Hide in the Herd: Uncertainty and Informational Inefficiency*

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

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

March 2026

*We thank Jeffrey Callen, Jie Jay Cao, Yuting Chen, Ramy Elitzur, Bing Han, Gady Jacoby, Yifei Li, Jiatao Liu, Robinson Reyes Pena, Mehrdad Samadi, Albert Tsang, Pengfei Wang, John Wei, Jianfeng Yu and seminar participants at 2023 FMA annual meeting, the 19th Chinese Finance Annual Meeting, the 4th PHBS-CUHKSZ workshop, the 29th MFS annual conference, the 16th ABF&E annual meeting and Nanjing University, Renmin University of China, Texas Tech University, The Chinese University of Hong Kong, Shenzhen, The Hong Kong Polytechnic University, The University of Macau, Tongji University, Tsinghua University, Xi'an Jiaotong-Liverpool University.

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

‡Department of Finance and Business Economics, Faculty of Business Administration, 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.

Hide in the Herd: Uncertainty and Informational Inefficiency

ABSTRACT

We uncover a negative relationship between macroeconomic uncertainty and analysts' earnings forecast dispersion, driven by herding behavior that prioritizes consensus over accuracy. This convergence transmits noisier signals and contributes to informational inefficiencies. Controlling for firm characteristics, we show that "herding firms", those whose forecast dispersion falls when aggregated uncertainty rises, exhibit higher firm-level uncertainty, less informative stock prices, greater overpricing, and lower subsequent returns. By linking macro-level uncertainty to micro-level forecasting behavior, our study highlights a behavioral transmission channel through which uncertainty amplifies psychological biases and distorts information processing, offering new insight into how uncertainty affects market efficiency.

JEL Classification: G12, G14, D8, G41

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

I. Introduction

Uncertainty shocks constitute an active area of research in modern macroeconomics, with important implications for economic fluctuations, investment decisions, and policy transmission (e.g., Bloom (2009); Basu and Bundick (2017); Leduc and Liu (2016)). Recent work by Kozeniauskas et al. (2018) argues that macro- and micro-level uncertainty are conceptually distinct and need not comove positively. We extend this macro–micro perspective to asset pricing by showing that aggregate (macro-level) uncertainty operates through security analysts' strategic conformity (herding), which compresses the cross-sectional dispersion of earnings forecasts (micro-level), thereby generating a negative macro–micro correlation, lowering the precision of the consensus signal, and reducing stock-price informativeness.

The literature has traditionally interpreted uncertainty's impact on asset pricing through efficient risk-compensation mechanisms.[1] These frameworks, often assuming frictionless information aggregation, imply that prices adjust efficiently to reflect heightened uncertainty. However, the persistence of return anomalies—such as momentum, post earnings announcement drift, and broader predictability—challenges this view and signals systematic departures from informational efficiency, consistent with Grossman and Stiglitz (1980).[2] Related evidence further indicates that heightened uncertainty amplifies information frictions—raising asset-price volatility, making the pass-through from announcements to longer-maturity yields more state-dependent, and dampening the macroeconomic an-

[1]Classical risk-based asset-pricing models interpret uncertainty's effect on prices through efficient compensation for priced risk exposures—e.g., the CAPM (Sharpe, 1964), APT (Ross, 1976), ICAPM (Merton, 1973), and consumption-based frameworks (Lucas, 1978; Hansen and Singleton, 1982). Subsequent work embeds time-varying risk premia that rise in high-uncertainty states via habit formation and long-run risks (Campbell and Cochrane, 1999; Bansal and Yaron, 2004; Bansal and Shaliastovich, 2013), and examines policy uncertainty as a priced risk (Pastor and Veronesi, 2012). See also Mehra and Prescott (1985) for the equity-premium benchmark within the risk-compensation paradigm.

[2]Influential evidence of these anomalies includes: (i) momentum: Jegadeesh and Titman (1993); (ii) post-earnings-announcement drift (PEAD): Bernard and Thomas (1989); (iii) broader predictability via valuation ratios and long-horizon returns: Campbell and Shiller (1988); Fama and French (1988); and (iv) a gradual-information-diffusion mechanism consistent with these patterns: Hong and Stein (1999).

nouncement premium when the information environment is noisier (e.g., De Pooter et al. (2020); Swanson (2021); Zhang and Zhao (2023); Aquilina et al. (2024)). In this paper, we aim to complement the risk-based asset-pricing literature by highlighting a behavioral transmission channel through which macroeconomic uncertainty distorts information processing and impairs market efficiency.

Empirically, we proxy macro uncertainty with the U.S. Economic Policy Uncertainty (EPU) index of Baker et al. (2016). We adopt EPU for two reasons. First, as a news-based measure, EPU offers a broad gauge of investors' perceived macro uncertainty spanning capital-market conditions and real-economy decision making (e.g., Gulen and Ion (2016); Nagar et al. (2019); Kaviani et al. (2020); Zhang and Zhou (2023)). Second, its daily frequency aligns closely with the timing of analysts' forecast updates in the Institutional Brokers' Estimate System (IBES), which we use to construct our analyst-dispersion variable. Following the literature, analyst forecast dispersion is defined as the cross-sectional standard deviation of individual analysts' EPS forecasts for the current fiscal year in month t, scaled by the absolute value of the cross-sectional mean forecast (e.g., Diether et al. (2002)).[3] Our sample spans 1985–2024 and combines IBES, CRSP, and Compustat databases.

To study whether analyst herding generates firm-level information inefficiency, we examine how aggregate (macro) uncertainty co-moves with the cross-sectional dispersion of analysts' earnings forecasts (micro). A conventional view holds that macro- and micro-level uncertainty tend to rise together—i.e., higher aggregate uncertainty is associated with greater disagreement and volatility (e.g., Bloom (2009); Bachmann et al. (2013); Jurado et al. (2015); Zarnowitz and Lambros (1987)). Meanwhile, the herding literature suggests that when aggregate uncertainty and career or reputational concerns intensify, analysts shade their forecasts toward the consensus (e.g., Trueman, 1994; Welch, 2000; Hong et al., 2000; Clement and Tse, 2005; Jegadeesh and Kim, 2010). Guided by this

[3] All results are robust to alternative macro-uncertainty proxies, notably the VIX. Key findings with VIX are reported in Tables H2–H4 of Internet Appendix H.

mechanism, we identify firm–month episodes of herding by the sign of the time-varying relation between macro uncertainty and analyst-forecast dispersion.

Specifically, for each firm i and month t, we estimate a rolling 24-month regression, $\text{disp}_{i,\tau} = a_i + b_{i,t}U^m_\tau + \varepsilon_{i,\tau}$ for $\tau \in [t-23, t]$, and classify firm i in month t as a *herding firm* if $b_{i,t} < 0$ (*non-herding* otherwise). This firm-by-month, sign-based scheme reveals widespread cases in which dispersion falls as macro uncertainty rises, indicating a time-varying, firm-specific co-movement and motivating our subsequent firm-level tests of information transmission and price discovery.

Using this classification, we proceed by stating the tests and main results at the firm level. First, we show that *herding firms*—firms classified with negative rolling slopes $b_{i,t}$—are systematically associated with a poorer information environment: relative to non-herding firms, they are smaller and younger, receive fewer estimates and lower *analyst* coverage, and display higher cash-flow and return volatility (e.g., Zhang (2006)); in probits, both individual proxies and a composite firm-level information uncertainty index significantly predict a firm being classified as herding.

Second, we show that stocks of herding firms exhibit stronger monthly return continuity—in both momentum and post-earnings-announcement drift—relative to non-herding firms, a pattern consistent with lower price informativeness. A standard momentum strategy (long past winners, short past losers) earns 1.79%/month among herding firms versus 0.34%/month among non-herding firms (benchmarking price-delay via momentum: e.g., Jegadeesh and Titman, 1993; Chan et al., 1996), and post-earnings-announcement drift (PEAD) (long positive-surprise, short negative-surprise firms) is 0.65%/month versus 0.08%/month (benchmarking delayed incorporation of fundamentals: e.g., Bernard and Thomas, 1989; Sloan, 1996). These gaps remain after factor adjustments and in Fama–MacBeth regressions with firm-level uncertainty controls, where interaction terms linking return continuation to the herding classification are positive and significant.

Third, we find that stocks of herding firms earn lower next-month returns than those of non-herding firms, a pattern consistent with overpricing and lower subsequent returns for herding firms. A long–short portfolio that buys non-herding firms and sells herding firms delivers 0.28%–0.39%/month; the corresponding alphas are positive and statistically significant under the CAPM as well as the Fama–French three- and five-factor models. In cross-sectional (Fama–MacBeth) regressions, a firm-month herding indicator predicts lower next-month returns. The coefficient remains negative and significant after controlling for idiosyncratic volatility (Ang et al., 2006), the level of analyst dispersion (Diether et al., 2002), and an uncertainty beta (Bali et al., 2017), and standard characteristics (size, value, momentum, profitability, investment); moreover, it is not subsumed by nine widely studied return predictors—momentum (Jegadeesh and Titman, 1993), financial distress (O-score) (Ohlson, 1980), net stock issuance (Stambaugh et al., 2012), net operating assets (Hirshleifer et al., 2004), gross profitability (Novy-Marx, 2013), total accruals (Sloan, 1996), asset growth (Cooper et al., 2008), investment-to-assets (Titman et al., 2004), and return on assets (Fama and French, 2006).

To explain the empirical findings, we develope a parsimonious theoretical framework inspired by Keynes (1936)'s "beauty contest" analogy, where participants aim to forecast the average opinion—because prices are driven by what others think others will think, and professional payoffs reward conformity over independent accuracy. In our model, analysts observe a public and a private signal about earnings and choose forecasts that trade off accuracy against conformity to the consensus. As macro uncertainty rises, the weight on conformity increases, compressing forecast dispersion and lowering the precision of the consensus signal that investors use to set prices.

The model yields three implications that align with our empirical evidence: (i) Firms classified as *herding* (negative uncertainty–dispersion slope) tend to operate in poorer information environments, because when forecasting is harder, analysts optimally place more weight on matching the consensus, making dispersion fall as macro uncertainty increases; (ii) lower consensus precision makes prices less informative and produces stronger return continuity: with a noisier consensus, initial price moves underreact to news so some of the shock carries forward (momentum), and if a fraction of investors adjusts gradually at earnings dates, part of the surprise is incorporated only afterward (PEAD); both effects intensify for herding firms as conformity rises; and (iii) under short-sale constraints, a noisier consensus widens the dispersion of perceived valuations and, with pessimists unable to efficiently short, shifts pricing to the optimistic tail above fundamentals; consequently, herding firms are more overpriced and earn lower subsequent returns, and a long–non-herding/short–herding portfolio earns a positive average return. In this sense, although herding is not the sole source of market inefficiency, it is a behavioral distortion that worsens the effects of existing informational frictions.

