Do Financial Analysts Herd?*

Jin Yeub Kim† Yongjun Kim‡ Myungkyu Shim§

April 3, 2019

Abstract

Financial analysts may have strategic incentives to herd or to anti-herd when issuing forecasts of firms' earnings. This paper proposes a new approach to examine whether such incentives exist and to identify the form of strategic behavior. In doing so, we use the equilibrium properties of the finite-player forecasting game of Kim and Shim (2019): Forecast dispersion decreases (resp. increases) as the number of forecasters increases if and only if there is strategic complementarity (resp. substitutability) in their forecasts. Using the financial analysts' earnings forecast data drawn from the Thomson Reuters' I/B/E/S database, we find a strong evidence that supports strategic herding behavior of financial analysts.

JEL classification: D83, E37, G17

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

*We thank the seminar participants at the 2018 APIOC for helpful comments.

†Department of Economics, University of Nebraska-Lincoln, 730 N. 14th Street, Lincoln, NE 68588, USA, E-mail: shiningjin@gmail.com

‡College of Business Administration, University of Seoul, 163 Seoulsiripdae-ro, Dongdaemun-gu, Seoul, 02504, Republic of Korea, E-mail: jkim@uos.ac.kr

§School of Economics, Yonsei University, 50 Yonsei-ro Seodaemun-gu, Seoul 03722, Republic of Korea, E-mail: myungkyushim@yonsei.ac.kr

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 so-called consensus forecast—the average of all the forecasts from analysts tracking a particular stock.[1] In some other cases, analysts might prefer that their predictions are further away from the consensus forecast. It may even be that analysts only care about the accuracy of their own forecasts. This paper proposes a new empirical strategy to identify the form of forecasting behavior of financial analysts; in particular, whether there is strategic complementarity (or herding), strategic substitutability (or antiherding), or no strategic behavior in forecasting.

To identify the underlying strategic interaction among analysts, we consider a forecasting game played by a finite number of forecasters (Kim and Shim 2019), which is a version of an aggregate game.[2] In the forecasting game, each agent receives private and public signals about a variable of interest, and chooses an optimal forecast. Each agent cares both about being correct and about his distance to the average forecast. The payoff structure allows for either strategic complementarity or substitutability in forecasts. In our analysis, the finiteness of the number of agents is the key component for identifying the nature of strategic behavior. With a finite number of agents, each agent's forecast exerts a non-negligible effect on the consensus forecast in comparison to a large (competitive) forecasting game that is considered in the literature.

In the model economy, we can derive a unique prediction that strategic motives underlying the game determine the relationship between the forecast dispersion, which measures the extent to which forecasts are different from each other, and number of forecasters. In particular, sufficient and necessary condition for positive (resp. negative) relationship between forecast dispersion and numbers of forecasters is a strategic substitutability (resp.

[1] Croushore (1997) and Ottaviani and Sørensen (2006) point out that a professional forecaster may herd to avoid a reputation loss.

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

complementarity) between the forecasters. The economic intuition behind the prediction is simple: As the number of forecasters increases, the average forecast reveals more "common" information since it is less contaminated by the small sample. If there exists a herding motive ($r > 0$), each forecaster will put more weight on the average forecast when making a prediction. This reduces the degree of disagreement among the forecasters. If there exists no such strategic motive, on the other hand, the forecast dispersion and numbers of forecasters do not have any relationship. As a result, unveiling the relationship provides us an information about the coordination motive that is not directly observed.

In order to test the above hypothesis, we use financial analysts' earnings forecast data drawn from the I/B/E/S Historical Summary file, whose sample covers the period between 1990 and 2015. Guided by the theory, we perform a year-by-year regression that directly regresses the forecast dispersion, which is constructed following Diether, Malloy, and Scherbina (2002), on the numbers of analysts. Benchmark estimation yields the negative coefficient (-0.097), which is statistically significantly different from zero. This finding turns out to be robust: (1) inclusion of various control variables such as firm size, leverage, and turnover that can potentially affect our estimates, (2) considering size effect from the number of forecasters, (3) considering forecasts on earnings estimates at different horizons. This implies that there is a strategic complementarity motive between forecasters, according to our theory.

