Do Financial Analysts Herd?*

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Abstract

Financial analysts may have strategic incentives to herd or to anti-herd when issuing forecasts of firms' earnings. This paper develops and implements a new test to examine whether such incentives exist and to identify the form of strategic behavior. We use the equilibrium property of the finite-player forecasting game of Kim and Shim (2019) that forecast dispersion decreases as the number of forecasters increases if and only if there is strategic complementarity in their forecasts. Using the I/B/E/S database, we find strong evidence that supports strategic herding behavior of financial analysts. This finding is robust to different forecast horizons and sequential forecast release.

JEL classification: D83, E37, G17

Keywords: financial analysts, earnings forecasting, finite-player forecasting game, strategic interaction, herding

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1. Introduction

Financial analysts aim to accurately estimate a company's earnings on a stock over the coming years. Holding the accuracy fixed, analysts might prefer to herd toward the consensus forecast—the average of all the forecasts from analysts tracking a particular stock—to avoid a reputation loss when wrong. In some other cases, analysts might prefer to deviate from the consensus to stand out and appear talented.[1] Regardless of the underlying reason, analysts may have extraneous strategic incentives to herd or to anti-herd. On the contrary, it may be that analysts only care about the accuracy of their own forecasts without any strategic considerations.

This paper proposes a new empirical strategy to test for non-information-driven strategic behavior of financial analysts and, if such strategic incentives exist, to identify the form of their forecasting behavior. In doing so, we first consider a model of finite-player forecasting game (Kim and Shim, 2019).[2] We then use the results of our model to empirically investigate whether analysts exhibit herding, anti-herding, or non-strategic behavior in issuing earnings forecasts.

In our forecasting game, each analyst receives private and public signals about a firm's expected earnings, and chooses an optimal forecast. Each analyst cares both about being correct and about his distance to the average forecast.[3] The payoff structure allows for strategic complementarity, substitutability, or independence in forecasts, which respectively represent the analysts' intrinsic preference for herding, anti-herding, or non-strategic behavior. Importantly, the finiteness of the number of analysts adds another strategic consideration when analysts are issuing forecasts. That is, with a finite number of analysts,

[1] Croushore (1997) points out that professional forecasters may herd to avoid unfavorable publicity when wrong, while others might make bold forecasts to stand out. Ottaviani and Sørensen (2006) show that in the context of a winner-take-all contest, forecasters have incentives to differentiate their predictions from those of others. Also see Prendergast and Stole (1996) who show that agents without an established reputation exaggerate their differences with others to appear talented.

[2] Our game is a version of an aggregate game. Martimort and Stole (2012) give the general definition of aggregate games with a linear aggregate.

[3] For ease of exposition, we use male pronouns for the analyst.

each analyst's forecast exerts a non-negligible effect on the average forecast in comparison to a large (competitive) forecasting game that is extensively considered in the literature.

In our analysis, this finiteness of the number of analysts is the key mechanism for identifying the nature of strategic behavior. In the model, the analysts' underlying preference for herding/anti-herding uniquely pins down the relationship between the number of analysts and the forecast dispersion, measured by the variation in the equilibrium forecasts across analysts. Specifically, as the number of analysts increases, the forecast dispersion decreases (resp. increases) if and only if the analysts' intrinsic desire is to herd (resp. anti-herd).

The intuition is as follows. As the number of analysts increases, any analyst's forecast, thus his private information, has less of an influence on the average forecast; so all analysts strategically put less weight on private information and more weight on public information (which is a relatively better predictor of the average forecast) if the analysts tend to herd, generating a lower disagreement among analysts. The opposite is true if the analysts tend to anti-herd, and if there is no such strategic incentive, then the forecast dispersion is not affected by the number of analysts. Thus, by examining the relationship between the number of analysts and dispersion in the data, we can infer the analysts' (anti-)herding incentive that is not directly observed.

In order to test this equilibrium prediction of our model, we use financial analysts' earnings forecasts data drawn from the I/B/E/S Historical Summary file, which covers the period between 1990 and 2015. We fit a year-by-year regression model that regresses the forecast dispersion, which is constructed following Diether, Malloy, and Scherbina (2002), on the number of analysts. Our benchmark regression specification yields a negative coefficient of -0.0927, which is statistically significant from zero. This finding is robust to (a) inclusion of various control variables such as firm size, leverage, and turnover; (b) different forecasting horizons; and (c) the possibility of a size effect of the number of analysts. Our findings provide support for the strategic herding behavior of financial analysts.