Herding is the behavioral wedge in the model that links the negative uncertainty and dispersion relation to less informative prices, thereby rationalizing the stronger return continuity and lower subsequent returns for herding firms. By contrast, a purely information-driven (Bayesian) re-weighting—where noisier fundamentals simply shifts weight toward public signals—may reduce dispersion in special cases but preserves efficient aggregation of available information and thus *does not* produce the joint patterns of stronger momentum, larger PEAD, and systematically lower subsequent returns that we empirically document (as we show formally in the theory). We therefore model strategic conformity as the mechanism through which higher macro uncertainty tightens forecasts, degrades the consensus signal, and yields the return-based signatures of weaker price discovery.

We contribute to the literature in several related ways. *First*, we establish a cross sectional link between uncertainty and informational inefficiency mediated by analyst behavior: higher macro uncertainty induces strategic conformity (herding), which compresses forecast dispersion, lowers the precision of the consensus signal, and reduces price informativeness. *Second*, we uncover a behavioral macro–micro linkage: whereas macro and micro uncertainty often comove positively, we document that for a sizable subset of *herding firms* forecast dispersion declines when macro uncertainty rises—consistent with analysts optimally placing more weight on the consensus when firm-level uncertainty makes independent forecasting harder. *Third*, we shift herding from analyst traits to *firm-level determinants*, identifying which firms attract herding and linking that classification to weaker price discovery (stronger momentum and PEAD) and lower subsequent returns. *Finally*, we show that herding intensifies in high-uncertainty periods: to avoid personal blame, analysts strategically suppress disagreement, yielding less dispersed forecasts and a noisier consensus. This behavior distorts individual decision-making and impairs the market's aggregation of information, weakening price discovery. These findings underscore the importance of incorporating behavioral dynamics into asset-pricing models, particularly in uncertain environments.

The remainder of the paper proceeds as follows. Section 2 details the data and variable construction. Section 3 presents the empirical results. Section 4 develops the theoretical framework. Section 5 concludes.

II. Data

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

The firm-level uncertainty measures are: $mv_{i,t}$, the market capital for firm i by the end of month t; $age_{i,t}$, the number of years for firm i from the first month covered by

CRSP to month t; $vol_{i,t}$, firm i's daily return standard deviation over 12-month ending in month t; $bm_{i,t}$, book value of firm i's equity divided by its market value by the end of last fiscal year; $cvol_{i,t}$, the 5-year (ending at the last fiscal year) standard deviation of firm i's cash flow, scaled by the average total assets;[4] $cov_{i,t}$, 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.[5]

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; 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. $accruals_{i,t}$,

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

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

firm i's total accruals calculated as changes in noncash working capital minus depreciation expense scaled by average total assets for the previous two fiscal years. 10. $g\_asset_{i,t}$, firm i's asset growth measured as the growth rate of total assets in the previous fiscal year; 11. $\text{ITA}_{i,t}$, firm i's investment-to-assets measured as the annual change in gross property, plant, and equipment plus the annual change in inventories scaled by the lagged book value of assets. 12. $\text{ROA}_{i,t}$, firm i's return on asset of the last fiscal year with respect of month t.

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

Table 1 presents descriptive statistics of the macroeconomic uncertainty, analyst forecasts dispersion and other firm-level uncertainty variables, which can outline the main characteristics of the firms studied in our sample.[6] In order to compare U_t^m, the macroeconomic uncertainty, and the analysts' forecast dispersion, $disp_{i,t}$, at the similar scale, we divide the original EPU index by 100. The mean of $disp_{i,t}$ is 0.19 and the median is 0.04, indicating that unusually high dispersions are more likely to occur than the low ones. The statistics of the firm-level variables show that our sample has a wide range of coverage. The natural log of market value ranges from -1.24 to 15.04 corresponding to $288,562 to

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

\$3.39 billion. The firm age is from 1.9 to 99 years. The analysts coverage ranges from 2 to 65.

III. Empirical Results

A. Which firms herd? The information environment

We classify firm–months as *herding* or *non-herding* using the sign of a rolling slope that links macro uncertainty to analyst-forecast dispersion. For each firm i and month t, we estimate a 24-month rolling regression

$$\text{disp}_{i,\tau} \;=\; a_{i,t} \;+\; b_{i,t}\, U^m_\tau \;+\; \varepsilon_{i,\tau}, \qquad \tau \in [t-23,\, t], \tag{1}$$

and classify firm i in month t as *herding* if $b_{i,t} < 0$ (*non-herding* otherwise). We require at least ten observations per window; a conservative variant additionally requires $|t(b_{i,t})| \geq 1.65$. This sign-based scheme focuses on the *slope* rather than the *level* of dispersion, avoiding mechanical links between uncertainty and dispersion volatility.[7]

Table 2 provides three complementary views of the uncertainty–dispersion relation. *Panel A (pooled benchmark):* pooling all firm–months from 1985–2024 yields a significantly positive slope b, consistent with the conventional view that dispersion rises with macro uncertainty on average. *Panel B (firm-by-firm, whole-sample):* for each firm i, we run $\text{disp}_{i,t} = a_i + b_i U^m_t + \varepsilon_{i,t}$ over its full sample and report the cross-firm *means* of $\hat{b}_i$ and $t(\hat{b}_i)$ together with the *counts* of positive/negative (and significant) slopes; among 13,154 firms, 7,020 have $\hat{b}_i > 0$ and 6,134 have $\hat{b}_i < 0$, and restricting to $|t| \geq 1.65$, 1,852 of 5,290 are negative.[8] *Panel C (rolling windows):* across 1,140,673 firm–month windows, we report *counts* by sign (559,968 with $\hat{b}_{i,t} > 0$; 580,705 with $\hat{b}_{i,t} < 0$) and by significance (among $|t| \geq 1.65$, 137,244 of 326,122 are negative). Taken together, the pooled

[7]Equation (1) is intentionally bivariate to keep the classification transparent. We next relate the classification to firm characteristics (size, age, analyst coverage, number of estimates, cash-flow and return volatility, and a composite information-uncertainty index).

[8]Panel B is a static diagnostic of cross-sectional heterogeneity; the month-by-month classification used in the paper is based on the 24-month rolling specification in Equation (1).

average masks meaningful cross-sectional and time variation: negative comovement is common and time-varying, which motivates using the *sign of the rolling slope* to classify firm–months for the tests that follow.

Table 2 here

Figure 2 plots the macro-uncertainty series U_t^m together with the cross-sectional averages of dispersion for the groups formed each month by the rolling classification, $\text{Disp}_{\text{herd},t}$ and $\text{Disp}_{\text{non},t}$. Two patterns emerge. *First*, for herding firms, $\text{Disp}_{\text{herd},t}$ moves *negatively* with U_t^m: when macro uncertainty rises, their forecast dispersion compresses—i.e., the series is *pro-cyclical*. *Second*, for non-herding firms, $\text{Disp}_{\text{non},t}$ comoves *positively* with U_t^m and, like U_t^m itself, is *counter-cyclical* at business-cycle frequencies, in line with the pooled benchmark. Taken together, these series indicate that the negative uncertainty–dispersion relation is common in the cross-section yet concentrated among the firms identified as herding in a given month.[9]

Figure 2 here

We then compare firm-level information environment proxies between herding and non-herding groups using independent-samples t-tests under two complementary definitions.[10] *Panel A (firm-by-firm classification):* grouping firms by the sign of their full-sample slope shows statistically significant mean differences for seven of eight proxies; the composite index $u_{i,t}^{\text{com}}$ is highly significant ($t = 3.77$). In levels, herding firms tend to be smaller and younger, have lower analyst coverage and fewer estimates, display higher stock-return and cash-flow volatility, and exhibit more dispersed analyst opinions—consistent with a weaker information environment. *Panel B (rolling firm–month*

[9]This also cautions against using an unconditional aggregate of analyst-dispersion as a proxy for macro uncertainty: mixing herding and non-herding firms can attenuate or flip the sign of the relation. Conditioning on the monthly classification yields a cleaner dispersion-based proxy.

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

classification): using the same 24-month rolling classification from Equation (1), we run the t-tests in each month's cross-section and pool the results across time; the findings broadly mirror Panel A, with the exception that the mean differences in the levels of $\text{disp}_{i,t}$ and $\text{vol}_{i,t}$ are statistically insignificant. *Panel C (time-series of differences):* the month-t cross-sectional differences (herding minus non-herding) averaged over time confirm the Panel B results.

Although the composite measure $u^{\text{com}}_{i,t}$ is consistently higher for herding firms across all tests, two individual proxies warrant brief discussion. *First*, analyst-forecast dispersion reflects both firm-level uncertainty (which increases dispersion) and analyst behavior (herding compresses dispersion), making it a weak stand-alone indicator of firm-level uncertainty. *Second*, stock-return volatility can also move in opposite ways: underreaction (associated with higher uncertainty and conformity) can damp realized volatility even as fundamental uncertainty is high. These opposing forces explain the mixed results for these two individual measures.

Table 3 here

Next, We examine whether firm-level uncertainty proxies help explain which firms are classified as *herding* in a given month. Using the rolling-window classification in Equation (1), define the binary outcome

$$\text{herd}_{i,t} \;=\; \mathbf{1}\{\hat{b}_{i,t} < 0\}.$$

We estimate probit models of the form

$$\text{herd}^*_{i,t} \;=\; c \;+\; d'\,u_{i,t} \;+\; \varepsilon_{i,t}, \qquad \text{herd}_{i,t} \;=\; \mathbf{1}\{\text{herd}^*_{i,t} > 0\}, \tag{2}$$

where $u_{i,t}$ is either a single firm-level proxy (univariate specifications) or the full vector of proxies (multivariate specification).

Table 4 reports the results. The univariate probits are largely consistent with the differences-in-means in Table 3: proxies indicating a poorer information environment (smaller size, younger age, lower analyst coverage and fewer estimates, higher cash-flow and return volatility, greater opinion dispersion) are each associated with a higher probability that $\text{herd}_{i,t} = 1$. In the multivariate probit, the likelihood-ratio test yields a p-value below 0.01%, indicating that the set of proxies jointly has strong explanatory power for the probability of being classified as a herding firm in month t.

Table 4 here

In summary, analysts are more likely to herd when forecasting firms with poorer information environments, as cacaptured by higher firm-level uncertainty measures. These patterns are robust across classification choices and window lengths, and hold in both mean-comparison and probit specifications,

B. Return continuation: Evidence on price informativeness

Security analysts intermediate information between firms and investors. When analysts herd, forecasts converge toward the consensus, compressing dispersion and lowering the precision of the consensus signal; prices should then reflect fundamentals less accurately. We therefore ask whether *herding firms'* stock prices are less informative than those of *non-herding* firms.

We test this by examining *return continuity* along two standard dimensions of price delay: (i) momentum—the continuation of returns to past winners relative to losers; and (ii) post-earnings-announcement drift (PEAD)—the continuation of returns following earnings surprises.