It is worthwhile to note that there have been plenty of papers that study if such strategic motives exist; Hong, Kubik, and Solomon (2000), Trueman (1994), Bernhardt, Campello, and Kutsoati (2006), Jegadeesh and Kim (2010), and Clements (2018) are just few examples. For instance, Table 1 of Clements (2018) summarizes literature on herding behavior across macroforecasters. Our paper is different from the previous papers by adopting an aggregate game with dispersed information and explicitly considering the strategic interactions across the forecasters. Most importantly, we propose a novel identification strategy by exploiting the finite property of the forecasting game. Ottaviani and Sørensen (2006) is also close to our paper. However, the paper is different from ours in two dimensions. First, as is consistent with the previous literature, it considers a game with infinitely many agents, while the finiteness of the agents is crucial for our empirical analysis. Second, it is a theory paper so that it does not directly test their own theory's predictions.

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.

2. The model and predictions

In this section, we review the finite-player forecasting game of Kim and Shim (2019) but in the context of earnings forecasting by 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

There is a finite number of agents (financial analysts), each of whom is indexed by i, and the number of agents is $n \in \mathbb{N}$ where $n \geq 2$. We represent the true fundamentals, such as earnings of a firm, with an exogenous random variable $\theta \in \mathbb{R}$ drawn from the uniform distribution over the real line. Each agent i issues a prediction of θ, which we denote as forecast $a_i \in \mathbb{R}$, 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 agent puts on the average forecast relative to the fundamentals.[3]

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

While the payoff specification is quite stylized, it is general enough to encompass a variety of situations.[4] When $r = 0$, each agent cares only about being correct, generating a fundamental motive to be close to the true θ; so there is no strategic interaction across agents. When $r \neq 0$, each agent cares both about being correct and about his distance to the average forecast A_n, which entails two channels of strategic motives.[5] The first motive, which we call the *herding motive*, arises from the agents' intrinsic preferences for (anti-)herding—i.e, whether agents' forecasts are strategic complements ($r > 0$) or strategic substitutes ($r < 0$). The second motive, which we call the *market-power motive*, arises from the agents' ability to strategically influence the average forecast by changing his forecast, due to the finiteness of the number of agents ($n < \infty$).

Agents do not observe the realization of the true θ but instead observe noisy signals that are informative about the underlying fundamentals. 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.

In this finite-player forecasting game, the equilibrium forecast of agent i is characterized as follows, the proof of which is given in Kim and Shim (2019):

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

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

[4]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.

[5]For ease of exposition, we use male pronouns for the agent.

the convenience of the reader.

Result. *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 $r > 0$ and $\frac{\partial \lambda_n}{\partial n} > 0$ when $r < 0$.*

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

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

The equilibrium forecast in equation (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 agents (or the weight λ_n that measures the equilibrium use of information) is generally not observable. 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 the herding behavior of analysts in the data by estimating empirical patterns of forecast dispersion in relation to the number of analysts.

Second, we note that our model assumes that all agents release their forecasts simultaneously. One might consider a situation in which the agents provide their forecasts sequentially. The intuition suggests that if each agent has the flexibility to optimally choose when to disclose his forecast, the equilibrium in the case of sequential forecasting would be substantively equivalent to the equilibrium of simultaneous forecasting.[6] That is, an agent 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. If all agents are identical, there is no reason a prior to expect any particular agent will announce his forecast at a different date than others, so that all forecasts will be issued at the same time in equilibrium.

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 agents 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 equation (2.3) can 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 equation (2.3) changes in response to a change in the number of agents issuing those forecasts.

[6] Trueman (1994) analyzes the cases where the order in which the analysts disclose their forecasts is determined exogenously. The analysis suggests that analysts exhibit herding behavior, and so the order in which the forecasts are made must be taken into account in deriving the consensus forecast.

Prediction. *Suppose that the degree of the herding motive, r, does not depend on the number of agents issuing forecasts, and that r is the same across all agents 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:*

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

Proof. See Appendix A. □

The intuition behind the first prediction is as follows. Public information is a relatively better predictor of the average forecast than private information. While any agent's forecast, thus his private information, exerts a non-negligible effect on the average forecast, it becomes less influential as the number of agents increases. So as n increases, the agents whose preference is for herding ($r > 0$) rely less on private information, generating a lower disagreement among agents. On the other hand, when the agents want to deviate from the herd ($r < 0$), they find it optimal to use more private information, which leads to a higher disagreement among agents. 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 agents.

The first prediction 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 agents' 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, the second prediction is a direct implication of the first prediction: Given the assumption that the underlying degree of the herding motive, r, does not depend on the forecast horizon, varying the forecast horizon should not change the first prediction.

