Essays in Organizational Economics

by

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Abstract

This thesis is a collection of essays on organizational economics and finance-related topics.

Firms and individuals who sell opinions may bias their reports for either behavioral or strategic reasons. Chapter 1 proposes a new 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.

Chapter 2 examines whether career concerns can create an incentive for opinion-producing agents to exaggerate. We find that they can, the reason being that high-ability agents have opinions that are more different from the consensus on average and potential clients will learn more quickly about how different an agent's opinions are from the consensus on average that about whether or not they are exaggerating. The model predicts that agents should exaggerate more when they are under-rated by their clients, when the realizations of the variables they are forecasting are expected to be especially noisy, and when they expect to make fewer future forecasts. We find that these predictions are consistent with the empirical data on equity analyst's earnings forecasts.

In models by Fershtman and Judd (1987) and Sklivas (1987), firms competing in quantities benefit strategically from commiting to managerial incentives that are biased toward revenue maximization. Little empirical evidence has been produced in support of these models, and their assumption that incentive contracts are observable has been criticized as unrealistic. Chapter 3 proposes an alternative model in which firms competing in strategic substitutes commit to using less precise profit measures, which biases the optimal *unobservable* contract towards revenue maximization. This model performs better empirically. Firms that compete in strategic substitutes choose less precise profit measures across six different measures, and firms with less precise profit measures in turn have stock returns and thus managerial incentives that are driven

more by revenue growth.

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Contents

Chapter 1

Measuring herding and exaggeration by equity analysts

Summary 1 *Firms and individuals who sell opinions may bias their reports for either behavioral or strategic reasons. Chapter 1 proposes a new 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.*

1.1 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 downplay or exaggerate their differences with the consensus. Although it is impossible to determine whether a forecaster has herded on any given observation, our methodology allows us to draw a statistical inference about how much herding has occurred 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. Although exaggeration 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.[1]

The methodology in this paper has two main advantages over most prior empirical work on herding, which has inferred herding from a lack of forecast/opinion dispersion.[2] First, our methodology allows one to draw conclusions about the absolute amount of herding or exaggeration relative to unbiased forecasting, whereas inferring herding from forecast dispersion only allows one to draw relative conclusions about where there is more or less herding. Second,

[1] The theoretical literature on herding includes information cascade models (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992; Welch, 1994), 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).

[2] Examples include Lamont (1995), Ellison and Chevalier (1997 and 1999), and Hong, Kubik, and Solomon (2000). Graham (1999) takes a related approach, inferring more or less herding from more of less updating based on changes in the consensus.

our·n thodology controls for the independent private information content of 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) conclude that fund managers herd less in the last two months of the year when they are at a convex point in the inflow-performance relationship from the fact that they hold portfolios that are more different from the market portfolio. 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, learn too little from 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.

A useful by-product of our methodology for measuring exaggeration/herding controlling for forecast information content is a measure of forecast information content itself. 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.[3] While accuracy and forecast information content are related, using forecast 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.[4] 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

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

[4]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.

section describes the forecast information content measure. A conclusion follows.

1.2 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 measuring herding and/or exaggeration in particular. We then describe the data we use and how we implement the methodology and present the results.

1.2.1 Methodology

We would like to understand ow 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.

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:

$$F - C = g(E - C, \Omega^A, \Omega^P) \tag{1.1}$$

where $C = E(A|\Omega^P)$ is the consensus 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:

$$\begin{aligned} A - C &= g^{-1}(F - C, \Omega^A, \Omega^P) + \varepsilon. \\ \varepsilon &= A - E \end{aligned} \tag{1.2}$$

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

A simple model of exaggeration

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 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 think of the incentive for optimism as coming from an attempt to curry favor with management in order to secure underwriting business or future assess to information (Francis and Philbrick, 1993; Ackert and Athannanos, 1998; Lin and McNichols, 1998). We can think of the incentive for increasing or decreasing the deviation with the consensus as coming from an attempt to signal ability (e.g., Prendergast and Stole, 1996; Chapter 2), or from incentive convexities (e.g., Zweibel, 1995; Chevalier and Ellison, 1997 and 1999). We can write the analyst's problem as

$$\max_{F_t} \gamma(F_t - C_t)^2 + \mu E(F_t - A) - \lambda E(A - F_t)^2 \tag{1.3}$$

The first-order condition is

$$F_t - C_t = \underbrace{\frac{\lambda}{\lambda - \gamma}}_{b}(E_t - C_t) + \underbrace{\frac{\mu}{2(\lambda - \gamma)}}_{c}. \tag{1.4}$$

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

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:

$$\begin{aligned} (A_i - C_{it}) &= -\frac{c}{b} + b^{-1} \cdot (F_{it} - C_{it}) + \varepsilon_{it} \\ \varepsilon_{it} &= A_i - E_{it}. \end{aligned} \tag{1.5}$$

where i indexes different values of A being forecast. Notice that by construction the error term $A_i - E_{it} = A_i - E(A_i|\Omega_{it}^P, \Omega_{it}^A)$ 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:

$$\varepsilon_{it} = (A_i - E_{iT}) + \sum_{s=t}^{T-1}(E_{is+1} - E_{is}). \tag{1.6}$$

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 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.

1.2.2 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.

Forecast data

We estimate analyst exaggeration using the I/B/E/S Detail History dataset of analysts' earnings forecasts.[5] 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. 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 sample 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 roughly 1993. 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, analysts have entered their forecasts directly into the I/B/E/S system on the day they wish to make their forecast widely available

[5] 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.

(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 (Table A3). 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.

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 removed the need to condition on the independent variables to eliminate these outliers, i.e. eliminating penny stocks and micro-caps removes enough outliers that the results are no longer sensitive to the treatment of the remaining outliers.[6] 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

[6]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.