First, we compare the momentum effect between *herding* and *non-herding* firms (momentum as a benchmark for price delay/return continuation: e.g., Jegadeesh and Titman, 1993; Chan et al., 1996; Jegadeesh and Titman, 2001; Hong and Stein, 1999; Hou and Moskowitz, 2005). In each month t, we sort stocks within each group into deciles based on cumulative returns from t–11 to t–1 and form ten value-weighted portfolios (M1–M10). Table 5 reports next-month (t+1) portfolio returns (Panel A) and Fama–French three-factor alphas (Panel B). The momentum spread is defined as M10–M1.

Returns rise monotonically from M1 to M10 in both groups, confirming momentum in our sample. Crucially, the M10–M1 spread is *larger* for herding firms than for non-herding firms, and the difference is statistically significant; this pattern persists after factor adjustments in Panel B. Consistent with the information-transmission channel, analyst conformity compresses dispersion and lowers the precision of the consensus signal, producing greater underreaction and hence stronger return continuation among herding firms.

Table 5 here

To assess whether analyst herding exacerbates informational inefficiency beyond firm-level uncertainty, we estimate monthly Fama–MacBeth regressions of next-month returns on past returns, the herding indicator, and their interactions with firm-level uncertainty:

$$ret_{i,t+1} = e + f \cdot acret_{i,t} + g \cdot herd_{i,t} + h \cdot \left(acret_{i,t} \cdot herd_{i,t}\right) + i \cdot u_{i,t} + j \cdot \left(acret_{i,t} \cdot u_{i,t}\right) + \epsilon_{i,t+1}, \quad (3)$$

where $ret_{i,t+1}$ is the return for firm i in month t+1, $acret_{i,t}$ is the cumulative return over months $t-11$ to $t-1$, $herd_{i,t}$ is the rolling-window herding dummy, and $u_{i,t}$ is (one of) the firm-level uncertainty proxy(ies) measured at t.

Table 6 reports the time-series averages of the monthly slope estimates from Equation (3). After accounting for the level and interaction effects of firm-level uncertainty (i and j terms), the interaction coefficient h on $acret_{i,t} \cdot herd_{i,t}$ remains positive and statistically significant, indicating stronger return continuation among *herding* firms even conditional on firm-level uncertainty. This is consistent with analyst conformity compressing dispersion and lowering consensus precision, which slows information incorporation into prices.

Table 6 here

We next examine post-earnings-announcement drift (PEAD) for *herding* and *non-herding* firms (PEAD as a benchmark for delayed incorporation of fundamentals: e.g., Bernard and Thomas, 1989; Sloan, 1996). In each month t, we sort stocks within each group into deciles based on standardized unexpected earnings ($\mathrm{SUE}_{i,t}$) and form ten portfolios S1 (bad news) to S10 (good news). Table 7 reports next-month (t+1) portfolio returns (Panel A) and Fama–French three-factor alphas (Panel B) for S1–S10 in both groups . The S10–S1 spread is *larger* for herding firms than for non-herding firms, and the difference is statistically significant; this result persists after factor adjustments (Panel B), consistent with slower information incorporation when analysts conform more tightly to the consensus.

Table 7 here

To assess whether the PEAD difference survives controls for firm-level uncertainty, we estimate monthly Fama–MacBeth regressions:

$$ret_{i,t+1} = h + i \cdot \mathrm{SUE}_{i,t} + j \cdot herd_{i,t} + k \cdot \big(\mathrm{SUE}_{i,t} \cdot herd_{i,t}\big) + l \cdot u_{i,t} + m \cdot \big(\mathrm{SUE}_{i,t} \cdot u_{i,t}\big) + \epsilon_{i,t+1}, \quad (4)$$

where $ret_{i,t+1}$ is the return for firm i in month t+1, $\mathrm{SUE}_{i,t}$ is standardized unexpected earnings in month t, $herd_{i,t}$ is the rolling-window herding indicator, and $u_{i,t}$ is (one of) the firm-level uncertainty proxy(ies). Table 8 reports the time-series averages of the monthly slope estimates from Equation (4). The interaction coefficient on $\mathrm{SUE}_{i,t} \cdot herd_{i,t}$, k, remains positive and statistically significant after accounting for the level and interaction effects of firm-level uncertainty (the l and m terms), indicating stronger PEAD among *herding* firms even conditional on uncertainty controls.

Table 8 here

The stronger S10–S1 spreads and the positive k estimates show that the herding effect—captured by the negative macro-uncertainty/dispersion relation—coincides with *additional* informational frictions: prices of herding firms incorporate earnings news more slowly than those of non-herding firms, even after conditioning on firm-level uncertainty.

Taken together, the evidence shows that prices of *herding* firms incorporate information more slowly than those of *non-herding* firms. Both momentum and PEAD spreads are larger for herding firms and remain economically and statistically meaningful after standard adjustments and controls, indicating greater return continuity when analysts conform more tightly to the consensus, consistent with the interpretation that herding compresses dispersion, lowers the precision of the consensus signal, and thereby reduces price informativeness.

C. Cross-sectional return predictability: Overpricing and subsequent returns

The evidence above shows that, for *herding firms*—whose analyst forecasts compress when macro uncertainty increases—prices display stronger momentum and PEAD, consistent with slower incorporation of information. In such a weaker information environment, the analyst consensus signal is less precise (higher posterior variance), so investors' beliefs about future payoffs become more dispersed. When short-sale frictions bind, investors with low valuations cannot take sufficiently negative positions, so market clearing occurs on the long side. As belief dispersion increases, the marginal long investor is drawn from a more optimistic quantile of the valuation distribution, pushing the price toward the optimistic tail (e.g., Miller, 1977; Shleifer and Vishny, 1997). Hence, we expect *herding* firms to be more overpriced and to earn lower subsequent returns than *non-herding* firms.

We first test this implication using a simple portfolio design based on the rolling classification in Equation (1). Each month t, we (i) label firms as *herding* if $b_{i,t} < 0$ and *non-herding* otherwise; (ii) form two value-weighted portfolios using these labels; and (iii) report next-month ($t+1$) returns for a long–non-herding / short–herding strategy. For completeness, we also sort firms into deciles by $b_{i,t}$ each month, defining herding (non-herding) as the lowest (highest) decile, and evaluate performance using excess returns and factor adjusted alphas (CAPM, FF3, FF5).

Table 9 reports the means and t-statistics of excess and factor-adjusted returns (alphas from the CAPM, Fama–French three-factor, and Fama–French five-factor models). Columns (1)–(3) implement the sign-based classification ($b_{i,t} < 0$ vs. $b_{i,t} > 0$); Columns (4)–(6) implement the decile sort by $b_{i,t}$. Across both schemes, the long–non-herding / short–herding strategy delivers a positive average excess return and positive alphas under all benchmarks, consistent with herding firms being more overpriced and earning lower subsequent returns than non-herding firms.

Table 9 here

While the portfolio evidence is transparent, it does not condition on other known return predictors. We therefore turn to monthly Fama–MacBeth regressions to assess whether the *herding* signal has incremental predictive power after controlling for documented predictors—idiosyncratic volatility as a proxy for limits to arbitrage (Ang et al., 2006), the level of analyst-forecast dispersion as a proxy for differences of opinion (Diether et al., 2002), and an uncertainty beta measuring exposure to macro uncertainty (Bali et al., 2017)—as well as standard firm characteristics. Our focus is on whether the $herd_{i,t}$ coefficient remains negative and significant once these variables are included.

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

$$ret_{i,t+1} = n + o * herd_{i,t} + p * p_{i,t} + q * control_{i,t} + \epsilon_{i,t+1}, \quad (5)$$

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 (1) 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.[11] Table 10 presents the time-series averages of the coefficients of the cross-sectional regression in each month.

Table 10 here

Consistent with prior work, the coefficients on $ivol_{i,t}$, $disp_{i,t}$, and $\beta^U_{i,t}$ are statistically significant in most specifications. Importantly, the coefficient on $herd_{i,t}$, o, remains *negative and statistically significant* after including each predictor individually and adding the full control set, indicating that the herding signal has *incremental* predictive power for next-month returns beyond these known drivers. Economically, the magnitude of o is stable across specifications and robust, supporting the view that herding is associated with overpricing and lower subsequent returns even after accounting for limits-to-arbitrage, differences-of-opinion, and macro-uncertainty exposure.

To further assess the robustness of the herding signal's predictive power, we examine whether it is subsumed by well-documented cross-sectional anomalies. Specifically, we benchmark herding against nine canonical predictors and check both *composition* (which firms herd) and *incremental predictability*. Previous literature has documented that various anomaly variables predict cross-sectional stock returns, and our portfolio evidence above—showing that stocks of herding firms earn lower future returns—already suggests that the herding effect may operate alongside (or as) an anomaly. We therefore study the herding effect in conjunction with: (1) momentum $acret_{i,t}$ (Jegadeesh and Titman, 1993); (2) financial distress $O\_score_{i,t}$ (Ohlson, 1980); (3) net stock issuance $g\_share_{i,t}$ (Stambaugh et al., 2012); (4) net operating assets $\text{NOA}_{i,t}$ (Hirshleifer et al., 2004); (5) gross profitability $gp_{i,t}$ (Novy-Marx, 2013); (6) total accruals $accrual_{i,t}$ (Sloan, 1996); (7) asset growth $g\_asset_{i,t}$ (Cooper et al., 2008); (8) return on assets $\text{ROA}_{i,t}$ (Fama and French, 2006); and (9) investment-to-assets $\text{ITA}_{i,t}$ (Titman et al., 2004).

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

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

Table 11 here

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

$$ret_{i,t+1} = r + s * herd_{i,t} + t * anml_{i,t} + u * anml_{i,t} * herd_{i,t} + \epsilon_{i,t+1}, \tag{6}$$

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

The findings highlight that the herding effect is not subsumed by other well-documented anomalies and represents a unique behavioral anomaly driven by analysts' strategic responses to macroeconomic uncertainty. This is consistent with our theoretical framework, which posits that herding behavior distorts information transmission, leading to persistent mispricing.

IV. Theoretical framework

This section develops a formal equilibrium framework, rooted in a beauty-contest motive (Keynes, 1936), that links macro uncertainty, analyst conformity, and prices, and maps directly to our three empirical facts: (i) which firms are identified as herding (the information-environment result), (ii) lower price informativeness with stronger return continuity (momentum and PEAD), and (iii) overpricing and lower subsequent returns for herding firms.

