Measuring Herding and Exaggeration by Equity Analysts and Other Opinion Sellers

Eric Zitzewitz – Stanford GSB[1]

July 2001

JEL classification: G2, D8

Keywords: Herding, Analysts, Forecasting

[1]Stanford Graduate School of Business, 518 Memorial Way, Stanford, CA, 94305. Tel: 650-724-1860. Fax: 650-725-9932. Email: ericz@stanford.edu. The author would like to thank Glenn Ellison, Bengt Holmstrom, Dean Karlan, Leigh Linden, Sendhil Mullainathan, Nancy Rose, Jean Tirole, Ezra Zuckerman and seminar participants at Berkeley, Harvard, London Business School, Michigan, MIT, Northwestern, Stanford, Washington University-St. Louis, and Yale for helpful comments and suggestions. Particular thanks are due to my primary advisor, Robert Gibbons. All errors are my own. The financial support of an NSF Graduate Research Fellowship is gratefully acknowledged. I also thank I/B/E/S for providing me with access to their analyst data.

Abstract

Firms and individuals who sell opinions may bias their reports for either behavioral or strategic reasons. This paper proposes a methodology for measuring these biases, particularly whether opinion producers under or over emphasize their private information, i.e. whether they herd or exaggerate their differences with the consensus. Applying the methodology to I/B/E/S analysts reveals that they do not herd as is often assumed, but rather they exaggerate their differences with the consensus by an average factor of about 2.4. Analysts also overweight their prior-period private information and thus under-update based on last period's forecast error; this under-updating helps explain the apparently conflicting over and under-reaction results of DeBondt and Thaler (1990) and Abarbanell and Bernhard (1992). A useful by-product of the methodology is a measure of the incremental information content of an analyst's forecasts. Using this measure reveals that analysts differ greatly in performance: the information content of the future forecasts of the top 10 percent of analysts is roughly six times that of the bottom 40 percent.

Measuring Herding and Exaggeration by Equity Analysts and Other Opinion Sellers

1 Introduction

Each recent financial crisis has renewed concerns that financial market participants face incentives to underweight or even ignore their private information and herd with the existing consensus. In both finance and general management, when a group is collectively surprised by an event, outside observers often worry that they have been practicing "group think" and herding on each other's opinions. In practice, it is very difficult to determine whether a group has been surprised because they were herding and ignoring the warning signs or because warning signs simply were either not available or too weak to be rationally taken seriously. Nonetheless, we would like know whether herding occurs, so that consumers and organizations can adjust the way they use information or even alter contracts to diminish the incentives that foster it.

This paper proposes a new methodology to measure how much forecasters either herd or anti-herd with the existing consensus.[1] We define herding to be underweighting one's private information and issuing an opinion or forecast that is closer to the existing consensus than an optimally-formed expectation. Anti-herding or exaggeration is likewise defined as overweighting one's private information and forecasting further away from the consensus than an optimally-formed expectation. Although it is impossible to determine whether a forecaster has herded on any given observation

[1] Others, such as DeBondt and Thaler (1990), Keane and Runkle (1998), and Kutsoati and Bernhardt (1999), have run versions of the regression run in this paper. A contribution of this paper is that we show how the coefficient from this regression can be used to measure average herding or exaggeration.

if we do not observe her private information, our methodology allows us to draw a statistical inference about how her forecasts relate to unbiased forecasts on average across a set of observations.

We apply this methodology to equity analysts' earnings forecasts and find that analysts do not herd, but instead they exaggerate their differences with the consensus by an average factor of 2.4. In other words, when weighting their private information together with public information to produce a best estimate, forecasters overweight their private information and issue forecasts that are 2.4 times further away from the prior consensus than unbiased forecasts would be. Although the exaggeration factor of 2.4 varies slightly with forecast, firm, and analyst characteristics, in no subsample of our data do we find evidence of herding. This is perhaps surprising given the extensive theoretical literature on and popular discussion of herding.[2] The exaggeration we find could either be the result of a conscious forecasting strategy, an unconscious overconfidence in the quality of one's private information, or both.

Most prior empirical work on herding uses the dispersion of forecasts or opinions as a proxy, inferring that more herding is occurring when forecasts are more bunched together.[3] The methodology in this paper has two main advantages over this approach. First, it allows one to draw conclusions about the absolute amount of herding or

[2] The theoretical literature on herding includes information cascade models (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992), incentive-concavity models (Holmstrom and Ricart i Costa, 1986; Zweibel, 1995; Chevalier and Ellison, 1997, 1999; Laster, Bennett and Geoum, 1999), and career-concerns models (Scharfstein and Stein, 1990; Brandenburger and Polak, 1996; Trueman, 1994; Ehrbeck and Waldman, 1996; Prendergast and Stole, 1996; Avery and Chevalier, 1999; Ottaviani and Sorensen, 2000; Effinger and Polborn, 2000).

[3] Examples include Lamont (1995), Chevalier and Ellison (1997 and 1999), and Hong, Kubik, and Solomon (2000). Stickel (1990), Graham (1999) and Welch (2000) take a related approach, inferring that more herding is occuring when opinions are more correlated with those issued immediately before.

exaggeration relative to unbiased forecasting, whereas inferring herding from a lack of forecast dispersion only allows one to draw relative conclusions about where there is more or less herding. Second, our methodology controls for the amount of independent private information embodied in forecasts. Since forecasts can be bunched together either due to herding or simply if forecasters have limited amounts of independent private information, inferring herding from forecast dispersion requires the assumption that forecast information content is held constant.

This assumption of constant forecast information content is more appropriate in some past studies than in others. For example, Chevalier and Ellison (1997) find that fund managers hold portfolios more different from the market portfolio in the last two months of the year when they are at a convex point in the inflow-performance relationship (i.e., when the shape of the relationship between inflows and fund performance gives them an incentive to gamble) and conclude that the fund managers are herding less. An alternative hypothesis would be that these fund managers suddenly gained access to move private information in the last two months of the year, but the authors are probably on safe ground in ignoring this possibility. In contrast, Hong, Kubik, and Solomon (2000) conclude that less experienced analysts herd more than experienced analysts from the fact that they report forecasts that are closer to the consensus. Here, one might want to take more seriously the possibility that more experienced analysts have more private information. In fact, when we repeat the analysis of Hong, et. al. using our methodology, we find that less experienced analysts actually exaggerate more than experienced analysts, but they still report forecasts that are closer to the consensus since they have much less independent private information. So controlling for forecast information content is important in that it can sometimes change the conclusions of one's analysis.

In addition to finding that analysts overweight their current-period private information, we also find that they overweight their prior-period private information, or, equivalently, update too little based on last period's forecast error. In addition to documenting another way in which analysts over-weight their private information, this finding helps reconcile the apparently inconsistent over and under-reaction findings of DeBondt and Thaler (1990) and Abarbanell and Bernhard (1992), respectively. DeBondt and Thaler found that analysts were too optimistic as a group when they forecast above last period's earnings and interpreted this as overreaction; Abarbanell and Bernhard found that analysts were too pessimistic when earnings were trending up and interpreted this as underreaction. In both cases, analysts are underreacting to the information in last period's actual earnings. What we find is that controlling for the under-updating by individual analysts (i.e. for the serial correlation in individual analysts' forecast errors) eliminates all of the Abarbanell and Bernhard result and two-thirds of the DeBondt and Thaler result. Like current-period exaggeration, under-updating could be explained by either strategic behavior or overconfidence.

Finally, a useful by-product of our methodology for measuring exaggeration/herding controlling for forecast information content is a measure of forecast information content itself. We take the variance of the difference between an analyst's forecasts and the prior consensus and adjust it for exaggeration – this yields a measure of how much new information is embodied in an analyst's forecasts on average, i.e. of how much the analyst reduces the mean-squared error of the optimal public expectation of earnings. This measure is useful because it is proportional to what a mean-variance investor should be willing to pay for early access to an analyst's forecasts. Almost all past studies of analyst performance have evaluated analysts based on forecasting accuracy.[4] While accuracy and forecast information content are related, using forecast

[4]Studies evaluating analysts using forecast accuracy include O'Brien (1990), Butler and Lang (1991), Stickel (1992), Lim (1998), Jacob, Lys, and Neale (1999), and Mikhail, Walther, and Willis (1999).

accuracy as a measure of analyst ability has drawbacks almost perfectly analogous to those of inferring herding from a lack of forecast dispersion. First, measures of forecast accuracy can not be translated readily into a measure of the value of the forecast to its consumer, thus they cannot measure analyst ability in absolute terms that are economically meaningful. Second and more importantly, assuming that more accurate forecasters are higher ability involves assuming that the accuracy of the public information available to the analyst is constant, which will almost never be true, particularly when forecasts are made sequentially.[5] To illustrate this point, consider that any analyst could be very accurate by simply repeating the forecast of the historically most accurate analyst, but that investors would pay very little for early access to such an analyst's forecasts and they would not make money trading on the forecasts in an efficient market.

When we evaluate analysts using this new measure of forecast information content, we find large differences in analyst ability. The analysts ranked in the top 10 percent based on their historical performance make future forecasts that are roughly six times as valuable as those made by analysts ranked in the bottom 40 percent. The best predictor of an analyst's future forecast information content is her past forecast information content, although other variables such as experience and brokerage size/prestige are correlated with forecast information content.

The remainder of this paper is divided into two sections. The first section describes the exaggeration measurement methodology and the results for I/B/E/S analysts. The second section describes the forecast information content measure. A conclusion follows.

[5] Some researchers have recognized this problem and attempted to adjust for forecast timeliness, albeit in an ad hoc manner (e.g., Cooper, Day, and Lewis, 1999). The incremental forecast information content measure in this paper avoids the need for such a correction by incorporating the timeliness of a forecast directly into the measure of its value.

2 Exaggeration by equity analysts

This section presents evidence that equity analysts exaggerate their differences with the consensus by a factor of roughly 2.4. We begin by presenting a methodology for measuring biases in forecasting in general, and explain how to use this methodology to measure herding and/or exaggeration in particular. We then describe the data we use and how we implement the methodology and then present the results.

2.1 Methodology

We would like to understand how a forecaster translates her private information into a potentially biased forecast, especially the relationship between the forecaster's rational expectation and the forecast she actually reports. This relationship is impossible to examine for any one observation, since we cannot directly observe expectations. We can, however, draw conclusions about the relationship between expectations and forecasts over multiple observations by examining the relationship between actual values and forecasts, using the fact that expectational errors must not be predictable from any information known at the time of expectation formation.

