' forecast dispersion, $disp_{i,t}$, at the similar scale, we divide

[11]The descriptive statistics of other variables used in the paper are reported in Table G1 of Appendix.

the original EPU index by 100. The mean of $disp_{i,t}$ is 0.17 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 1.28 to 14.74 corresponding to \$359,562 to \$2,525 billion. The firm age is from 1.9 to 96 years. The analysts coverage ranges from 2 to 62.

# IV. Empirical Results

## A. Herding and Uncertainty: *Hypothesis I*

To empirically test the hypotheses, 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:

$$disp_{i,t} = a + b * U_t^m + \epsilon_{i,t}, \tag{38}$$

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 $t$.[12] Panel A of Table 2 presents the result of the pooled regression over the whole sample period from January 1985 to December 2021. The coefficient $b$ is significantly positive, indicating that overall, the analysts' forecast dispersion increases with the macroeconomic uncertainty, consistent with the existing literature.

To zoom in the relation between the macroeconomic uncertainty and the analyst forecasts dispersion for each firm, we run the regression (38) firm by firm over each firm's whole sample period.[13] The means of the coefficient $b$ and its t-value cross all the firms

[12]Equation (38) is meant to identify the comovement (or correlation) between macroeconomic uncertainty and analyst forecasts dispersion. Other variables, which may affect the comovement, are omitted at this stage and will be studied later in the paper. At the first stage, we identify the different correlations; At the second stage, we show that the other factors e.g. size, age, analyst coverage etc., are related to the correlations and the relationship is consistent with the *Hypothesis I*.

[13]To ensure the regression with sufficient statistical power, we drop the firms, whose sample size is smaller than 10.

in our sample are reported in Panel B. Among the total 9,438 firms, 5,169 firms have positive coefficients $b$s, while 4,269 firms are with negative ones. If we focus on the observations with the statistically significant $b$s ($t \geq 1.65$) , 1,304 out of 3,832 firms are with the negative coefficients.

In addition, we also run the regression (38) for each firm $i$ in month $t$ over the firm's 24-month rolling window period from month $t-23$ to $t$ with the minimum number of observations of 10. The results are also shown in Panel B. Among the 897,536 firm-month observations, 431,580 are with the positive coefficients $b$s while 465,956 are with the negative coefficients. For the observations with the statistically significant $b$s, 111,336 out of 253,613 firm-month observations have the negative coefficients. The evidence shows that the negative correlation between the macroeconomic uncertainty and the analyst forecasts dispersion is not rare, but quite common over time and cross firms.

Table 2 here

We then create a dummy variable $herd_{i,t}$, which equals one if the coefficient $b$ is negative for firm $i$ in month $t$ over the corresponding sample period, zero otherwise, and define firm $i$ as a herding firm in month $t$ if $herd_{i,t}$ equals one. Figure 1 presents time series plots of $U_t^m$, the macroeconomic uncertainty, and $Disp_{herd,t}$ ($Disp_{non,t}$), the monthly aggregated analyst forecasts dispersion for herding (non-herding) firms classified by $herd_{i,t}$ estimated over firm $i$'s past 24-month rolling window ending in month $t$.

Figure 1 here

From the graph, one can clearly see the negative comovement between the macroeconomic uncertainty and the security analyst forecasts dispersion of the herding firms. While $U_t^m$ and $Disp_{non,t}$ are both counter-cyclical, $Disp_{herd,t}$ is strikingly pro-cyclical.[14]

[14]It also raises the warming flag for using the aggregated analyst forecasts dispersion as a proxy for macroeconomic uncertainty. A better measure should exclude the herding firms' analyst forecasts dispersions as they negatively comove with the macroeconomic uncertainty.

Next, to test the *Hypothesis I* that the firm-level uncertainty is higher for the herding firms than the non-herding firms, we first conduct t-tests comparing the means of the firm-level uncertainty variables between the herding and non-herding firms.[15] Panel A of Table 3 presents the results of the independent samples t-tests, where the samples are classified by the dummy variable $herd_{i,t}$ whose value is determined by running the regression (38) over each firm's whole sample period (month $t$ is the end of each firm's corresponding sample period). As one can see, the difference in means is statistically significant between the herding and non-herding firms for seven out of eight individual firm-level uncertainty variables with the composite measure $u_{i,t}^{com}$ highly significant with t-value of 3.77. The result indicates that the herding firms are smaller and younger; their stock return and cash flow are more volatile; they have less analyst's coverage and estimations, their analysts' opinions are more dispersed. The evidence is largely consistent with the hypothesis that the herding firms are the ones with higher firm-level uncertainty and their values are harder to estimate.

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 (38) over firm $i$'s past 24-month 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

[15]For the following empirical analysis, we present the results for the observations with statistically significant coefficient $b$ (with $t \geq 1.65$). The results are robust for all the observations, which are presented in Table G5-12 of Appendix.

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 the herding firms than the non-herding firms across all the tests, two individual uncertainty measures deserve further discussion. The analyst forecasts dispersion is not only determined by the firm's uncertainty but also by the analyst behavior. High firm-level uncertainty may increase analyst forecasts dispersion while analyst herding behavior may reduce it. The joint forces make the analyst forecasts dispersion a weak measure for firm-level uncertainty; The stock return volatility is also influenced by mixed forces. The lower return volatility of the herding firms could be due to the fact that the firm's stock price underreacts to the news because of high uncertainty and thus reduces the magnitude of the stock price fluctuation over time. This mechanism coexists with the one of high return volatility associated with high uncertainty about the firm. It can explain the mixed results of the two individual measures.

To further test the hypothesis, we run the probit regressm-level uncertainty variables on a binary response variable, $herd_{i,t}$, which equals one if the coefficient $b$ in the equation (38) is negative for firm $i$ in month $t$ over the corresponding samples, zero otherwise.

$$herd_{i,t} = c + d * u_{i,t} + \sigma_{i,t}, \tag{39}$$

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 using $herd_{i,t}$ determined over the 24-month rolling window sample. 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 whole can significantly explain the probability of being a herding firm.

Table 4 here

In sum, analysts have the stronger tendency to herd when the forecasted firms are the ones with more opaque information environment and there is greater uncertainty associated with the firms' values. The evidence presented in this subsection strongly supports *Hypothesis I*: the herding firms are the ones with higher firm-level uncertainty.

## B. Herding and Information Transmission: *Hypothesis II*

The security analysts, who collect, analyze and convey value related information to investors, are part of the information transmission process in the financial market. If the analysts suffer from behaviorial biases, the information transmission process in the market becomes less efficient and the stock price is more likely to deviate from the fundamental value of the firm. *Hypothesis II* states that stock prices of the herding firms are less informative.

We test the hypothesis by checking the stock price continuity. First, we compare the momentum effect between the herding and non-herding firms. In each month $t$, we sort stocks into deciles based on the accumulated return from month $t-11$ to $t-1$ and form ten equally weighted portfolios. Panel A of Table 5 shows portfolio M1 to M10 returns for both herding and non-herding firms. In addition, we also independently sort stocks into deciles based on the slope coefficient of equation (38) in month t and classify the herding (non-herding) firms as the ones in the lowest (highest) decile to compare the momentum effects. In both cases, we not only see the generally increasing pattern of the returns from M1 to M10 for both herding and non-herding groups, verifying the existence of the momentum effect in our sample, but also observe that the trading strategy of longing M10 (the past winners) and shorting M1 (the past losers) earns higher return for the herding firms than the non-herding firms, and the difference of trading strategy spreads between the herding and non-herding firms is statistically significant at a reasonable level. Panel B reports the results using the Fama-Frech 3-factor model adjusted returns, which are consistent with the results in Panel A.

Previous literature attributes the momentum effect to a gradual stock price response to information (e.g., Chan et al. (1996), Barberis et al. (1998), and Daniel et al. (1998)), and our theoretical framework clearly shows that the stronger analyst herding tendency is associated with 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

As shown in the last subsection, the herding firms are the ones with higher firm-level uncertainty. Zhang (2006a) shows that the momentum effect is stronger for the firms with higher firm-level uncertainty. We further examine whether the herding behavior intensifies informational inefficiency beyond the documented effect of uncertainty by running the Fama-MacBeth cross-sectional regression in each month:

$$ret_{i,t+1} = e + f*acret_{i,t} + g*herd_{i,t} + h*acret_{i,t}*herd_{i,t} + i*u_{i,t} + j*acret_{i,t}*u_{i,t} + \epsilon_{i,t+1}, \quad (40)$$

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, which equals one (zero) with the negative (positive) coefficient of regressing the analysts forecast dispersion on the macroeconomic uncertainty over firm $i$'s 24-month rolling window ending in month $t$, $u_{i,t}$ is one of the firm-level uncertainty measures. Table 6 reports the time-series averages of the slope coefficients from the monthly regressions (40). As one can see, after controlling for the effect of the firm-level uncertainty, the average slope coefficients of the cross term of $acret_{i,t}$ and $herd_{i,t}$ are still positive and significant, indicating that security analysts are important part of information transmission process and the herding behavior of analysts further hinders informational efficiency in the market.

Table 6 here

Furthermore, we also test the post-earnings-announcement drift (PEAD) for herding and non-herding firms. In each month $t$, we sort stocks into deciles based on $\text{SUE}_{i,t}$,

standardized unexpected earnings, and form ten portfolios, S1 (bad-news firms) to S10 (good-news firms). Panel A of Table 7 shows portfolio S1 to S10 returns for both herding and non-herding firms. In addition, we also independently sort stocks into deciles based on the slope coefficient of equation (38) in month t and classify the herding (non-herding) firms as the ones in the lowest (highest) decile to compare the PEAD effects. We observe in both ways that the trading strategy of longing S10 and shorting S1 earns higher return for the herding firms than the non-herding firms, and the difference of trading strategy spreads between the herding and non-herding firms is statistically significant at a reasonable level. Panel B reports the results using the Fama-Frech 3-factor model adjusted returns. These evidences further support the hypothesis that the stock prices of the herding firms are less informative about the firms' fundamental values and thus exhibit stronger price continuity in the process of converting to their intrinsic values.

Table 7 here

## C. Herding and Overpricing: *Hypothesis III*

Since the herding firms suffer more severe informational inefficiency, we show in the theoretical framework that the short-sell constraint causes these firms' stocks more overpriced. The *Hypothesis III* states that the herding firms' stocks are more overpriced and tend to have lower subsequent returns. We first test it by conducting univariate portfolio analysis. In each month $t$, based on the slope coefficient of $U_t^m$ in equation (38) over 24-month rolling window, we identify the herding and non-herding firms and calculate the value-weighted portfolio returns of month $t+1$ for the two groups. The trading strategy is to long the non-herding firm portfolio and short the herding firm portfolio.

The means and t-statistics of the excess returns and the bench-mark adjusted returns of the long leg, the short leg and the long-short strategy spread are reported in Panel A of Table 8. The excess return is the portfolio return minus the risk-free rate. The bench-mark 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-French 3-factor model); 3). the market, size, value, profitability and investment factors (Fama-French 5-factor model). Essentially, the bench-mark adjusted return reported here is the estimated intercept, $\alpha_i$, of the corresponding factor model. Column (1)-(3) present the results with herding and non-herding firms, classified by the sign of the slope coefficient of equation (38): negative for the herding firms and the positive for the non-herding firms; while column (4)-(6) present the results with the classification as sorting stocks into deciles based on the slope coefficient of equation (38) in month t and classifying the herding firms as the ones in the lowest decile and non-herding firms as the ones in the highest decile. As one can see, the long-short strategy produces significant positive average return spreads in terms of the excess return, and all the bench-mark adjusted returns, for both classifications. The long-short trading spread can be as high as 0.42% per month. These results are consistent with the hypothesis that the herding firms' stocks are overpriced and earn lower future returns.