A. Set-up

We consider a single firm in partial equilibrium to isolate the information channel.[12] Each share of the firm has terminal value $V + v$, where V denotes the earnings disclosed at the announcement date and v is the residual (undisclosed) component realized at liquidation.[13] We assume V and v are independent and normally distributed,

$$V \sim \mathcal{N}(\bar{V}, \tau_V^{-1}), \qquad v \sim \mathcal{N}(0, \tau_v^{-1}). \tag{7}$$

To separate aggregate (macro) from firm-level (micro) uncertainty, we decompose the variance of V into macro uncertainty σ_m^2 and idiosyncratic uncertainty σ^2,

$$\tau_V^{-1} = \sigma_m^2 + \sigma^2. \tag{8}$$

[14] A risk-free bond (zero net return, zero net supply) serves as the numéraire.

[12] We abstract from portfolio equilibrium and priced risk to focus on the information-aggregation channel documented in the empirical evidence: stronger conformity reduces consensus precision, slows incorporation (momentum/PEAD), and, with short-sale frictions, tilts prices upward (e.g., Grossman and Stiglitz (1980); Miller (1977); Shleifer and Vishny (1997)).

[13] The variance of v reflects the quality of the earnings announcement: a higher τ_v^{-1} implies the announcement leaves more uncertainty about total firm value.

[14] *Macro uncertainty* σ_m^2 captures economy-wide shocks (e.g., policy or aggregate-demand uncertainty) that shift the precision of the common information environment faced by all firms. *Firm-level (idiosyncratic) uncertainty* σ^2 captures the quality/sparsity of information specific to a firm—reflecting its information environment (e.g., size, age, analyst coverage, number of estimates, and cash-flow/return volatility). This distinction underpins our empirical design: the macro proxy U^m enters Equation (1) to classify herding by the sign of the macro–dispersion slope, while firm-level proxies (and a composite index) in Section A. characterize which firms herd and why.

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

Figure 1 here

B. Analysts

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

$$c = V + \eta, \tag{9}$$

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

$$s_i = V + \varepsilon_i, \tag{10}$$

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

$$\mathrm{E}^i[\cdot] = \mathrm{E}[\cdot \mid c, s_i], \qquad \mathrm{Var}^i(\cdot) = \mathrm{Var}(\cdot \mid c, s_i). \tag{11}$$

All analysts simultaneously report forecasts of V at $t = 0$. Analyst i chooses f_i to maximize

$$u_i(f_i) = -(1-\delta)\,\mathrm{E}^i[(f_i - V)^2] \;-\; \delta\,\mathrm{E}^i[(f_i - \bar{f})^2], \tag{12}$$

where $\bar{f}$ is the consensus (the cross-sectional average of forecasts),

$$\bar{f} \;=\; \int_0^1 f_i\, di. \tag{13}$$

Following Morris and Shin (2002) and Keynes (1936), we adopt a beauty-contest motive: beyond accuracy, analysts also prefer to stay close to the consensus.[15] The parameter

[15] Herding motives such as reputation/career concerns (e.g., Scharfstein and Stein (1990)) are omitted here to keep focus on how herding directly creates information frictions and market inefficiency.

$\delta \in (0, 1)$ measures the strength of this herding incentive. We further assume that δ decreases with τ_V,

$$\frac{d\delta}{d\tau_V} < 0. \tag{14}$$

When the fundamental is less precise (lower τ_V), two forces raise the incentive to conform. First, *forecast risk*: the expected squared error from relying on one's idiosyncratic view increases, so the marginal benefit of putting weight on the private signal s_i falls relative to the safer action of matching the consensus $\bar{f}$. Second, *evaluation/coordination*: with noisier fundamentals it is harder ex post to separate skill from noise, so deviations from $\bar{f}$ carry a larger reputational/benchmarking penalty, and because others likewise tilt toward $\bar{f}$, strategic complementarity makes conformity a stronger best response. Together, these considerations imply $d\delta/d\tau_V < 0$.[16]

Given (c, s_i), the Bayesian expectation of V is

$$\mathrm{E}^i[V] \;=\; \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon s_i}{\tau_V + \tau_\eta + \tau_\varepsilon}, \tag{15}$$

a weighted average of the prior $\bar{V}$, the public signal c, and the private signal s_i. With the beauty-contest term, the optimal forecast tilts toward the consensus (under-weighting the private signal). The equilibrium forecast is:

Lemma 1. *There exists a unique linear equilibrium in which*

$$f_i \;=\; \frac{\tau_V \bar{V} + \tau_\eta c + (1-\delta)\tau_\varepsilon s_i}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}, \tag{16}$$

and the consensus is

$$\bar{f} \;=\; \frac{\tau_V \bar{V} + \tau_\eta c + (1-\delta)\tau_\varepsilon V}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}. \tag{17}$$

Proof. See Internet Appendix A. □

[16] See beauty-contest environments where consensus-tracking strengthens as fundamentals become noisier (Morris and Shin, 2002), and evidence that uncertainty amplifies behavioral frictions and slows information aggregation (Hirshleifer, 2001).

The cross-sectional dispersion of forecasts is

$$D \;=\; \int_0^1 (f_i - \bar{f})^2\, di \;=\; \frac{(1-\delta)^2\, \tau_\varepsilon}{\big(\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon\big)^2}. \tag{18}$$

Macro uncertainty (σ_m^2) affects D through two channels: *(i) precision*—via $\tau_V^{-1} = \sigma_m^2 + \sigma^2$—and *(ii) conformity*—because δ rises when fundamentals are less precise ($\frac{d\delta}{d\tau_V} < 0$).

Benchmark (no herding). If there is no strategic herding in the Keynes (1936) beauty-contest setting ($\delta = 0$), each analyst truthfully reports their Bayesian expectation of V:

$$f_i \;=\; \mathrm{E}^i[V] \;=\; \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon s_i}{\tau_V + \tau_\eta + \tau_\varepsilon}, \tag{19}$$

and the forecast dispersion simplifies to

$$D \;=\; \frac{\tau_\varepsilon}{\big(\tau_V + \tau_\eta + \tau_\varepsilon\big)^2} \quad\Rightarrow\quad \frac{dD}{d\sigma_m^2} \;>\; 0, \tag{20}$$

implying a *positive* macro–micro relation, as widely noted in prior work.

Purely Bayesian re-weighting . One might argue that for firms with higher firm-level uncertainty (e.g., lower τ_ε or lower τ_V) analysts *rationally* place relatively more weight on the public signal c and less on the private signal s_i even with $\delta = 0$, which can reduce D under strong parameter restrictions.[17] Crucially, however, when $\delta = 0$ there is *no loss of information*: $f_i = \mathrm{E}^i[V]$ remains the Bayesian posterior and the consensus $\bar{f}$ is the proper aggregator of (c, s_i) across analysts. At equilibrium, prices that are set off $\bar{f}$ incorporate available information efficiently, and cannot generate the documented patterns of slower incorporation (stronger momentum/PEAD) or systematic overpricing in our empirical anaysis. In short, purely Bayesian re-weighting may lower D in special cases but does *not* produce market-level informational inefficiency.

Behavioral wedge (herding). The negative correlation we document between macro uncertainty and forecast dispersion is instead associated with strategic conformity ($\delta > 0$) that

[17] Formally, a decline in τ_ε (or in τ_V holding other terms fixed) can make D fall in the no-herding case only in a restricted region of the parameter space; we detail the conditions in Internet Appendix B.

under-weights the private signal below its Bayesian weight. As fundamentals become less precise (lower τ_V), δ rises, compressing dispersion through the conformity channel and, at the same time, reducing the precision of the consensus used for pricing—thereby slowing information aggregation and enabling the return-predictability patterns we observe. The first proposition follows.

Proposition 1. *If δ is decreasing in τ_V, then for sufficiently small τ_V the dispersion D decreases as macro uncertainty σ_m^2 increases.*

Proof. See Internet Appendix C. □

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

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

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

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

Thus, when firm-level uncertainty σ is sufficiently high, greater macroeconomic uncertainty σ_m^2 raises the incentive to conform (higher δ), which compresses analyst-forecast dispersion D; formally,

$$\frac{\partial D}{\partial \sigma_m^2} < 0 \quad \text{for high-}\sigma \text{ firms.}$$

The macro–micro relation is state-dependent: for firms with high firm-level uncertainty, forecast dispersion and macro uncertainty are *negatively* related $\left(\frac{\partial D}{\partial \sigma_m^2} < 0\right)$; for firms with low firm-level uncertainty, the relation is *positive* $\left(\frac{\partial D}{\partial \sigma_m^2} > 0\right)$. This prediction maps directly to our first main empirical result in Section A..

Because the consensus $\bar{f}$ is informationally equivalent to a signal whose precision is strictly decreasing in δ, an increase in herding (higher δ) makes prices less informative.

We exploit this mapping in the next subsection.

C. Investors

We assume there are Θ shares outstanding. The market opens at $t = 1, 2$ for a unit mass of investors; at $t = 2$ earnings V are announced, and at $t = 3$ the residual uncertainty v is realized (see Figure 1). Risk-free rate is normalized to zero, and all shocks are Gaussian and mutually independent unless otherwise noted.

Consensus formation and herding. At $t = 1$, investors aggregate analysts' reports into the consensus $\bar{f}$ (Equation17), which can be written as a convex combination of the prior $\bar{V}$ and an effective signal s_f:

$$\bar{f} = \omega \bar{V} + (1-\omega) s_f, \qquad \omega = \frac{\tau_V}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}, \tag{21}$$

$$s_f = V + \frac{\tau_\eta}{\tau_\eta + (1-\delta)\tau_\varepsilon}\eta, \qquad s_f \sim \mathcal{N}\big(\bar{V},\, \tau_V^{-1} + \tau_f^{-1}\big).$$

The herding parameter $\delta \in [0, 1)$ attenuates the idiosyncratic component of analyst signals. The consensus $\bar{f}$ is informationally equivalent to s_f with precision

$$\tau_f = \frac{\big(\tau_\eta + (1-\delta)\tau_\varepsilon\big)^2}{\tau_\eta}, \qquad \frac{d\tau_f}{d\delta} < 0, \tag{22}$$

so stronger herding ($\delta \uparrow$) lowers the information content (precision) of $\bar{f}$ about V.

Information sets and preferences. Investors use $\bar{f}$ to form portfolios. Let P_t denote the equilibrium price at time t and $\mathcal{F}_t$ the information set:

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

With CARA utility and final trading-profits wealth,

$$\max_{x_t} \mathbb{E}_t\big[-e^{-\lambda W_3}\big], \qquad W_3 = (P_2 - P_1)x_1 + (P_3 - P_2)x_2,$$

where $\mathbb{E}_t[\cdot] = \mathbb{E}[\cdot \,|\, \mathcal{F}_t]$ and $\text{Var}_t(\cdot) = \text{Var}(\cdot \,|\, \mathcal{F}_t)$.

Liquidity traders and market clearing. To facilitate trading, liquidity demand follows AR(1):

$$\theta_1 = z_1, \qquad \theta_2 = \beta\theta_1 + z_2, \qquad 0 \le \beta \le 1,\ z_1, z_2 \sim \mathcal{N}(0,1).$$

Market clearing at $t = 1, 2$ requires $x_t + \theta_t = \Theta$.