This paper adds to the literature that examines financial analysts' (anti-)herding behavior, which offers mixed results (e.g., Bernhardt, Campello, and Kutsoati, 2006; Clements, 2018; Hong, Kubik, and Solomon, 2000; Jegadeesh and Kim, 2010). Clements (2018) provides a summary of the recent literature on macro forecasting that supports either herding or anti-herding. Bernhardt, Campello, and Kutsoati (2006) develop a test for herding in the earnings forecasts by financial analysts, and find that analysts anti-herd in the direction of their private information. In contrast, there is a large stream of both theoretical and empirical research that supports the herding hypothesis. For example, Trueman (1994) shows that analysts exhibit herding behavior that is not driven by analysts' information. Although Trueman (1994) considers a sequential forecasting model while we use a simultaneous forecasting model, our empirical results are consistent with Trueman's model.[4] Hong, Kubik, and Solomon (2000) empirically document a link between herding behavior and career concerns in the labor market for security analysts. Jegadeesh and Kim (2010) further investigate whether the market recognizes herding behavior by analyzing analysts' recommendations instead of earnings forecasts and testing for herding based on market price reactions around recommendation revisions.

While our paper is consistent the previous papers that support the herding hypothesis, we differ from those studies in two ways. First, we adopt the framework of aggregate games with dispersed information and explicitly consider two types of strategic incentives arising from the intrinsic preference structure and from the finiteness of the number of agents. Second, the finite property of our model allows us to propose a novel identification strategy to draw inferences about analysts' tendencies to herd. This finiteness of the number of agents is crucial for our empirical analysis, which has not been explored.

The remainder of the paper is organized as follows. Section 2 reviews a theoretical framework that provides testable implications for the data. Section 3 describes our data, presents our empirical findings, and considers their robustness. Section 4 concludes the paper.

[4] We show in Section 3.4 that our result for herding is robust to differing the time interval between forecast announcements, supporting the herding hypothesis regardless of the timing of forecast announcements.

2. The model and predictions

In this section, we review briefly the finite-player forecasting game of Kim and Shim (2019) but in the specific context of earnings forecasting by financial analysts, and use its equilibrium properties to derive testable predictions for the form of strategic interaction (if any) among analysts.

2.1. *Finite-player forecasting game*

Consider a simple economy in which there are one risky firm and n financial analysts, each of whom is indexed by i and issues a forecast of the firm's earnings, $\theta \in \mathbb{R}$. We assume that nature draws θ from an improper uniform distribution over the real line. Agents receive noisy signals that are informative about the firm's earnings. That is, each agent i observes a public signal $p = \theta + (\alpha_p)^{-1/2}\varepsilon$ and a private signal $x_i = \theta + (\alpha_x)^{-1/2}\varepsilon_i$. The ε and ε_i are, respectively, common and idiosyncratic noises that are independent of each other as well as of θ, and both follow $N(0, 1)$. We let α_p and α_x denote the precision of public and private signals, respectively.

After observing his signals, each analyst i releases a forecast of θ, which we denote as $a_i \in \mathbb{R}$, and receives a payoff u_i, which is given by $u_i(a_i, A_n, \theta) = -\frac{1}{2}\left((1-r)(a_i - \theta) + r(a_i - A_n)\right)^2$ or, equivalently,

$$u_i(a_i, A_n, \theta) = -\frac{1}{2}\left(a_i - (1-r)\theta - rA_n\right)^2, \tag{2.1}$$

where $A_n \equiv \frac{1}{n}\sum_{i=1}^{n} a_i$ denotes the average forecast across the population and the parameter $r \in (-1, 1)$ gives the weight that the analyst puts on the average forecast relative to the fundamentals.[5]

While the payoff specification is quite stylized, it is general enough to encompass a

[5]For tractability, we assume that analyst's preferences are quadratic to ensure linearity in the best responses. The equilibrium is unique if and only if $r < 1$.