Table 8 here

Furthermore, Panel B shows the slope coefficients, and their corresponding t-statistics of regressing the long-short spread on the risk factors of the factor models. Most of the coefficients of the risk factors are statistically insignificant. The evidence also suggests that the herding effect is an anomaly, which cannot be explained by the existing factor models. We will come back to this point when we discussing the herding effect with various well-documented anomalies in the following.

### C..1 Herding and Predictors

Existing literature documents several predictors with statistically significant relationships with the future stock returns. Idiosyncratic volatility, *ivol*, has been widely used in literature as a proxy for limits to arbitrage. Ang et al. (2006) documents the negative

relationship between idiosyncratic volatility and stock returns. In addition to the firm-level uncertainty measure, dispersion in analysts' earning forecasts is also used as a proxy for difference of opinion among investors (Diether et al. 2002). Combining heterogeneity of investors' beliefs and the short-sell constraint, Chen et al. (2001) produce cross-sectional asset pricing predictions: the greater the divergence in the valuations of the optimists and the pessimists, the higher the price of a stock in equilibrium, and hence the lower the subsequent returns. Moreover, Bali et al. (2017) document that stock exposure to an economic uncertainty index, the uncertainty beta ($\beta^U_{i,t}$), negatively predicts the future return.

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

$$ret_{i,t+1} = k + l * herd_{i,t} + m * p_{i,t} + n * control_{i,t} + \epsilon_{i,t+1}, \tag{41}$$

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 (38) 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.[16] Table 9 presents the time-series averages of the coefficients of the cross-sectional regression in each month.

Table 9 here

Generally consistent with the literature, the coefficients of the predictors are statistically significant in most cases. Controlling for these predictors, the herding dummy variable can still negatively predicts the one-month ahead return with high significance, well supporting *Hypothesis III* and also indicating that the herding effect exerts influence

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

on the stock future return beyond the impact of these predictors documented in existing literature.

### C..2 Herding and Anomalies

Previous literature documents that various anomaly variables can also predict cross-sectional stock returns. In the beginning of this subsection, the portfolio analysis showing that the herding firms' stocks tend to earn lower future returns already suggests that the herding effect may be another anomaly. Here, we further examine the herding effect along with nine widely-cited anomalies: 1. $acret_{i,t}$, the momentum effect (Jegadeesh and Titman(1993)), 2. $O_score_{i,t}$, financial constrain (Ohlson (1980)), 3. $g_share_{i,t}$ net stock issues (Stamburg et al. (2012)), 4. $\text{NOA}_{i,t}$, net operating asset (Hirshleifer, et al.(2004)), 5. $gp_{i,t}$, gross profitability (Novy-Marx (2010)), 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 10 reports the results of difference-in-means tests of each anomaly variable between the herding and the non-herding firms. The t-values are statistically significant across most of the anomaly variables with the exception of the gross profitability. In general, the herding firms are the ones with greater financial constrains, issuing more shares in the past, having higher net operating assets, more accruals, higher asset growth rate, higher investment-to-assets ratio and lower return on assets. Basically, these results suggest that the firms in the short-legs of the long-short trading strategies based on these anomalies are likely to be the herding firms.

Table 10 here

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

$$ret_{i,t+1} = o + p * herd_{i,t} + q * anml_{i,t} + r * anml_{i,t} * herd_{i,t} + \epsilon_{i,t+1}, \tag{42}$$

where $ret_{i,t+1}$ is the return for firm $i$ in month $t+1$ and $anml_{i,t}$ is one of the nine anomaly variables. Panel B presents the time-series averages of the slope coefficients. The slope coefficient of $herd_{i,t}$ is negative across all the regressions and statistically significant for seven out of nine, indicating that the herding effect has significant impact on the future stock returns beyond the influence of these anomalies. In addition, the slope coefficient of the cross term $anml_{i,t} * herd_{i,t}$ is statistically significant for $acret_{i,t}$ the momentum effect, $g_share_{i,t}$ net stock issues and $accrual_{i,t}$ the total accruals, suggesting that the herding effect can enhance or weaken some of the anomalies. For instance, the momentum and accrual anomalies are stronger for the herding firms while the stock issuing anomaly is weaker for the herding firms. How to incorporate the herding effect to improve anomaly based trading strategy is also an interesting topic, which we will explore further in the future study.

Overall, the results in this subsection show that informational inefficiency associated with the herding effect significantly and negatively predicts the subsequent stock return, consistent with the *Hypothesis III*. Moreover, this effect cannot be explained by the well-documented predictors in existing literature, suggesting more work needed to be done to deepen our understanding about the impact of informational inefficiency on the financial market.

# V. Conclusion

The positive correlation between pairs of various types of uncertainties is well documented in literature. In this paper, we uncover a novel negative correlation between macroeconomic uncertainty and analyst forecasts dispersion. Motivated by Keynes' beauty contest argument (Keynes (1936)), we develop a theoretical framework showing that this negative correlation is due to analyst herding behavior: the analysts tend to hide in the herd when they face greater uncertainty, and the herding behavior is associated with informational inefficiency in the stock market.

Empirically, we find the evidence well supporting the hypotheses. Firstly, the empirical analysis shows that the herding firms, whose analyst forecasts dispersions negatively co-move with the macroeconomic uncertainty, are the ones with higher firm-level uncertainty, and their values are harder to estimate. The results are consistent with our theoretical reasoning that higher uncertainty is associated with stronger analyst tendency to herd, and the argument that greater uncertainty about the underlying fundamentals of the firms leave more room for psychological biases (Hirshleifer (2001)).

Furthermore, empirical results confirm that the herding behavior contributes to informational inefficiency in the stock market. The stock prices of the herding firms are less reflective of their fundamental values, leading to greater price continuity. As a result, these stocks exhibit stronger momentum patterns and display more pronounced post-earnings announcement drift.

Additionally, our theoretical analysis shows that herding-driven informational inefficiency exacerbates stock overpricing under short-selling constraints. Empirical findings reveal that the one-month-ahead returns of herding firms are significantly lower than those of non-herding firms, supporting the argument that herding firms, due to greater informational inefficiency, are more likely to be overpriced and earn lower subsequent returns. These results remain robust after controlling for various established predictors and anomalies. Moreover, recent advancements in machine learning could potentially enhance the related trading profitability further, presenting an interesting avenue for future research.

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## 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. 2021.

**A: Summary statistics**

| | N | Mean | Std | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| $U_t^m$ | 897,536 | 1.05 | 0.57 | 0.37 | 0.69 | 0.89 | 1.23 | 5.56 |
| $disp_{i,t}$ | 897,536 | 0.17 | 1.24 | 0.00 | 0.02 | 0.04 | 0.09 | 276.75 |
| $mv_{i,t}$ | 897,536 | 6.91 | 1.74 | 1.28 | 5.68 | 6.79 | 8.01 | 14.74 |
| $age_{i,t}$ | 897,536 | 19.84 | 17.47 | 1.90 | 6.70 | 14.80 | 26.70 | 96.10 |
| $vol_{i,t}$ | 897,536 | 0.03 | 0.01 | 0.00 | 0.02 | 0.02 | 0.03 | 0.33 |
| $bm_{i,t}$ | 839,277 | 0.52 | 0.41 | -15.89 | 0.28 | 0.46 | 0.70 | 13.30 |
| $cvol_{i,t}$ | 636,133 | 0.08 | 0.11 | 0.00 | 0.03 | 0.05 | 0.10 | 11.03 |
| $cov_{i,t}$ | 895,990 | 11.59 | 8.67 | 2.00 | 5.00 | 9.00 | 16.00 | 62.00 |
| $num_{i,t}$ | 897,536 | 9.68 | 7.42 | 2.00 | 4.00 | 7.00 | 13.00 | 52.00 |
| $u_{i,t}^{com}$ | 897,536 | 0.51 | 0.17 | 0.04 | 0.38 | 0.51 | 0.63 | 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. 2021.

**A: Pooled Regression**

| | Parameter | Std. Err. | t Value | P Value |
|---|---|---|---|---|
| Intercept | 0.128 | 0.005 | 21.200 | $< 0.0001$ |
| $U^m$ | 0.056 | 0.006 | 10.744 | $< 0.0001$ |
| N | 897,536 | | | |

**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 | 9,438 | -0.01 | 3,832 | 0.07 | 897,536 | 0.01 | 253,613 | 0.11 |
| t-stat | | 0.8 | | 2.05 | | 0.16 | | 0.84 |
| Positive b | 5,169 | 0.23 | 2,528 | 0.31 | 431,580 | 0.21 | 142,277 | 0.36 |
| t-stat | | 2.56 | | 4.43 | | 1.60 | | 3.37 |
| Negative b | 4,269 | -0.30 | 1,304 | -0.39 | 465,956 | -0.18 | 111,336 | -0.22 |
| t-stat | | -1.33 | | -2.57 | | -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 (38) 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. 2021.

| | $mv_{i,t}$ | $age_{i,t}$ | $vol_{i,t}$ | $bm_{i,t}$ | $cvol_{i,t}$ | $cov_{i,t}$ | $disp_{i,t}$ | $num_{i,t}$ | $u_{i,t}^{com}$ |
|---|---|---|---|---|---|---|---|---|---|
| **A: Whole sample by the firm** | | | | | | | | | |
| Herd | 5.961 | 13.967 | 0.035 | 0.704 | 0.131 | 6.657 | 0.379 | 5.660 | 0.637 |
| N | 1,304 | 1,304 | 1,304 | 488 | 375 | 1,234 | 1,304 | 1,304 | 1,202 |
| Non-Herd | 7.032 | 19.703 | 0.030 | 0.727 | 0.116 | 8.714 | 0.215 | 7.296 | 0.562 |
| N | 2,528 | 2,528 | 2,528 | 489 | 329 | 2,472 | 2,528 | 2,528 | 2,480 |
| Diff | -1.072 | -5.736 | 0.005 | -0.024 | 0.015 | -2.057 | 0.164 | -1.636 | 0.075 |
| t-stat | (-3.260) | (-5.840) | (2.480) | (-0.520) | (1.920) | (-2.510) | (2.920) | (-2.550) | (3.770) |
| **B: Rolling window_independent** | | | | | | | | | |
| Herd | 6.853 | 18.909 | 0.027 | 0.513 | 0.083 | 11.537 | 0.149 | 9.570 | 0.513 |
| Non-Herd | 6.948 | 20.844 | 0.026 | 0.550 | 0.076 | 11.937 | 0.174 | 9.952 | 0.498 |
| Diff | -0.096 | -1.935 | 0.001 | -0.038 | 0.007 | -0.401 | -0.025 | -0.381 | 0.016 |
| t-stat | (-1.880) | (-7.010) | (1.400) | (-3.910) | (4.810) | (-2.320) | (-1.590) | (-2.920) | (5.090) |
| **C: Rolling window_dependent** | | | | | | | | | |
| Diff | -0.095 | -1.935 | 0.001 | -0.037 | 0.007 | -0.401 | -0.025 | -0.381 | 0.016 |
| t-stat | (-3.210) | (-9.060) | (1.400) | (-6.670) | (5.370) | (-3.390) | (-1.320) | (-3.470) | (4.150) |
| N | 433 | 433 | 433 | 433 | 433 | 433 | 433 | 433 | 433 |