Solving by backward induction (see Internet Appendix D) yields

$$P_2 = V + \lambda\tau_v^{-1}\big(\beta z_1 + z_2\big) - \lambda\tau_v^{-1}\Theta, \tag{23}$$

$$P_1 = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v}(1-\beta)\right)\right] z_1 - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta. \tag{24}$$

Since τ_f is strictly decreasing in δ by (22), stronger herding reduces the informational content of the interim price P_1:

Proposition 2 (Price informativeness)**.** *Given other primitives fixed, analysts' stronger tendency to herd ($\delta \uparrow$) makes price less informative about the fundamental:*

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

Proof. See Internet Appendix D. □

Momentum and PEAD. The loss of price informativeness in high-δ states is precisely what underlies short-horizon return continuation: when P_1 places less weight on V and more on transient, non-fundamental price movements, returns tend to carry over into the next month (momentum); if some investors update only partially at $t = 2$, post-earnings-announcement drift (PEAD) also emerges. Section B. empirically tests these implications. We now formalize the two predictions (momentum and PEAD).

Proposition 3 (Momentum and herding)**.** *There exists a threshold β_c such that* $\mathrm{Cov}(P_3 - P_2,\ P_2 - P_1) > 0$ *(momentum) if and only if $\beta > \beta_c$ and* $\mathrm{Var}(V \mid \bar{f}) > \mathrm{Var}(v)$*. Moreover,*

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

so, all else equal, momentum is more likely when herding is stronger.

Proof. See Internet Appendix E. □

Let earnings surprise ES := $V - \bar{f}$ and post-earnings return PR := $V + v - P_2$. To capture PEAD, we extend the base model by assuming that at $t = 2$ a fraction $\alpha \in (0, 1)$ of investors are *inattentive* and form demand on time-1 beliefs:[18]

$$x_2^{\text{in}} = \frac{\mathbb{E}_1[V + v] - P_2}{\lambda \operatorname{Var}_1(V + v)}, \qquad (1 - \alpha)x_2 + \alpha x_2^{\text{in}} + \theta_2 = \Theta.$$

Proposition 4 (PEAD and herding)**.** *If $\alpha > 0$, then*

$$\operatorname{Cov}(\text{ES}, \text{PR}) = \frac{\alpha}{\tau_V + \tau_f + \tau_v} > 0, \qquad \frac{d \operatorname{Cov}(\text{ES}, \text{PR})}{d\delta} > 0,$$

so PEAD strengthens as herding intensifies (since τ_f decreases in δ).[19]

Proof. See Internet Appendix F. □

Propositions 3–4 correspond to Section B., where we test that (i) when the interim price P_1 is less informative (high-δ states), short-horizon returns *continue* (momentum), and (ii) partial belief updating at $t = 2$ generates *PEAD*. We next examine overpricing and predictability under short-sale constraints.

Overpricing and predictability. Impose short-sale constraints for the marginal investors and let P_t^{ss} denote constrained prices. Define expected overpricing at $t = 1$:

$$\Delta := \mathbb{E}[P_1^{ss}] - \mathbb{E}[P_1].$$

[18]In the *base* model, there is no PEAD: once V is announced at $t = 2$, information is fully incorporated into P_2 and $\operatorname{Cov}(\text{ES}, \text{PR}) = 0$; the herding effect is confined to P_1. To match the empirical persistence of inefficiencies, we allow a fraction α of investors to remain *inattentive* at $t = 2$, consistent with evidence that heightened uncertainty exacerbates psychological biases and limits attention (e.g., Hirshleifer (2001); Hirshleifer et al. (2009); Hung et al. (2015)).

[19]Inattentive investors' demand uses time-1 beliefs, which makes the price adjustment at $t = 2$ incomplete and delivers $\operatorname{Cov}(\text{ES}, \text{PR}) = \alpha/(\tau_V + \tau_f + \tau_v) > 0$. Because herding lowers the consensus precision (τ_f strictly decreasing in δ), the variance of surprises $\operatorname{Var}(\text{ES}) = \operatorname{Var}(V - \bar{f}) = \tau_V^{-1} + \tau_f^{-1}$ rises with δ, which increases $\operatorname{Cov}(\text{ES}, \text{PR})$ even for fixed α. (iv) If the inattentive share α also co-moves positively with uncertainty (and thus with δ), the amplification is stronger.

When δ is higher, P_1 is less informative (more weight on optimistic valuations under constraints), implying:

Proposition 5 (Overpricing). *Analyst herding δ is positively correlated with expected overpricing at $t = 1$:*

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

Proof. See Internet Appendix G. □

Corollary 5.1 (Lower subsequent returns). *Under short-sale constraints, expected next-period returns satisfy*

$$\frac{d\,\mathbb{E}[R^{ss}]}{d\delta} < 0, \qquad \mathbb{E}[R^{ss}] := \mathbb{E}[P_2^{ss}] - \mathbb{E}[P_1^{ss}],$$

so stronger herding predicts lower subsequent returns.

Propositions 5–5.1 align well with Section C.: stronger herding is associated with greater overpricing at $t = 1$ and lower subsequent returns, thereby rationalizing the portfolio and cross-sectional return evidence reported previously.

D. Discussion

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

V. Conclusion

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

Our empirical findings demonstrate that herding behavior is concentrated in firms with greater valuation uncertainty and is associated with a range of inefficiency patterns, including momentum, post-earnings-announcement drift, and cross-sectional predictability. These effects are not fully explained by traditional risk factors or known anomalies, underscoring the distinct role of this behavioral dynamic in shaping asset prices. Beyond its implications, the paper also challenges the conventional wisdom that macro and micro uncertainties move in tandem. We show that strategic analyst behavior can invert this relationship, revealing a novel behavioral linkage between macroeconomic conditions and firm-level information quality.

In addition, our theoretical framework isolates strategic conformity as the behavioral wedge: higher macro uncertainty compresses forecasts, degrades consensus precision, and weakens price discovery, tying firms' information environments to the observed inefficiencies. By contrast, a pure information (Bayesian) reweighting preserves efficient aggregation and cannot deliver these joint facts. More broadly, our results suggest that understanding uncertainty in asset markets requires not only modeling risk premia, but also studying how uncertainty changes the behavior of information intermediaries.

Taken together, our analysis suggests that uncertainty influences market outcomes not only through standard risk channels but also through its impact on the behavior of information intermediaries. This dual perspective provides a unified interpretation of dispersion dynamics, price-formation frictions, and return predictability in uncertain times. Future research could examine how technological advances—such as AI-assisted forecasting, alternative-data pipelines, and algorithmic trading—interact with behavioral herding under uncertainty, potentially amplifying or mitigating its effects on market efficiency, and explore policy-relevant levers (e.g., disclosure or communication design) that might attenuate conformity incentives when uncertainty is elevated.

References

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

Aquilina, M., Lombardi, M. J., and Zhu, S. (2024). The return of monetary policy uncertainty. *BIS Quarterly Review*. Box in the Overview chapter.

Bachmann, R., Elstner, S., and Sims, E. R. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, 5(2):217–249.

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

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

Bansal, R. and Shaliastovich, I. (2013). A long-run risks explanation of predictability puzzles in bond and currency markets. *Review of Financial Studies*, 26(1):1–33.

Bansal, R. and Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *Journal of Finance*, 59(4):1481–1509.

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

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

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

Campbell, J. Y. and Cochrane, J. H. (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, 107(2):205–251.

Campbell, J. Y. and Shiller, R. J. (1988). Stock prices, earnings, and expected dividends. *Journal of Finance*, 43(3):661–676.

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

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

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

De Pooter, M., Favara, G., Modugno, M., and Wu, J. (2020). Monetary policy uncertainty and monetary policy surprises. Finance and Economics Discussion Series (FEDS) 2020-032, Board of Governors of the Federal Reserve System.

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

Fama, E. F. and French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, 22(1):3–25.

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

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

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

Hansen, L. P. and Singleton, K. J. (1982). Generalized instrumental variables estimation of nonlinear rational expectations models. *Econometrica*, 50(5):1269–1286.

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

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

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

Hong, H., Kubik, J. D., and Solomon, A. (2000). Security analysts' career concerns and herding of earnings forecasts. *RAND Journal of Economics*, 31(1):121–144.

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

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

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

Jegadeesh, N. and Kim, W. (2010). Do analysts herd? an analysis of recommendations and market reactions. *Review of Financial Studies*, 23(2):901–937.

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

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

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

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

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

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

Leduc, S. and Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, 82:20–35.

Lim, T. (2001). Rationality and analysts' forecast bias. *The journal of Finance*, 56(1):369–385.

Lucas, Robert E., J. (1978). Asset prices in an exchange economy. *Econometrica*, 46(6):1429–1445.

Mehra, R. and Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of Monetary Economics*, 15(2):145–161.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica*, 41:867–887.

Miller, M. H. (1977). Risk, uncertainty, and divergence of opinion. *Journal of Finance*, 32:1151–1168.

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

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

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

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

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

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3):341–360.

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

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

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, 19:425–442.

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

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

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

Swanson, E. T. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, 118:32–53.

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

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

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

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

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

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

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

Table 1: Descriptive statistics

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

A: Summary statistics

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

B: Correlations

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

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

The table reports the results of the regression:

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

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

A: Pooled Regression

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

B: Regressions by firms

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

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

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

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

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

The table presents the results of the probit regression:

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

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

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

Table 5: Herding and momentum: portfolio analysis

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

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

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

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

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

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

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

Table 7: Herding and Post Earning Announcement Drift

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

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

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

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

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

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

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

Table 9: Herding and predictability: portfolio analysis

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

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

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

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

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

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

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

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

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

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

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

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

Figure 1: Timeline of the model

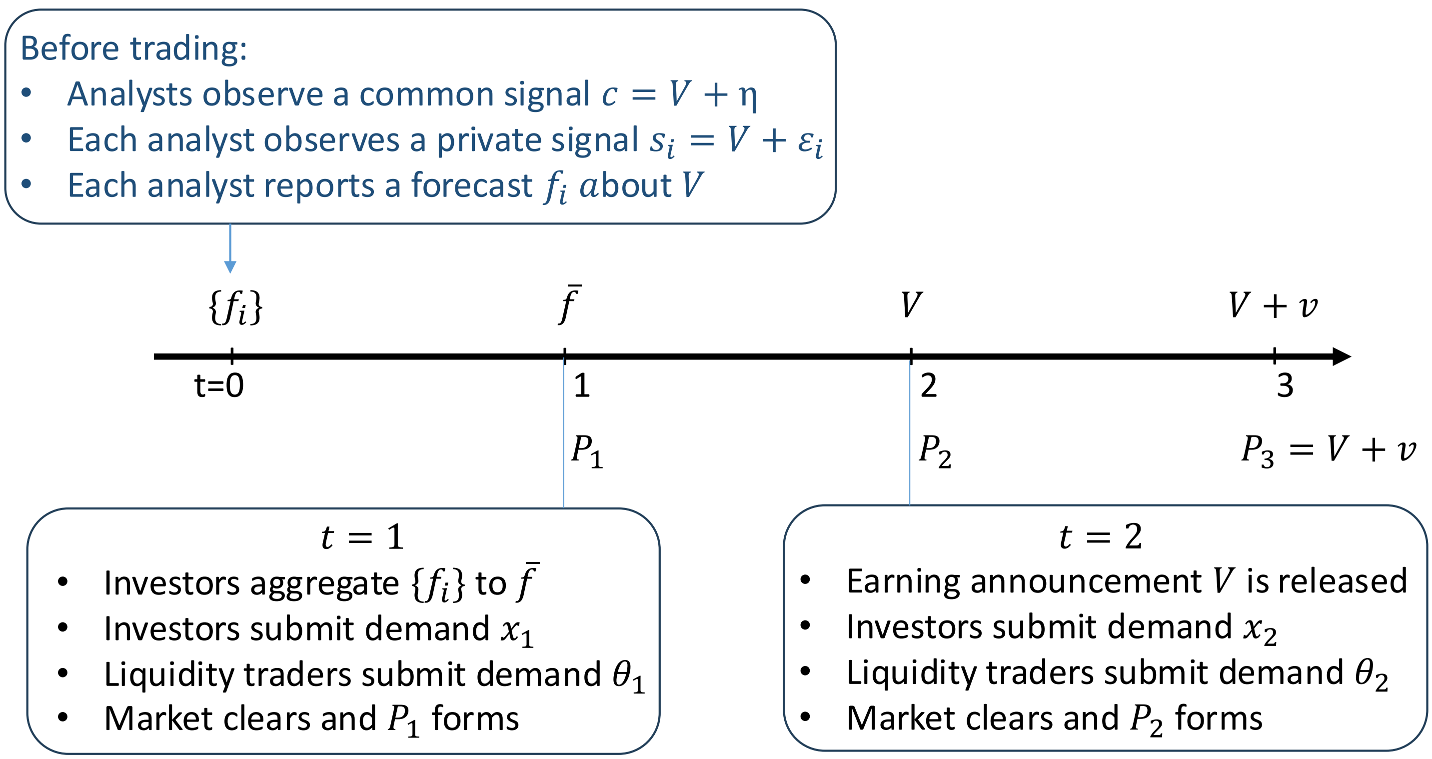
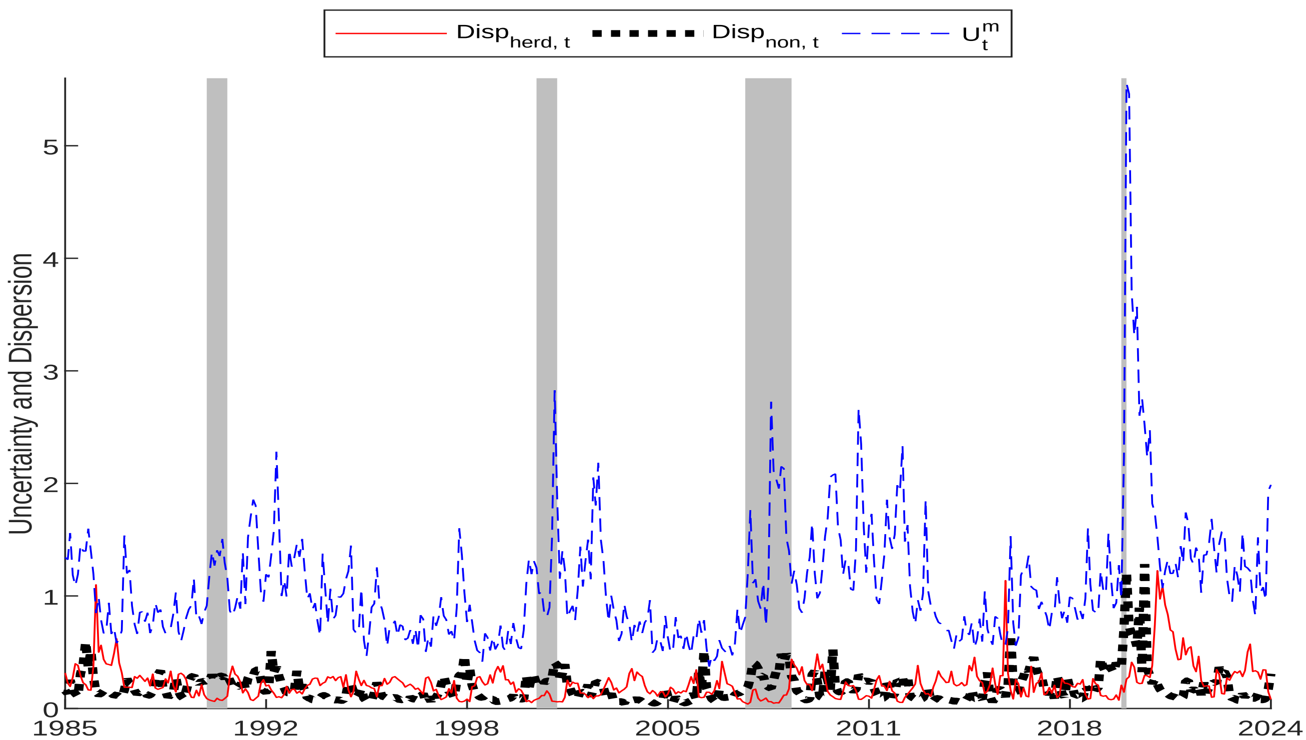


Figure 2: Macroeconomic Uncertainty and Analyst Forecasts Dispersion

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



Internet Appendix

A Proof of lemma 1

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

$$f_i = (1-\kappa_1-\kappa_2)\bar{V} + \kappa_1 s_i + \kappa_2 c. \tag{25}$$

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

$$\mathrm{E}^i[\bar{f}] = (1-\kappa_1-\kappa_2)\bar{V} + \kappa_1\frac{\tau_V\bar{V}+\tau_\eta c+\tau_\varepsilon s_i}{\tau_V+\tau_\eta+\tau_\varepsilon} + \kappa_2 c. \tag{26}$$

Note that in order to maximize the utility function Eq (12), analyst i best response is

$$f_i = (1-\delta)\mathrm{E}^i[V] + \delta\mathrm{E}^i[\bar{f}]. \tag{27}$$

By substituting Eq (26) into above equation, we have

$$\begin{aligned} f_i = &\left(\delta(1-\kappa_1-\kappa_2) + (1-\delta+\delta\kappa_1)\frac{\tau_V}{\tau_V+\tau_\eta+\tau_\varepsilon}\right)\bar{V} \\ &+(1-\delta+\delta\kappa_1)\frac{\tau_\varepsilon}{\tau_V+\tau_\eta+\tau_\varepsilon}s_i + (1-\delta+\delta\kappa_1)\frac{\tau_\eta}{\tau_V+\tau_\eta+\tau_\varepsilon}c. \end{aligned} \tag{28}$$

Comparing coefficients in Eq (25) and Eq (28), we therefore have

$$\kappa_1 = \frac{(1-\delta)\tau_\varepsilon}{\tau_V+\tau_\eta+(1-\delta)\tau_\varepsilon}, \tag{29}$$

$$\kappa_2 = \frac{\tau_\eta}{\tau_V+\tau_\eta+(1-\delta)\tau_\varepsilon}. \tag{30}$$

Thus, the equilibrium forecast f_i is given by

$$f_i = \frac{\tau_V\bar{V}+\tau_\eta c+(1-\delta)\tau_\varepsilon s_i}{\tau_V+\tau_\eta+(1-\delta)\tau_\varepsilon}. \tag{31}$$

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

$$\mathrm{E}^i[V] = \frac{\tau_V \bar{V} + \tau_\varepsilon s_i + \tau_\eta c}{\tau_V + \tau_\varepsilon + \tau_\eta}. \tag{32}$$

Thus, the average expectation of V across all analysts is

$$\bar{\mathrm{E}}[V] = \int_0^1 \mathrm{E}^i[V] di = \frac{\tau_V \bar{V} + \tau_\varepsilon V + \tau_\eta c}{\tau_V + \tau_\varepsilon + \tau_\eta}. \tag{33}$$

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

$$\begin{aligned}
\bar{\mathrm{E}}^{\mathrm{n}}[V] &= \frac{\tau_V \bar{V}}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n} \mu^{k-1} + \frac{\tau_\eta c}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n} \mu^{k-1} + \mu^n V, \\
\mathrm{E}^i[\bar{\mathrm{E}}^{\mathrm{n}}[V]] &= \frac{\tau_V \bar{V}}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n+1} \mu^{k-1} + \frac{\tau_\eta c}{\tau_V + \tau_\eta + \tau_\varepsilon} \sum_{k=1}^{n+1} \mu^{k-1} + \mu^{n+1} s_i,
\end{aligned} \tag{34}$$

where

$$\mu = \frac{\tau_\varepsilon}{\tau_V + \tau_\eta + \tau_\varepsilon}, \tag{35}$$

It is easy to verify that Eq (34) holds for $n = 1$, then the proof is by induction on n.

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

$$f_i = (1-\delta)\mathrm{E}^i[V] + \delta \mathrm{E}^i[\bar{f}]. \tag{36}$$

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

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

This is exactly the unique linear equilibrium we identified earlier.

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

$$\bar{f} = \omega \bar{V} + (1-\omega) s_f, \tag{37}$$

where

$$\omega = \frac{\tau_V}{\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon}, \quad s_f = V + \frac{\tau_\eta}{\tau_\eta + (1-\delta)\tau_\varepsilon}\eta \sim \mathcal{N}(\bar{V}, \tau_V^{-1} + \tau_f^{-1}), \tag{38}$$

and

$$\tau_f = \frac{(\tau_\eta + (1-\delta)\tau_\varepsilon)^2}{\tau_\eta}. \tag{39}$$

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

$$\frac{d\mathrm{Var}(V \mid \bar{f})}{d\delta} > 0, \tag{40}$$

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

□

B Explanation without strategic herding

If there is no beauty contest, analysts have no incentive to herd and therefore report their forecasts truthfully:

$$f_i = \mathrm{E}^i[V] = \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon s_i}{\tau_V + \tau_\eta + \tau_\varepsilon}. \tag{41}$$

The resulting consensus forecast is

$$\bar{f} = \frac{\tau_V \bar{V} + \tau_\eta c + \tau_\varepsilon V}{\tau_V + \tau_\eta + \tau_\varepsilon}. \tag{42}$$

In this case, analysts' private-information precision, τ_ε, is independent of macro uncertainty, σ_m^2. As a result, forecast dispersion, D, always increases with macro uncertainty, σ_m^2.