variety of situations.[6] When $r = 0$, each analyst cares only about being correct, generating a fundamental motive to be close to the true θ; so there is no strategic interaction across analysts. When $r \neq 0$, each analyst cares both about being correct and about the distance of his forecast to the average forecast A_n, which entails two channels of strategic motives. The first motive, which we call the *herding motive*, arises from the analysts' intrinsic preferences for (anti-)herding—i.e, whether analysts' forecasts are strategic complements ($r > 0$) or strategic substitutes ($r < 0$). The second motive, which we call the *market-power motive*, arises from the analysts' ability to strategically influence the average forecast by changing his forecast, due to the finiteness of the number of analysts ($n < \infty$).

In this game, the equilibrium forecast of agent i is uniquely characterized as follows.[7]

$$a_i(x_i, p) = \lambda_n x_i + (1 - \lambda_n)p, \ \forall i \in \{1, \dots, n\}, \tag{2.2}$$

where $\lambda_n = \frac{\alpha_x}{\alpha_x + \frac{1}{1-\gamma}\alpha_p}$ and $\gamma \equiv \frac{r(n-1)}{n-r}$. The coefficient λ_n measures how the agents allocate their use of private information relative to public information in equilibrium. This equilibrium weight λ_n reflects a combination of both the herding and market-power motives, the degrees of which are together captured by the parameter γ.

Lemma 2 of Kim and Shim (2019) establishes the following result, which we restate for the convenience of the reader.

Result 1. *For any given α_x and α_p and for any given n such that $2 \leq n < \infty$, $\frac{\partial \lambda_n}{\partial n} < 0$ when $r > 0$, $\frac{\partial \lambda_n}{\partial n} = 0$ when $r = 0$, and $\frac{\partial \lambda_n}{\partial n} > 0$ when $r < 0$.*

Proof. The proof is immediate: $\frac{\partial \lambda_n}{\partial n} = -r\frac{\alpha_x \alpha_p}{n^2(1-r)}\left(\alpha_x + \frac{n-r}{n(1-r)}\alpha_p\right)^{-2} \lesseqqgtr 0$ iff $r \gtreqqless 0$ □

That is, as the number of analysts increases, the analysts put less (resp. more) weight on private information when their forecasts are strategic complements (resp. strategic substi-

[6]The forecasting game described here is an example of an aggregate game in which each agent's payoff is a function of his own strategy and some aggregator of the strategy profile of all agents. Aggregate games are studied in Acemoglu and Jensen (2013), Cornes and Hartley (2012), Martimort and Stole (2012), among many others.

[7]The detailed proof can be found in Kim and Shim (2019).

tutes). The intuition comes from the fact that with a finite number of analysts the average forecast of the population contains the analysts' private noises, which disappear as n goes to infinity. Accordingly, as more analysts participate in issuing forecasts, any analyst's private information has less of an influence on the average forecast; so all analysts strategically put less weight on private information when their intrinsic desire is to herd ($r > 0$), whereas the opposite happens when the analysts' intrinsic desire is to be distinctive from the herd ($r < 0$). When agents do not care about what others do ($r = 0$), then the number of analysts has no effect on λ_n.

The equilibrium forecast in Eq. (2.2) can be rewritten as $a_i = \theta + \lambda_n(\alpha_x)^{-1/2}\varepsilon_i + (1 - \lambda_n)(\alpha_p)^{-1/2}\varepsilon$. Then the equilibrium level of forecast dispersion for any given realizations of θ and p is given by

$$Var(a_i|\theta, p) = \left(\lambda_n \left(\alpha_x\right)^{-1/2}\right)^2. \tag{2.3}$$

This measure of forecast dispersion depends directly on the weight λ_n, which is defined in terms of r and n in addition to signal precisions.

2.2. Discussion of the model

First of all, the study of a finite-player model is pertinent due to the following reason. The preference parameter r that measures the underlying behavior of analysts and the weight λ_n that measures the allocation of information signals are generally not observable to researchers. The model with a finite number of agents enables us to explore the relationship between n and $Var(a_i|\theta, p)$, which can be observed in the data. We can then infer from the data whether analysts exhibit herding or anti-herding behavior by estimating empirical patterns of forecast dispersion in relation to the number of analysts.