## 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 (38) 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. 2021.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.055 | 0.082 | 0.140 | 0.083 | 0.058 | 0.059 | 0.062 | -0.078 | 0.360 | -0.212 |
| p-value | (< .0001) | (< .0001) | (< .0001) | (< .0001) | (< .0001) | (< .0001) | (< .0001) | (< .0001) | ( < .0001) | (< .0001) |
| $mv_{i,t}$ | -0.020 | | | | | | | | -0.024 | 0.002 |
| p-value | (< .0001 ) | | | | | | | | (< .0001) | (0.279) |
| $age_{i,t}$ | | -0.002 | | | | | | | -0.001 | 0.000 |
| p-value | | (< .0001) | | | | | | | (< .0001) | (0.572) |
| $vol_{i,t}$ | | | -3.428 | | | | | | -6.471 | -8.038 |
| p-value | | | (< .0001) | | | | | | (< .0001) | (< .0001) |
| $bm_{i,t}$ | | | | -0.017 | | | | | -0.015 | 0.036 |
| p-value | | | | (< .0001) | | | | | (< .0001) | (< .0001) |
| $cvol_{i,t}$ | | | | | 0.264 | | | | 0.427 | 0.144 |
| p-value | | | | | (< .0001) | | | | (< .0001) | (< .0001) |
| $cov_{i,t}$ | | | | | | -0.001 | | | 0.005 | 0.005 |
| p-value | | | | | | (< .0001) | | | (< .0001) | (< .0001) |
| $num_{i,t}$ | | | | | | | -0.001 | | -0.003 | 0.003 |
| p-value | | | | | | | (< .0001) | | (< .0001) | (< .0001 ) |
| $u^{com}_{i,t}$ | | | | | | | | 0.249 | | 0.752 |
| p-value | | | | | | | | (< .0001) | | (< .0001) |
| N | 253,613 | 253,613 | 253,613 | 227,948 | 173,502 | 253,177 | 253,613 | 253,613 | 172,969 | 172,969 |

**Table 5**
**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 (38) 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. 2021.

**Panel A: By negative and positive coefficients**

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | M10-M1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio returns | | | | | | | | | | | |
| Herd | 0.19 | 0.50 | 0.69 | 0.84 | 0.83 | 0.49 | 0.91 | 0.92 | 0.89 | 2.03 | 1.84 |
| t-stat | | | | | | | | | | | (3.44) |
| Non-herd | 0.99 | 0.99 | 1.04 | 1.09 | 0.90 | 0.84 | 0.98 | 1.18 | 0.98 | 1.11 | 0.12 |
| t-stat | | | | | | | | | | | (0.25) |
| Diff. | -0.80 | -0.48 | -0.35 | -0.25 | -0.06 | -0.35 | -0.07 | -0.26 | -0.09 | 0.92 | 1.72 |
| t-stat | | | | | | | | | | | (3.07) |
| FF 3-factor adjusted portfolio returns | | | | | | | | | | | |
| Herd | -1.19 | -0.68 | -0.32 | -0.11 | -0.09 | -0.44 | 0.04 | 0.03 | -0.08 | 1.03 | 2.22 |
| t-stat | | | | | | | | | | | (4.25) |
| Non-herd | -0.37 | -0.25 | -0.18 | 0.02 | -0.14 | -0.15 | 0.04 | 0.16 | 0.00 | 0.09 | 0.47 |
| t-stat | | | | | | | | | | | (0.98) |
| Diff. | -0.81 | -0.43 | -0.15 | -0.13 | 0.05 | -0.29 | 0.00 | -0.13 | -0.08 | 0.94 | 1.75 |
| t-stat | | | | | | | | | | | (3.14) |

**Panel B: By coefficient deciles**

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | M10-M1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio returns | | | | | | | | | | | |
| Herd | 0.14 | 0.38 | 0.48 | 0.45 | 0.66 | 0.95 | 1.01 | 0.89 | 1.18 | 2.02 | 1.88 |
| t-stat | | | | | | | | | | | (3.88) |
| Non-herd | 0.42 | 0.57 | 0.86 | 0.35 | 0.73 | 1.15 | 1.47 | 1.10 | 0.94 | 1.05 | 0.63 |
| t-stat | | | | | | | | | | | (1.32) |
| Diff. | -0.28 | -0.19 | -0.38 | 0.11 | -0.06 | -0.20 | -0.47 | -0.21 | 0.24 | 0.96 | 1.24 |
| t-stat | | | | | | | | | | | (2.55) |
| FF 3-factor adjusted portfolio returns | | | | | | | | | | | |
| Herd | -1.32 | -0.95 | -0.72 | -0.70 | -0.52 | -0.16 | 0.00 | -0.22 | 0.08 | 0.89 | 2.21 |
| t-stat | | | | | | | | | | | (4.58) |
| Non-Herd | -1.19 | -0.86 | -0.47 | -0.87 | -0.52 | 0.06 | 0.37 | -0.01 | -0.17 | -0.07 | 1.12 |
| t-stat | | | | | | | | | | | (2.39) |
| Diff. | -0.13 | -0.09 | -0.25 | 0.17 | 0.00 | -0.22 | -0.37 | -0.21 | 0.24 | 0.95 | 1.08 |
| t-stat | | | | | | | | | | | (2.20) |

**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 (38) 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. 2021.

| | $mv_{i,t}$ | $age_{i,t}$ | $vol_{i,t}$ | $bm_{i,t}$ | $cvol_{i,t}$ | $cov_{i,t}$ | $disp_{i,t}$ | $num_{i,t}$ | $u^{com}_{i,t}$ |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 1.29 | 0.95 | 1.14 | 0.90 | 0.99 | 1.03 | 1.03 | 1.06 | 1.05 |
| t-stat | (2.94) | (3.29) | (5.08) | (3.26) | (4.03) | (3.90) | (4.19) | (3.92) | (4.34) |
| $acret_{i,t}$ | -0.22 | 0.21 | 0.36 | 0.00 | -0.29 | -0.19 | -0.05 | -0.12 | -0.06 |
| t-stat | (-0.37) | (0.78) | (0.84) | (0.01) | (-0.89) | (-0.64) | (-0.20) | (-0.42) | (-0.11) |
| $herd_{i,t}$ | -0.32 | -0.33 | -0.29 | -0.26 | -0.31 | -0.33 | -0.33 | -0.34 | -0.30 |
| t-stat | (-3.40) | (-3.46) | (-3.26) | (-2.82) | (-3.01) | (-3.42) | (-3.48) | (-3.56) | (-3.22) |
| $acret_herd_{i,t}$ | 0.52 | 0.59 | 0.45 | 0.57 | 0.90 | 0.57 | 0.64 | 0.60 | 0.57 |
| t-stat | (2.10) | (2.42) | (1.90) | (2.23) | (2.89) | (2.33) | (2.54) | (2.46) | (2.33) |
| $u_{i,t}$ | -0.04 | 0.00 | -10.31 | -0.01 | -0.20 | 0.00 | -0.13 | -0.01 | -0.18 |
| t-stat | (-0.98) | (0.88) | (-1.03) | (-0.07) | (-0.23) | (-0.43) | (-0.55) | (-0.92) | (-0.39) |
| $acret_u_{i,t}$ | 0.03 | -0.01 | -8.27 | -0.23 | 1.17 | 0.02 | 0.01 | 0.02 | 0.24 |
| t-stat | (0.40) | (-2.04) | (-0.73) | (-0.73) | (0.87) | (1.33) | (0.03) | (0.95) | (0.30) |
| N | 577 | 577 | 577 | 535 | 406 | 576 | 577 | 577 | 577 |
| Adj $R^2$ | 3.71% | 3.13% | 5.67% | 3.66% | 4.47% | 3.30% | 3.04% | 3.31% | 4.11% |

**Table 7**
**Herding and Post Earning Announcement Drift**

The table reports the average returns and the Fama-Frech 3-factor model adjusted returns 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 (38) 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. 2021.

| **Panel A: By negative and positive coefficients** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S10-S1 |
| Portfolio returns | | | | | | | | | | | |
| Herd | 0.64 | 0.60 | 0.62 | 0.85 | 0.87 | 0.86 | 1.27 | 0.89 | 1.27 | 1.13 | 0.49 |
| t-stat | | | | | | | | | | | (1.85) |
| Non-herd | 1.25 | 1.05 | 1.14 | 1.06 | 1.22 | 1.13 | 1.21 | 1.19 | 1.26 | 1.35 | 0.10 |
| t-stat | | | | | | | | | | | (0.43) |
| Diff. | -0.61 | -0.45 | -0.52 | -0.21 | -0.35 | -0.28 | 0.05 | -0.30 | 0.00 | -0.22 | 0.39 |
| t-stat | | | | | | | | | | | (1.72) |
| FF 3-factor adjusted portfolio returns | | | | | | | | | | | |
| Herd | -0.39 | -0.39 | -0.40 | -0.20 | -0.13 | -0.13 | 0.28 | -0.09 | 0.20 | 0.08 | 0.48 |
| t-stat | | | | | | | | | | | (1.85) |
| Non-herd | 0.11 | -0.12 | 0.04 | -0.03 | 0.09 | 0.04 | 0.18 | 0.09 | 0.14 | 0.26 | 0.15 |
| t-stat | | | | | | | | | | | (0.65) |
| Diff. | -0.51 | -0.27 | -0.43 | -0.16 | -0.21 | -0.18 | 0.10 | -0.18 | 0.05 | -0.18 | 0.33 |
| t-stat | | | | | | | | | | | (1.78) |
| **Panel B: By coefficient deciles** | | | | | | | | | | | |
| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S10-S1 |
| Portfolio returns | | | | | | | | | | | |
| Herd | 0.58 | 0.88 | 0.56 | 0.80 | 0.51 | 1.02 | 1.19 | 0.85 | 1.15 | 1.39 | 0.81 |
| t-stat | | | | | | | | | | | (2.49) |
| Non-herd | 0.91 | 1.14 | 0.81 | 1.04 | 1.33 | 1.14 | 1.32 | 1.30 | 1.25 | 1.35 | 0.44 |
| t-stat | | | | | | | | | | | (1.56) |
| Diff. | -0.33 | -0.26 | -0.25 | -0.23 | -0.82 | -0.11 | -0.13 | -0.44 | -0.10 | 0.04 | 0.37 |
| t-stat | | | | | | | | | | | (1.94) |
| FF 3-factor adjusted portfolio returns | | | | | | | | | | | |
| Herd | -0.77 | -0.20 | -0.62 | -0.29 | -0.65 | -0.21 | -0.02 | -0.37 | -0.06 | 0.19 | 0.96 |
| t-stat | | | | | | | | | | | (2.94) |
| Non-herd | -0.47 | -0.22 | -0.47 | -0.21 | 0.06 | -0.08 | 0.12 | 0.09 | 0.02 | 0.13 | 0.61 |
| t-stat | | | | | | | | | | | (1.36) |
| Diff. | -0.29 | 0.02 | -0.16 | -0.08 | -0.71 | -0.13 | -0.13 | -0.46 | -0.07 | 0.06 | 0.35 |
| t-stat | | | | | | | | | | | (1.95) |

**Table 8**
**Herding and predictability: portfolio analysis**

Panel A presents the means and t-statistics of the excess returns (in percentage) and the bench-mark 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 (38) 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 bench-mark 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. 2021.