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 in the 1993-99 sample. Table A4 reports summary statistics for the major variables used in the exaggeration analysis.

Measuring the consensus

A practical issue in estimating (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 2.3.3, 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.[7] The equal-weighted mean of all forecasts is an intuitive and popular measure of the consensus. An issue with this measure is that if information is available to later forecasters or if analysts incorporate prior forecasts into their estimates, then a properly constructed expectation will put more weight on later forecasts. Measuring the consensus as the mean of the last three forecasts or the econometric expectation of earnings addresses this issue in a more and less ad hoc fashion, respectively.

[7] The econometric expectation is constructed using the model: $A-M = \alpha+\beta(\overline{F}_{t-1}-M)+\gamma(\overline{F}_{t-2}-M)$, where A is actual earnings, M is the mean of all previous forecasts, and $\overline{F}_{t-1}$ and $\overline{F}_{t-2}$ are the mean of all forecasts on the two most recent days on which forecasts were made. We estimate this model allowing for different β and γ depending on the number of forecasts on each of the two days. The results of this regression run for the entire 1993-99 period are presented in Table A1. To avoid any data-snooping bias in constructing our consensus measure, we used 1993-96 data to estimate the model used for 1997-99 consensus measures and vice versa.

Many financial market participants and journalists use the simple average of forecasts as a consensus measure, while other market participants use *ad hoc* measures that capture the trend in forecasts or an econometric prediction of earnings (e.g., I/B/E/S's ESP model). Stock return evidence suggests that the difference between sophisticated and unsophisticated consensus measures are only 50 percent reflected in stock prices, implying that users of "unsophisticated" consensus measures play a role in setting market prices.[8] This evidence suggests that we should be somewhat agnostic about how the market constructs its consensus. We conduct most of our analysis using the econometric expectation as our consensus measure, but test the sensitivity of the results to using the mean of all forecasts.

1.2.3 Results

Non-parametric results

Figure 1 presents a non-parametric estimation of the function g^{-1} in equation (2). The figure suggests that the relationship between $F - C$ and the expected value of $A - C$ is roughly linear. 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.[9] Given this, the rest of the paper will focus on assuming that the relationship is linear and estimating the determinants of its slope.

Linear exaggeration regression results

Table 1 presents estimations of equation (5). In all regressions, we normalize actual and forecast EPS by the share price and weight observations by their market capitalization to reduce heteroskedasticity.[10] One other study that we know of has run a version of this regression, and

[8] Table A2 presents this evidence. Zitzewitz (2001b) examines this issue in more detail.

[9] 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.

[10] 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 propor-

we begin by replicating those results. Keane and Runkle (1998) estimated a version of equation (5) that did not subtract the consensus from both sides of the equation. They analyzed six different industries and found that on average, b^{-1} was roughly one. They concluded from this that analysts forecasts were unbiased on average, and interpreted 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 seriously biases the regression coefficient toward one.

The first two lines of each panel of Table 1 estimate Keane and Runkle's version of (5), limiting the sample to their six industries. We also find a coefficient of over 0.9 and do not always reject the hypothesis that $b^{-1} = 1$, i.e. that analysts neither exaggerate or herd. This estimate is reduced to roughly 0.8 if we expand the sample to include all the industries in the I/B/E/S sample (Table 1, lines 3 and 4).[11] Once we subtract the consensus from both sides, however, the results change. Lines 5-7 of Table 1 estimate (5) using the three different measures of the consensus discussed above. As the measure of the consensus becomes more "sophisticated," the bias due to consensus mismeasurement is reduced and the coefficient moves further away from one.

In order to further reduce potential consensus mismeasurement problems, lines 8-10 of Table 1 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

tionally with market cap, so weighting observations by market-cap is very close to the FGLS estimator.

[11] A potential explanation for the reduced coefficient is that the Keane and Runkle industries (airlines, aluminium, auto assembly, chemicals, other non-ferrous metals, and railroads) 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.

the measurement error (e.g., the stock price change since the last earnings forecast) do not significantly affect the results (Table A5).[12]

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:

$$\begin{aligned} A_i - C_{it} &= \delta Z_{it} + (\gamma Z_{it})(F_i - C_{it}) + \varepsilon_{it} \\ -\frac{c_{it}}{b_{it}} &= \delta Z_{it} \\ b_{it}^{-1} &= \gamma Z_{it} \end{aligned} \tag{1.7}$$

where Z_{it} is a vector of forecast, firm, and analyst characteristics that includes a constant (Table 2).

Past exaggeration by an analyst is the best predictor of future exaggeration.[13] 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 A5).

[12] 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 also 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.

[13] 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 2 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.

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 herding using a methodology that controls for forecast information content, rather than inferring herding from a lack of forecast dispersion. In Table 4, 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.

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

$$A_{it} - A_{it-1} = \beta(C_{it} - A_{it-1}) + \varepsilon_{it}, \tag{1.8}$$

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:

$$A_{it} - C_{it} = \beta(A_{it-1} - A_{it-2}) + \varepsilon_{it} \tag{1.9}$$

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 3 estimates the model:

$$A_{it} - C_{it} = \alpha + \beta(F_{it} - C_{it}) + \gamma(C_{it} - A_{it-1}) + \delta(A_{it-1} - A_{it-2}) + \theta(A_{it-1} - F_{it-1}) + \varepsilon_{it}, \tag{1.10}$$

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 last regression in Table 1 and reestimate it for the sample for which all the variables in (9) 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.[14] 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 3 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

[14] 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 3 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.

beliefs about a company. 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.