The last prediction comes from the feature of our model in which there are two strategic effects, one due to the finiteness of the number of agents and the other due to the agents' 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

We now implement various tests of herding using the predictions above. First, we describe our data.

3.1. Data and sample

We draw financial analysts' earnings forecast 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 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 since the estimates are shown to be persistent at higher frequency.[7]

Table 3.1: Descriptive Statistics

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

In Table 3.1, we document descriptive statistics of main variables used for 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.

3.3. Main Results

The first prediction 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 portfolios sort on the number of analysts. In Table 3.2, we report time-series average of median dispersion in each portfolio. We find a decreasing pattern across portfolios, implying herding behavior of analysts.

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

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
# 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 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. After we estimate the above regressions for each year, we 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 equation 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. We consider a set of variables that represent dimensions of firm riskiness, as it may be more difficult to predict risky firms. Controls include firm size, book-to-market ratio, dividend paying dummy, idiosyncratic risk, stock turnover, past 1-year stock return momentum.[8]

[8] Firm Size is the logarithm of firm assets; B/M is the log book-to-market ratio; Dividend is a dummy variable equals to 1 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.

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)
# 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

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

In Table 3.3, we report the time-series average of first-stage cross-sectional regression coefficients. In column (1), the benchmark case, we find a significant and negative coefficient on the number of analysts (# of analysts), consistent with the previous portfolio sort.[9] In columns from (2) to (7), we consider additional controls that may drive forecast dispersion to check the robustness of result. In column (8), we include all control variables in a single specification. Nonetheless, the sign of estimated coefficients are significantly negative in all specifications considered, implying the herding motive of the analysts.

It is also noteworthy that the signs of control variables are reasonable enough. The coefficient on firm size is negative, suggesting that the dispersion across analysts becomes smaller when evaluating large 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 idiosyncratic risk are predicted, since these variables are regarded as proxy for firm riskiness, making firms difficult to value. Having high past stock performance, and paying dividend also lower the dispersion, while high turnover increases it. The estimated coefficient of turnover is counter-intuitive because liquid stocks are usually less ambiguous.[10]

We next test the Prediction 2. The I/B/E/S data also contains various earnings estimates in terms of the forecast horizons, from current-fiscal-quarter to period beyond 5 years.[11] To further check the robustness of herding, we repeat the analysis using estimates of different forecast horizons and findings are reported in Table 3.4.[12]

In any specifications, it seems that the negative relation between analyst coverage and forecast dispersion is a robust feature of the data. When baseline specification (without any control) is used, for example, the estimated coefficients are -0.1084 (Panel A), -0.1422 (Panel B), and -.0535 (Panel C), respectively. In addition, we cannot observe a systematic pattern

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

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

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

[12] We only report coefficient estimates for the intercept and the number of analysts for brevity.

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.

of the estimated coefficients when the forecast horizon changes.

Overall, our findings show that analysts do behave strategically, and their forecast on earnings complements each other. One might suspect that this coordination motive itself may be sensitive to numbers of forecasters (Prediction **??**). Suppose that there exists only few analysts covering a specific firm, then each analyst may have more incentive to coordinate since any large deviation from consensus is particularly riskier. In this regard, we test whether the complementarity incentive is actually more severe for firms covered by few analysts. To investigate Prediction 3, we divide our sample into three groups based on the analyst coverage. Group 1 contains observations covered by analysts less than or equal to five, group 2 contains more than five and less then or equal to ten, and group 3 contains more than ten. In Table 3.5, we report the time-series average of 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 1

	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)
# 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

* Note: 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.

As predicted, as more analysts make predictions, the marginal effect of coordination diminishes. In other words, moving from Group 1 to 3, we find that the magnitude of coefficient estimate on the number of analysts decrease. For group 1, the estimates hovers around -0.12 and -0.15 depending on the specifications. However, they are estimated -0.06 (Group 2) or -0.04 (Group 3) for baseline specification without controls. Moreover, in Group 3, the estimate becomes indistinguishable from zero when all controls are included, while the sign of estimate is negative.