| **A: Benchmark adjusted returns** | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Non-herd | Herd | Long - Short | Non-herd | Herd | Long - Short |
| Excess return | 0.91 | 0.62 | 0.29 | 0.91 | 0.49 | 0.42 |
| t-stat | (3.41) | (2.49) | (2.80) | (2.72) | (1.53) | (3.34) |
| CAPM adj return | 0.08 | -0.14 | 0.22 | -0.08 | -0.47 | 0.39 |
| t-stat | (0.66) | (-1.23) | (2.16) | (-0.50) | (-3.01) | (3.09) |
| FF 3-factor adj return | 0.04 | -0.16 | 0.20 | -0.09 | -0.44 | 0.35 |
| t-stat | (0.56) | (-1.94) | (1.95) | (-0.90) | (-4.68) | (2.82) |
| FF 5-factor adj return | 0.04 | -0.21 | 0.25 | 0.03 | -0.33 | 0.36 |
| t-stat | (0.50) | (-2.60) | (2.39) | (0.24) | (-3.60) | (2.79) |
| **B: Factor models** | | | | | | |
| $\alpha_t$ | 0.22 | 0.20 | 0.25 | 0.39 | 0.35 | 0.36 |
| t-stat | (2.16) | (1.95) | (2.39) | (3.09) | (2.82) | (2.79) |
| $\text{Mkt}_t$ | 0.09 | 0.10 | 0.08 | 0.04 | 0.05 | 0.04 |
| t-stat | (2.00) | (1.69) | (1.68) | (1.29) | (1.79) | (1.33) |
| $\text{SMB}_t$ | | -0.01 | -0.04 | | 0.04 | 0.06 |
| t-stat | | (-0.41) | (-0.98) | | (0.91) | (1.28) |
| $\text{HML}_t$ | | 0.09 | 0.14 | | 0.19 | 0.22 |
| t-stat | | (1.67) | (1.21) | | (1.69) | (1.10) |
| $\text{RMW}_t$ | | | -0.08 | | | 0.05 |
| t-stat | | | (-1.59) | | | (0.93) |
| $\text{CMA}_t$ | | | -0.08 | | | -0.12 |
| t-stat | | | (-1.15) | | | (-1.40) |
| N | 433 | 433 | 433 | 433 | 433 | 433 |
| Adj $R^2$ | 3.31% | 4.75% | 5.09% | 0.15% | 4.72% | 4.97% |

**Table 9**
**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 (38 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. 2021.

| | | $ivol_{i,t}$ | | $disp_{i,t}$ | | $\beta^U_{i,t}$ | |
|---|---|---|---|---|---|---|---|
| Intercept | 1.28 | 1.32 | 1.41 | 1.17 | 1.25 | 1.96 | 2.06 |
| t-stat | (4.51) | (4.86) | (5.25) | (4.14) | (4.41) | (4.04) | (4.22) |
| $herd_{i,t}$ | -0.24 | | -0.29 | | -0.23 | | -0.24 |
| t-stat | (-2.29) | | (-3.21) | | (-2.23) | | (-2.57) |
| $p_{i,t}$ | | -0.23 | -0.23 | -0.35 | -0.33 | 0.00 | 0.00 |
| t-stat | | (-3.90) | (-3.87) | (-1.70) | (-1.58) | (0.68) | (0.63) |
| control | | Y | Y | Y | Y | Y | Y |
| N | 577 | 459 | 459 | 577 | 577 | 352 | 352 |
| R | 7.07% | 5.40% | 5.57% | 7.03% | 7.49% | 6.19% | 6.37% |

## Table 10
## 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). $NOA_{i,t}$, 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). $ITA_{i,t}$, 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). $ROA_{i,t}$, 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 (38 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. 2021.

| **A: Anomalies** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Herd | 0.17 | -1656.19 | 0.15 | 0.62 | 0.31 | 0.07 | 0.20 | 0.09 | 0.01 |
| Non_herd | 0.16 | -1943.68 | 0.11 | 0.60 | 0.31 | 0.06 | 0.18 | 0.09 | 0.01 |
| Diff | 0.01 | 287.49 | 0.04 | 0.02 | 0.01 | 0.00 | 0.03 | 0.01 | 0.00 |
| t-stat | (0.41) | (2.51) | (1.95) | (3.18) | (1.69) | (1.75) | (3.21) | (1.99) | (-1.94) |
| **B: Herding and anomalies** | | | | | | | | | |
| intercept | 1.02 | 1.12 | 1.09 | 1.37 | 0.85 | 1.15 | 1.13 | 1.17 | 0.96 |
| t-stat | (4.09) | (3.78) | (4.05) | (4.84) | (3.00) | (4.15) | (4.22) | (4.21) | (3.47) |
| $herd_{i,t}$ | -0.38 | -0.34 | -0.25 | -0.19 | -0.08 | -0.28 | -0.24 | -0.20 | -0.22 |
| t-stat | (-3.94) | (-3.23) | (-2.59) | (-1.21) | (-0.56) | (-2.73) | (-2.46) | (-1.93) | (-2.26) |
| $anml_{i,t}$ | -0.01 | 0.00 | -0.19 | -0.43 | 0.79 | -0.37 | -0.39 | -0.74 | 11.44 |
| t-stat | (-0.05) | (0.15) | (-0.80) | (-2.78) | (2.91) | (-0.60) | (-2.34) | (-2.17) | (5.28) |
| $anml_herd_{i,t}$ | 0.69 | 0.00 | -0.07 | -0.14 | -0.62 | -1.20 | 0.05 | -1.11 | 0.46 |
| t_stat | (2.94) | (-1.68) | (-0.16) | (-0.62) | (-1.82) | (-1.39) | (0.20) | (-1.88) | (0.17) |
| N | 537 | 400 | 494 | 444 | 494 | 387 | 493 | 424 | 493 |
| Adj $R^2$ | 2.28% | 0.44% | 0.57% | 0.93% | 1.16% | 0.73% | 0.96% | 0.67% | 1.51% |

Figure 1: Timeline of the model.

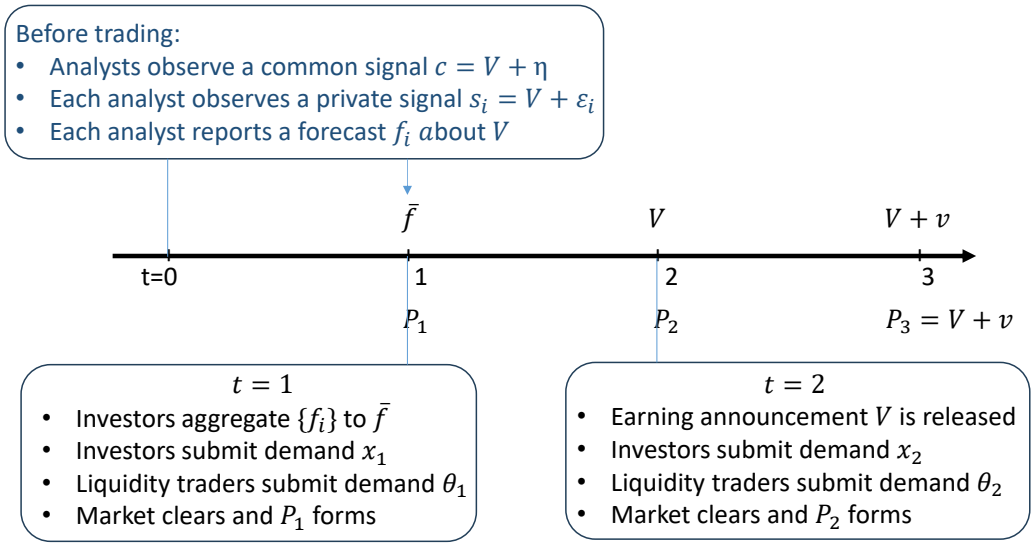
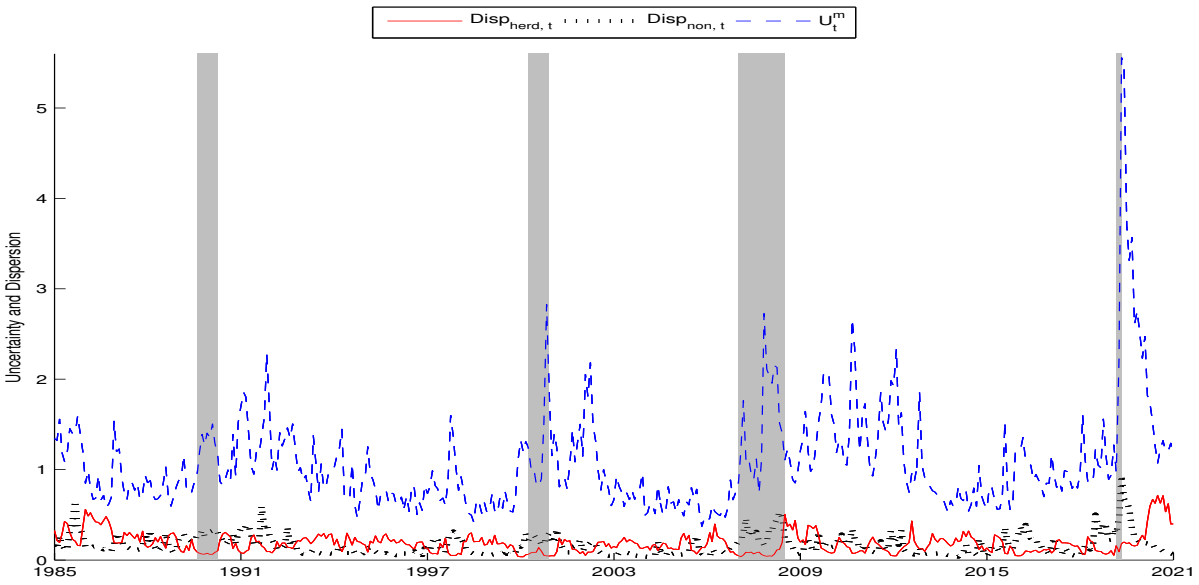


Figure 2: Macroeconomic Uncertainty and Analyst Forecasts Dispersion

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. 2021.



# Appendix

## A Proof of lemma 1

*Proof.* We will now show the existence and uniqueness of analysts' equilibrium forecast strategy. Following Morris and Shin (2004), 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

$$f_i = (1 - \kappa_1 - \kappa_2)\bar{V} + \kappa_1 s_i + \kappa_2 c. \tag{43}$$

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

$$\mathrm{E}^i[\bar{f}] = (1 - \kappa_1 - \kappa_2)\bar{V} + \kappa_1 \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon s_i}{\tau_V + \tau_\eta + \tau_\varepsilon} + \kappa_2 c. \tag{44}$$

Note that in order to maximize the utility function Eq (8), analyst $i$ best response is

$$f_i = (1 - \delta)\mathrm{E}^i[V] + \delta \mathrm{E}^i[\bar{f}]. \tag{45}$$

By substituting Eq (44) into above equation, we have

$$\begin{aligned} f_i = &\left(\delta(1 - \kappa_1 - \kappa_2) + (1 - \delta + \delta\kappa_1)\frac{\tau_V}{\tau_V + \tau_\eta + \tau_\varepsilon}\right)\bar{V} \\ &+(1 - \delta + \delta\kappa_1)\frac{\tau_\varepsilon}{\tau_V + \tau_\eta + \tau_\varepsilon} s_i + (1 - \delta + \delta\kappa_1)\frac{\tau_\eta}{\tau_V + \tau_\eta + \tau_\varepsilon} c. \end{aligned} \tag{46}$$

Comparing coefficients in Eq (43) and Eq (46), we therefore have

$$\kappa_1 = \frac{(1 - \delta)\tau_\varepsilon}{\tau_V + \tau_\eta + (1 - \delta)\tau_\varepsilon}, \tag{47}$$

$$\kappa_2 = \frac{\tau_\eta}{\tau_V + \tau_\eta + (1 - \delta)\tau_\varepsilon}. \tag{48}$$

Thus, the equilibrium forecast $f_i$ is given by

$$f_i = \frac{\tau_V \bar{V} + \tau_\eta c + (1-\delta)\tau_\varepsilon s_i}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}. \tag{49}$$

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

$$\mathrm{E}^i[V] = \frac{\tau_V \bar{V} + \tau_\varepsilon s_i + \tau_\eta c}{\tau_V + \tau_\varepsilon + \tau_\eta}. \tag{50}$$

Thus, the average expectation of $V$ across all analysts is

$$\bar{\mathrm{E}}[V] = \int_0^1 \mathrm{E}^i[V] di = \frac{\tau_V \bar{V} + \tau_\varepsilon V + \tau_\eta c}{\tau_V + \tau_\varepsilon + \tau_\eta}. \tag{51}$$

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

$$\begin{aligned}
\bar{\mathrm{E}}^{\mathrm{n}}[V] &= \frac{\tau_V \bar{V}}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n} \mu^{k-1} + \frac{\tau_\eta c}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n} \mu^{k-1} + \mu^n V, \\
\mathrm{E}^i[\bar{\mathrm{E}}^{\mathrm{n}}[V]] &= \frac{\tau_V \bar{V}}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n+1} \mu^{k-1} + \frac{\tau_\eta c}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n+1} \mu^{k-1} + \mu^{n+1} s_i,
\end{aligned} \tag{52}$$

where

$$\mu = \frac{\tau_\varepsilon}{\tau_V + \tau_\eta + \tau_\varepsilon}, \tag{53}$$

It is easy to verify that Eq (52) holds for $n = 1$, then the proof is by induction on $n$.