Figures A1 and A2 provide a non-parametric analysis of the bivariate relationships between current-period forecast error and either prior-period earnings change or prior-period same-analyst forecast error, respectively. Both graphs show evidence of a kink at zero, suggesting that analysts under-react more to negative earnings changes and/or are more stubborn about revising their past beliefs downward. Easterwood and Nutt (1999) test for asymmetric over/under reaction to past earnings changes (Figure A1) and find evidence of overreaction to positive earnings changes and under-reaction to negative changes. In our sample, however, we find that spline regressions find evidence of a statistically significant kink at zero only for same-analyst forecast error (Figure A2) and then only if the 5 percent most extreme observations in each direction are excluded.

Interpretation of results

Taken together, the results in Tables 1 and 3 suggest that analysts are simultaneously behaving like the young and old agents 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.[15] Conscious exaggeration for career-concerns or 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.

1.3 Forecast information content

A useful byproduct 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.

1.3.1 Measuring forecast information content

For notional convenience, define $y = A-C = A-E(A|\Omega^P)$ and $x = F-C$. Assume that 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 the results in the prior section suggest, then $E(y|x) = \beta x$ and the expected value of a forecast is equal to $E[(\beta x)^2] = \beta^2 Var(x)$. This measure, if estimated at the analyst level using historical data, is exaggeration-proof: 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.

[15] 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.

1.3.2 Relationship between forecast value and information content in non-financial environments

In a financial market environment, it is natural to assume that information is used to make investments in relatively liquid assets and thus that information is valuable only if it is not known by other market participants and thus not already reflected in asset prices. In a non-financial market environment, it might be more natural to think of the value of information as being related to the improvement in the accuracy of understanding of the variable being forecast. In this section we show that under some circumstances, this improvement in accuracy will also be equal to $Var[E(y|x)]$, the measure motivated in a financial context above.

The formal relationship between accuracy and information content is between the level of information content and the improvement a forecast makes to the accuracy of one's beliefs. This improvement in accuracy of beliefs can be decomposed into three components:

$$\underbrace{E[(A-\widetilde{C})^2]-E[(A-F)^2]}_{\substack{\text{Reduction}\\ \text{in MSE}}}=\underbrace{E[(\widetilde{C}-C)^2]}_{\substack{\text{Noise in}\\ \text{consensus}}}+\underbrace{E[(E-C)^2]}_{\substack{\text{Information}\\ \text{content}}}-\underbrace{E[(F-E)^2]}_{\substack{\text{Translation}\\ \text{cost}}},\tag{1.11}$$

where A is actual earnings, C is the prior consensus, $\widetilde{C}$ is the potentially noisy version of the consensus observed by the client, E is the clients' rational expectation of earnings given the forecast, and F is the clients' actual expectation of earnings.[16] Notice that $E[(E-C)^2]$ is the same as the $Var[E(y|x)]$ measure in the section above.

If clients are fully able to translate forecasts into expectations, then $F = E$ and the last term is zero; if clients are completely unable to translate forecasts, then F will be the analyst's forecast and $(F-E)^2$ will increase as the analyst herds or exaggerates. If clients observe the consensus without noise and if they can perfectly translate forecasts into unbiased expectations, (9) implies that the improvement in accuracy is exactly the information content of the forecast. If clients' understanding of the consensus is noisy, however, then the $(\widetilde{C}-C)^2$ term will be

[16] To derive equation (9), note that it can be rewritten as the expectation of: $2(F-C)(A-E) = 2(A-C)(\widetilde{C}-C)$. Both sides of this expression are zero in expectation, since, by construction, $A-E$ is uncorrelated with all variables known at the time the expectation is formed, including $F-C$, and the noise in the noisy consensus measure $\widetilde{C}-C$ should not be correlated with $A-C$.

positive, since simply restating the consensus provides some value. And if clients are unwilling or unable to translate forecasts into unbiased expectations, then exaggerating or herding can reduce the value of a forecast.

This suggests that when clients are aware of the consensus and able to translate forecasts into rational expectations, then the forecast information content fully captures a forecast's value even in a non-financial context. When these conditions do not hold, absolute forecast accuracy can be a useful additional measure. We believe that the former situation better describes the environment in which equity analysts operate, and therefore use information content as our primary measure of forecast value.

1.3.3 Differences in information content across analysts

In this section, 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, 200, and 500 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 5 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.[17] 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.[18]

Table 6 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 2 are controlled for.

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

[17] 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.

[18] The point estimates of β in Table 5 are highest for intermediate levels of ability, which is suggestive of the "middle-status conformity" discussed by Phillips and Zuckerman (1999). Neither the concavity nor the slight upward slope in the relationship between β and past information content is statistically significant, however. We should also note that the Phillips and Zuckerman model is about status rather than ability.

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 6, then an analyst could raise estimates of her ability by exaggerating. This issue is examined in more detail in Chapter 2.

1.3.4 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 7). 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.[19] 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 (Table A7).

[19]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.

1.4 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 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 byproduct 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.

Table 1. Regressions testing for herding or exaggerating of forecasts

This table estimates average herding across multiple forecasts by regressing (ACT - CONS) on (FOR - CONS); equation (2) 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. To show the sources of differences with Keane and Runkle (1998), we first estimate results using their specification and sample definition and our data, expand the sample to our sample definition, and then change to our specification.