One might argue, however, that analysts' information precision should not be treated as independent of macro uncertainty, since it is endogenously determined by market conditions, including the level of macro uncertainty. We now examine this argument and show that, even when information precision is endogenously determined, it remains difficult to generate a decline in dispersion as macro uncertainty rises, so long as there is no behavioral distortion and analysts report their forecasts truthfully.

We first endogenize the precision, τ_ε, of analysts' private information. In the absence of behavioral bias, analysts truthfully report forecasts based on both their common and private information. We assume that analysts are endowed with common information, but must incur a cost to acquire private information. Following Lim (2001), we assume that the cost is a quadratic function of private-information precision:

$$C(\tau_\varepsilon) = \frac{k}{2}\tau_\varepsilon^2, \tag{43}$$

where $k > 0$ is a constant. The objective function of analyst i is therefore

$$\max_{\tau_\varepsilon} \; -\mathrm{E}^i\big[(f_i - V)^2\big] - \frac{k}{2}\tau_\varepsilon^2, \tag{44}$$

which, under truthful reporting, is equivalent to

$$\max_{\tau_\varepsilon} \; -\frac{1}{\tau_V + \tau_\eta + \tau_\varepsilon} - \frac{k}{2}\tau_\varepsilon^2. \tag{45}$$

The first-order condition implies that the optimal τ_ε satisfies

$$\frac{1}{(\tau_V + \tau_\eta + \tau_\varepsilon)^2} = k\tau_\varepsilon. \tag{46}$$

Thus, τ_ε indeed depends on macro uncertainty through τ_V, and

$$\frac{d\tau_\varepsilon}{d\tau_V} = -\frac{2\tau_\varepsilon}{\tau_V + \tau_\eta + 3\tau_\varepsilon} < 0. \tag{47}$$

Since τ_V decreases with macro uncertainty σ_m^2, it follows that

$$\frac{d\tau_\varepsilon}{d\sigma_m^2} > 0. \tag{48}$$

That is, as macro uncertainty rises, analysts have an incentive to acquire more precise private information, because the marginal benefit of such information is greater when macro uncertainty is higher.

Under truthful reporting, forecast dispersion is given by

$$D = \frac{\tau_\varepsilon}{(\tau_V + \tau_\eta + \tau_\varepsilon)^2}. \tag{49}$$

Therefore, the effect of macro uncertainty on forecast dispersion is

$$\frac{dD}{d\sigma_m^2} = \frac{\frac{d\tau_\varepsilon}{d\tau_V}(\tau_V + \tau_\eta - \tau_\varepsilon) - 2\tau_\varepsilon}{(\tau_V + \tau_\eta + \tau_\varepsilon)^3} \frac{d\tau_V}{d\sigma_m^2}. \tag{50}$$

It follows that

$$\frac{dD}{d\sigma_m^2} > 0. \tag{51}$$

Hence, under a quadratic information-acquisition cost, even though private-information precision τ_ε is endogenously determined by macro uncertainty, forecast dispersion still increases monotonically with macro uncertainty. This is summarized by the following Lemma.

Lemma 2. *In the absence of herding ($\delta = 0$), suppose analysts incur a quadratic cost of acquiring private information,*

$$C(\tau_\varepsilon) = \frac{k}{2}\tau_\varepsilon^2, \tag{52}$$

where $k > 0$ is a constant. Then private-information precision τ_ε is endogenously determined by macro uncertainty through τ_V, and satisfies

$$\frac{d\tau_\varepsilon}{d\sigma_m^2} > 0. \tag{53}$$

Moreover, forecast dispersion always increases with macro uncertainty:

$$\frac{dD}{d\sigma_m^2} > 0. \tag{54}$$

One might further argue that analysts' private-information precision could decline with macro uncertainty. The intuition is that higher macro uncertainty, by increasing fundamental uncertainty τ_V^{-1}, may make it more difficult for analysts to acquire precise private information, thereby reducing τ_ε. Consequently, as macro uncertainty rises, analysts place relatively greater weight on the common signal c than on their private signal s_i, which may in turn reduce forecast dispersion.

To capture this idea, suppose that the cost parameter k is no longer constant, but instead increases with fundamental uncertainty τ_V^{-1}, so that

$$\frac{dk}{d\tau_V} < 0. \tag{55}$$

Under this assumption,

$$\frac{d\tau_\varepsilon}{d\tau_V} = -\frac{\tau_\varepsilon}{k + \frac{2}{(\tau_V+\tau_\eta+\tau_\varepsilon)^3}} \left(\frac{dk}{d\tau_V} + \frac{2k}{\tau_V + \tau_\eta + \tau_\varepsilon} \right). \tag{56}$$

Therefore, forecast dispersion decreases with macro uncertainty if and only if

$$\frac{dD}{d\sigma_m^2} < 0 \qquad \Longleftrightarrow \qquad \tau_V + \tau_\eta - \tau_\varepsilon > 0 \quad \text{and} \quad \frac{\frac{dk}{d\tau_V}}{k} < -\frac{4}{\tau_V + \tau_\eta - \tau_\varepsilon}. \tag{57}$$

The necessary and sufficient condition is quite strong. It requires the cost parameter k to rise sufficiently rapidly as macro uncertainty increases. This is summarized by the following Lemma.

Lemma 3. *Under the assumptions of Lemma 2, suppose the information-acquisition cost parameter k is not a constant but satisfies*

$$\frac{dk}{d\tau_V} < 0. \tag{58}$$

Then

$$\frac{dD}{d\sigma_m^2} < 0 \tag{59}$$

if and only if

$$\tau_V + \tau_\eta - \tau_\varepsilon > 0 \quad \textit{and} \quad \frac{1}{k}\frac{dk}{d\tau_V} < -\frac{4}{\tau_V + \tau_\eta - \tau_\varepsilon}. \tag{60}$$

Thus, in the absence of herding, a negative relation between macro uncertainty and forecast dispersion can arise only if the cost of private-information acquisition increases sufficiently strongly with macro uncertainty. This requirement is restrictive, and no functional form for k generically guarantees that it holds globally. Even if this condition can generate a negative correlation, analysts still report their forecasts truthfully in the absence of behavioral bias ($\delta = 0$). As a result, there is no information loss that would impair financial market efficiency, which is inconsistent with our empirical findings.

C Proof of Proposition 2

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

$$\frac{dD}{d\sigma_m^2} = \frac{dD}{d\tau_V}\frac{d\tau_V}{d\sigma_m^2} = \frac{2(1-\delta)\tau_\varepsilon\tau_V^2}{(\tau_V + \tau_\eta + (1-\delta)\tau_\varepsilon)^3}\left[\delta'(\tau_V)(\tau_V+\tau_\eta) + (1-\delta)\right]. \tag{61}$$

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

$$g(\tau_V) < 0. \tag{62}$$

Note that

$$g(0) = \delta'(0)\tau_\eta < 0, \tag{63}$$

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

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

$$\delta''(\tau_V)(\tau_V+\tau_\eta) > 0 \qquad \Leftrightarrow \qquad \delta''(\tau_V) > 0. \tag{64}$$

It follows:

$$for \quad \tau_V < (>)\tau_V^c, \quad g(\tau_V) < (>)0 \quad and \quad \frac{dD}{d\sigma_m^2} < (>)0. \tag{65}$$

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

$$\delta > (<)\delta_c \iff \frac{dD}{d\sigma_m^2} < (>)0. \tag{66}$$

□

D Proof of Proposition 2

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

Lemma 4. *Let u be an $n \times 1$ normal vector with mean $\bar{u}$ and covariance matrix Σ, A a scalar, B an $n \times 1$ vector, C an $n \times n$ symmetric matrix, I the $n \times n$ identity matrix, and $|M|$ the determinant of a matrix M. Then,*

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

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

$$x_2 = \frac{\mathrm{E}_2[V + v] - P_2}{\lambda \mathrm{Var}_2(V + v)} = \frac{V - P_2}{\lambda \tau_v^{-1}}. \tag{67}$$

By market clearing condition, the equilibrium price is

$$P_2 = V + \lambda\tau_v^{-1}\left(\beta z_1 + z_2\right) - \lambda\tau_v^{-1}\Theta. \tag{68}$$

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

$$J_2 = -e^{-\lambda\left[\left(V + \frac{\lambda}{\tau_v}(\theta_2 - \Theta) - P_1\right)x_1 + \frac{1}{2}\frac{\lambda}{\tau_v}(\theta_2 - \Theta)^2\right]}. \tag{69}$$

By Lemma 4, we solve

$$\max_{x_1} \mathrm{E}_1[J_2], \tag{70}$$

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

$$x_1 = \left(\lambda \text{Var}_1(V) + \frac{\lambda}{\tau_v} \frac{\lambda^2}{\lambda^2 + \tau_v}\right)^{-1} \left[\text{E}_1[V] - P_1 + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v}\right)(\beta z_1 - \Theta)\right], \quad (71)$$

where

$$\text{E}_1[V] = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f}, \quad \text{and} \quad \text{Var}_1(V) = \frac{1}{\tau_V + \tau_f}. \quad (72)$$

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

$$P_1 = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v}(1 - \beta)\right)\right] z_1 - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta. \quad (73)$$

Hence, P_1 is informationally equivalent to the following signal

$$s_p = s_f + \lambda\left(b + \frac{b\tau_V + 1}{\tau_f}\right) z_1, \quad (74)$$

where

$$b = \frac{1}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v}(1 - \beta)\right). \quad (75)$$

Therefore,

$$\text{Var}(V \mid P_1) = \text{Var}(V \mid s_p) = \frac{1}{\tau_V + \tau_f + \lambda^{-2}\left(b + \frac{b\tau_V + 1}{\tau_f}\right)^{-2}}. \quad (76)$$

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

$$\frac{d\text{Var}(V \mid P_1)}{d\delta} > 0, \quad (77)$$

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

□

E Proof of Proposition 3

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

$$\text{Cov}(P_3 - P_2, P_2 - P_1) = \frac{\lambda^2}{\tau_v^2}\left[\beta\left(\frac{\tau_v}{\tau_V + \tau_f} + \frac{\lambda^2}{\lambda^2 + \tau_v}(1 - \beta)\right) - 1\right]. \quad (78)$$

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

$$f(\beta) := \beta \left(\frac{\tau_v}{\tau_V + \tau_f} + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z}(1 - \beta) \right) - 1 > 0, \tag{79}$$

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

$$a = \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z} \in (0, 1), \quad x = \frac{\tau_v}{\tau_V + \tau_f} \in (0, +\infty). \tag{80}$$

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

$$f(\beta) = -a\beta^2 + (x + a)\beta - 1. \tag{81}$$

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

$$(x + a)^2 - 4a > 0 \Longleftrightarrow x > 2\sqrt{a} - a, \tag{82}$$

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

$$\beta_c = \frac{x + a - \sqrt{(x + a)^2 - 4a}}{2a}, \quad \beta_d = \frac{x + a + \sqrt{(x + a)^2 - 4a}}{2a}. \tag{83}$$