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

$$f_i = (1-\delta)\mathrm{E}^i[V] + \delta \mathrm{E}^i[\bar{f}]. \tag{54}$$

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.

□

# B Proof of Proposition 1

*Proof.* Let $g(\tau_V) = \frac{d\delta}{d\tau_V}(\tau_V+\tau_\eta) + (1-\delta)$. , taking derivative of $g(\tau_V)$ with respect of $\tau_V$:

$$\frac{\partial g(\tau_V)}{\partial \tau_V} = \frac{d^2\delta}{d\tau_V^2}(\tau_V+\tau_\eta). \tag{55}$$

If $\delta$ is a decreasing linear or concave function of $\tau_V$, we have $\frac{d^2\delta}{d\tau_V^2} \leq 0$, it follows that

$$\frac{\partial g(\tau_V)}{\partial \tau_V} \leq 0. \tag{56}$$

The relationship between analyst forecasts dispersion and macro uncertainty is

$$\begin{aligned} \frac{\partial D}{\partial \sigma_m^2} &= \frac{2(1-\delta)\tau_\varepsilon\tau_V^2}{(\tau_V+\tau_\eta+(1-\delta)\tau_\varepsilon)^3}\left[\frac{d\delta}{d\tau_V}(\tau_V+\tau_\eta)+(1-\delta)\right] \\ &= \frac{2(1-\delta)\tau_\varepsilon\tau_V^2}{(\tau_V+\tau_\eta+(1-\delta)\tau_\varepsilon)^3}g(\tau_V). \end{aligned} \tag{57}$$

When $\delta = 0$, we have $\frac{\partial D}{\partial \sigma_m^2} > 0$. As $\delta \in [0,1]$, when $\delta = 0$, $\tau_V$ reaches its maximum value, $\tau_V = Max(\tau_V)$. Therefore,

$$When \quad \tau_V = Max(\tau_V), \quad \frac{\partial D}{\partial \sigma_m^2} > 0. \tag{58}$$

Since $\frac{\partial g(\tau_V)}{\partial \tau_V} \leq 0$, for any $\tau_V < Max(\tau_V)$, $\frac{\partial D}{\partial \sigma_m^2}(\tau_V) > 0$, which means that $\frac{\partial D}{\partial \sigma_m^2}$ is always positive. It is against our empirical findings that there exist both positive and negative correlations between macro uncertainty and analyst forecasts dispersion. Therefore, we conclude that $\delta$ must be a decreasing convex function of $\tau_V$: $\frac{d^2\delta}{d\tau_V^2} > 0$.

Let $\tau_V^c$ denote the solution for $\frac{d\delta}{d\tau_V}(\tau_V + \tau_\eta) + (1 - \delta) = 0$:

$$g(\tau_V^c) = 0. \tag{59}$$

Take derivative of $g(\tau_V)$ with respect of $\tau_V$:

$$\frac{dg(\tau_V)}{d\tau_V} = \frac{d^2\delta}{d\tau_V^2}(\tau_V + \tau_\eta). \tag{60}$$

Since $\delta(\tau_V)$ is a decreasing convex function of $\tau_V$, $\frac{d^2\delta}{d\tau_V^2} > 0$ and $\frac{dg(\tau_V)}{d\tau_V} > 0$. It follows:

$$for \quad \tau_V < (>)\tau_V^c, \quad g(\tau_V) < (>)0 \quad and \quad \frac{\partial D}{\partial \sigma_m^2} < (>)0. \tag{61}$$

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

$$\delta > (<)\delta_c \iff \frac{\partial D}{\partial \sigma_m^2} < (>)0. \tag{62}$$

□

# C Proof of Proposition 2

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

**Lemma 2.** *Let $u$ be an $n \times 1$ normal vector with mean $\bar{u}$ and covariance matrix $\Sigma$, $A$ 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

$$x_2 = \frac{\mathrm{E}_2[V + v] - P_2}{\lambda \mathrm{Var}_2(V + v)} = \frac{V - P_2}{\lambda \tau_v^{-1}}. \tag{63}$$

By market clearing condition, the equilibrium price is

$$P_2 = V + \lambda \tau_v^{-1} (\beta z_1 + z_2) - \lambda \tau_v^{-1} \Theta. \tag{64}$$

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

$$J_2 = -e^{-\lambda \left[ \left( V + \frac{\lambda}{\tau_v}(\theta_2 - \Theta) - P_1 \right) x_1 + \frac{1}{2} \frac{\lambda}{\tau_v} (\theta_2 - \Theta)^2 \right]}. \tag{65}$$

By Lemma 2, we solve

$$\max_{x_1} \mathrm{E}_1[J_2], \tag{66}$$

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

$$x_1 = \left( \lambda \mathrm{Var}_1(V) + \frac{\lambda}{\tau_v} \frac{\lambda^2}{\lambda^2 + \tau_v} \right)^{-1} \left[ \mathrm{E}_1[V] - P_1 + \frac{\lambda}{\tau_v} \left( 1 - \frac{\lambda^2}{\lambda^2 + \tau_v} \right) (\beta z_1 - \Theta) \right], \tag{67}$$

where

$$\mathrm{E}_1[V] = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f}, \quad \text{and} \quad \mathrm{Var}_1(V) = \frac{1}{\tau_V + \tau_f}. \tag{68}$$

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

$$P_1 = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} + \left[ \frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v} \left( \beta + \frac{\lambda^2}{\lambda^2 + \tau_v} (1 - \beta) \right) \right] z_1 - \left( \frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v} \right) \Theta. \tag{69}$$

Hence, $P_1$ is informationally equivalent to the following signal

$$s_p = s_f + \lambda \left( b + \frac{b\tau_V + 1}{\tau_f} \right) z_1, \tag{70}$$

where

$$b = \frac{1}{\tau_v} \left( \beta + \frac{\lambda^2}{\lambda^2 + \tau_v} (1 - \beta) \right). \tag{71}$$

Therefore,

$$\mathrm{Var}(V \mid P_1) = \mathrm{Var}(V \mid s_p) = \frac{1}{\tau_V + \tau_f + \lambda^{-2} \left( b + \frac{b\tau_V + 1}{\tau_f} \right)^{-2}}. \tag{72}$$

As $\delta$ increases, $\tau_f$ decreases, leading to an increase in $\text{Var}(V \mid P_1)$,

$$\frac{d\text{Var}(V \mid P_1)}{d\delta} > 0, \tag{73}$$

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

□

# D Proof of Proposition 3

*Proof.* From Eq. (**??**), the necessary and sufficient condition for a positive return correlation is

$$f(\beta) := \beta \left( \frac{\tau_v}{\tau_V + \tau_f} + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z}(1 - \beta) \right) - 1 > 0, \tag{74}$$

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

$$a = \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z} \in (0, 1), \quad x = \frac{\tau_v}{\tau_V + \tau_f} \in (0, +\infty). \tag{75}$$

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

$$f(\beta) = -a\beta^2 + (x + a)\beta - 1. \tag{76}$$

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

$$(x + a)^2 - 4a > 0 \Longleftrightarrow x > 2\sqrt{a} - a, \tag{77}$$

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

$$\beta_c = \frac{x + a - \sqrt{(x + a)^2 - 4a}}{2a}, \quad \beta_d = \frac{x + a + \sqrt{(x + a)^2 - 4a}}{2a}. \tag{78}$$

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

$$\beta_c < \beta < \beta_d. \tag{79}$$

Note $0 \leq \beta \leq 1$, however, under the condition of Eq.(77),

$$\beta_d > 1. \tag{80}$$

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

$$\beta_c < 1 \Longleftrightarrow x > 1. \tag{81}$$

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

$$x > 1, \quad \text{and} \quad \beta > \beta_c, \tag{82}$$

where

$$x > 1 \Longleftrightarrow \text{Var}(v) < \text{Var}(V \mid \bar{f}), \tag{83}$$

and

$$\frac{d\beta_c}{d\delta} = \underbrace{\frac{d\beta_c}{dx}}_{<0} \underbrace{\frac{dx}{d\delta}}_{>0} < 0. \tag{84}$$

□

# E Proof of Proposition 4

*Proof.* By market clearing condition (32), we have time-2 equilibrium price

$$P_2 = \frac{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} V + \frac{\frac{\alpha}{\tau_v}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} - \frac{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\lambda}{\tau_v} (\Theta - \theta_2). \tag{85}$$

Thus, the post-earning return

$$\text{PR} = v + \frac{\frac{\alpha}{\tau_v}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\tau_V (V - \bar{V}) - \tau_f \varepsilon_f}{\tau_V + \tau_f} + \frac{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\lambda}{\tau_v} (\Theta - \theta_2). \tag{86}$$

Then the variance of the post-earning return is

$$\text{Var}(\text{PR}) = \frac{1}{\tau_v} + \frac{w_\alpha^2}{\tau_V + \tau_f} + (1 - w_\alpha)^2 \frac{\lambda^2}{\tau_v^2} (1 + \beta^2), \tag{87}$$

where

$$w_\alpha = \frac{\frac{\alpha}{\tau_v}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}. \tag{88}$$

The earning surprise is

$$\text{ES} = \frac{\tau_V(V - \bar{V}) - \tau_\eta \eta}{\tau_V + \tau_\eta + \tau_\varepsilon(1-\delta)}, \tag{89}$$

and its variance is

$$\text{Var}(\text{ES}) = \frac{\tau_V + \tau_\eta}{(\tau_V + \tau_\eta + \tau_\varepsilon(1-\delta))^2}. \tag{90}$$

The covariance between the two is positive,

$$\text{Cov}(\text{ES}, \text{PR}) = \frac{w_\alpha}{\tau_V + \tau_f} = \frac{\alpha}{\tau_V + \tau_f + \tau_v} > 0. \tag{91}$$

Obviously,

$$\frac{\partial \text{Var}(\text{ES})}{\partial \delta} = \frac{2\tau_\varepsilon(\tau_V + \tau_\eta)\left(\tau_V + \tau_\eta + \tau_\varepsilon(1-\delta)\right)}{\left(\tau_V + \tau_\eta + \tau_\varepsilon(1-\delta)\right)^4} > 0. \tag{92}$$

$$\frac{\partial \text{Cov}(\text{ES}, \text{PR})}{\partial \delta} = -\frac{\alpha}{(\tau_V + \tau_f + \tau_v)^2}\frac{\partial \tau_f}{\partial \delta} > 0. \tag{93}$$