2.1.1 Estimating the forecast function

Formally, we are interested in how analysts convert expectations into forecasts, i.e. in the function

$$F = f(E, \Omega^A, \Omega^P)$$

where F is a forecast of A (for actual earnings) and $E = E(A|\Omega^A, \Omega^P)$ is the expectation of A given all the public (Ω^P) and private (Ω^A) information known to the analyst at the time of forecasting. Since we are especially interested in whether analysts herd or exaggerate their differences with the consensus, we are particularly interested in the function:

$$F - C = g(E - C, \Omega^A, \Omega^P) \tag{1}$$

where $C = E(A|\Omega^P)$ is the consensus expectation before the analyst forecasts, defined as the expectation of A given all public information at time of forecasting.

Given a sample of data, we can learn about the relationship between $F - C$ and $E - C$ by studying the relationship between $F - C$ and $A - C$. Specifically, we can invert g and write:

$$\begin{aligned} A - C &= g^{-1}(F - C, \Omega^A, \Omega^P) + \varepsilon. \\ \varepsilon &= A - E \end{aligned} \tag{2}$$

Since the expectational error $A - E$ must be mean-zero with respect to any variable known at time of forecasting, $E(\varepsilon|F - C, \Omega^A, \Omega^P) = 0$, we can study g^{-1} and thus g using standard parametric or non-parametric regression techniques.

2.1.2 A simple model of exaggeration or herding

In order to generate some intuition for what economic variables might affect the forecasting function in (1), consider the following simple model. T analysts forecast a variable A in an exogenously given sequence. Analyst t observes public information Ω_t^P, which includes the $t-1$ prior forecasts, and private information Ω_t^A. We define $C_t = E(A|\Omega_t^P)$ and $E_t = E(A|\Omega_t^P, \Omega_t^A)$ as above.

Assume that analysts face three reduced-form incentives: an incentive for minimizing forecast mean-squared error (λ), an incentive for optimistically or pessimistically biasing her forecasts (μ), and an incentive for either increasing or decreasing the deviation between her forecast and the consensus (γ). We can write the analyst's problem as:

$$\max_{F_t} -\lambda E(A - F_t)^2 + \mu E(F_t - A) + \gamma (F_t - C_t)^2. \tag{3}$$

As mentioned in the introduction, forecast accuracy is a popular metric for evaluating analysts. Many have argued that analysts face an incentive for optimism coming from the need to curry favor with management in order to secure underwriting business or future access to information (Francis and Philbrick, 1993; Ackert and Athannanos, 1998; Lin and McNichols, 1998). Incentives for increasing or decreasing the deviation from the consensus could come from an attempts to signal ability or from incentive convexities. If the difference between high and low ability analysts is access to private information, then since high-ability analysts will have unbiased views that are more different from the consensus on average, forecasting further away from the consensus can signal ability (Prendergast and Stole, 1996; Zitzewitz, 2001).[6] If the difference between high and low ability analysts is the ability to interpret public information, then with additional assumptions one can get an equilibrium where analysts herd in order to signal that they "get it" (Prendergast, 1993). Alternatively, analysts may face incentive convexities (e.g., no reward for deviating and being right, but you get fired for deviating and being wrong) that create incentives to gamble or act conservatively (e.g., Zweibel, 1995; Chevalier and Ellison, 1997 and 1999).

The first-order condition from (3) is

$$F_t - C_t = \underbrace{\frac{\lambda}{\lambda - \gamma}}_{b}(E_t - C_t) + \underbrace{\frac{\mu}{2(\lambda - \gamma)}}_{c}. \tag{4}$$

We assume that $\lambda > \gamma$, i.e. that the incentive for accuracy is large enough to assure an interior optimum. The analyst multiplies her differences with the consensus by a factor b and adds an bias c. When $\gamma > 0$, $b > 1$ and the analyst exaggerates her

[6] In Prendergast and Stole (1996) and Zitzewitz (2001), consumers of analyst's reports anticipate that analysts will exaggerate and back the exaggeration out, but it still remains optimal for analysts to exaggerate. Exaggeration by a finite factor is an equilibrium if and only if there is a sufficiently large incentive for absolute accuracy, otherwise infinite exaggeration results (see also Ottaviani and Sorenson, 2000).

differences with the consensus; when $\gamma < 0$, $b < 1$ and the analyst herds.[7]

2.1.3 Estimating average exaggeration

We can estimate the exaggeration factor in (4) across multiple observations using the approach outlined above in (2) by rewriting it as the regression equation:

$$\begin{aligned} (A_i - C_{it}) &= -\frac{c}{b} + b^{-1} \cdot (F_{it} - C_{it}) + \varepsilon_{it} \\ \varepsilon_{it} &= A_i - E_{it}. \end{aligned} \tag{5}$$

where i indexes different values of A being forecast. Notice that by construction the error term $A_i - E_{it} = A_i - E(A_i|\Omega^P_{it}, \Omega^A_{it})$ is zero in expectation given all information known by the analyst at time of forecasting, and thus is zero in expectation for all values of $E_{it} - C_{it}$ and $F_{it} - C_{it}$. The slope coefficient from this regression is b^{-1}, the inverse of the exaggeration factor, so a coefficient less than one implies exaggeration and one greater than one implies herding.

If our estimation includes multiple forecasts of a given value of A_i, we must take into account a non-traditional correlation in the error terms. We can rewrite the error term as:

$$\varepsilon_{it} = (A_i - E_{iT}) + \sum_{s=t}^{T-1} (E_{is+1} - E_{is}). \tag{6}$$

Each error term is the sum of $T-t+1$ uncorrelated (by construction) terms. Given this error term structure, OLS estimates of (5) will be consistent, but standard errors will be biased. Keane and Runkle (1998) present a GMM procedure to estimate standard

[7] In Zitzewitz (2001), a model in which the incentive for excess deviation comes from customers learning about the analyst's ability rather than an assumed reduced-form incentive as in (3), exaggeration by a constant factor as in (4) is also optimal. In this model, the optimal exaggeration factor is higher when analysts are under-rated by their clients, when they the variables they are forecasting will be observed with more noise, or when they expect to have a short career length – these predictions are consistent with the analyst data as discussed in Zitzewitz (2001).

errors when errors are correlated as in (6). When we follow this procedure, we find that standard errors are very similar to standard errors that allow for clustering of errors for forecasts of the same i; the intuitive reason for this is that the variance of the first term in (6) is very large relative to the other terms.

2.2 Implementation issues

In order to estimate the regression equations in (2) and (5), we need forecast data and a methodology for measuring C_{it}, the consensus expectation of A_i prior to an analyst's forecast.

2.2.1 Forecast data

We estimate analyst exaggeration using the I/B/E/S Detail History dataset of analysts' earnings forecasts.[8] The I/B/E/S data is free of survivorship bias and most analysts who make publicly available earnings forecasts provide their forecasts to I/B/E/S.[9] Since past research has shown that the predictive power of long-term earnings forecasts is very low (e.g., Crichfield, et. al, 1978), we restrict our sam-

[8]In contrast to some prior studies, we use I/B/E/S actual earnings rather than COMPUSTAT earnings. Although the basic exaggeration result is not sensitive to this choice, we use I/B/E/S actuals because they are recorded on same basis that analysts make their forecasts for I/B/E/S. If potential clients use the I/B/E/S data to evaluate analysts, they are most likely to compare I/B/E/S forecasts with I/B/E/S actuals, and therefore the I/B/E/S actual is the number the analyst should focus on forecasting with her I/B/E/S forecast. Past researchers, e.g. Philbrick and Ricks (1991), had noted problems with I/B/E/S actuals and recommended using Compustat actuals. Abarbanell and Lehavy (2000) find that the quality of I/B/E/S actuals has improved significantly since 1992 and that after 1992 earnings response coefficients are significantly higher when I/B/E/S forecasts are matched with I/B/E/S rather than Compustat actuals.

[9]For example, 96 percent of the analysts ranked by Institutional Investor from 1996-99 appear in the IBES dataset.

ple to quarterly earnings forecasts made up to 6 months prior to earnings release.

We want to measure how much analysts exaggerate their information relative to the current consensus; it is therefore important to know the dates and order in which forecasts were made public with some precision. This has only been possible with I/B/E/S data since the early 1990s. I/B/E/S dates forecasts using the date it was entered into the I/B/E/S system. It has been well documented (e.g., by O'Brien, 1988) that the lags between a forecast becoming public and its entry into the I/B/E/S system were substantial in the 1980s (i.e., up to a month). In the 1980s, analysts mailed their forecasts, often in monthly batches, to I/B/E/S where they were hand entered into the system. Since 1991-92, however, almost all analysts have entered their forecasts directly into the I/B/E/S system on the day they wish to make their forecast widely available (Kutsoati and Bernhardt, 1999). Current practice for analysts is now usually to publicly release forecasts within 24 hours of providing them to clients. I/B/E/S analysts have real-time access to each other's forecasts through this system, so an analyst entering a forecast into the system on Wednesday knows about forecasts entered on Tuesday and could potentially revise her forecast to incorporate their information. We tested the claim that the consistency between I/B/E/S and public release dates has improved dramatically since the 1980s by examining the event returns accompanying a forecast above or below the consensus. From 1991-93 there was a dramatic increase in the concentration of the event returns around the I/B/E/S date of the forecast, we interpret this as evidence in support of the claim that the accuracy of the dates has increased.[10] An additional advantage of the post-92 data is the shift from retrospective data entry by a specialist to real-time data entry by either the analyst or her employee should have considerably reduced data-entry-related measurement error.

[10] An analysis showing this is available from the author.

In addition to limiting the sample to 1993-99, we also eliminate observations with current share prices of less than $5 or current market capitalizations of less than $100 million (in 1999 CPI-deflated dollars). This restriction eliminated about 7 percent of the potential sample. We do this primarily because extreme outliers were concentrated among these stocks and using these sample restrictions removes enough outliers that the results are no longer sensitive to the treatment of the remaining outliers.[11] We should note that these sample inclusion criteria are much more liberal than in many other studies; limiting the sample to companies covered by at least 10 analysts, a common restriction, eliminates about 40 percent of the potential sample. In order to convince ourselves that the exaggeration result does not depend on the sample inclusion criteria, we run the exaggeration regression on the pre-93, penny-stock, and micro-cap observations, and find similar results once we have removed outliers.