Dep. Variable	Indep. Variable	Sample	Obs.	Coeff.	S.E.
ACT	FOR	A	15,911	0.92	0.026
ACT	FOR	B	49,175	0.90	0.026
ACT	FOR	C	836,639	0.81	0.034
ACT	FOR	D	728,325	0.82	0.034
ACT - MEAN	FOR - MEAN	D	728,325	0.67	0.051
ACT - LAST3	FOR - LAST3	D	728,325	0.54	0.037
ACT - CONS	FOR - CONS	D	728,325	0.55	0.043
ACT - MEAN	FOR - MEAN	E	455,710	0.50	0.052
ACT - LAST3	FOR - LAST3	E	455,710	0.42	0.029
ACT - CONS	FOR - CONS	E	455,710	0.41	0.037

Variable definitions	(All earnings variables are divided by the share price)
ACT	Actual I/B/E/S earnings per share
FOR	Forecast of earnings per share
MEAN	Mean of all previously outstanding estimates
LAST3	Mean of last 3 estimates (or fewer if fewer available)
CONS	Expected earnings, from model in Table A1

Sample defintions

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

Notes:

1. Standard errors are heteroskedasticity robust and adjusted for clustering within firms-quarter combinations. 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 2. 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 1 (equation 5 in the text). Only the interaction coefficients on the interactions with (FOR - CONS) are reported, although regressions include the uninteracted variables and (FOR - CONS).

	(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 D in Table 1

B Sample E 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 clustering within firms-quarter combinations.

Table 3. 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 assess the independence of the finding that analysts exaggerate their differences with the consensus from DT's and AB's findings and whether all three findings are robust to controlling for the individual analyst's prior quarter error.

			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 3

Sample defintions

A Sample E in Table 1

B Sample E in Table 1, including only forecasts for which last quarter's earnings are known

Notes:

1. Standard errors are heteroskedasticity robust and adjusted for clustering within firm-quarter combinations.

Table 4. Exaggeration by career stage

This table examines how the average exaggeration factor changes with an analyst's experience. Forecast dispersion increases with experience, however, 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		Attrition rate
Decile	Min	Max	Coeff.	S.E.	SD(x)	Var[E(y|x)]	Abs(F - C)	Abs(F - M)	Percent
0	50	94	0.35	0.07	21	55	7.4	8.6	0.36
1	95	150	0.27	0.10	23	40	7.3	8.4	0.22
2	151	217	0.37	0.06	21	58	7.4	8.5	0.20
3	218	294	0.41	0.08	21	74	7.9	9.1	0.14
4	295	382	0.24	0.08	25	34	8.0	9.0	0.13
5	383	485	0.38	0.06	20	55	8.0	9.4	0.10
6	486	610	0.34	0.14	23	59	8.1	9.4	0.09
7	611	776	0.43	0.07	20	76	8.0	9.1	0.06
8	777	1051	0.49	0.07	19	85	7.9	9.0	0.06
9	1052	4744	0.67	0.05	20	174	9.0	10.3	0.06
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.

Table 5. 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	1295	29,975	0.56	0.08	21	147	0.57	0.05	21	152
8	2899	29,975	0.38	0.11	26	102	0.38	0.10	28	109
9	51486	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 6.
4. Standard errors are heteroskedasticity robust and adjusted for clustering within firm-quarter combinations.

Table 6. 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 predicted based on past performance. 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.

				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	332,537	0.25	0.03				
		Yes	332,537	0.18	0.02				
	CONS	No	332,537	0.26	0.03				
		Yes	332,537	0.20	0.02				
Ln{Var[E(y|x)]}	MEAN	No	332,537			0.23	0.05	0.65	0.07
		Yes	332,537			0.19	0.05	0.51	0.05
	CONS	No	332,537			0.18	0.06	0.68	0.06
		Yes	332,537			0.16	0.05	0.56	0.05
Ln(Beta)	MEAN	No	332,537			0.09	0.02	0.01	0.02
		Yes	332,537			0.08	0.02	-0.01	0.02
	CONS	No	332,537			0.08	0.02	0.02	0.02
		Yes	332,537			0.07	0.02	0.02	0.02
Ln[SD(x)]	MEAN	No	332,537			0.03	0.02	0.32	0.02
		Yes	332,537			0.02	0.02	0.26	0.02
	CONS	No	332,537			0.01	0.02	0.32	0.02
		Yes	332,537			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 clustering within analysts.

Table 7. 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 5 and 6. Absolute forecast MSE is the average forecast mean squared error. Relative forecast error 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.

	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	17.8	14.4	8.9	9.5	11.1	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	17.6	7.4	5.9	7.8	7.4	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. Regressions estimating the posterior expectation of actual EPS given estimates on current and most recent day
Dependent variable: ACTUAL - MEANEST

The posterior expectation of actual EPS is estimated regressing ACTUAL earnings on the mean of all forecasts on the current and most recent day on which estimates were made (MDAY and LAST, respectively) plus the mean of all previous estimates (coefficient not shown). The coefficients are allowed to vary with the number of estimates on each day; in most cases they increase with the number of estimates on that day. Regressions are market-cap-weighted. The coefficient on MEAN is between -0.1 and -0.2 for all subsamples.

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

Variable definitions
MDAY Mean of all forecasts on the current day
LAST Mean of all forecasts on the most recent day on which estimates were made
MEAN Mean of all outstanding forecasts made prior to current day
ACTUAL Actual I/B/E/S earnings per share

Table A2. Short-run and long-run market reaction to components of expected earnings surprise

These regressions breaks expected earnings surprise (defined as the difference between the expectation of earnings following the current day's estimates and the mean of all estimates) into three components. The first two regressions suggest that each component is roughly equally predictive of actual earnings surprise (the difference between actual earnings and the mean estimate). The event returns regressions suggest that all three components are associated with both current and future returns, even though the last two components are known before the current day's estimates.