□

# F Proof of Proposition 5

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

$$0 \leq \theta_2 \leq \Theta, \quad 0 \leq \theta_1 \leq \Theta. \tag{94}$$

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

$$0 \leq z_1 \leq \Theta, \tag{95}$$

and given $z_1$, the range for $z_2$ should be

$$-\beta z_1 \leq z_2 \leq \Theta - \beta z_1. \tag{96}$$

Thus, under short-sale constraint,

$$\mathrm{E}_0^{ss}[\theta_1] = \Delta_1, \tag{97}$$

$$\mathrm{E}_1^{ss}[\theta_2] = \beta z_1 + \Delta_2, \tag{98}$$

where superscript $.^{ss}$ stand for short-sale constraint. $\Delta_t$ in the above expression are

$$\Delta_1 = \mathrm{E}[z_1 \mid 0 \leq z_1 \leq \Theta] = \frac{\phi(0) - \phi(\Theta)}{\Phi(\Theta) - \Phi(0)}, \tag{99}$$

$$\Delta_2 = \mathrm{E}[z_2 \mid -\beta z_1 \leq z_2 \leq \Theta - \beta z_1] = \frac{\phi(\beta z_1) - \phi(\Theta - \beta z_1)}{\Phi(\Theta - \beta z_1) - \Phi(-\beta z_1)}, \tag{100}$$

where $\phi$ and $\Phi$ are probability density function and cumulative distribution function of standard normal respectively. Obviously,

$$\Delta_1 > 0, \qquad \frac{\partial \Delta_2}{\partial \beta} < 0. \tag{101}$$

Under short-sale constraint, the condition variance of $\theta_2$ is

$$\mathrm{Var}_2^{ss}(\theta_2) < \mathrm{Var}_2(\theta_2) = 1, \tag{102}$$

and obviously

$$\tau_z^{ss} := \frac{1}{\mathrm{Var}_2^{ss}(\theta_2)} > 1. \tag{103}$$

Under the short-sale constraint, by solving

$$\max_{x_1} \mathrm{E}_1^{ss}[J_2], \tag{104}$$

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

$$x_1^{ss} = \left(\lambda \mathrm{Var}_1^{ss}(V) + \frac{\lambda}{\tau_v} \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)^{-1} \left[\mathrm{E}_1^{ss}[V] - P_1 + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)(\beta z_1 - \Theta + \Delta_2)\right], \tag{105}$$

where

$$\mathrm{E}_1^{ss}[V] = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f}, \quad \text{and} \quad \mathrm{Var}_1^{ss}(V) = \frac{1}{\tau_V + \tau_f}, \tag{106}$$

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

$$P_1^{ss} = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)\Delta_2 + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}(1-\beta)\right)\right] z_1, \tag{107}$$

noting that $\Delta_2$ is a function of $\beta z_1$. Therefore, the expected equilibrium price with short-sale constraint is

$$\mathrm{E}[P_1^{ss}] = \bar{V} - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)\mathrm{E}[\Delta_2 \mid 0 \le z_1 \le \Theta] + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}(1-\beta)\right)\right]\Delta_1, \tag{108}$$

where by symmetry,

$$\mathrm{E}[\Delta_2 \mid 0 \le z_1 \le \Theta] = 0. \tag{109}$$

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

$$\Delta = \mathrm{E}[P_1^{ss}] - \mathrm{E}[P_1] = \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}(1-\beta)\right)\right]\Delta_1 > 0, \tag{110}$$

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

$$\frac{\partial \Delta}{\partial \delta} = -\frac{\lambda \Delta_1}{(\tau_V + \tau_f)^2}\frac{\partial \tau_f}{\partial \delta} > 0, \tag{111}$$

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

$$\mathrm{E}[P_2] = \bar{V} - \frac{\lambda}{\tau_v}\Theta. \tag{112}$$

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

$$\mathrm{E}[P_2^{ss}] = \bar{V} + \frac{\lambda}{\tau_v}(\Delta_1 - \Theta), \tag{113}$$

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

$$\mathrm{E}[R^{ss}] = \mathrm{E}[P_2^{ss}] - \mathrm{E}[P_1^{ss}] = \frac{\lambda}{\tau_V + \tau_f}(\Theta - \Delta_1) + \frac{\lambda(1-\beta)\tau_z^{ss}}{\lambda^2 + \tau_v \tau_z^{ss}}\Delta_1. \tag{114}$$

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

$$\frac{\partial \mathrm{E}[R^{ss}]}{\partial \delta} = \frac{\lambda(\Theta - \Delta_1)}{(\tau_V + \tau_f)^2}\frac{\partial \tau_f}{\partial \delta} < 0, \tag{115}$$

□

# G Complementary Empirical Results

### Table G1
### Descriptive statistics

The table shows the summary statistics of the variables: (1). $\text{MV}_{i,t}$, 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). $\text{SUE}_{i,t}$, 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). $\beta_{i,t}^{mkt}$, the slope coefficient of the market factor in the Fama-French 3-factor model; (6). $\beta_{i,t}^{U}$, 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; (7). $O_score_{i,t}$, the Ohlson(1980) O-score measures; (8). $g_shares_{i,t}$, the growth of the split-adjusted shares outstanding of firm i in the last fiscal with respect of month t; (9). $\text{NOA}_{i,t}$, firm i's net operating asset; (10). $gp_{i,t}$, firm i's gross profit of the last fiscal year; (11). $accruals_{i,t}$, firm i's total accruals; (12). $g_asset_{i,t}$, firm i's asset growth measured as the growth rate of total assets in the previous fiscal year; (13). $\text{ITA}_{i,t}$, 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. (14). $\text{ROA}_{i,t}$, firm i's return on asset of the last fiscal year with respect of month t. The sample spans from Jan. 1985 to Dec. 2021.

| | N | Mean | Std | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| $\text{MV}_{i,t}$ | 1,124,095 | 5,538 | 26,313 | 0.14 | 226 | 712 | 2,568 | 2,525,084 |
| $ret_{i,t}$ | 910,485 | 1.04 | 12.61 | -98.13 | -5.16 | 0.82 | 6.89 | 1,625.05 |
| $\text{SUE}_{i,t}$ | 752,555 | -0.14 | 1.71 | -7.93 | -0.74 | 0.01 | 0.69 | 4.11 |
| $ivol_{i,t}$ | 835,188 | 0.02 | 0.01 | 0.00 | 0.01 | 0.02 | 0.02 | 0.71 |
| $\beta_{i,t}^{mkt}$ | 872,064 | 1.05 | 0.88 | -23.98 | 0.55 | 0.99 | 1.47 | 28.20 |
| $\beta_{i,t}^{U}$ | 872,064 | 3.90 | 123.96 | -4,153.27 | -34.79 | 2.04 | 42.01 | 11,476.87 |
| $O_score_{i,t}$ | 715,063 | -2,114.87 | 7,095.51 | -224,526.87 | -1,225.46 | -341.46 | -105.76 | 41.70 |
| $g_shares_{i,t}$ | 856,108 | 0.14 | 5.97 | -1.69 | 0.00 | 0.01 | 0.05 | 1,591.90 |
| $\text{NOA}_{i,t}$ | 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 G2
## 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 (38) 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 macro uncertainty measure is $\text{VIX}_t$. The sample spans from Jan. 1985 to Dec. 2021.

| **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 | 6.22 | 14.78 | 0.04 | 0.65 | 0.14 | 7.09 | 0.37 | 5.97 | 0.62 |
| t-stat | 3408 | 3408 | 3408 | 1133 | 846 | 3265 | 3408 | 3408 | 2656 |
| Non-herd | 6.76 | 17.61 | 0.03 | 0.69 | 0.13 | 8.05 | 0.30 | 6.75 | 0.59 |
| t-stat | 4802 | 4802 | 4802 | 1183 | 846 | 4663 | 4802 | 4802 | 4081 |
| Diff | -0.54 | -2.82 | 0.00 | -0.04 | 0.01 | -0.96 | 0.07 | -0.78 | 0.03 |
| t-stat | (-2.28) | (-2.80) | (1.73) | (-1.20) | (1.35) | (-1.90) | (1.09) | (-1.87) | (1.98) |
| **B: Rolling window_independent** | | | | | | | | | |
| Herd | 7.096 | 20.592 | 0.026 | 0.511 | 0.083 | 11.632 | 0.177 | 9.705 | 0.512 |
| Non-Herd | 7.209 | 21.206 | 0.026 | 0.510 | 0.079 | 12.023 | 0.146 | 10.092 | 0.502 |
| diff | -0.113 | -0.613 | 0.000 | 0.001 | 0.005 | -0.392 | 0.031 | -0.387 | 0.011 |
| t-stat | (-2.520) | (-2.250) | (0.070) | (0.150) | (4.610) | (-3.740) | (3.030) | (-3.650) | (5.430) |
| **C: Rolling window_dependent** | | | | | | | | | |
| Diff | -0.113 | -0.613 | 0.000 | 0.001 | 0.005 | -0.392 | 0.031 | -0.387 | 0.011 |
| t-stat | (-5.910) | (-4.660) | (0.350) | (0.390) | (6.540) | (-5.340) | (2.730) | (-5.440) | (4.150) |
| N | 369 | 369 | 369 | 369 | 369 | 369 | 369 | 369 | 369 |

**Table G3**
**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 portfolios M1 (the lowest accumulated returns) to M10 (the highest accumulated returns) by equally weighting the stocks for herding and non-herding firms, which are classified by the slope coefficient of the equation (38) 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. The macro uncertainty measure is $\text{VIX}_t$. Newey-West adjusted t-statistics are reported in parentheses. The sample spans from Jan. 1985 to Dec. 2021.