The sample we use contains 836,639 forecasts, 728,325 of which follow at least one forecast and thus can have their difference with the consensus measured. These forecasts cover 7,008 firms, and 87,303 firm-quarter combinations. An average of 10 forecasts are made for a given firm-quarter combination; the median forecast is made for a firm-quarter with 17 other forecasts made. The sample includes forecasts by 5,688 individual analysts and 490 brokerage firms; each are identified in the I/B/E/S data by a unique code. There are an average of 155 forecasts per analyst in the sample, the median forecast is made by an analyst who makes a total of 423 forecasts

[11] The companies covered by I/B/E/S analysts with market capitalizations under $100 million tend to be formerly larger cap companies that have experienced stock price declines. These companies tend to have very large variances in earnings/price ratios, which increases the heteroskedasticity in sample and makes it difficult to distinguish data entry errors from true outliers due to a low market cap in the denominator. Eliminating penny stocks from the sample also has the advantage of reducing discreteness problems that result from analysts forecasting and companies reporting earnings as a whole number of pennies per share.

in the 1993-99 sample. Table 1 reports summary statistics for the major variables used in the exaggeration analysis.

2.2.2 Measuring the consensus

A practical issue in estimating (2) and (5) is measuring C_{it}, the consensus prior expectation of earnings given all prior forecasts and public information. Measuring the consensus well is important, since measurement error would bias the estimated coefficient in (5) toward one, biasing us toward finding unbiased forecasting. We use three different measures of the consensus that imply different levels of sophistication on the part of market participants. We find that using a more sophisticated consensus measure reduces our estimated coefficient slightly, consistent with reduced omitted variable bias. In section 2.3.2, we find that our results are robust to the inclusion of several variables that may proxy for any remaining consensus mismeasurement.

The three consensus measures we use are the mean of all outstanding forecasts, the mean of the three most recent forecasts, and an econometric expectation of earnings. The equal-weighted mean of all outstanding forecasts is an intuitive and popular measure of the consensus. An issue with this measure is that if more information is available to later forecasters or if analysts incorporate prior forecasts into their estimates, then a properly constructed expectation should put much more weight on later forecasts. Measuring the consensus as the mean of the last three forecasts addresses this issue in a fairly *ad hoc* fashion, but it yields results that are very similar to less *ad hoc* econometric expectation described below.

The idea behind using the econometric expectation of earnings as a consensus measure is to let the data tell us how much extra weight to put on more recent forecasts. We divide the sample into subsamples for 1993-96 and 1997-99 and estimate the model:

$$A_i - M_{it} = a + b(\overline{F}^1_{i,t} - M_{it}) + c(\overline{F}^2_{i,t} - M_{it}) + dM_{it} \tag{7}$$

where A_i is actual earnings, M_{it} is the mean of all outstanding forecasts prior to forecast t, and $\overline{F}^1_{i,t}$ and $\overline{F}^2_{i,t}$ are the mean of all forecasts on the two most recent days before the date of forecast t on which forecasts were made. The coefficients estimated for one-half of the data are used to generate predicted values of A for the other half, and these predicted values are our econometric estimate of the expectation of A given all public forecasts made before forecast t. We split the sample in this way in order to avoid a data-snooping bias in our consensus measure. We allow the coefficients to vary depending on the number of forecasts made on each of the two most recent days – the idea is that an average of multiple forecasts should be given more weight, but how much more weight depends on the correlation of the private information embodied in these forecasts, so we want the data to tell us how much more weight (Table 2).[12]

We use the econometric expectation of earnings as our primary consensus measure since of the three measures it should most closely approximate the optimal expectation of earnings given the history of public forecasts. In practice, however, the results are very similar if we use the mean of the last three forecasts.

2.3 Results

2.3.1 Non-parametric results

[12] In these regressions, as in all the regressions in the paper, we normalize actual and forecasted earnings-per-share by the share price and weight observations by their market capitalization to reduce heteroskedasticity. Results from equal-weighted regressions are qualitatively similar but have larger heteroskedasticity-robust standard errors. An analysis of the residuals reveals that the variance of the residual increases roughly proportionally with market cap, so weighting observations by market-cap is very close to the FGLS estimator.

The model of analyst incentives in section 2.1.2 predicts that analysts will exaggerate by a constant factor, i.e. that the relationship between $A-C$ and $F-C$ in (2) and (5) will be affine. Before proceeding with an analysis that assumes an affine relationship, however, we check this assumption by performing a simple non-parametric estimation of the function g^{-1} in equation (2). We sort the data into 100 groups according to the right-hand side variable $F-C$ and plot the means of the left and right-hand side variables in Figure 1. The figure suggests that the relationship between $F-C$ and the expected value of $A-C$ is roughly linear with a slope of less than one; this implies that analysts are exaggerating rather than herding. There is some evidence of a kink at zero, with more exaggeration for forecasts above the consensus than for those below, but spline regressions suggest that this kink is not statistically significant.[13] Given this, the rest of the paper focuses on assuming that the relationship is affine and estimating the determinants of its slope.

2.3.2 Linear exaggeration regression results

Table 3 presents estimations of equation (5). Lines 1-3 of Table 3 estimate (5) using the three different measures of the consensus discussed above. The estimated coefficient is higher when the "less sophisticated" consensus measure of the mean of all outstanding forecasts is used, this is consistent with a mismeasurement of C biasing the estimated coefficient toward one, as one would expect in a regression of $A-C$ on

[13] A specification of (2) allowing for a change of slope at zero finds a slope of 0.574 (0.083) below zero and a slope change at zero of -0.113 (0.154), standard errors in parentheses. The slope change is insignificant. Results are insensitive to slight variations in the location of the breakpoint. Excluding the 10 percent of the data with an estimate-consensus difference greater than half a percent of the share price changes the results to a slope of 0.812 (0.068) below zero and a slope change of -0.460 (0.129); this significant slope change suggests that there may be asymmetric exaggeration for non-extreme forecasts. This non-linearity is potentially deserving of future study, however it does not appear overwhelming enough distract us from an analysis based on constant exaggeration.

$F - C$.

In order to further reduce potential consensus mismeasurement problems, lines 4-6 of Table 3 estimate (5) excluding two types of forecasts for which there is likely to be public information that is not reflected in the consensus measure: forecasts immediately following the prior quarter's earnings announcement and forecasts occurring on multi-forecast days (which usually indicates a news release or earnings warning from the company). This reduces the estimate of b^{-1} to roughly 0.41, which implies $b = 2.4$, i.e. that analysts exaggerate their differences with the consensus by a factor of 2.4. Further attempts to control for any remaining consensus mismeasurement by including variables in the regression that may be correlated with the measurement error (e.g., the stock price change since the last earnings forecast) do not significantly affect the results (Table 4).[14]

Keane and Runkle (1998) run a version of this regression, and we close Table 3 by replicating those results. Keane and Runkle (1998) estimate a version of equation (5) that does not subtract the consensus from both sides of the equation. They analyze six different industries and find that on average, b^{-1} was roughly one. They conclude

[14] We also considered the possibility of measurement error in F, since this measurement error would bias the estimated coefficient toward zero and thus bias us in favor of finding exaggeration. We limited our sample to 1993-99 in part so that we would be using only data entered by the analyst on a real-time basis, which should have fewer measurement error problems. We found that our estimated coefficient changed by less than 0.01 when we excluded observations with extreme values of $(F - C)$ in the 1993-99 sample, whereas excluding these observations made a large difference in the 1984-92 data. We tested whether the results were affected by forecast discreteness, i.e. by the fact that analysts usually forecast earnings in whole numbers of pennies per share. Including only forecasts that differ from the consensus by more than two cents changes our estimate of b^{-1} by less than 0.01, a finding that should not be surprising given the linearity of the non-parametric estimate in Figure 1. Other robustness checks included the inclusion of analyst-firm fixed effects and controls for the firm, forecast, and analyst characteristics in Table 5.

from this that analysts' forecasts are unbiased on average, and interpret this finding as a confirmation of rational expectations. An issue with this result, however, is that if we believe that analysts have some common prior information, then by not subtracting the consensus from both sides we are essentially adding a number to both sides of our regression equation whose variance is large relative to the variance of our dependent and independent variables. This is essentially an extreme form of consensus mismeasurement, and should seriously bias the regression coefficient toward one.

Lines 7-10 of Table 3 estimate Keane and Runkle's version of (5). Lines 7 and 8 find a coefficient of 0.8 for our full sample, which increases to 0.9 in lines 9 and 10 if we limit the sample to Keane and Runkle's industries.[15] The difference between the coefficient of 0.82 in line 7 and 0.55 when the consensus is subtracted from both sides suggests that controlling for common public information is important.

2.3.3 Cross-sectional variation in exaggeration

In this subsection, we examine how measured exaggeration varies with forecast, firm, and analyst characteristics by interacting the right-hand side of (5) with these characteristics. In particular, we estimate the standard interaction specification:

$$\begin{aligned} A_i - C_{it} &= \delta Z_{it} + (\gamma Z_{it})(F_i - C_{it}) + \varepsilon_{it} \\ -\frac{c_{it}}{b_{it}} &= \delta Z_{it} \\ b_{it}^{-1} &= \gamma Z_{it} \end{aligned} \tag{8}$$

[15] A potential explanation for the higher coefficient in the Keane and Runkle industries (airlines, aluminium, auto assembly, chemicals, other non-ferrous metals, and railroads) is that they are all industries with publicly available input costs that affect earnings in fairly well understood ways. Analysts may therefore have more information to work with for these industries and thus have less need to exaggerate; alternatively, there may be less earnings uncertainty and thus less opportunity to get away with exaggeration.

where Z_{it} is a vector of forecast, firm, and analyst characteristics that includes a constant (Table 5).

Past exaggeration by an analyst is the best predictor of future exaggeration.[16] Outside of past exaggeration, b^{-1} does not vary much with forecast, firm, and analyst characteristics. In particular, it does not vary significantly with market capitalization, the number of covering analysts, the standard deviation of outstanding forecasts, or the time left before earnings release. Furthermore, when we divide the sample based on the forecast, firm, and analyst characteristics, the hypothesis of unbiased forecasting ($b = 1$) can be rejected for almost every subsample of the data (Table A1).

There are some exceptions to this general conclusion that b^{-1} does not vary. Sector effects are significant; analysts' forecasts appear very exaggerated for the health care sector, while the hypothesis that b^{-1} is equal to one cannot be rejected for finance and consumer nondurables, although the point estimates are still less than one. There are also statistically significantly differences in exaggeration by year, with less exaggeration in 1995 and 1996 than in other years. Interactions with analyst career variables also reveal some variations in b^{-1}. Analysts at brokerage firms with more I/B/E/S analysts, which also are usually the more prestigious firms, exaggerate less, and analysts with a longer forecasting experience also exaggerate slightly less.