Second, our model assumes that all analysts release their forecasts simultaneously. One might consider a situation in which analysts provide their forecasts sequentially. If the analysts have the flexibility to optimally choose when to disclose their forecasts, any analyst might have an incentive to delay his announcement so that he can have access to more information and condition his forecast on any previously released forecast. However if all analysts are symmetric in terms of preferences, then there is no reason a prior to expect any particular analyst will announce his forecast at a different date than others, so that all forecasts will be issued at the same time in equilibrium. Hence, the equilibrium in the case of sequential forecasting would be substantively equivalent to the equilibrium of simultaneous forecasting.[8]

Lastly, while we focus on the static model, one natural extension is to consider a dynamic model. For example, we may assume that the fundamental variable θ_t follows AR(1) process and analysts observe noisy private and public signals in each period together with θ_{t-1}. Under some conditions, we can show that the analysis of the static model is exactly preserved in this dynamic version of forecasting game. In particular, the expression of forecast dispersion that is essentially equivalent to Eq. (2.3) can also be derived for the dynamic model, thus we focus on the static model for simplicity of analysis.

2.3. Testable implications

To derive testable implications about strategic interaction in analysts' forecasts, we focus on how the dispersion of forecasts in Eq. (2.3) changes in response to a change in the number of analysts issuing those forecasts. The following predictions lay the basis for our empirical tests in Section 3.

Prediction. *Suppose that the degree of the herding motive, r, does not depend on the number of analysts issuing forecasts, and that r is the same across all analysts and across different forecast horizons. For any given value of α_x and α_p, as the number of analysts increases, the following results hold:*

[8] Trueman (1994) analyzes the case where the order in which the analysts disclose their forecasts is determined exogenously. In such case, the paper finds that analysts tend to behave according to their non-information related incentive to herd.

1. *The forecast dispersion decreases iff $r > 0$, does not change iff $r = 0$, and increases iff $r < 0$.*

2. *The above relationship is preserved across different forecast horizons.*

3. *The magnitude of the effect of an additional analyst on the forecast dispersion becomes smaller if $r \neq 0$, whereas there is no such size effect if $r = 0$.*

Proof. Prediction 1: An observation of Eq. (2.3) yields $\frac{\partial Var(a_i|\theta,p)}{\partial n} \propto \frac{\partial \lambda_n}{\partial n}$. Then the proof follows from Result 1. Prediction 2 is a direct implication of Prediction 1. Prediction 3: Following from the proof of Result 1, $\partial \left(|\frac{\partial \lambda_n}{\partial n}| \right) / \partial n < 0$ when $r \neq 0$, and is zero otherwise. □

The intuition behind Prediction 1 is as follows. Public information is a relatively better predictor of the average forecast than private information. While any analyst's forecast, thus his private information, exerts a non-negligible effect on the average forecast, it becomes less influential as the number of analysts increases. So as n increases, the analysts whose preference is for herding ($r > 0$) rely less on private information, generating a lower disagreement among analysts. On the other hand, when the analysts want to deviate from the herd ($r < 0$), they find it optimal to use more private information, which leads to a higher disagreement among analysts. Finally when the agents do not care about the herd ($r = 0$), there is also no finite-player strategic consideration in place, and so the forecast dispersion is independent from the number of analysts.

Prediction 1 provides the key channel for identifying the underlying (anti-)herding behavior of financial analysts. We can exploit the relationship between the number of analysts issuing earnings forecasts of a firm and the forecast dispersion observed in the data to infer such strategic interaction, if there is any.

Financial analysts issue earnings forecasts of companies at different forecast horizons. Intuitively, it is more difficult to forecast long-run earnings than short- or medium-run earnings; and differences among analysts' information signals tend to matter more at short forecast horizons where signals are stronger (as noted by Patton and Timmermann (2010)). A varying length of the forecast horizon can be captured by changing signal precisions in our model. Hence, given the assumption that the underlying degree of the herding motive, r, does not depend on the forecast horizon, varying forecast horizons should not change Prediction 1.

Prediction 3 comes from the feature of our model in which there are two strategic effects, one due to the finiteness of the number of analysts and the other due to the analysts' preference for (anti-)herding. If those two forces are at play for financial analysts, then the marginal effect of an additional analyst on forecast dispersion should be larger when fewer analysts are issuing forecasts.