**Panel A: By negative and positive coefficients**

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | M10-M1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio returns | | | | | | | | | | | |
| Herd | -0.40 | 0.43 | 0.52 | 1.18 | 0.48 | 1.01 | 0.95 | 1.09 | 1.10 | 1.60 | 2.00 |
| t-stat | | | | | | | | | | | (3.03) |
| Non-herd | 0.64 | 1.04 | 0.72 | 0.83 | 1.01 | 1.06 | 0.98 | 0.87 | 1.16 | 1.09 | 0.45 |
| t-stat | | | | | | | | | | | (0.86) |
| Diff. | | | | | | | | | | | 1.55 |
| t-stat | | | | | | | | | | | (2.28) |
| FF 3-factor adjusted portfolio returns | | | | | | | | | | | |
| Herd | -1.91 | -0.68 | -0.53 | 0.41 | -0.31 | 0.03 | 0.13 | 0.23 | 0.21 | 0.58 | 2.49 |
| t-stat | | | | | | | | | | | (4.21) |
| Non-herd | -0.75 | -0.34 | -0.42 | -0.26 | -0.18 | 0.21 | 0.19 | -0.16 | 0.10 | 0.08 | 0.83 |
| t-stat | | | | | | | | | | | (1.65) |
| Diff. | | | | | | | | | | | 1.66 |
| t-stat | | | | | | | | | | | (2.63) |

**Panel B: By coefficient deciles**

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | M10-M1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio returns | | | | | | | | | | | |
| herd | -0.38 | 0.04 | 0.29 | 0.96 | 0.75 | 1.12 | 0.73 | 0.46 | 1.32 | 2.01 | 2.39 |
| t-stat | | | | | | | | | | | (3.20) |
| non-herd | 1.47 | 0.62 | 1.31 | 0.79 | 1.05 | 1.05 | 1.10 | 1.25 | 1.38 | 0.87 | -0.60 |
| t-stat | | | | | | | | | | | (-1.12) |
| diff | | | | | | | | | | | 2.99 |
| t-stat | | | | | | | | | | | (3.20) |
| FF 3-factor adjusted portfolio returns | | | | | | | | | | | |
| Herd | -2.05 | -1.19 | -1.18 | -0.21 | -0.16 | -0.06 | -0.40 | -0.47 | 0.26 | 0.70 | 2.75 |
| t-stat | | | | | | | | | | | (3.64) |
| Non-herd | 0.00 | -0.57 | -0.14 | -0.81 | -0.40 | 0.19 | 0.22 | -0.33 | -0.41 | -0.03 | -0.03 |
| t-stat | | | | | | | | | | | (-0.46) |
| Diff | | | | | | | | | | | 2.78 |
| t-stat | | | | | | | | | | | (3.15) |

**Table G4**
**Herding and predictability: portfolio analysis**

Panel A presents the means and t-statistics of the excess returns (in percentage) and the bench-mark 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 (38) 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 bench-mark 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. The macro uncertainty measure is $\text{VIX}_t$. Newey-West adjusted t-statistics are reported in parentheses The sample spans from Jan. 1985 to Dec. 2021.

| **A: Benchmark adjusted returns** | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Non-herd | Herd | Long - Short | Non-herd | Herd | Long - Short |
| Excess return | 0.96 | 0.67 | 0.29 | 1.08 | 0.57 | 0.52 |
| t-stat | (3.36) | (2.54) | (2.53) | (2.77) | (1.67) | (2.44) |
| CAPM adj return | 0.10 | -0.11 | 0.21 | -0.01 | -0.38 | 0.37 |
| t-stat | (0.76) | (-0.86) | (1.82) | (-0.03) | (-1.99) | (1.97) |
| FF 3-factor adj return | 0.01 | -0.17 | 0.19 | -0.07 | -0.43 | 0.35 |
| t-stat | (0.17) | (-1.86) | (1.65) | (-0.44) | (-2.83) | (1.69) |
| FF 5-factor adj return | 0.01 | -0.22 | 0.23 | 0.09 | -0.35 | 0.44 |
| t-stat | (0.13) | (-2.26) | (1.93) | (0.53) | (-2.28) | (2.03) |
| **B: Factor models** | | | | | | |
| $\alpha_t$ | 0.21 | 0.19 | 0.23 | 0.37 | 0.35 | 0.44 |
| t-stat | (1.71) | (1.65) | (1.93) | (1.97) | (1.69) | (2.03) |
| $\text{Mkt}_t$ | 0.11 | 0.11 | 0.10 | 0.19 | 0.16 | 0.13 |
| t-stat | (2.36) | (1.79) | (1.68) | (2.00) | (1.65) | (1.79) |
| $\text{SMB}_t$ | | 0.04 | 0.00 | | 0.19 | 0.16 |
| t-stat | | (0.82) | (0.07) | | (1.09) | (1.64) |
| $\text{HML}_t$ | | 0.08 | 0.09 | | 0.07 | 0.15 |
| t-stat | | (1.20) | (0.91) | | (0.60) | (1.05) |
| $\text{RMW}_t$ | | | -0.11 | | | -0.11 |
| t-stat | | | (-1.12) | | | (-1.17) |
| $\text{CMA}_t$ | | | 0.05 | | | -0.14 |
| t-stat | | | (0.62) | | | ( -0.88) |
| N | 369 | 369 | 369 | 369 | 369 | 369 |
| Adj $R^2$ | 4.44% | 5.66% | 6.47% | 3.73% | 5.53% | 5.55% |

## Table G5
## 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 (38) 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. 2021.

| | $mv_{i,t}$ | $age_{i,t}$ | $vol_{i,t}$ | $bm_{i,t}$ | $cvol_{i,t}$ | $cov_{i,t}$ | $disp_{i,t}$ | $num_{i,t}$ | $u_{i,t}^{com}$ |
|---|---|---|---|---|---|---|---|---|---|
| **A: Whole sample by the firm** | | | | | | | | | |
| Herd | 6.00 | 13.81 | 0.04 | 0.68 | 0.14 | 6.75 | 0.43 | 5.70 | 0.65 |
| N | 4269 | 4269 | 4269 | 1525 | 1094 | 4091 | 4269 | 4269 | 4269 |
| Non-Herd | 6.61 | 17.61 | 0.03 | 0.68 | 0.12 | 7.91 | 0.29 | 6.61 | 0.59 |
| N | 5169 | 5169 | 5169 | 1307 | 889 | 5025 | 5169 | 5169 | 5169 |
| Diff. | -0.61 | -3.90 | 0.00 | 0.00 | 0.02 | -1.16 | 0.14 | -0.91 | 0.05 |
| t-stat | (-2.58) | (-5.13) | (2.60) | (-0.11) | (3.20) | (-1.90) | (2.41) | (-1.89) | (3.46) |
| **B: Rolling window_independent** | | | | | | | | | |
| Herd | 6.848 | 18.909 | 0.027 | 0.526 | 0.083 | 11.572 | 0.186 | 9.570 | 0.514 |
| Non-Herd | 6.920 | 20.844 | 0.026 | 0.535 | 0.076 | 11.745 | 0.167 | 9.952 | 0.502 |
| Diff. | -0.073 | -1.935 | 0.001 | -0.009 | 0.007 | -0.173 | 0.019 | -0.381 | 0.012 |
| t-stat | (-1.850) | (-3.850) | (1.400) | (-1.450) | (5.740) | (-1.720) | (2.410) | (-2.080) | (4.520) |
| **C: Rolling window_dependent** | | | | | | | | | |
| Diff. | -0.073 | -0.957 | 0.001 | -0.009 | 0.006 | -0.173 | 0.019 | -0.201 | 0.012 |
| t-stat | (-4.030) | (-8.300) | (2.490) | (-3.200) | (8.500) | (-2.490) | (1.590) | (-3.100) | (3.890) |
| N | 433 | 433 | 433 | 433 | 433 | 433 | 433 | 433 | 433 |

## Table G6
## Herding and momentum: portfolio analysis

The table reports the average returns in month $t+1$ (in percentage) of portfolio M1 to M10 and the trading strategy of longing M10 and shorting M1 for ten groups of firms, H1 to H10. In each month $t$, we independently sort stocks based on the accumulated return from month $t-11$ to $t-1$, and coef_$U^m_{i,t}$, the slope coefficient of regressing the analysts forecast dispersion on the macroeconomic uncertainty over the past 24-month rolling window up to month $t$ respectively, and form the portfolios by equally weighting the stocks. M1 (M10) is the portfolio with the lowest (highest) past return while H1 (H10) is the one with the lowest (highest) coefficients. Newey-West t-statistics are given in parentheses. The sample spans from Jan. 1985 to Dec. 2021.

| | coef_$U^m$ | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | M10 - M1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| H1 | -0.99 | 0.14 | 0.38 | 0.48 | 0.45 | 0.66 | 0.95 | 1.01 | 0.89 | 1.18 | 2.02 | 1.88 |
| | | | | | | | | | | | | (3.88) |
| H2 | -0.11 | 0.44 | 0.42 | 0.84 | 0.76 | 0.79 | 0.40 | 0.61 | 0.50 | 0.76 | 1.40 | 0.96 |
| | | | | | | | | | | | | (1.85) |
| H3 | -0.04 | 0.41 | 0.31 | 0.74 | 0.85 | 0.29 | 0.63 | 0.79 | 0.66 | 0.80 | 0.99 | 0.57 |
| | | | | | | | | | | | | (1.22) |
| H4 | -0.02 | 0.41 | 0.71 | 0.87 | 0.69 | 0.84 | 0.73 | 0.72 | 1.08 | 1.07 | 1.20 | 0.79 |
| | | | | | | | | | | | | (1.49) |
| H5 | -0.01 | 0.41 | 0.80 | 0.84 | 0.72 | 0.77 | 0.49 | 0.87 | 0.82 | 0.78 | 1.06 | 0.65 |
| | | | | | | | | | | | | (1.27) |
| H6 | 0.00 | 0.61 | 0.91 | 0.68 | 0.60 | 0.73 | 0.81 | 0.87 | 0.85 | 0.94 | 0.90 | 0.28 |
| | | | | | | | | | | | | (0.58) |
| H7 | 0.02 | 0.25 | 0.95 | 0.60 | 0.91 | 0.78 | 0.83 | 0.85 | 1.18 | 0.86 | 1.14 | 0.89 |
| | | | | | | | | | | | | (1.79) |
| H8 | 0.04 | 0.24 | 0.46 | 0.94 | 0.92 | 0.96 | 0.81 | 0.92 | 0.76 | 1.07 | 1.07 | 0.83 |
| | | | | | | | | | | | | (1.87) |
| H9 | 0.10 | 0.68 | 0.77 | 0.80 | 1.02 | 0.74 | 0.62 | 0.60 | 0.87 | 1.11 | 1.06 | 0.38 |
| | | | | | | | | | | | | (0.74) |
| H10 | 1.06 | 0.42 | 0.57 | 0.86 | 0.35 | 0.73 | 1.15 | 1.47 | 1.10 | 0.94 | 1.05 | 0.63 |
| | | | | | | | | | | | | (1.32) |
| H1-H10 | | | | | | | | | | | | 1.24 |
| | | | | | | | | | | | | (2.55) |

**Table G7**
**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, and $u_{i,t}$ is one of the firm-level uncertainty measures: $mv_{i,t}$, 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; $cov_{i,t}$, the number of analysts covering firm $i$ at the last fiscal year end; $disp_{i,t}$, the cross-sectional standard deviation of analyst forecasts scaled by the absolute value of the cross-sectional mean; $num_{i,t}$, the number of earning estimations for firm $i$ in month $t$. Newey-West t-statistics are given in parentheses. The sample spans from Jan. 1985 to Dec. 2021.

| | $mv_{i,t}$ | $age_{i,t}$ | $vol_{i,t}$ | $bm_{i,t}$ | $cvol_{i,t}$ | $cov_{i,t}$ | $disp_{i,t}$ | $num_{i,t}$ |
|---|---|---|---|---|---|---|---|---|
| Intercept | 0.977 | 0.922 | 1.167 | 0.884 | 0.925 | 0.946 | 0.985 | 0.981 |
| t-stat | (3.800) | (3.210) | (5.630) | (3.260) | (3.870) | (3.600) | (3.960) | (3.640) |
| $acret_{i,t}$ | 0.382 | 0.600 | 0.470 | 0.319 | 0.275 | 0.280 | 0.333 | 0.389 |
| t-stat | (1.840) | (3.150) | (1.670) | (1.520) | (1.090) | (1.430) | (1.590) | (2.040) |
| $herd_{i,t}$ | -0.158 | -0.148 | -0.141 | -0.109 | -0.120 | -0.140 | -0.151 | -0.144 |
| t-stat | (-3.170) | (-3.080) | (-3.300) | (-2.300) | (-2.540) | (-2.800) | (-3.020) | (-2.920) |
| $acret_herd_{i,t}$ | 0.174 | 0.165 | 0.148 | 0.103 | 0.230 | 0.181 | 0.174 | 0.179 |
| t-stat | (1.830) | (1.820) | (1.630) | (1.730) | (2.000) | (1.870) | (1.670) | (1.850) |
| $u_{i,t}$ | 0.002 | 0.002 | -12.522 | -0.055 | -0.264 | 0.002 | -0.091 | -0.002 |
| t-stat | (0.420) | (0.760) | (-1.360) | (-0.410) | (-0.400) | (0.350) | (-1.830) | (-0.330) |
| $acret_u_{i,t}$ | -0.006 | -0.014 | 1.282 | 0.213 | 0.388 | 0.009 | 0.172 | 0.000 |
| t-stat | (-0.530) | (-3.010) | (0.210) | (1.090) | (0.620) | (0.940) | (1.740) | (-0.030) |
| N | 1921 | 1921 | 1921 | 1845 | 1363 | 1918 | 1921 | 1921 |
| Adj $R^2$ | 1.930% | 2.408% | 4.572% | 2.569% | 2.913% | 2.392% | 1.856% | 2.400% |