The conclusion that analysts with longer forecasting experience exaggerate less provides an opportunity to illustrate the importance of measuring exaggeration or

[16] This statement is based on two analyses. First, the R^2 from an estimation of (2) increases from 0.0099 to 0.0253 when β is interacted with the past β for the analyst. Interacting β with the additional 24 forecast, firm, and analyst characteristics in Table 5 only increases R^2 to 0.0372. Second, if we predict a β for each observation based on the coefficients in the interaction regression, the standard deviation of the predicted β is 0.22 when past β is the only interaction variable; it increases to only 0.29 when the other 24 interaction variables are added.

herding using a methodology that controls for forecast information content, rather than inferring herding from a lack of forecast dispersion. In Table 6, we present measures of forecast dispersion and the exaggeration coefficients estimated using equation (5) for analysts with different amounts of forecasting experience. The measures of absolute forecast dispersion reveal that less experienced analysts deviate less from the consensus. Hong, et. al. (2000) interpreted this as implying that less experienced analysts herded more, but the estimates of b^{-1} imply that less experienced analysts actually exaggerate more even though they deviate from the consensus less. The reconciliation of these two seemingly conflicting results is that less experienced analysts have much less forecast information content, using the $Var[E(y|x)]$ measure that we will discuss in the next section.

2.3.4 Relationship of findings to over/under-reaction literature

In part as a potential explanation for stock price momentum results, a literature has developed investigating whether analysts over or under-react to information. DeBondt and Thaler (1990) estimate the model

$$A_{it} - A_{it-1} = \beta(C_{it} - A_{it-1}) + \varepsilon_{it}, \tag{9}$$

where A_{it} and $A_{i,t-1}$ are the current and prior-year actual earnings and C_{it} is the mean of all earnings forecasts. They find $\beta < 1$ and interpret this finding as analysts collectively overreacting to new information. Abarbanell and Bernard (1992) estimate the model:

$$A_{it} - C_{it} = \beta(A_{it-1} - A_{it-2}) + \varepsilon_{it} \tag{10}$$

using quarterly data, find $\beta > 0$, and interpret this finding as under-reaction to new information, since it implies that analysts as a group are too pessimistic when earnings are trending up.

This paper offers a potential resolution of these seemingly conflicting findings. We find that analysts exaggerate (or overreact to) their own new private information, but they under-react to new information that suggests that their previous private information was wrong. Controlling for this effect explains all of the Abarbanell-Bernard under-reaction and almost all of the DeBondt-Thaler over-reaction. Table 7 estimates the model:

$$A_{it}-C_{it} = \alpha+\beta(F_{it}-C_{it})+\gamma(C_{it}-A_{it-1})+\delta(A_{it-1}-A_{it-2})+\theta(A_{it-1}-F_{it-1})+\varepsilon_{it}, \quad (11)$$

where $A_{i,t-1} - F_{i,t-1}$ is the individual analyst's forecast error in the last quarter. The first two lines restate the regression in line 6 of Table 3 and reestimate it for the sample for which all the variables in (11) are non-missing and for which the forecast was made after last quarter's earnings were known. The next line replicates DeBondt and Thaler's result, with our $\gamma + 1$ being equal to their β. We are using quarterly rather than annual data, so this suggests that the DeBondt and Thaler result is present at higher frequencies as well.[17] The following line adds the $\beta(F_t - C_t)$ term to the regression, finding that neither coefficient is reduced significantly. The conclusion from this would be that analysts exaggerate their own information and, in addition, overreact to (or fail to back out the exaggeration in) other agent's forecasts.

The second panel of Table 7 replicates Abarbanell and Bernard's finding and finds that the coefficient is reduced only slightly by including $\beta(F_{it} - C_{it})$. In the third panel, however, we find that adding the lagged analyst error term to the model $\theta(A_{it-1} - F_{it-1})$ reduces the estimate of γ by two thirds and reduces the magnitude and changes the sign of the estimate of δ. The large and significant estimate for θ implies that analysts are very stubborn in updating their beliefs about a company.

[17] One might worry that the results in this section are an artifact of seasonality in earnings. To check this, we replicated the results in Table 7 replacing $C_t - A_{t-1}$ with $C_t - A_{t-4}$ and $A_{t-1} - A_{t-2}$ with $\sum_{s=1}^{4}(A_{t-s} - A_{t-s-4})$ and found qualitatively the same results.

The reduction in the estimate of δ suggests that analysts appear to under-react to trends in earnings because of this stubbornness. The reduction in the estimate of γ suggests that analysts appear to overreact to new, post-earnings information in part because they are really under-reacting to the earnings information itself and over-weighting their old beliefs.

2.3.5 Interpretation of results

Taken together, the results in Tables 3 and 7 suggest that analysts are simultaneously behaving like the "impetuous youngsters" and the "jaded old-timers" in Prendergast and Stole (1996). The young agents in Prendergast and Stole exaggerate their differences with the consensus to signal ability; the older agents under update their old forecasts to avoid signalling a lack of ability in the past. Our evidence suggests that analysts exaggerate their private information in the current period while also exaggerating, or under-updating, their old private information.

There are at least two potential explanations for the observed exaggeration and under-updating. Analysts could be exaggerating and under-updating in order to mimic higher-ability analysts. Current-period exaggeration could also be the result of analysts attempting to either stimulate trading volume for their employers or to produce higher event returns for their priviledged clients. Alternatively, both current-period exaggeration and under-updating could be the result of analysts overweighting both their current-period and prior-period private information because they are overly confident in its precision.[18] Conscious exaggeration for career-concerns or

[18] A final possibility is that analysts are neither consciously overweighting their information nor overconfident, but rather the have been surprised in the entire 1984-99 period (we find exaggeration to roughly the same degree in the pre-93 data once outliers are removed) by actual earnings failing to reflect their private signals as fully as they anticipated. We believe this to be unlikely, but cannot rule it out as a possibility.

other incentive-related reasons is very difficult to distinguish from unconscious exaggeration due to overconfidence. Although we believe that this section provides fairly strong evidence of exaggeration, we do not claim to be able to determine whether the exaggeration is conscious or not.

3 Forecast information content

A useful by-product of the methodology for measuring exaggeration is a measure of forecast information content that under some assumptions can be interpreted as a measure of a forecast's economic value to its users. Clients of I/B/E/S analysts are typically investors who pay for early access to their earnings forecasts and other opinions; usually the "payment" involves directing transactions to the analyst's brokerage. The value of early access to a forecast to an investor is the profit they can make from adjusting their portfolio before the forecast becomes public.

3.1 Measuring forecast information content

In this subsection, we derive our measure of forecast information content as the value of early access to a forecast to a mean-variance investor. For notional convenience, define y and x to be $A-C$ and $F-C$ less their means. Assume that future abnormal security returns are linear in y and that the event returns when a forecast is released are proportional to $E(y|x)$ and have a fixed and known variance. A mean-variance investor facing zero transactions costs with access to x before it becomes public information will make investments proportional to the expected event returns, thus the expected value of early access to x for such an investor will be proportional to $E[E(y|x)^2] = Var[E(y|x)]$. If the relationship between $E(y|x)$ and x is linear, as Figure 1 suggests, then $E(y|x) = \beta x$ and the expected value of a forecast is proportional to $E[(\beta x)^2] = \beta^2 Var(x)$.

This measure can be thought of as the variance of $F - C$ adjusted for an analyst's exaggeration. In other words, it is a measure of how much new information is embodied in an analyst's forecast once exaggeration is corrected for. Notice that an analyst cannot increase this measure by exaggerating: exaggerating by an additional factor of 2 will raise $Var(x)$ by a factor of 4 but lower β by a factor of 2, leaving $\beta^2 Var(x)$ unchanged.

3.2 Differences in information content across analysts

In this subsection, we examine whether the past forecasting record of an analyst is informative about the future information content of their forecasts. To do this, we rank analysts according to our $Var[E(y|x)] = \beta^2 Var(x)$ measure of forecast value and then compare the value of future forecasts made by analysts with different past performances. Treating $\beta^2 Var(x)$ as a measure of forecast value that we can aggregate across observations involves assuming that prior knowledge of a given change in earnings expectations as a percent of market-cap has equal value across observations. In practice, this involves assuming that earnings-response coefficients (ERCs) and depth are equal across firms. While this is probably not the case, measuring ERCs and depth is notoriously difficult. Instead of incorporating a noisy measure of depth and the ERC into our measure of forecast information content, we will instead control in our analysis for firm characteristics likely to affect depth or the ERC.

In calculating the $\beta^2 Var(x)$ measure, we require a minimum of 50 observations. This cutoff is arbitrary; the general idea is to avoid having a large and heterogeneous amount of noise in the $\beta^2 Var(x)$ measure. We experimented with and found similar results for cutoffs of 25, 100, and 200 forecasts. Only half of the 5,688 analysts in the sample made 50 or more forecasts in the 1993-99 period, but these analysts accounted for over 95 percent of all forecasts and over 80 percent of forecasts were made by analysts who had already made 50 or more forecasts. In all the analyses of forecasting performance that follow we exclude the first forecast after an earnings announcement and forecasts on multi-forecast days since these forecasts appear to incorporate a significant amount of public information that is not captured in our consensus measure. These two restrictions reduce the sample to 299,747 observations from the original 728,325.

Table 8 divides analysts into ten deciles according to their $\beta^2 Var(x)$ and estimates the β, $Var(x)$, and $\beta^2 Var(x)$ of their next forecast. Analysts are reranked after every forecast so the same analyst could appear in different deciles at different times. The deciles are constructed in two ways: by ranking all analysts together and by ranking analysts within their sector of expertise.[19] The results suggest that analysts in the top decile have forecast information contents roughly 5-6 times that of the bottom 40 percent. Top-decile analysts not only report forecasts that are twice as far from the consensus as those of the bottom analysts but they also exaggerate by slightly less in the process. This is possible only if the top-decile analysts have much more differential information than bottom ones.

Table 9 tests the statistical significance and robustness of this finding of persistence in information content. The first panel presents regressions that predict the $\ln[\beta^2 Var(x)]$ of an analyst's next 50 forecasts (or fewer if less than 50 are made before the sample period ends) based on her historical estimated $\ln[\beta^2 Var(x)]$. We find a positive coefficient that remains significant and of roughly the same magnitude regardless of the definition of the consensus used or whether the forecast, firm, and analyst characteristics in Table 5 are controlled for.