			POSTERIOR - PRIOR		PRIOR - LAST3		LAST3 - MEAN	
Dep. Variable	Controls	Obs.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
ACTUAL - MEAN	No	766,547	0.98	0.08	1.09	0.10	1.20	0.07
	Yes	670,806	0.96	0.08	1.16	0.13	1.26	0.09
EVENT RETURN [-1,0]	No	638,300	4.89	0.04	3.94	0.11	2.08	0.04
	Yes	563,336	4.94	0.60	4.54	0.74	2.75	0.37
EVENT RETURN [+1, E+10]	No	528,310	2.39	0.15	2.39	0.36	0.71	0.13
	Yes	466,431	1.62	0.45	1.68	1.57	1.95	0.80

Variable defintions

POSTERIOR	Expectation of actual earnings after current day's forecasts, based on model in Table 3.
PRIOR	Expectation of actual earnings before current day's forecasts, based on model in Table 3.
LAST3	Average of last three forecasts made before current day.
MEAN	Average of all outstanding earnings forecasts
ACTUAL	Actual earnings
EVENT RETURN [-1,0]	Stock return less market return for day before and current day
EVENT RETURN [+1, E+10]	Stock return less market from day after current day to 10 business days after earnings announcement

Notes:

1. Regressions with controls include log market cap., the log of the standard deviation of the estimate/price ratio, and sector and year dummies.

Table A3. Abnormal returns surrounding earnings forecasts, by year and event window

This table reports the coefficients from a regression of abnormal stock returns (defined as stock returns less the CRSP value-weighted index) on the difference between an analyst's estimate and the mean outstanding estimate for four different event windows around the date of the analyst's announcement, as indicated in I/B/E/S. These results provide support for I/B/E/S's claim that estimates have been recorded in I/B/E/S within one day of being made available to clients since approximately 1993.

	Coefficients from regression of abnormal returns on (forecast - consensus)/price					
	Event window (trading days, relative to I/B/E/S recording date)					
Year	-29 to -6	-5 to -2	-1 to 0	1 to 10	-29 to 0	% in -1 to 0
1984	1.8	0.2	0.2	0.1	2.2	9%
1985	2.7	0.2	0.0	0.2	2.9	1%
1986	2.2	0.1	0.1	0.4	2.5	6%
1987	1.3	0.2	0.0	0.0	1.4	-1%
1988	2.0	0.2	0.1	0.3	2.3	6%
1989	3.7	0.5	0.2	0.7	4.4	5%
1990	3.6	1.0	0.3	0.5	4.9	5%
1991	3.6	0.8	0.3	0.5	4.7	6%
1992	4.1	1.3	0.8	0.3	6.2	13%
1993	3.7	1.4	1.3	0.4	6.3	20%
1994	4.2	1.8	1.9	0.8	7.9	24%
1995	4.7	1.9	2.7	1.1	9.3	29%
1996	4.5	2.1	3.0	0.8	9.6	31%
1997	6.0	3.0	4.7	0.8	13.6	34%
1998	7.6	3.4	4.8	1.2	15.8	31%
1999	7.5	3.5	6.0	0.8	17.0	35%

Notes:
1. Regressions are ordinary least squares, standard errors for each coefficient are approximately 0.1.
2. Since the pre-93 estmates data is more noisy than the post-93 data, there was a risk that measurement error would make the event returns appear lower before 1993. To limit this problem, observations where the estimate differed from the consensus by more than 1% of the market value of the firm were treated as differing by 1% of the market value for all years. This censoring was done for 7% of pre-93 observations and 3% of post-93 observations.

Table A4. Summary statistics

Samples used in this paper							
Sample 1. (Tables 1 and 3; Table 2, Col. 1)							
Total forecasts	879,396						
Forecasts following at least one other forecast	766,547						
Firm-quarter combinations	87,303						
Firms	7,008						
Analysts	5,688						
Sample 2. (Table 2, Cols. 2 and 3; Tables 4-7)							
Forecasts following at least one other forecast	322,537						
Analysts	1,497						
Summary statistics for sample 1	Abbreviation	Mean	S.D.	Skew	Median	IQ range	
Earnings variables (all are 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

Sample 1 includes all firm-quarter combinations from 1993-99
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

Table A5. 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 1 and discussed in Section 2.2. The measure of information content, Var[E(y|x)], is described in Section 3.

		Beta			
	Obs.	Coeff.	S.E.	SD(x)	Var[E(y|x)]
Forecast characteristics					
Number of estimates that day					
1	508,134	0.44	0.05	0.63	0.12
2	113,964	0.54	0.21	0.72	0.21
3+	111,224	0.59	0.16	0.73	0.25
First forecast after last quarter's earning announcement					
No	635,229	0.44	0.07	0.65	0.13
Yes	98,093	0.73	0.10	0.68	0.36
Business days since last forecast					
1	179,592	0.45	0.11	0.53	0.11
2	72,915	0.30	0.13	0.56	0.05
3-4	94,930	0.48	0.11	0.59	0.14
5-9	134,278	0.44	0.09	0.62	0.12
10-19	121,374	0.42	0.19	0.77	0.13
20+	122,338	0.61	0.09	0.84	0.31
Revised forecast?					
No	344,369	0.57	0.09	0.71	0.23
Yes	388,953	0.40	0.08	0.60	0.10
Analyst career-related variables					
Number of analysts at brokerage firm					
Under 10	51,732	0.41	0.12	0.61	0.10
10-24	149,052	0.38	0.06	0.56	0.08
25-49	162,490	0.44	0.13	0.66	0.12
50-79	182,675	0.65	0.10	0.66	0.28
80+	177,712	0.44	0.11	0.72	0.14
Number of forecasts in analyst's career					
Under 10	31,103	0.50	0.07	0.73	0.19
10-49	105,363	0.41	0.11	0.68	0.11
50-99	98,352	0.40	0.09	0.71	0.11
100-199	143,886	0.36	0.09	0.65	0.08
200-499	227,972	0.60	0.12	0.64	0.23
500+	126,646	0.56	0.12	0.62	0.19
Number of forecasts made by analyst in current year					
Under 20	35,315	0.38	0.07	0.90	0.13
20-49	108,036	0.37	0.11	0.70	0.10
50-99	257,591	0.53	0.08	0.65	0.18
100-199	258,229	0.45	0.12	0.61	0.13
200+	69,801	0.73	0.18	0.64	0.34
Years since first forecast by analyst					
0	142,894	0.42	0.10	0.68	0.12
1	150,341	0.62	0.15	0.69	0.26
2	126,299	0.42	0.09	0.60	0.11
3	103,537	0.57	0.12	0.66	0.21
4	85,152	0.43	0.13	0.62	0.12
5+	125,099	0.41	0.14	0.67	0.11