3. Empirical analysis

In this section, we first describe our data and implement various tests of herding using the predictions above.

3.1. Data and sample

We draw financial analysts' earnings forecasts data from the Thomson Reuters' Institutional Brokers Estimate System (I/B/E/S) database. The database provides analysts' historical earnings estimates for more than 20 forecast measures, including earnings per share. In particular, we utilize the I/B/E/S Historical Summary file from 1990 to 2015, which provides useful statistics for the number of analysts following a firm as well as mean and standard deviation values. We extract firm-level data from the Center for Research on Security Prices (CRSP) files and the Compustat database. Our sample firms are basically all public firms listed on the stock market. The coverage of constructed sample is 75% of the CRSP-Compustat data in terms of total assets.

3.2. Measure of analyst forecast dispersion

Our empirical proxy of analyst forecast dispersion is constructed following Diether, Malloy, and Scherbina (2002), which is defined as the monthly standard deviation scaled by the mean of current-fiscal-year earnings estimates across analysts. By construction, we only include earnings forecasts in our sample covered by two or more analysts during the period. We take the yearly average values of dispersion because the estimates are shown to be persistent at higher frequency.[9]

In Table 3.1, we document descriptive statistics of the main variables used for our empirical analysis. The numbers show that both forecast dispersion and analyst coverage seem positively skewed considering the non-negativeness of measures. The median of analyst coverage is five while its standard deviation is 6.8, implying a reasonable distribution of coverage.

Table 3.1
Descriptive statistics.

	Mean	Median	SD	P25	P75
Dispersion	0.1669	0.0460	0.4197	0.0190	0.1260
Number of Analysts	7.9224	5	6.7599	3	10

3.3. Main results

Prediction 1 implies that we should observe a negative (resp. positive) relationship between the number of analysts and the forecast dispersion if the analysts' underlying strategic behavior is herding (resp. anti-herding) in the data. To capture the relationship between the number of analysts and the forecast dispersion, we begin our empirical investigation by forming quintile dispersion portfolios sort on the number of analysts each year. Then we

[9] Similar results are obtained when monthly data is instead used for the empirical analysis. Results are available upon request.

report time-series average of median dispersion of each portfolio in Table 3.2. In sum, we find a decreasing pattern across portfolios, implying herding behavior of analysts.

Table 3.2
Average forecast dispersion sort on the number of analysts.

	Low	2	3	4	High
Dispersion	0.1000	0.0772	0.0582	0.0450	0.0351
Number of Analysts	2.1739	3.6864	5.8475	9.5426	18.0817

To formally test the prediction, we employ the Fama-MacBeth type of regressions following the cross-sectional asset pricing literature, because the procedure effectively allows us to focus on the analyst herding in a given time period. Our benchmark regression specification is as follows.

$$Dispersion_{i,t} = \alpha_t + \beta_t \; Number\ of\ analysts_{i,t} + \epsilon_{i,t} \tag{3.1}$$

where $Dispersion_{i,t}$ is the dispersion in analysts' earnings forecasts for firm i in year t, $Number\ of\ analysts_{i,t}$ is the number of analysts who cover firm i in year t, α_t is time fixed effect, and $\epsilon_{i,t}$ is an error term. The coefficient of interest is β_t, which measures whether an additional analyst covering the firm increases or decreases the dispersion of forecasts across analysts. We estimate the regression model of Eq. (3.1) for each year, and calculate the time-series average of β_t obtained for all years.

To study whether our findings are robust to control variables, we also estimate the following regression specification for each year:

$$Dispersion_{i,t} = \alpha_t + \gamma_t \chi_t + \beta_t \; Number\ of\ analysts_{i,t} + \epsilon_{i,t} \tag{3.2}$$

where χ_t is a vector of control variables and γ_t is the corresponding vector of coefficients. Because it may be more difficult to predict risky firms, we consider a set of control variables that represent the dimensions of firm riskiness. The controls include firm size, book-to-market ratio, dividend paying dummy, idiosyncratic risk, stock turnover, past 1-year stock return momentum.