[19] Eighty-five percent of forecasts are in the analyst's sector of specialization. Results are similar if deciles are formed using only forecasts made in an analyst's sector of specialization.

The second panel decomposes the historical log forecast value into $\ln(\beta)$ and $\ln[SD(x)]$ and predicts future forecast value using these two variables. We find a significantly larger coefficient for $\ln[SD(x)]$ than for $Ln(\beta)$. The implication of this is that an analyst can raise the econometric prediction of her future forecast value by exaggerating, since exaggerating raises $\ln[SD(x)]$ and lowers $\ln(\beta)$ by equal amounts.

To determine the source of this difference, in the third and fourth panels we decompose the future $\ln[\beta^2 Var(x)]$ into its additive components $\ln(\beta)$ and $\ln[SD(x)]$. We find that past exaggeration predicts future exaggeration and past deviation from the consensus predicts future deviation from the consensus, but that the two variables do not predict each other. The own lag coefficient is much lower for $\ln(\beta)$ than for $\ln[SD(x)]$. One interpretation of this result is that the large variance in earnings realizations makes estimates of β much more noisy than estimates of $SD(x)$. This difference in coefficients implies than an analyst could raise her a linear econometric expectation of her future forecast information content to infinity by exaggerating infinitely, although if analysts face any incentive for absolute accuracy they will not choose to exaggerate infinitely. This does suggest, however, that if potential clients of an analyst attempt to determine the future value of her forecasts using her forecasting track record and if their methodology approximates that of the regression in Table 9, then an analyst could raise estimates of her ability by exaggerating. This issue is examined in more detail in Zitzewitz (2001).

3.3 Evidence that information content matters

Section 3.1 argues that an analyst's clients *should* care about the new information content in forecasts, rather than about their accuracy, but is there any evidence that they do? We examine this issue by looking at the characteristics of the prior and subsequent forecasts of analysts according to their ranking in the 1996 *Institutional*

Investor poll, a survey in which institutional investors rank analysts according to a subjective assessment of their overall value (Table 10). We find that first-team analysts have 4-6 times as much information in both their prior and subsequent forecasts. In contrast, the prior forecasts of first-team analysts are actually less accurate (i.e., have higher mean-squared error) than those of lower or unranked analysts. Ranked analysts do perform slightly better in terms of relative forecast accuracy, suggesting that one reason for their lower forecast accuracy is that they forecast firms with harder to predict earnings.[20] Probit regressions predicting first-team membership based on 1993-95 performance find a significant predictive role for both forecast information content and relative forecast accuracy (available from author).

4 Conclusion

This paper presents a new methodology for measuring herding or exaggeration across a group of forecasts. When we apply the methodology to equity analysts, we find that they exaggerate their differences with the consensus by a factor of 2.4. This result of exaggeration, or anti-herding, is robust to different specifications and is present in nearly all subsamples of the data. Exaggeration does not vary significantly with forecast, firm, and analyst characteristics, but it is predicted by an analyst's past exaggeration. In addition to finding evidence of exaggeration, we also find evidence that analysts under-update based on last period's forecasting error; controlling for this under-updating and the resulting serial correlation in analyst's forecasting errors helps explain the apparently conflicting results of DeBondt and Thaler (1990) and Abarbanell and Bernhard (1992). The methodology for measuring exaggeration in

[20] The measure of relative forecast accuracy used is the same measure as in Hong, Kubik, and Solomon (2000), i.e. the analyst's average accuracy ranking for each firm-quarter they forecast, where the accuracy rankings are scaled 0 to 1.

this paper controls for forecast information content, which is important, since failing to do so can change the conclusions of certain analyses, e.g., the analysis of whether exaggeration increases or decreases with forecasting experience.

A useful by-product of the methodology for measuring exaggeration is a measure of the information content of an analyst's forecasts that is economically meaningful in that it is proportional to what an investor should be willing to pay for early access to a forecast. Using this measure we find that analysts differ greatly in the information content of their forecast; the information content of the future forecasts of the top 10 percent of analysts is roughly 5-6 times that of the bottom 40 percent.

The issues examined in this paper potentially apply to opinion-producing agents other than equity analysts. A large number of agents produce opinions that can be thought of as forecasts of random variables; example include macroeconomic or weather forecasters, wine or movie critics, strategic planners, and management consultants. These agents may exaggerate for overconfidence or career concerns reasons like the equity analysts studied in this paper, or they may understate their differences with the consensus as predicted by the herding literature. A better theoretical and empirical understanding of when and why to expect exaggeration or herding would be helpful both to consumers of opinions and to organizations that wish to elict unbiased reports.

References

Abarbanell, J. and Lehavy, R.: 2000, Differences in commercial database reported earnings: Implications for inferences concerning analyst forecast rationality, the association between prices and earnings, and firm reporting discretion. University of North Carolina Mimeo.

Abarbanell, J. S. and Bernard, V.: 1992, Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior, *Journal of Finance* **47**, 1181–1207.

Ackert, L. F. and Athanassakos, G.: 1997, Prior uncertainty, analyst bias, and subsequent abnormal returns, *Journal of Financial Research* **20**, 263–273.

Avery, C. N. and Chevalier, J. A.: 1999, Herding over the career, *Economics Letters* **63**, 327–333.

Banerjee, A.: 1992, A simple model of herd behavior, *Quarterly Journal of Economics* **107**, 797–817.

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

Brandenburger, A. and Polak, B.: 1996, When managers cover their posteriors: Making decisions the market wants to see, *RAND Journal of Economics* **27**, 523–541.

Butler, K. C. and Lang, L. H. P.: 1991, The forecast accuracy of individual analysts: Evidence of systematic optimism and pessimism, *Journal of Accounting Research* **29**, 150–156.

Chevalier, J. A. and Ellison, G. D.: 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* **105**, 1167–1200.

Chevalier, J. A. and Ellison, G. D.: 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* **114**, 389–432.

Cooper, R. A., Day, T. E. and Lewis, C. M.: 1999, Following the leader: A study of individual analysts earnings forecasts. Vanderbilt University Mimeo.

Crichfield, T., Dyckman, T. R. and Lakonishok, J.: 1978, An evaluation of security analysts' forecasts, *Accounting Review* **53**, 651–668.

DeBondt, W. F. M. and Thaler, R. H.: 1990, Do security analysts overreact?, *American Economic Review* **80**, 52–57.

Effinger, M. R. and Polborn, M. K.: 2000, Herding and anti-herding: a model of reputational differentiation. University of Munich Mimeo.

Ehrbeck, T. and Waldmann, R.: 1996, Why are professional forecasts biased? agency versus behavioral explanations, *Quarterly Journal of Economics* **111**, 21–40.

Fama, E. F. and MacBeth, J. D.: 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* **81**, 607–636.

Francis, J. and Philbrick, D.: 1993, Analysts decisions as products of a multi-task environment, *Journal of Accounting Research* **31**, 216–230.

Graham, J. R.: 1999, Herding among investment newsletters, *Journal of Finance* **54**, 237–268.

Holmstrom, B. and i Costa, J. R.: 1986, Managerial incentives and capital management, *Quarterly Journal of Economics* **101**, 835–860.

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

Keane, M. P. and Runkle, D. E.: 1998, Are financial analysts' forecasts of corporate profits rational, *Journal of Political Economy* **106**, 768–805.

Kutsoati, E. and Bernhardt, D.: 1999, Can relative performance evaluation explain analysts' forecasts of earnings. Tufts University Mimeo.

Lamont, O.: 1995, Macroeconomic forecasters and microeconomic forecasts. NBER Working Paper 5284.

Laster, D., Bennett, P. and Geoum, I. S.: 1999, Rational bias in macroeconomic forecasts, *Quarterly Journal of Economics* **114**, 293–318.

Lim, T.: 1998, Essays in empirical finance. Ph.D. Dissertation.

Lin, H.-W. and McNichols, M. F.: 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* **25**, 101–127.

Mikhail, M. B., Walther, B. R. and Willis, R. H.: 1999, Does forecast accuracy matter to security analysts?, *The Accounting Review* **74**, 185–200.

O'Brien, P.: 1988, Analysts' forecasts as earnings recommendations, *Journal of Accounting and Economics* **10**, 53–83.

O'Brien, P.: 1990, Forecast accuracy of individual analysts in nine industries, *Journal of Accounting and Economics* **12**, 286–304.

Ottaviani, M. and Sorensen, P.: 2000, Professional advice. University College London Mimeo.

Philbrick, D. R. and Ricks, W. E.: 1991, Using value line and ibes analyst forecasts in accounting research, *Journal of Accounting Research* **29**, 397–417.

Prendergast, C.: 1993, A theory of "yes men", *American Economic Review* **83**, 757–770.

Prendergast, C. and Stole, L.: 1996, Impetuous youngsters and jaded old-timers: Acquiring a reputation for learning, *Journal of Political Economy* **104**, 1105–1134.

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

Stickel, S.: 1990, Predicting individual analyst earnings forecasts, *Journal of Accounting Research* **28**, 409–417.

Stickel, S.: 1992, Reputation and performance among security analysts, *Journal of Finance* **47**, 1811–1836.

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**, 369–396.

Zitzewitz, E.: 2001, Opinion-producing agents: career concerns and exaggeration. MIT Mimeo.

Zweibel, J.: 1995, Corporate conservativism and relative performance compensation, *Journal of Political Economy* **103**, 1–25.

Table 1. Summary statistics

This table presents summary statistics for the sample of I/B/E/S quarterly earnings forecasts and actuals used in this paper. Sample 1 includes all forecasts for fiscal quarters ending between 1993 and 1999 made within six months of the reporting date. Sample 2 excludes the first forecast after prior-quarter earnings announcements, forecasts on multi-forecast days, and forecasts made by analysts with less than 50 prior forecasts in the 1993-99 sample.