3.4. Robustness Checks

Our model setup has established upon simultaneous forecast game framework, implying that analysts provide their estimate at the same time. However, as the timing of forecast announcement differs across agents, one may argue that the sequential game framework is more appropriate. The key of the sequential game is that the next forecaster can observe the forecast by the previous forecaster, which might be a valid characterization of the prediction game when the time interval between the forecast is actually substantial. Hence, we also examine this issue empirically by considering the effect of the time interval between estimates on the parameter of interest: If there is no large time gap between the forecast, the forecaster may not have enough time to infer private information from other forecasters, which is the key aspect of our simultaneous prediction game. On the contrary, if there is a large time gap between the forecasts, we may regard it as the equilibrium outcome from the sequential game. In this regard, we use the number of days between the first and last estimates in a given month scaled by 30 as a measure of interval. Based on the measure, we form three groups similar to Table 3.5. In Table 3.6, we report the time-series average of coefficient on the number of analysts for each subset. We only report results based on the current-fiscal-year forecasts.

Table 3.6: Estimation Results: Subsample Analysis 2

	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)
# 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

* Note: Group 1 includes sample with Interval$\leq$ 0.25 forecasters, Group 2 includes the sample with 0.25 $<$Interval$\leq$ 0.5 forecasters, and Group 3 includes the sample with 0.5 $<$Interval forecasters.

Overall, we find that the coefficient estimates on analyst coverage are negative and significant regardless of time interval, implying that strategic incentive of forecasters has not altered at least. There seems a decreasing pattern of absolute magnitude from Group 1 to 3, but the difference is not huge for the baseline specification without controls. This decreasing pattern is somewhat counter-intuitive since it implies that the coordination motive has reduced as the game becomes more sequential.

It is known that many analysts do revise their forecast as soon as firms announce earnings. Based on this observation, we only collect earnings forecasts has been made at or day after earnings announcement dates since those estimates are more likely to be affected by arrival of new information rather than forecasts made by others. As such, it may be more appropriate testing scheme more consistent to our theoretical model framework of simultaneous forecasting game. Table 3.7 reports the estimation results. In the baseline specification without any control, we find a significant and negative coefficient on the number of analysts supporting the herding hypothesis. However, the coefficient becomes insignificant (but still negative at least) when all control variables are included.

Table 3.7: Estimation Results: Subsample Analysis 3

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 incentives when making predictions about market outcomes. To this end, we propose a new approach, using the equilibrium predictions derived from the finite-player forecasting game of Kim and Shim (2019), and examine whether such incentives exist. Our finding, which is robust to various empirical tests, indicates that financial analysts exhibit herding behavior in their forecasts.

Appendix A. Appendix

A.1. Proof of prediction

To be added.

References

BERNHARDT, D., M. CAMPELLO, AND E. KUTSOATI (2006): "Who herds?," *Journal of Financial Economics*, 80, 657–675.

CLEMENTS, M. P. (2018): "Do Macroforecasters Herd?," *Journal of Money, Credit and Banking*, 50(2-3), 265–292.

CROUSHORE, D. (1997): "The Livingston Survey: Still Useful After All These Years," *Business Review - Federal Reserve Bank of Philadelphia*, 2, 1–12.

DIETHER, K. B., C. J. MALLOY, AND A. SCHERBINA (2002): "Differences of Opinion and the Cross Section of Stock Returns," *Journal of Finance*, 57(5), 2113–2141.

HONG, H., J. D. KUBIK, AND A. SOLOMON (2000): "Security Analysts' Career Concerns and Herding of Earnings Forecasts," *RAND Journal of Economics*, 31(1), 121–144.

JEGADEESH, N., AND W. KIM (2010): "Do Analysts Herd? An Analysis of Recommendations and Market Reactions," *Review of Financial Studies*, 23(2), 901–937.

KIM, J. Y., AND M. SHIM (2019): "Forecast Dispersion in Finite-Player Forecasting Games," *The B.E. Journal of Theoretical Economics*, 19(1).

MARTIMORT, D., AND L. STOLE (2012): "Representing Equilibrium Aggregate in Aggregate Games with Applications to Common Agency," *Games and Economic Behavior*, 76, 753–772.

Ottaviani, M., and P. N. Sørensen (2006): "The Strategy of Professional Forecasting," *Journal of Financial Economics*, 81(2), 441–466.

Patton, A. J., and A. Timmermann (2010): "Why Do Forecasters Disagree? Lessons from the Term Structure of Cross-Sectional Dispersion," *Journal of Monetary Economics*, 57(7), 803–820.

Sharpe, S. A. (2005): "How does the market interpret analysts' long-term growth forecasts?," *Journal of Accounting, Auditing & Finance*, 20(2), 147–166.

Trueman, B. (1994): "Analyst Forecasts and Herding Behavior," *Review of Financial Studies*, 7(1), 97–124.