Table A5 (cont.) Exggeration and information content for subsamples

	Obs.	Beta Coeff.	S.E.	SD(x)	Var[E(y|x)]
Firm characteristics					
Market capitalization (1999$)					
$100m-$499m	162,050	0.50	0.09	1.06	0.27
$500m-$1.9b	220,325	0.41	0.14	0.67	0.12
$2b-$4.9b	143,938	0.51	0.07	0.39	0.10
$5b-$20b	137,938	0.56	0.04	0.28	0.09
Over $20b	69,071	0.55	0.05	0.19	0.06
SD(forecast)-to-price ratio					
Under 0.0001	472,470	0.72	0.06	0.30	0.16
0.0001 to 0.001	141,253	0.46	0.15	0.71	0.15
0.001 to 0.01	32,774	0.51	0.09	1.51	0.39
Over 0.01	86,825	0.42	0.12	1.20	0.21
Number of analysts covering stock					
Under 5	114,521	0.48	0.12	0.86	0.20
5-9	232,537	0.54	0.12	0.72	0.21
10-19	280,231	0.44	0.10	0.58	0.11
20+	106,033	0.37	0.33	0.40	0.05
Other control variables					
S&P industry sector					
Finance	90,877	0.93	0.21	0.62	0.53
Health Care	72,829	-0.02	0.25	0.64	0.00
Consumer nondurables	40,223	0.89	0.11	0.72	0.57
Consumer services	121,152	0.46	0.06	0.60	0.13
Consumer durables	26,163	0.73	0.14	0.51	0.27
Energy	62,302	0.32	0.16	0.50	0.05
Transportation	20,201	0.61	0.10	1.31	0.49
Technology	132,487	0.44	0.18	0.65	0.13
Basic materials	72,300	0.40	0.15	0.67	0.11
Capital equipment	49,436	0.47	0.30	0.47	0.10
Utilities	40,871	0.38	0.10	0.76	0.11
Calendar year of quarter					
1993	67,544	0.38	0.20	0.59	0.08
1994	87,735	0.59	0.19	0.78	0.27
1995	97,062	0.82	0.10	0.58	0.39
1996	101,402	0.68	0.12	0.54	0.25
1997	111,051	0.33	0.10	0.65	0.07
1998	130,459	0.32	0.12	0.71	0.07
1999	138,069	0.46	0.19	0.69	0.15

Table A6. Regressions including addition 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