Samples used in this paper							
Sample 1. (Tables 2, 3, and 6; Table 4, Col. 1)							
Total forecasts	836,639						
Forecasts following at least one other forecast	728,325						
Firm-quarter combinations	87,303						
Firms	7,008						
Analysts	5,688						
Sample 2. (Table 4, Cols. 2 and 3; Tables 5, 7-10)							
Forecasts following at least one other forecast	299,747						
Analysts	1,497						
Summary statistics for sample 1	**Abbreviation**	**Mean**	**S.D.**	**Skew**	**Median**	**IQ range**	
Earnings variables (all are EPS divided by the share price and expressed in percent)						Low	High
Actual quarterly earnings	ACT	1.240	2.22	-3.8	1.260	0.706	1.862
Actual earnings less forecast	ACT - FOR	-0.064	2.02	2.8	0.012	-0.174	0.121
Forecast earnings less consensus	FOR - CONS	-0.053	0.60	-16.3	-0.054	-0.093	0.056
Consensus less mean of prior forecasts	CONS - MEAN	-0.014	0.29	-3.5	-0.002	-0.030	0.010
Actual less last quarter's actual	ACT - ACT(-1)	-0.026	1.98	-0.3	0.051	-0.246	0.282
Consensus less last quarter's actual	CONS - ACT(-1)	0.040	1.99	-2.5	0.042	-0.167	0.312

Table 2. Regressions used for constructing the econometric expectation of earnings
Dependent variable: ACT - MEAN

The expectation of actual earnings (ACT) given the prior forecasting history is estimated by regressing ACT - MEAN on the mean of all forecasts (MEAN) and the differences between this mean and the mean of all forecasts made on the two most recent days on which forecasts were made (LAST - MEAN and LAST2 - MEAN, respectively). The coefficients are allowed to vary with the number of estimates on each day (each cell is a separate regression); in most cases they increase with the number of estimates on that day as one might expect. Regressions are market-cap-weighted and include a constant term. The coefficient on MEAN (not shown) is between -0.1 and -0.2 for all subsamples. The coefficients shown are for the entire 1993-99 period, however to avoid a data snooping bias, the consensus measure is constructing by splitting the sample into 1993-96 and 1997-99 and using the coefficients from one half of the sample to construct the consensus measure for the other half.

		Number of estimates on most recent day		
No. estimates on second most recent day		One	Two	Three+
One	LAST - MEAN	0.46	0.77	0.90
		(0.05)	(0.12)	(0.16)
	LAST2 - MEAN	0.30	0.30	0.14
		(0.06)	(0.07)	(0.14)
	Obs.	438,758	86,728	70,505
Two	LAST - MEAN	0.41	0.73	0.61
		(0.06)	(0.13)	(0.13)
	LAST2 - MEAN	0.56	0.75	0.33
		(0.14)	(0.19)	(0.17)
	Obs.	48,281	16,042	17,808
Three+	LAST - MEAN	0.55	0.57	0.23
		(0.16)	(0.22)	(0.24)
	LAST2 - MEAN	0.75	0.50	0.86
		(0.18)	(0.27)	(0.22)
	Obs.	19,766	10,732	22,817

Variable definitions (all earnings variables are per share, divided by the share price)

ACT	Actual I/B/E/S earnings
MEAN	Mean of all outstanding forecasts made prior to current day
LAST	Mean of all forecasts on the most recent day on which estimates were made
LAST2	Mean of all forecasts on the second most recent day on which estimates were made

Table 3. Regressions testing for herding or exaggerating of forecasts

This table estimates average herding across multiple forecasts by regressing (ACT - CONS) on (FOR - CONS); equation (5) in the text. A regression coefficient of one implies unbiased forecasting, a coefficient greater than one implies herding, and a coefficient less than one implies anti-herding or exaggeration of differences. Sample B excludes observations for which the consensus is likely to be mismeasured, which would bias the estimated coefficient toward one. Our preferred specification is in line 6. To show the sources of differences with Keane and Runkle (1998), we replicate their results using our data -- first using our sample (lines 7 and 8) and then approximating their sample (lines 9 and 10).

					Beta		Constant (in basis points)	
	Dep. Variable	Indep. Variable	Sample	Obs.	Coeff.	S.E.	Coeff.	S.E.
1	ACT - MEAN	FOR - MEAN	A	728,325	0.67	0.051	-0.6	0.8
2	ACT - LAST3	FOR - LAST3	A	728,325	0.54	0.037	-0.3	0.8
3	ACT - CONS	FOR - CONS	A	728,325	0.55	0.043	-0.1	0.8
4	ACT - MEAN	FOR - MEAN	B	455,710	0.50	0.052	-0.5	0.7
5	ACT - LAST3	FOR - LAST3	B	455,710	0.42	0.029	-0.1	0.7
6	ACT - CONS	FOR - CONS	B	455,710	0.41	0.037	0.2	0.7
7	ACT	FOR	A	728,325	0.82	0.034	20.8	4.2
8	ACT	FOR	C	836,639	0.81	0.034	21.4	4.1
9	ACT	FOR	D	77,871	0.89	0.028	20.0	5.4
10	ACT	FOR	E	25,088	0.90	0.030	20.9	6.8

Variable definitions (earnings per share divided by the share price)

ACT	Actual I/B/E/S earnings
FOR	Forecast of earnings
MEAN	Mean of all previously outstanding forecasts
LAST3	Mean of last 3 forecasts (or fewer if fewer available)
CONS	Expected earnings, from model in Table 2

Sample defintions

A	All industries, forecasts with one or more prior forecasts
B	All industries, one or more prior forecasts, excluding first forecast after earnings announcements and forecasts on multi-forecast days
C	All industries
D	Keane and Runkle (1998) industries (airlines, railroads, auto assembly, chemicals, aluminium, and other non-ferrous metals), all firms
E	Keane and Runkle (1998) industries, 20 largest firms

Notes:

1. Standard errors are heteroskedasticity robust and adjusted for correlation of residuals within firms-quarter combinations as specified in (6).
2. Standard errors for the specification including the econometrically estimated CONS are adjusted for the inclusion of a predicted value on the right-hand side.

Table 4. Regressions including additional variables to control for consensus mismeasurement

This regressions attempt to control for the bias created by any measurement error in the construction of CONS by including variables that may be correlated with any measurement error. The variables included are the abnormal stock return (return less market return) since the day of the most recent forecast, the level of CONS (the consensus earnings-price ratio), and differences between alternative measures of the consensus.

			FOR - CONS		Return since last FOR		CONS		CONS - LAST3		LAST3 - MEAN	
Dep. Variable	Sample	Obs.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
ACT - CONS	A	455,710	0.41	0.037								
ACT - CONS	B	386,723	0.41	0.045								
ACT - CONS	B	386,723	0.41	0.045	0.0043	0.0006						
ACT - CONS	B	386,723	0.38	0.044	0.0018	0.0007	-0.16	0.035				
ACT - CONS	B	386,723	0.37	0.042	0.0018	0.0007	-0.16	0.035	-0.42	0.171		
ACT - CONS	B	386,723	0.38	0.046	0.0017	0.0007	-0.16	0.035	-0.05	0.113	0.29	0.151

Sample defintions
A Sample B in Table III
B Sample B in Table III, including only forecasts for which abnormal return since last forecast is known

Notes:
1. Standard errors are heteroskedasticity robust and adjusted for correlation of residuals within firms-quarter combinations as specified in (6).
2. Regressions contain a constant term.

Table 5. Variation in exaggeration with forecast, firm, and analyst characteristics

The cross-section variation in exaggeration with forecast, firm, and analyst characteristics is estimated by interacting these characteristics with the right-hand side of the model in Table 3 (equation 8 in the text). Only the interaction coefficients on the interactions with (FOR - CONS) are reported, although regressions include the uninteracted variables, (FOR - CONS), and a constant.

	(1)		(2)		(3)		Summary statistics	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Mean	S.D.
Sample defintion	A		B		B			
Observations	670,971		290,548		290,548			
Forecast characteristics (binary variables)								
First post-earnings forecast?	0.21	0.05					0.13	
Multiple forecast day?	0.13	0.04					0.29	
Revised forecast?	-0.14	0.04	0.03	0.07	0.04	0.07	0.34	
1-2 days after last forecast?	-0.11	0.04	-0.17	0.05	-0.14	0.05	0.52	
Firm characteristics								
Ln(Market cap)	0.026	0.016	0.031	0.027	0.034	0.027	0.7	1.6
Ln(SD-price ratio)	-0.023	0.009	-0.013	0.014	-0.011	0.015	-6.6	3.7
Ln(Number of covering analysts)	-0.070	0.054	-0.116	0.081	-0.118	0.088	2.2	0.7
Analyst characteristics								
Past analyst exaggeration rank					0.69	0.15	0.5	0.29
Ln(Number of analysts at brokerage firm)	0.07	0.02	0.08	0.03	0.06	0.03	3.7	0.9
Forecast # in career/1000	0.07	0.07	0.29	0.17	0.31	0.16	0.26	0.34
Sector dummies (Finance omitted)								
Health care	-0.82	0.12	-0.28	0.17	-0.25	0.16	0.10	
Consumer nondurables	-0.09	0.09	-0.05	0.11	-0.06	0.10	0.05	
Consumer services	-0.26	0.08	-0.12	0.12	-0.08	0.12	0.17	
Consumer durables	-0.22	0.08	-0.09	0.12	-0.03	0.11	0.04	
Energy	-0.46	0.09	-0.35	0.14	-0.27	0.12	0.09	
Transportation	-0.07	0.13	0.14	0.17	0.23	0.14	0.03	
Technology	-0.28	0.08	-0.07	0.14	-0.05	0.13	0.18	
Basic materials	-0.32	0.13	-0.24	0.20	-0.21	0.18	0.10	
Capital equipment	-0.16	0.10	-0.34	0.16	-0.29	0.14	0.07	
Utilities	-0.40	0.10	-0.38	0.12	-0.32	0.11	0.06	
Other	-0.48	0.16	-0.35	0.23	-0.36	0.23	0.004	
Year dummies (1993 omitted)								
1994	0.01	0.11	0.06	0.37	0.01	0.36	0.12	
1995	0.22	0.07	0.29	0.33	0.21	0.32	0.13	
1996	0.22	0.06	0.35	0.33	0.25	0.31	0.14	
1997	0.00	0.07	0.15	0.34	0.08	0.32	0.15	
1998	0.11	0.08	0.31	0.35	0.21	0.34	0.18	
1999	0.12	0.08	0.29	0.35	0.20	0.33	0.19	

Sample defintions

A Sample A in Table 1

B Sample B in Table 1, including only forecasts for analysts who have made 50 or more forecasts

Notes:

1. P-values for test of joint significance of sector and year dummies in specification (1) are 0.0005 and 0.0289, respectively.
2. Standard errors are heteroskedasticity robust and adjusted for correlation of residuals within firms-quarter combinations as specified in (6).