In Table 3.3, we report the time-series average of first-stage cross-sectional regression coefficients. Column (1) presents the estimates for our benchmark regression specification. We find a significant and negative coefficient on the number of analysts, consistent with the previous portfolio sort.[10] In columns from (2) to (7), we consider each additional control that may drive the forecast dispersion to check the robustness of the result. In column (8), we include all of the control variables in a single regression. The estimated coefficients on the number of analysts are still negative and significant in all specifications that we consider, indicating that financial analysts exhibit herding behavior when issuing forecasts.

Table 3.3
Estimation results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.3866	0.4230	0.3991	0.4108	0.3058	0.3632	0.3864	0.3152
	(25.94)	(28.14)	(31.65)	(27.62)	(15.20)	(23.14)	(25.78)	(14.17)
Number of Analysts	-0.0927	-0.0777	-0.0875	-0.0778	-0.0750	-0.1076	-0.0918	-0.0660
	(-18.41)	(-13.61)	(-17.16)	(-13.93)	(-13.65)	(-16.51)	(-17.39)	(-9.33)
Firm Size		-0.0097						0.0029
		(-4.49)						(1.07)
B/M			0.0333					0.0446
			(6.42)					(9.03)
Dividend				-0.1106				-0.0986
				(-20.88)				(-10.30)
Idiosyn					0.0479			0.0435
					(5.43)			(5.52)
Turnover						0.0343		0.0249
						(18.20)		(8.80)
Momentum							-0.0008	-0.0012
							(-2.20)	(-2.87)
Avg R^2	0.0194	0.0226	0.0282	0.0358	0.027	0.0321	0.0213	0.0604
N	80956	80956	70920	80956	80956	80956	80956	70920

Notes: Firm Size is the logarithm of firm assets; B/M is the log book-to-market ratio; Dividend is a dummy variable that equals one if the firm pays dividend at that fiscal year; Idiosyn is the idiosyncratic risk computed as the logistic transformation of the coefficient of determination from a regression of daily excess returns on the Fama-French three factor model; Turnover is the yearly average of monthly stock turnover; Momentum is the past 12 month return of the stock. The numbers in parentheses are t-statistics based on the White (1980) standard errors.

[10] We use the logarithm of (1+Number of analysts) in the regression analysis.

Note that the signs of the coefficients on the control variables seem reasonable. The coefficient on firm size is negative, suggesting that the forecast dispersion across analysts becomes smaller when evaluating larger firms; however the coefficient on firm size becomes indistinguishable from zero when other controls are included in the specification as reported in column (8). The positive coefficients on book-to-market ratio and on idiosyncratic risk are predicted, because these variables are regarded as proxies for firm riskiness, which make firms difficult to value. Paying a dividend and having a higher past stock performance also lower the forecast dispersion, while a higher high turnover increases it. The estimated coefficient on turnover may seem counter-intuitive because liquid stocks are usually less ambiguous.[11]

We next test Prediction 2. The I/B/E/S data also contain various earnings estimates in terms of different forecast horizons, from current-fiscal-quarter to period beyond five years.[12] We repeat the regression analysis using the estimates of different forecast horizons, and the findings are reported in Table 3.4, where we only report the coefficient estimates for the intercept and the number of analysts for brevity.

In any specification, the results suggest that the negative relation between analyst coverage and forecast dispersion is a robust feature of the data. When the benchmark specification without any controls is used, the estimated coefficients are -0.1084 (Panel A), -0.1422 (Panel B), and -.0535 (Panel C). In addition, we do not observe a systematic pattern of the estimated coefficients when the forecast horizon changes.

These findings provide support for strategic behavior of analysts in a way that their forecasts on earnings complement each other. One might suspect that such herding behavior itself may be sensitive to the number of analysts, which leads us to Prediction 3. Suppose that there exists only few analysts covering a specific firm and that the analysts exhibit herding behavior. Then each analyst may have a stronger incentive to herd because any deviation from the consensus can be particularly riskier. In this regard, we test whether the

[11]The results are robust to the inclusion of lagged dispersion. Results are available upon request.

[12]The long-term growth forecasts of analysts do not have well-defined horizons, but Sharpe (2005) finds that the market applies these forecasts to an average horizon somewhere in the range of five to ten years.