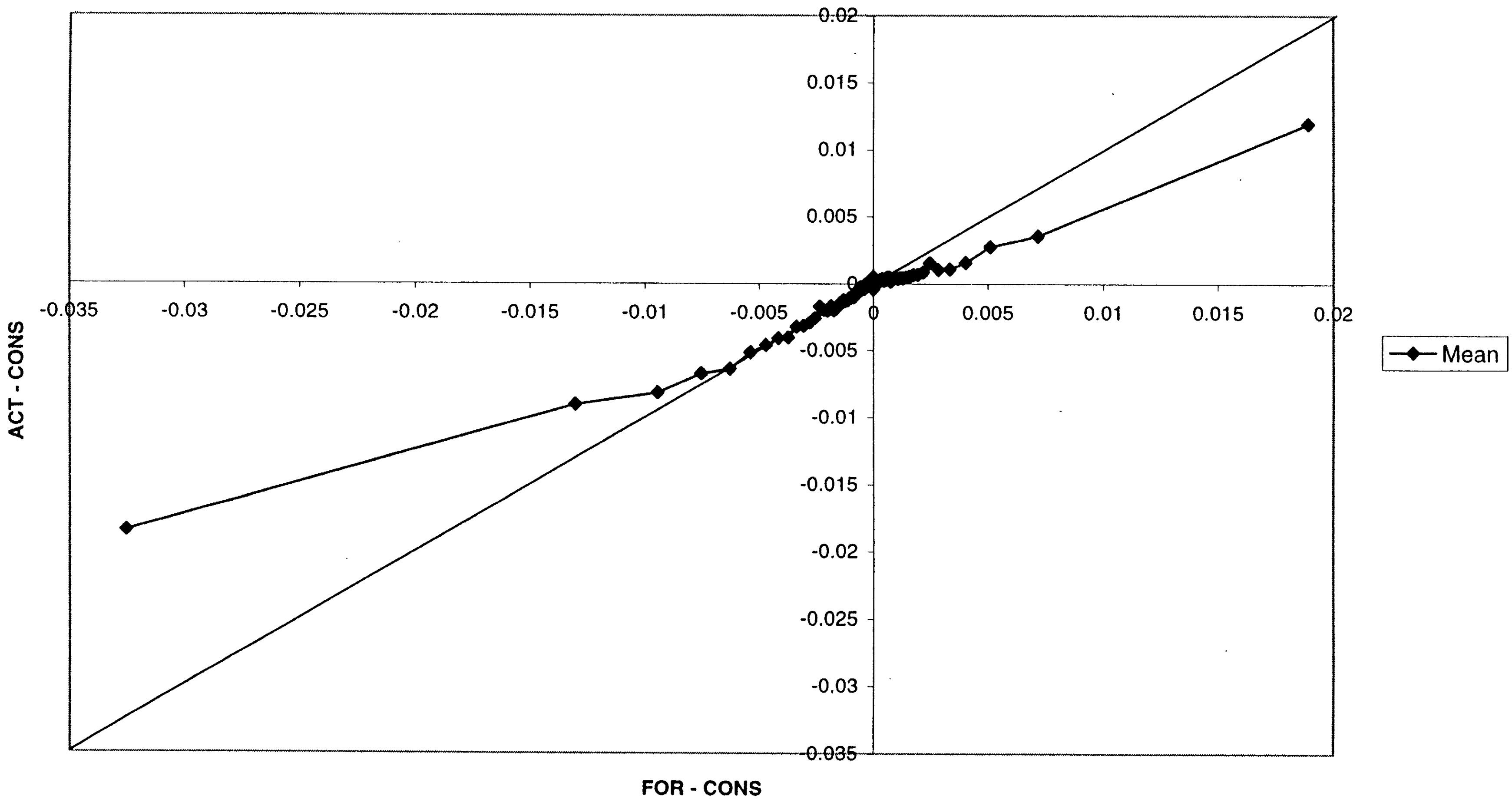
A Sample E in Table 1

B Sample E in Table 1, including only forecasts for which abnormal return since last forecast is known

Notes:

1. Standard errors are heteroskedasticity robust and adjusted for clustering within firm-quarter combinations.

Figure 1. Actual less consensus vs. forecast less consensus



Each point represents one percent of the data, sorted by (FOR - CONS). Variables are EPS divided by the share price.

Chapter 2

Opinion-producing agents: career concerns and exaggeration

Summary 2 *Chapter 2 examines whether career concerns can create an incentive for opinion-producing agents to exaggerate. We find that they can create, the reason being that high-ability agents have opinions that are more different from the consensus on average and potential clients will learn more quickly about how different an agent's opinions are from the consensus on average that about whether or not they are exaggerating. The model predicts that agents should exaggerate more when they are under-rated by their clients, when the realizations of the variables they are forecasting are expected to be especially noisy, and when they expect to make fewer future forecasts. We find that these predictions are consistent with the empirical data on equity analyst's earnings forecasts.*

2.1 Introduction

Much of the information in the so-called information economy is not verifyable information as economists normally define it, but is rather opinion. Opinion goods such as forecasts, consulting advice, and product reviews are sold in markets, and the production of these and other types of opinions is also the primary job of many professionals within organizations. Unlike most traditional goods, the quality of information or opinion goods cannot be readily observed prior to purchase. In addition, opinions that are not verifiable can be manipulated by their producer. Reputational or career concerns are thus likely to be especially important to opinion producers.

This paper examines the relationship between the reputational or career concerns of opinion producers and their incentives to engage in a particular type of opinion manipulation, namely exaggerating their differences with the existing consensus. It essentially asks the question: do people exaggerate in order to appear smart? Most opinions can be thought of as forecasts of a random variable that will be realized in the future. We develop a model in which potential clients attempt to learn the ability of forecasters from their track record. In the model, an incentive to exaggerate arises because high-ability agents have access to more private information and thus have unbiased beliefs that are more different from the prior consensus on average. Clients learn more quickly about how different an agent's forecasts are from the consensus on average than about whether or not they are exaggerating, and thus agents can temporarily raise estimates of their ability by exaggerating.

The model also yields cross-sectional predictions about when we should expect agents to exaggerate more. This is potentially useful to consumers of opinions, since they will want to back out expected exaggeration to form unbiased beliefs. One source of variation arises from the fact that the difference in learning speed discussed above is more pronounced when forecast variable realizations are noisier, so agents should exaggerate more under these circumstances. Likewise, agents expecting a shorter future career length should exaggerate more. Agents should also exaggerate more when they have had bad luck in the past and are under-rated by the market in order to increase the weighting on future observations of their ability. We find that both the general finding of exaggeration and these cross-sectional predictions are consistent with the empirical evidence when we examine the exaggeration of equity analysts forecasting earnings using the methodology developed in Chapter 1.

The model of career concerns and exaggeration in this paper draws on the literature on career concerns, reputational concerns for producers of goods of unobservable quality, and herding theory.[1] It is particularly related to two recent papers. In Prendergast and Stole

[1]For general career concerns theory see Fama (1980), Holmstrom (1982), and Gibbons and Murphy (1992). The industrial organizations literature on reputational concerns includes Nelson (1974), Schmalensee (1978), Klein and Leffler (1981), and Shapiro (1983). Herding models include information cascade models (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992; Welch, 1999), incentive-concavity models (Holmstrom and

(1996), "impetuous youngsters" take more extreme actions in order to signal that they have access to better private information. In Avery and Chevalier (1999), more experienced agents are expected to have developed private information about their ability and an equilibrium exists where agents of all abilities always disagree with prior forecasts to signal ability. Relative to Prendergast and Stole, a contribution of this paper is to examine an environment in which there is learning from forecast variable realizations. This seemingly trival extension yields the cross-sectional predictions about the degree of exaggeration that we can test empirically.

The remainder of the paper is organized into two sections. The first develops the model and the cross-sectional predictions. The second section presents evidence that equity analyst's earnings forecasts are consistent with these predictions. A conclusion follows.

2.2 Career-concerns model

In this section, we model the incentives created by the career concerns of an agent who forecasts a series of random variables. We first present a two-period model in which agents issue forecasts in the first period and receive revenue in the second period proportional to clients' valuation of their forecasts based on their first period performance. We then extend the model to three periods in order to examine how past forecasting performance affects an agent's incentives to exaggerate. From the two-period model we conclude that agents have an incentive to exaggerate and this incentive to exaggerate will be greater when earnings realizations are expected to be noisy or when agents expect to make a limited number of forecasts in the future. From the three-period model, we conclude that agents will also exaggerate more when they have had bad luck in the past and thus are underrated by their clients.