Table 6. Exaggeration by career stage

This table examines how the average exaggeration factor changes with an analyst's experience. Forecast dispersion increases with experience, especially if it is measured using the absolute difference between the forecast and the prior consensus. Prior studies (e.g., Hong, et. al., 2000) have interpreted this as implying less herding or more exaggeration by experienced analysts. But we find that exaggeration, as estimated in this paper, decreases with experience, as evidenced by the increase in beta. The reconciliation of these seemingly conflicting findings is that more experienced analysts have higher forecasts information content, and thus can deviate more from the consensus while exaggerating less.

	Forecasts in career		Exagg. coefficient Beta		Dispersion	Info content	Other dispersion measures	
Decile	Min	Max	Coeff.	S.E.	SD(x)	Var[E(y|x)]	Abs(F - C)	Abs(F - M)
0	50	94	0.35	0.07	21	55	7.4	8.6
1	95	150	0.27	0.10	23	40	7.3	8.4
2	151	217	0.37	0.06	21	58	7.4	8.5
3	218	294	0.41	0.08	21	74	7.9	9.1
4	295	382	0.24	0.08	25	34	8.0	9.0
5	383	485	0.38	0.06	20	55	8.0	9.4
6	486	610	0.34	0.14	23	59	8.1	9.4
7	611	776	0.43	0.07	20	76	8.0	9.1
8	777	1051	0.49	0.07	19	85	7.9	9.0
9	1052	4744	0.67	0.05	20	174	9.0	10.3
Coefficient from regression on (forecasts in career)/1000								
Coeff.			0.168				1.04	1.33
S.E.			0.042				0.07	0.10

Notes:

1. Forecasts in career are the number of I/B/E/S quarterly earnings forecasts made by the analyst since 1984. The sample only includes forecasts from 1993-99, as in the rest of the paper.
2. Standard errors are heteroskedasticity robust and adjusted for correlation of residuals within firms-quarter combinations as specified in (6).

Table 7. Relationship of exaggeration to over/under-reaction results

The exaggeration result in this paper is related to the over-reaction result of DeBondt and Thaler (1990) and the under-reaction result of Abarbanell and Bernhard (1992). DT regress ACT - CONS on CONS - ACT(-1) and find a negative coefficient; AB regress ACT - CONS on ACT(-1) - ACT(-2) and find a positive coefficient. The regressions find that the exaggeration coefficient is not significantly affected by controlling for either the DT or the AB terms (line 2 vs. lines 4 and 6), nor is it affected by controlling for the analyst's prior-period forecast error (line 2 vs. line 7). The DT and AB results are significantly reduced by controlling for the prior-period forecast error, however, suggesting that what was driving the seemingly inconsistent results of DT and AB was under-updating by analysts.

			FOR - CONS		CONS - ACT(-1)		ACT(-1) - ACT(-2)		ACT(-1) - FOR(-1)	
Dep. Variable	Sample	Obs.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
ACT - CONS	A	455,710	0.41	0.037						
ACT - CONS	B	217,076	0.41	0.044						
ACT - CONS	B	217,076			-0.33	0.062				
ACT - CONS	B	217,076	0.37	0.045	-0.33	0.062				
ACT - CONS	B	217,076					0.04	0.016		
ACT - CONS	B	217,076	0.41	0.044			0.04	0.015		
ACT - CONS	B	217,076	0.44	0.041					0.63	0.068
ACT - CONS	B	217,076	0.42	0.041	-0.11	0.022			0.54	0.058
ACT - CONS	B	217,076	0.45	0.042			-0.09	0.018	0.66	0.067
ACT - CONS	B	217,076	0.43	0.043	-0.16	0.025	-0.13	0.021	0.55	0.052

Variable definitions	(All earnings variables are divided by the share price)
ACT	Actual I/B/E/S earnings per share
ACT(-x)	Actual earnings, lagged x quarters
FOR	Forecast of earnings per share
FOR(-1)	Last forecast by same analyst in last quarter
CONS	Expected earnings, from model in Table 2

Sample defintions

A Sample B in Table 3

B Sample B in Table 3, including only forecasts for which last quarter's earnings are known

Notes:

1. Standard errors are heteroskedasticity robust and adjusted for correlation of residuals within firms-quarter combinations as specified in (6).

Table 8. Future forecast information content of analysts based on past performance decile

Analysts who have made more than 50 forecasts are divided into deciles based on the information content in their past forecasts. We then calculate the information content in the next forecast made by analysts in each decile as Var(y|x)=Beta^2*Var(x), a measure which is derived in Section 3.1.

			Deciles formed across sectors				Deciles formed within each sector			
			Exaggeration/herding		Deviation from consensus	Forecast info content	Exaggeration/herding		Deviation from consensus	Forecast info content
Decile	Historical info content	Obs.	Coeff.	S.E.	SD(x)	Var[E(y|x)]	Coeff.	S.E.	SD(x)	Var[E(y|x)]
0	5	29,975	0.41	0.06	14	33	0.41	0.05	15	38
1	32	29,975	0.33	0.08	16	29	0.30	0.08	17	26
2	79	29,975	0.36	0.05	16	32	0.36	0.05	17	36
3	148	29,974	0.27	0.06	18	23	0.30	0.05	17	24
4	262	29,975	0.50	0.06	16	65	0.52	0.07	16	73
5	442	29,975	0.50	0.06	19	93	0.58	0.05	18	107
6	726	29,974	0.53	0.05	20	109	0.48	0.06	19	83
7	1,295	29,975	0.56	0.08	21	147	0.57	0.05	21	152
8	2,899	29,975	0.38	0.11	26	102	0.38	0.10	28	109
9	51,486	29,974	0.43	0.15	30	165	0.42	0.16	29	147
Top 20% - Bottom 20% ratio			1.1		1.9	4.4	1.1		1.8	4.0
Top 10% - Bottom 40% ratio			1.2		1.9	5.7	1.2		1.8	4.7

Notes:

1. In the headings, y = ACT-CONS and x = FOR-CONS.
2. The first forecast after last quarter's earnings announcement and forecasts made on multi-forecast days are excluded from this analysis.
3. The statistical significance of the differences in future forecast information content across deciles is tested in Table 9.
4. Standard errors are heteroskedasticity robust and adjusted for correlation of residuals within firms-quarter combinations as specified in (6).

Table 9. Predicting future information content, exaggeration, and average deviation from past forecasting performance

Regressions in this table predict an analyst's forecast information content, exaggeration, and deviation from the consensus over the next 50 forecasts, or fewer if that's all that is available. In the first panel, future performance is shown to be positively related to past performance, whether or not controls are included. In the second panel, the logarithim of the information content measure is additively decomposed into its exaggeration and deviation from the consensus components. The (statistically significantly) higher coefficient on Ln[SD(x)] implies that analysts can raise the econometric prediction of their future performance by exaggerating. The results in panels 3 and 4 suggest that the higher coefficient on Ln[SD(x)] is due to a higher own-own coefficient.

				Independent variables					
	Consensus			Ln{Var[E(y|x)]}		Ln(Beta)		Ln[SD(x)]	
Dep. Variable	definition	Controls	Obs.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Ln{Var[E(y|x)]}	MEAN	No	299,747	0.25	0.03				
		Yes	299,747	0.18	0.02				
	CONS	No	299,747	0.26	0.03				
		Yes	299,747	0.20	0.02				
Ln{Var[E(y|x)]}	MEAN	No	299,747			0.23	0.05	0.65	0.07
		Yes	299,747			0.19	0.05	0.51	0.05
	CONS	No	299,747			0.18	0.06	0.68	0.06
		Yes	299,747			0.16	0.05	0.56	0.05
Ln(Beta)	MEAN	No	299,747			0.09	0.02	0.01	0.02
		Yes	299,747			0.08	0.02	-0.01	0.02
	CONS	No	299,747			0.08	0.02	0.02	0.02
		Yes	299,747			0.07	0.02	0.02	0.02
Ln[SD(x)]	MEAN	No	299,747			0.03	0.02	0.32	0.02
		Yes	299,747			0.02	0.02	0.26	0.02
	CONS	No	299,747			0.01	0.02	0.32	0.02
		Yes	299,747			0.01	0.02	0.24	0.02

Notes:

1. Regressions with controls include the mean log market cap of stocks for past forecasts, sector dummies, brokerage size, and number of forecasts in career.
2. Standard errors are heteroskedasticity robust and adjusted for correlation of residuals within firms-quarter combinations as specified in (6).

Table 10. Characteristics of analysts by 1996 Institutional Investor ranking

This table provides information on the past (1993-95) and future (1997-99) forecasts of analysts according to whether they were ranked in the October 1996 issue of Instititional Investor. Beta, SD(x), and forecast value are defined as in Tables 8 and 9. Absolute forecast MSE is the average forecast mean squared error. Relative forecast error is the same measure as in Hong, et. al. (2000); it is the analyst's average forecast accuracy ranking for each firm-quarter combination in which they forecast, where the ranking is scaled between 0 (most accurate) and 1 (least accurate), with a mean of 0.5. The results suggest that first teamers exaggerate less and have higher forecast information content in both their past and future forecasts.

	1996 Institutional Investor ranking					
	First-team	Team 2+	Hon. Mention	Unranked	Total	
Number of analysts	32	420	605	3,302	4,359	Units
1993-95 forecasts						
Number of forecasts per analyst	137	115	88	43	65	#
Beta	0.70	0.58	0.41	0.33	0.44	
SD(x)	26	25	22	29	25	Basis points
Info content	315.9	206.9	79.7	90.9	123.8	Basis points
Relative forecast error	0.485	0.501	0.503	0.509	0.504	Scaled 0-1
Absolute forecast error	5.3	4.0	3.6	5.0	4.3	Basis points
LN(market cap in $billions)	0.5	0.7	0.4	0.2	0.4	99$, CPI deflated
Number of analysts at brokerage	58	54	42	36	43	#
1997-99 forecasts						
Number of forecasts per analyst	276	246	188	56	95	#
Beta	0.90	0.45	0.33	0.35	0.37	
SD(x)	20	16	18	22	20	Basis points
Info content	309.0	55.3	34.3	61.5	54.9	Basis points
Relative forecast error	0.482	0.488	0.496	0.500	0.496	Scaled 0-1
Absolute forecast error	2.4	4.0	3.2	5.0	4.3	Basis points
LN(market cap)	0.7	1.0	0.7	0.4	0.6	99$, CPI deflated
Number of analysts at brokerage	91	86	65	51	62	#