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

$$\beta_c < \beta < \beta_d. \tag{84}$$

Note $0 \leq \beta \leq 1$, however, under the condition of Equation(82),

$$\beta_d > 1. \tag{85}$$

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

$$\beta_c < 1 \Longleftrightarrow x > 1. \tag{86}$$

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

$$x > 1, \quad \text{and} \quad \beta > \beta_c, \tag{87}$$

where

$$x > 1 \Longleftrightarrow \mathrm{Var}(v) < \mathrm{Var}(V \mid \bar{f}), \tag{88}$$

and

$$\frac{d\beta_c}{d\delta} = \underbrace{\frac{d\beta_c}{dx}}_{<0}\underbrace{\frac{dx}{d\delta}}_{>0} < 0. \tag{89}$$

□

F Proof of Proposition 4

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

$$P_2 = \frac{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} V + \frac{\frac{\alpha}{\tau_v}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} - \frac{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\lambda}{\tau_v}(\Theta - \theta_2). \tag{90}$$

Thus, the post-earning return

$$\mathrm{PR} = v + \frac{\frac{\alpha}{\tau_v}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\tau_V (V - \bar{V}) - \tau_f \varepsilon_f}{\tau_V + \tau_f} + \frac{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}} \frac{\lambda}{\tau_v}(\Theta - \theta_2). \tag{91}$$

Then the variance of the post-earning return is

$$\mathrm{Var}(\mathrm{PR}) = \frac{1}{\tau_v} + \frac{w_\alpha^2}{\tau_V + \tau_f} + (1 - w_\alpha)^2 \frac{\lambda^2}{\tau_v^2}(1 + \beta^2), \tag{92}$$

where

$$w_\alpha = \frac{\frac{\alpha}{\tau_v}}{\frac{1}{\tau_v} + \frac{1}{\tau_V + \tau_f}}. \tag{93}$$

The earning surprise is

$$\mathrm{ES} = \frac{\tau_V (V - \bar{V}) - \tau_\eta \eta}{\tau_V + \tau_\eta + \tau_\varepsilon (1 - \delta)}, \tag{94}$$

and its variance is

$$\mathrm{Var}(\mathrm{ES}) = \frac{\tau_V + \tau_\eta}{(\tau_V + \tau_\eta + \tau_\varepsilon (1 - \delta))^2}. \tag{95}$$

The covariance between the two is positive,

$$\mathrm{Cov}(\mathrm{ES},\mathrm{PR}) = \frac{w_\alpha}{\tau_V+\tau_f} = \frac{\alpha}{\tau_V+\tau_f+\tau_v} > 0. \tag{96}$$

Hence,

$$\frac{d\mathrm{Var}(\mathrm{ES})}{d\delta} = \frac{2\tau_\varepsilon(\tau_V+\tau_\eta)\left(\tau_V+\tau_\eta+\tau_\varepsilon(1-\delta)\right)}{\left(\tau_V+\tau_\eta+\tau_\varepsilon(1-\delta)\right)^4} > 0. \tag{97}$$

$$\frac{d\mathrm{Cov}(\mathrm{ES},\mathrm{PR})}{d\delta} = -\frac{\alpha}{\left(\tau_V+\tau_f+\tau_v\right)^2}\frac{d\tau_f}{d\delta} > 0. \tag{98}$$

□

G Proof of Proposition 5

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

$$0 \leq \theta_2 \leq \Theta, \quad 0 \leq \theta_1 \leq \Theta. \tag{99}$$

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

$$0 \leq z_1 \leq \Theta, \tag{100}$$

and given z_1, the range for z_2 should be

$$-\beta z_1 \leq z_2 \leq \Theta - \beta z_1. \tag{101}$$

Thus, under short-sale constraint,

$$\mathrm{E}_0^{ss}[\theta_1] = \Delta_1, \tag{102}$$

$$\mathrm{E}_1^{ss}[\theta_2] = \beta z_1 + \Delta_2, \tag{103}$$

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

$$\Delta_1 = \mathrm{E}[z_1 \mid 0 \leq z_1 \leq \Theta] = \frac{\phi(0)-\phi(\Theta)}{\Phi(\Theta)-\Phi(0)}, \tag{104}$$

$$\Delta_2 = \mathrm{E}[z_2 \mid -\beta z_1 \leq z_2 \leq \Theta - \beta z_1] = \frac{\phi(\beta z_1)-\phi(\Theta-\beta z_1)}{\Phi(\Theta-\beta z_1)-\Phi(-\beta z_1)}, \tag{105}$$

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

$$\Delta_1 > 0, \qquad \frac{\partial \Delta_2}{\partial \beta} < 0. \tag{106}$$

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

$$\mathrm{Var}_2^{ss}(\theta_2) < \mathrm{Var}_2(\theta_2) = 1, \tag{107}$$

and obviously

$$\tau_z^{ss} := \frac{1}{\mathrm{Var}_2^{ss}(\theta_2)} > 1. \tag{108}$$

Under the short-sale constraint, by solving

$$\max_{x_1} \mathrm{E}_1^{ss}[J_2], \tag{109}$$

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

$$x_1^{ss} = \left(\lambda \mathrm{Var}_1^{ss}(V) + \frac{\lambda}{\tau_v}\frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)^{-1} \left[\mathrm{E}_1^{ss}[V] - P_1 + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)(\beta z_1 - \Theta + \Delta_2)\right], \tag{110}$$

where

$$\mathrm{E}_1^{ss}[V] = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f}, \quad \text{and} \quad \mathrm{Var}_1^{ss}(V) = \frac{1}{\tau_V + \tau_f}, \tag{111}$$

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

$$\begin{aligned} P_1^{ss} = \frac{\tau_V \bar{V} + \tau_f s_f}{\tau_V + \tau_f} - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)\Delta_2 \\ + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}(1 - \beta)\right)\right] z_1, \end{aligned} \tag{112}$$

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

$$\begin{aligned} \mathrm{E}[P_1^{ss}] = \bar{V} - \left(\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\right)\Theta + \frac{\lambda}{\tau_v}\left(1 - \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}\right)\mathrm{E}[\Delta_2 \mid 0 \le z_1 \le \Theta] \\ + \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}(1 - \beta)\right)\right]\Delta_1, \end{aligned} \tag{113}$$

where by symmetry,

$$\mathrm{E}[\Delta_2 \mid 0 \leq z_1 \leq \Theta] = 0. \tag{114}$$

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

$$\Delta = \mathrm{E}[P_1^{ss}] - \mathrm{E}[P_1] = \left[\frac{\lambda}{\tau_V + \tau_f} + \frac{\lambda}{\tau_v}\left(\beta + \frac{\lambda^2}{\lambda^2 + \tau_v \tau_z^{ss}}(1-\beta)\right)\right]\Delta_1 > 0, \tag{115}$$

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

$$\frac{d\Delta}{d\delta} = -\frac{\lambda \Delta_1}{(\tau_V + \tau_f)^2}\frac{d\tau_f}{d\delta} > 0, \tag{116}$$

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

$$\mathrm{E}[P_2] = \bar{V} - \frac{\lambda}{\tau_v}\Theta. \tag{117}$$

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

$$\mathrm{E}[P_2^{ss}] = \bar{V} + \frac{\lambda}{\tau_v}(\Delta_1 - \Theta), \tag{118}$$

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

$$\mathrm{E}[R^{ss}] = \mathrm{E}[P_2^{ss}] - \mathrm{E}[P_1^{ss}] = \frac{\lambda}{\tau_V + \tau_f}(\Theta - \Delta_1) + \frac{\lambda(1-\beta)\tau_z^{ss}}{\lambda^2 + \tau_v \tau_z^{ss}}\Delta_1. \tag{119}$$

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

$$\frac{d\mathrm{E}[R^{ss}]}{d\delta} = \frac{\lambda(\Theta - \Delta_1)}{(\tau_V + \tau_f)^2}\frac{d\tau_f}{d\delta} < 0. \tag{120}$$

□

H Supplementary Empirical Results

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

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

Table H5 through H7 present results parallel to those in Tables 3, 5, and 9, with herding and non-herding firms classified based on the sign of the slope coefficient from regression (1), without the requirement that the t-statistic exceeds 1.65 in absolute value.

Table H1: Descriptive statistics

The table shows the summary statistics of the variables: (1). $\text{MV}_{i,t}$, 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). $\beta^{U}_{i,t}$, the slope coefficient of the economic uncertainty index of Jurado et al. (2015) in the model with the Fama-French three factors plus the uncertainty index as the explanatory variables; (6). $O\_score_{i,t}$, the Ohlson(1980) O-score measures; (7). $g\_shares_{i,t}$, the growth of the split-adjusted shares outstanding of firm i in the last fiscal with respect of month t; (8). $\text{NOA}_{i,t}$, firm i's net operating asset; (9). $gp_{i,t}$, firm i's gross profit of the last fiscal year; (10). $accruals_{i,t}$, firm i's total accruals; (11). $g\_asset_{i,t}$, firm i's asset growth measured as the growth rate of total assets in the previous fiscal year; (12). $\text{ITA}_{i,t}$, 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. (13). $\text{ROA}_{i,t}$, firm i's return on asset of the last fiscal year with respect of month t. The sample spans from Jan. 1985 to Dec. 2024.

	N	Mean	Std	Min	P25	P50	P75	Max
$\text{MV}_{i,t}$	1,140,673	7,114	36,769	0.29	329	1,047.65	3,689	3,385,742
$ret_{i,t}$	1,134,075	0.97	12.49	-98.13	-5.21	0.76	6.80	1,625.05
$\text{SUE}_{i,t}$	937,538	-0.12	1.66	-7.53	-0.73	0.00	0.68	4.11
$ivol_{i,t}$	1,096,428	0.02	0.01	0.00	0.01	0.01	0.02	0.72
$\beta^{U}_{i,t}$	1,181,769	3.49	118.01	-4,230.17	-31.86	1.83	38.63	10,565.8
$O\_score_{i,t}$	715,063	-2,114	7,095	-224,526	-1,225	-341	-105	41
$g\_shares_{i,t}$	856,108	0.14	5.97	-1.69	0.00	0.01	0.05	1,591.90
$\text{NOA}_{i,t}$	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 H2: Herding and firm-level uncertainty: t-test

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

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

Table H3: Herding and momentum: portfolio analysis

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

Panel A: Portfolio returns

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

Panel B:FF 3-factor adjusted portfolio returns

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

Table H4: Herding and predictability: portfolio analysis

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

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

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

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

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

Table H6: Herding and momentum: portfolio analysis

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

Panel A: Portfolio returns

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

Panel B:FF 3-factor adjusted portfolio returns

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

Table H7: Herding and predictability: portfolio analysis

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

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