## Table G8
## Herding and momentum: portfolio analysis

The table reports the average returns in month $t+1$ (in percentage) of portfolio S1 to S10 and the trading strategy of longing S10 and shorting S1 for ten groups of firms, H1 to H10. In each month $t$, we independently sort stocks into deciles based on standardized unexpected earnings ($\text{SUE}_{i,t}$), and $\text{coef_}U^m_{i,t}$, the slope coefficient of regressing the analysts forecast dispersion on the macroeconomic uncertainty over the past 24-month rolling window up to month $t$ respectively, and form portfolios by equally weighting the stocks. S1 (S10) is the portfolio with the lowest (highest) $\text{SUE}_{i,t}$ while H1 (H10) is the one with the lowest (highest) coefficients. Newey-West t-statistics are given in parentheses. The sample spans from Jan. 1985 to Dec. 2021.

| | $\text{coef_}U^m$ | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S10 - S1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| H1 | -0.82 | 0.58 | 0.88 | 0.56 | 0.80 | 0.51 | 1.02 | 1.19 | 0.85 | 1.15 | 1.39 | 0.81 |
| | | | | | | | | | | | | (2.49) |
| H2 | -0.06 | 0.73 | 0.78 | 0.95 | 0.80 | 1.05 | 0.93 | 0.94 | 1.12 | 0.98 | 1.63 | 0.90 |
| | | | | | | | | | | | | (3.77) |
| H3 | -0.02 | 0.86 | 0.92 | 0.88 | 0.74 | 0.90 | 0.95 | 1.12 | 1.13 | 1.15 | 1.38 | 0.52 |
| | | | | | | | | | | | | (2.10) |
| H4 | -0.01 | 0.87 | 0.98 | 1.06 | 1.10 | 1.06 | 0.99 | 1.10 | 1.26 | 1.37 | 1.44 | 0.57 |
| | | | | | | | | | | | | (2.49) |
| H5 | -0.00 | 0.68 | 1.02 | 0.99 | 1.10 | 1.03 | 1.17 | 1.11 | 1.24 | 1.36 | 1.22 | 0.54 |
| | | | | | | | | | | | | (2.06) |
| H6 | 0.00 | 1.13 | 1.08 | 1.10 | 1.16 | 1.10 | 1.15 | 1.21 | 1.38 | 1.14 | 1.53 | 0.40 |
| | | | | | | | | | | | | (2.31) |
| H7 | 0.01 | 0.97 | 1.18 | 1.14 | 1.32 | 1.18 | 1.27 | 1.26 | 1.19 | 1.31 | 1.37 | 0.40 |
| | | | | | | | | | | | | (2.00) |
| H8 | 0.02 | 1.02 | 0.84 | 1.31 | 1.22 | 1.19 | 1.20 | 1.28 | 1.32 | 1.40 | 1.38 | 0.36 |
| | | | | | | | | | | | | (1.74) |
| H9 | 0.05 | 1.05 | 0.94 | 1.18 | 1.10 | 1.41 | 1.02 | 1.27 | 1.53 | 1.44 | 1.42 | 0.37 |
| | | | | | | | | | | | | (1.59) |
| H10 | 0.89 | 0.91 | 1.14 | 0.81 | 1.04 | 1.33 | 1.14 | 1.32 | 1.30 | 1.25 | 1.35 | 0.44 |
| | | | | | | | | | | | | (1.56) |
| H1-H10 | | | | | | | | | | | | 0.37 |
| | | | | | | | | | | | | (1.94) |

**Table G9**
**Herding and predictability: with idiosyncratic volatility**

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

$$ret_{i,t+1} = e + f * herd_{i,t} + g * ivol_{i,t} + h * herd_{i,t} * ivol_{i,t} + i * control_{i,t} + \epsilon_{i,t},$$

where $ret_{i,t+1}$ is the return for firm $i$ in month $t+1$, $ivol_{i,t}$ 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, $herd_{i,t}$ equals one (zero) with the negative (positive) slope coefficient of regressing the analysts forecast dispersion on the macroeconomic uncertainty over the past 24-month rolling window up to month $t$, 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. 2021.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intercept | 1.302 | 1.253 | 1.307 | 1.238 | 1.259 | 1.332 |
| t-stat | (5.800) | (5.520) | (5.790) | (5.510) | (5.550) | (5.780) |
| $herd_{i,t}$ | -0.109 | | -0.114 | 0.033 | | -0.118 |
| t-stat | (-2.400) | | (-2.510) | (0.430) | | (-1.760) |
| $ivol_{i,t}$ | | -0.140 | -0.135 | | -0.118 | -0.153 |
| t-stat | | (-3.640) | (-3.620) | | (-2.960) | (-3.440) |
| $herd * ivol_{i,t}$ | | | | -0.081 | -0.041 | 0.016 |
| t-stat | | | | (-2.470) | (-1.850) | (0.400) |
| Control | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1,353 | 1,353 | 1,353 | 1,353 | 1,353 | 1,353 |
| Adj $R^2$ | 4.796% | 4.934% | 4.997% | 4.906% | 5.033% | 5.064% |

**Table G10**
**Herding and predictability: with analyst forecasts dispersion**

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

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

where $ret_{i,t+1}$ is the return for firm $i$ in month $t+1$, $disp_{i,t}$ is the analysts' forecast dispersion, $herd_{i,t}$ equals one (zero) with the negative (positive) coefficient of regressing the analysts forecast dispersion on the macroeconomic uncertainty over the past 24-month rolling window up to month $t$, 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. 2021.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intercept | 1.302 | 1.227 | 1.281 | 1.276 | 1.235 | 1.278 |
| t-stat | (5.800) | (5.450) | (5.710) | (5.680) | (5.480) | (5.690) |
| $herd_{i,t}$ | -0.109 | | -0.119 | -0.086 | | -0.100 |
| t-stat | (-2.400) | | (-3.820) | (-1.820) | | (-2.150) |
| $disp_{i,t}$ | | -0.120 | -0.110 | | -0.076 | -0.122 |
| t-stat | | (-3.840) | (-2.450) | | (-0.730) | (-1.150) |
| $herd_disp_{i,t}$ | | | | -0.281 | -0.265 | -0.161 |
| t-stat | | | | (-2.140) | (-1.620) | (-0.980) |
| Control | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1353 | 1353 | 1353 | 1353 | 1353 | 1353 |
| Adj $R^2$ | 4.796% | 4.829% | 4.891% | 4.873% | 4.893% | 4.950% |

**Table G11**
**Macroeconomic uncertainty coefficient, market beta and uncertainty beta**

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

$$ret_{i,t+1} = o + p * herd_{i,t} + q * \text{coef_}U^m_{i,t} + r * \beta^{mkt}_{i,t} + s * \beta^U_{i,t} + t * control_{i,t} + \epsilon_{i,t},$$

where $ret_{i,t+1}$ is the return for firm $i$ in month $t$+1, $\beta^{mkt}_{i,t}$ is the coefficient of the market factor in the Fama-French 3-factor model, $\beta^U_{i,t}$ 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, $herd_{i,t}$ equals one (zero) with the negative (positive) slope coefficient, coef_$U^m_{i,t}$, of regressing the analysts forecast dispersion on the macroeconomic uncertainty over the past 24-month rolling window up to month $t$, 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. 2021.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intercept | 1.302 | 1.250 | 1.181 | 1.178 | 1.248 | 1.202 |
| t-stat | (5.790) | (5.540) | (5.350) | (5.250) | (5.750) | (5.520) |
| $herd_{i,t}$ | -0.109 | | | | -0.095 | |
| t-stat | (-2.400) | | | | (-2.130) | |
| coef_$U^m_{i,t}$ | | 6.497 | | | | 7.249 |
| t-stat | | (1.820) | | | | (2.050) |
| $\beta^{mkt}_{i,t}$ | | | 0.035 | | 0.029 | 0.031 |
| t-stat | | | (0.570) | | (0.460) | (0.490) |
| $\beta^U_{i,t}$ | | | | 0.001 | 0.000 | 0.000 |
| t-stat | | | | (0.280) | (0.200) | (0.180) |
| control | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1353 | 1353 | 1353 | 1353 | 1353 | 1353 |
| Adj $R^2$ | 4.796% | 4.802% | 5.279% | 5.266% | 5.770% | 5.783% |

## Table G12
## Herding and anomalies

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). $NOA_{i,t}$, 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). $ITA_{i,t}$, 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). $ROA_{i,t}$, 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:

$$ret_{i,t+1} = u + v * herd_{i,t} + w * anml_{i,t} + x * anml_{i,t} * herd_{i,t} + \epsilon_{i,t},$$

where $ret_{i,t+1}$ is the return for firm $i$ in month $t+1$ 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. 2021.

| **A: Anomalies** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Herd | 0.17 | -1832.09 | 0.15 | 0.62 | 0.31 | 0.07 | 0.20 | 0.09 | 0.76 |
| Non_herd | 0.16 | -1919.46 | 0.11 | 0.60 | 0.31 | 0.06 | 0.19 | 0.09 | 0.91 |
| Diff | 0.01 | 87.37 | 0.04 | 0.02 | 0.00 | 0.00 | 0.02 | 0.01 | -0.15 |
| t-stat | (1.72) | (2.80) | (3.91) | (6.73) | (0.54) | (3.75) | (6.44) | (4.16) | (-6.40) |
| **B: Herding and anomalies** | | | | | | | | | |
| Intercept | 0.97 | 1.07 | 1.09 | 1.30 | 0.85 | 1.13 | 1.12 | 1.13 | 0.95 |
| t-stat | (3.86) | (3.73) | (4.11) | (4.88) | (3.21) | (4.21) | (4.26) | (4.18) | (3.53) |
| $herd_{i,t}$ | -0.16 | -0.13 | -0.12 | -0.07 | -0.06 | -0.10 | -0.12 | -0.11 | -0.09 |
| t-stat | (-3.11) | (-2.59) | (-2.30) | (-0.84) | (-0.82) | (-1.84) | (-2.27) | (-2.23) | (-1.78) |
| $anml_{i,t}$ | 0.37 | 0.00 | -0.35 | -0.38 | 0.70 | -0.66 | -0.34 | -0.59 | 9.71 |
| t-stat | (1.78) | (-0.01) | (-2.79) | (-3.54) | (3.72) | (-1.89) | (-3.39) | (-2.49) | (7.19) |
| $anml_herd_{i,t}$ | 0.17 | 0.00 | 0.26 | -0.06 | -0.19 | -0.64 | 0.06 | -0.35 | -0.66 |
| t-stat | (1.75) | (-0.65) | (1.93) | (-0.57) | (-1.37) | (-1.66) | (0.60) | (-1.59) | (-0.58) |
| N | 1921 | 1513 | 1846 | 1655 | 1845 | 1453 | 1843 | 1600 | 1843 |
| Adj $R^2$ | 1.66% | 0.42% | 0.37% | 0.50% | 0.77% | 0.38% | 0.59% | 0.45% | 0.86% |