Table A1. Exggeration and information content for subsamples

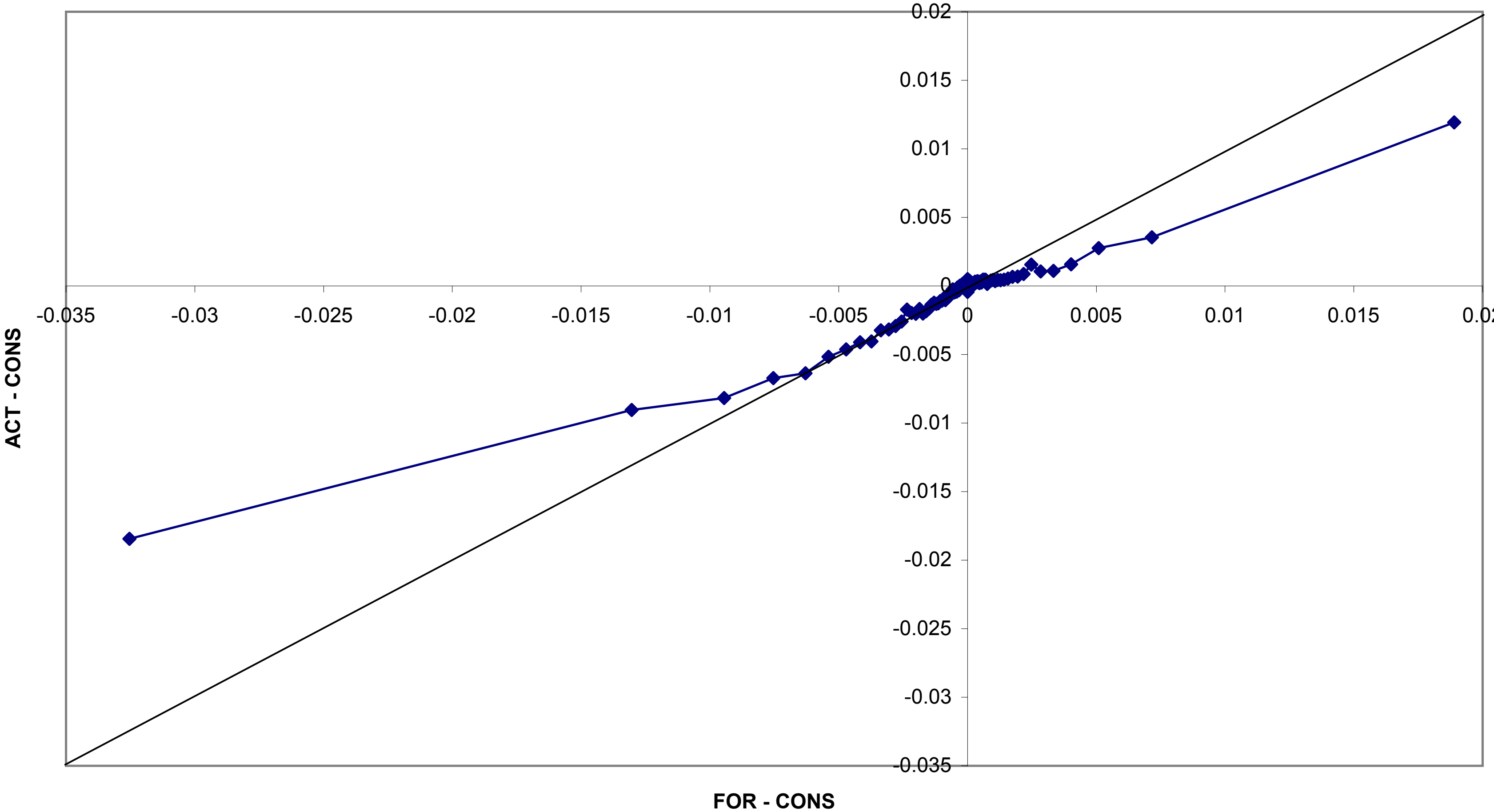
This table estimates exaggeration, deviation from the consensus, and forecast information content for subsamples of the dataset. The beta is from a regression of y=(ACT - CONS) on x=(FOR - CONS), the specification in Table 3 and discussed in Section 2. The measure of information content, Var[E(y|x)], is described in Section 3. The sample is sample B from Table 3, except for the first two characteristics which use sample A.

		Beta				Constant (in basis points)	
	Obs.	Coeff.	S.E.	SD(x)	Var[E(y|x)]	Coeff.	S.E.
Forecast characteristics							
Number of estimates that day							
1	503,693	0.46	0.04	22	103	0.2	0.7
2	113,964	0.59	0.09	22	165	0.5	0.9
3+	111,224	0.59	0.09	23	250	-0.6	1.1
First forecast after last quarter's earning announcement							
No	631,179	0.51	0.04	22	129	-0.2	0.8
Yes	97,146	0.86	0.08	23	400	0.6	0.8
Business days since last forecast							
1	67,814	0.41	0.05	18	52	0.0	0.8
2	29,445	0.46	0.19	18	68	0.3	0.9
3-4	53,582	0.41	0.06	21	72	0.1	0.9
5-9	108,247	0.38	0.06	20	56	0.3	0.8
10-19	87,210	0.36	0.08	23	66	0.2	0.7
20+	109,412	0.47	0.07	31	213	0.6	0.6
Revised forecast?							
No	268,056	0.34	0.04	21	52	-0.1	0.7
Yes	187,654	0.51	0.07	22	128	0.7	0.9
Days before earnings announcement							
90+	208,695	0.46	0.04	20	86	-2.4	0.8
60-89	87,678	0.48	0.04	21	96	0.9	0.8
30-59	86,707	0.33	0.11	24	64	3.0	0.9
15-29	41,098	0.43	0.08	26	125	5.1	0.8
1-14	30,066	0.19	0.09	19	13	4.7	0.9
Analyst career-related variables							
Number of analysts at brokerage firm							
Under 10	36,706	0.44	0.10	22	94	0.4	5.1
10-24	100,444	0.29	0.05	21	37	0.3	0.9
25-49	106,267	0.40	0.06	23	82	0.3	0.9
50-79	115,175	0.46	0.06	21	95	0.1	0.8
80+	97,118	0.46	0.08	22	99	0.1	0.8
Number of forecasts in analyst's career							
Under 10	18,382	0.52	0.13	30	249	0.5	0.8
10-49	47,564	0.49	0.06	23	122	2.4	1.1
50-99	43,129	0.25	0.08	24	37	2.0	1.2
100-199	63,694	0.36	0.10	21	56	0.6	1.0
200-499	130,273	0.31	0.06	23	49	1.6	0.8
500+	152,668	0.55	0.06	19	113	0.2	0.9
Number of forecasts made by analyst in current year							
Under 20	31,719	0.45	0.06	32	208	-0.8	0.7
20-49	89,205	0.29	0.07	24	49	2.2	1.0
50-99	170,440	0.35	0.05	20	48	1.7	0.9
100-199	128,281	0.52	0.05	20	103	0.3	0.7
200+	36,065	0.63	0.08	24	234	-0.6	1.0
Years since first forecast by analyst							
0	98,244	0.43	0.06	27	133	-1.1	1.0
1	98,849	0.39	0.08	23	80	0.4	1.3
2	80,488	0.39	0.10	21	68	1.3	1.2
3	63,961	0.41	0.09	24	93	-0.6	1.1
4	51,163	0.35	0.05	16	32	-0.1	0.8
5+	63,005	0.48	0.11	18	74	0.1	0.9
Historical beta by analyst (past forecasts only)							
Less than 0.0	45,406	0.02	0.12	21	0	1.0	1.2
0.0 to 0.5	83,637	0.37	0.04	19	48	-0.2	0.8
0.5 to 1.0	96,254	0.47	0.08	21	93	-0.2	0.7
Over 1.0	74,450	0.69	0.08	20	186	-0.4	0.7

Table A1 (cont.) Exggeration and information content for subsamples

	Obs.	Beta Coeff.	Beta S.E.	SD(x)	Var[E(y|x)]	Constant Coeff.	Constant S.E.
Firm characteristics							
Market capitalization (1999$)							
$100m-$499m	113,283	0.47	0.07	80	1412	-10.9	3.7
$500m-$1.9b	145,187	0.39	0.09	55	449	0.4	3.0
$2b-$4.9b	88,203	0.43	0.04	28	148	0.3	1.8
$5b-$20b	75,523	0.42	0.04	20	68	-2.1	1.0
Over $20b	33,514	0.37	0.04	11	17	1.4	1.0
SD(forecast)-to-price ratio							
Under 0.0001	209,003	0.35	0.09	15	27	1.3	0.4
0.0001 to 0.001	148,227	0.45	0.03	14	38	-1.2	1.2
0.001 to 0.01	81,890	0.50	0.03	33	277	-0.4	2.6
Over 0.01	16,590	0.38	0.08	107	1633	-0.7	11.3
Number of analysts covering stock							
Under 5	78,315	0.44	0.08	65	823	2.5	1.7
5-9	161,901	0.37	0.10	35	168	2.0	0.9
10-19	166,370	0.45	0.04	20	79	-0.7	1.2
20+	49,124	0.38	0.04	12	21	0.6	1.0
Other control variables							
S&P industry sector							
Finance	60,156	0.65	0.10	19	147	2.6	1.3
Health Care	45,075	0.27	0.07	13	12	0.1	0.9
Consumer nondurables	24,571	0.53	0.09	15	62	-3.7	1.3
Consumer services	74,137	0.29	0.08	24	50	-1.0	1.3
Consumer durables	17,012	0.49	0.06	35	289	2.5	8.4
Energy	38,530	0.37	0.06	19	52	-1.3	3.6
Transportation	13,080	0.60	0.13	50	921	-8.3	6.5
Technology	73,456	0.48	0.08	16	63	0.7	1.7
Basic materials	47,302	0.30	0.15	38	130	-2.5	1.7
Capital equipment	31,974	0.28	0.13	19	29	-3.0	2.1
Utilities	28,269	0.32	0.09	21	45	6.6	3.8
Calendar year of quarter							
1993	46,417	0.38	0.06	26	92	-1.8	2.6
1994	61,360	0.29	0.18	28	66	1.0	2.5
1995	65,846	0.64	0.06	23	220	-1.6	2.2
1996	67,580	0.51	0.05	22	122	-0.6	1.2
1997	71,933	0.25	0.04	21	29	0.5	1.2
1998	70,879	0.51	0.07	21	113	-3.6	1.2
1999	71,695	0.34	0.05	17	35	4.8	1.4

Figure 1. Actual less consensus vs. forecast less consensus



Each point represents the means of one percent of sample B in Table 3, sorted by (FOR - CONS). Variables are EPS divided by the share price.