Table 3.4
Estimation results: different forecasting horizons.

Panel A: Very Short-term (1-quarter)								
Intercept	0.4559	0.4836	0.4730	0.4799	0.3555	0.4355	0.4555	0.3462
	(23.14)	(25.73)	(29.46)	(24.00)	(13.99)	(20.38)	(23.16)	(14.41)
# of Analysts	-0.1084	-0.0939	-0.0979	-0.0973	-0.0839	-0.1290	-0.1069	-0.0928
	(-19.28)	(-13.33)	(-15.19)	(-17.27)	(-11.66)	(-16.84)	(-18.05)	(-9.94)
Control	No	Firm Size	B/M	Dividend	Idiosyn	Turnover	Momentum	All
Avg R^2	0.0223	0.0262	0.0353	0.0371	0.0324	0.039	0.0246	0.0693
N	70226	70226	61897	70226	70226	70226	70226	61897

Panel B: Intermediate-term (2-5 years)								
Intercept	0.5390	0.7176	0.5525	0.5951	0.4169	0.5104	0.5397	0.5284
	(15.53)	(12.51)	(18.32)	(14.24)	(10.98)	(13.28)	(15.49)	(9.30)
# of Analysts	-0.1422	-0.0539	-0.1558	-0.1140	-0.1049	-0.1825	-0.1432	-0.0863
	(-13.44)	(-5.95)	(-14.73)	(-9.41)	(-12.08)	(-11.32)	(-12.71)	(-8.72)
Control	No	Firm Size	B/M	Dividend	Idiosyn	Turnover	Momentum	All
Avg R^2	0.0172	0.0452	0.0243	0.0597	0.0378	0.0458	0.0206	0.0901
N	75479	75479	66206	75479	75479	75479	75479	66206

Panel C: Long-term Growth (beyond 5 years)								
Intercept	0.4005	0.2654	0.4011	0.3835	0.3730	0.3771	0.3990	0.1780
	(9.95)	(12.09)	(10.56)	(10.62)	(9.71)	(11.26)	(10.04)	(8.95)
# of Analysts	-0.0535	-0.0938	-0.0219*	-0.0543	-0.0458	-0.0641	-0.0522	-0.0708
	(-3.49)	(-5.22)	(-1.92)	(-3.64)	(-3.19)	(-3.67)	(-3.47)	(-4.18)
Control	No	Firm Size	B/M	Dividend	Idiosyn	Turnover	Momentum	All
Avg R^2	0.0047	0.0303	0.0449	0.009	0.0103	0.0137	0.0073	0.0758
N	50066	50066	44057	50066	50066	50066	50066	44057

Note: The numbers in parentheses are t-statistics based on the White (1980) standard errors.

degree of herding behavior is more severe for firms that are covered by few analysts.

To test Prediction 3, we divide our sample into three groups based on the analyst coverage. Group 1 contains observations covered by less than or equal to five analysts, group 2 contains those covered by more than five and less then or equal to ten analysts, and group 3 contains more than ten analysts. In Table 3.5, we report the time-series average of the coefficient on the number of analysts for each subset. We only report results based on the current-fiscal-year forecasts.

Table 3.5
Estimation results: subsample analysis by the number of analysts.

	Group 1		Group 2		Group 3	
Intercept	0.4778	0.4143	0.3018	0.2491	0.2195	0.1271
	(18.77)	(13.28)	(8.54)	(4.49)	(10.85)	(4.02)
Number of Analysts	-0.1494	-0.1179	-0.0610	-0.0375	-0.0407	-0.0144
	(-10.27)	(-8.03)	(-3.74)	(-2.34)	(-5.69)	(-1.06)
Control	No	All	No	All	No	All
Avg R^2	0.0044	0.0438	0.002	0.0596	0.0061	0.1164
N	35059	30656	23341	20598	22556	19666

Notes: Group 1 includes sample with $n \leq 5$ forecasters, Group 2 includes the sample with $5 < n \leq 10$ forecasters, and Group 3 includes the sample with $10 < n$ forecasters.

Moving from Group 1 to 3, we find that the magnitude of the coefficient estimates on the number of analysts decreases. For group 1, the estimates hover around -0.12 and -0.15 depending on regression specifications. But the coefficients are estimated to about -0.06 for group 2 and -0.04 for Group 3, under the benchmark specification without any controls.[13] This finding indicates that as more analysts issue forecasts, the marginal effect of an additional analyst on forecast dispersion diminishes, confirming Prediction 3 and implying that the degree of herding is smaller with more analysts.

[13] For group 3, the coefficient becomes indistinguishable from zero when all controls are included, while the sign is still negative.

3.4. Robustness checks

Our model is based on the framework of simultaneous forecasting game in which analysts provide their forecasts at the same time. However because the timing of forecast announcements differs across financial analysts, one might argue that the sequential game framework better captures analyst behavior. In a sequential game, an analyst who issues his forecast later can observe the announced forecasts of previous analysts. When the time interval between forecast announcements is substantial, then sequential forecasting might be an appropriate characterization of the game.

We examine this issue by considering the effect of the time interval between forecast announcements on the parameter of interest. If there is no large time gap between announcements, then analysts may not have enough time to infer private information from previously announced forecasts by other analysts. For such case, even if the announcement timing differs, the equilibrium of our simultaneous game can be representative of the actual forecasting behavior. On the contrary, if there is a large time gap between announcements, the equilibrium outcome of the sequential game must be used as an approximation.

We use the number of days between the first and last forecasts in a given month scaled by thirty as a measure of the interval. Then we form three groups based on the interval measure. In Table 3.6, we report the time-series average of the coefficient on the number of analysts for each subset. We only report results based on the current-fiscal-year forecasts.

We find that the coefficient estimates on analyst coverage are negative and significant regardless of the time interval, implying that the strategic incentive of analysts is not affected by differing timings of announcements. Although there is a decreasing pattern of the absolute magnitude of coefficients from Group 1 to 3, but the difference is not so large for the benchmark specification without controls. In fact, the decreasing pattern is counter-intuitive because it implies that the degree of herding behavior decreases as the game becomes more sequential.

Table 3.6
Estimation results: subsample analysis by the announcement interval.

	Group 1		Group 2		Group 3	
Intercept	0.4738	0.4687	0.4689	0.4075	0.5138	0.4059
	(22.53)	(15.81)	(20.63)	(12.43)	(18.26)	(9.21)
Number of Analysts	-0.1595	-0.1277	-0.1335	-0.1015	-0.1184	-0.0549
	(-16.74)	(-14.95)	(-15.88)	(-10.47)	(-12.77)	(-3.10)
Control	No	All	No	All	No	All
Avg R^2	0.0217	0.0671	0.0348	0.0795	0.034	0.1247
N	41143	35908	27837	24435	11976	10577

Notes: Group 1 includes sample with Interval$\leq$ 0.25 analysts, Group 2 includes the sample with 0.25 <Interval$\leq$ 0.5 analysts, and Group 3 includes the sample with 0.5 <Interval analysts.

Many analysts often revise their forecast as soon as the firm announces its earnings. To take this into account, we collect earnings forecasts that are issued at or a day after the date of firm's earnings announcement. Those forecasts are more likely to be affected by the arrival of new information rather than forecasts made by other analysts. The result under such sample may be more consistent with our theoretical framework of simultaneous forecasting. Hence, we want to make sure that our regression results are robust to this different sample of analysts' forecasts.

Table 3.7 reports the estimation results. In the benchmark specification without any control, we find a significant and negative coefficient on the number of analysts, providing support for our herding hypothesis. However, the coefficient becomes insignificant (but still negative) when all control variables are included.

Table 3.7
Estimation Rresults: subsample analysis around the announcement date.

Intercept	0.2277	0.3144
	(7.42)	(6.14)
# of Analysts	-0.0273	-0.0139
	(-2.27)	(-1.30)
Control	No	All
Avg R^2	0.0024	0.0413
N	29117	25801

4. Conclusion

In this paper, we analyze whether financial analysts have strategic herding or anti-herding incentives when issuing forecasts about firms' earnings. To this end, we propose a new approach using the equilibrium predictions from the finite-player forecasting game of Kim and Shim (2019), and examine whether such incentives exist. Our findings indicate that financial analysts exhibit strategic herding behavior in their forecasts.

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