2.2.1 Two-period model

The model has two periods. In the first period, the agent issues forecasts of J random variables after observing a private signal and a common prior. In the second period, the agent sells early

Ricart i Costa, 1986; Zweibel, 1995; Chevalier and Ellison, 1997 and 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).

access to their forecasts to clients, receiving revenue proportional to clients' valuation of their forecasts based on their first-period performance. Agents also face an exogenous incentive for forecast accuracy, and thus receive revenue proportional to $\widehat{v} - \lambda \cdot MSE$, where $\widehat{v}$ is the estimate of the value of new information in the agents forecasts and λ is the size of the incentive for accuracy. The role of the incentive for accuracy is to make the language analysts use relevant; we can think of this incentive as the result of clients' costs of translating exaggerated forecasts into unbiased expectations or industry institutions that measure analysts based on mean squared error.

The timing of the model is as follows:

1. Nature chooses an ability, a, and an accuracy incentive, λ, for the agent from a prior distribution $g(a, \lambda)$. Both parameters are observed by the agent but are unknown to their potential customers.

2. The agent forecasts a series of J random variables A_j. For each A_j, the agent observes a public consensus prior that A_j is distributed $N(C_j, \Sigma^{-1})$, where Σ is the precision of the prior. Since C_j is public, we can think of the agent as forecasting $y_j = A_j - C_j$, i.e. the difference between the actual realization and its consensus prior expectation.

3. In addition, the agent observes an independent private signal $s_j \sim N(A_j, p^{-1})$, where $p = \frac{a\Sigma^2}{(1-a\Sigma)} > 0$ is the precision of the signal. p is an increasing function of a; higher ability agents receive higher precision private signals.

4. Based on the consensus priors and her private signals, the agent issues forecasts using a forecasting rule $\mathbf{x} = \mathbf{x}(\mathbf{s}, \mathbf{C}, p, \lambda)$, where $x_j = F_j - C_j$ is a forecast of y_j. All forecasts are made before any of the earnings variables are realized.

5. Clients with early access to forecasts can make investments in securities with returns that are proportional to y_j.

6. Clients observe the forecasts $\mathbf{x}$ and realizations $\mathbf{y}$ and estimate the value of the information content of the agent's forecasts using a valuation rule $\widehat{v} = v(\mathbf{x}, \mathbf{y}, .)$.

7. Agents sell early access to their second-period forecasts and receive revenue proportional to $\widehat{v} - \lambda \cdot MSE$. Agents consume and experience linear utility.

Forecast information content and clients valuation of forecasts

After the agent observes the consensus prior and the private signal, her optimal posterior expectation of y_j is

$$E(y_j|C_j, s_j) = (s_j - C_j)\frac{p}{p + \Sigma}, \tag{2.1}$$

where a higher-precision private signal receives a higher weight. Notice that the variance of the difference between an agent's unbiased beliefs and the prior consensus is increasing in p:

$$Var[E(y_j|s_j, C_j)] = \frac{p}{(p + \Sigma)\Sigma} = a. \tag{2.2}$$

Higher-ability agents have opinions that are more different from the consensus, on average. We will also refer to this variance as the information content of an agent's forecasts, since it is equal to the reduction in mean-squared error in the expection of y_j or A_j due to the agent's private information:

$$Var[E(y_j|s_j, C_j)] = Var(y_j|C_j) - Var[y_j - E(y_j|s_j, C_j)].^2 \tag{2.3}$$

A mean-variance client with early access to a forecast investing in a security with returns that are linear in y_j will invest to maximize

$$\max_{I_j} I_j \cdot E(y_j|x_j) - I_j^2 \cdot \frac{r}{2} \cdot Var(y_j|x_j), \tag{2.4}$$

where I_j is the client's exposure to y_j and r is the coefficient of absolute risk aversion. The optimal investment is:

$$I_j^* = \frac{E(y_j|x_j)}{r \cdot Var(y_j|x_j)} \tag{2.5}$$

and such an investment has an ex-ante certainty-equivalent value of

$$CE = \frac{[E(y_j|x_j)]^2}{2r \cdot Var(y_j|x_j)}. \tag{2.6}$$

The value of early access to an agent's forecasts will be proportional to the variance of $E(y_j|x_j)$. If an agent's forecasts are fully revealing of her signal, this will be the same as

[2]This is true since by the law of iterated expectations, $y_j - E(y_j|s_j, C_j)$ must be uncorrelated with $E(y_j|s_j, C_j) - E(y_j|C_j)$.

$Var[E(y_j|s_j, C_j)] = a$, otherwise it will be a less a discount for uncertainty regarding an agent's forecasting strategy. For simplicity, we will assume that the information lost in communicating the signal is small in the long run and thus that clients are interested in estimating a as the long-run value of a client's forecasts, so $\widehat{v} = \widehat{a}$.[3]

Solution

We will look for a consistent-exaggeration forecasting equilibrium in which agents use the forecasting rule: $x_j = b(a, \lambda) \cdot E(y_j|s_j, C_j)$ with some constant exaggeration factor b that can depend on a or λ. This forecasting rule implies that agents exaggerate their differences with the consensus when $b > 1$, herd when $b < 1$, and report their expectation when $b = 1$.

The standard solution approach would be to solve for a Bayesian equilibrium in which the analyst chooses her forecasts to maximize expected utility, given the clients' valuation rule, and the valuation rule produces an unbiased and efficient estimate, given the analyst's forecasting rule. Unfortunately, the standard Bayesian estimate of $v(\mathbf{x}, \mathbf{y}) = E[a|\mathbf{x}, \mathbf{y}, g(), b()]$ is very intractable and conjugate prior distribution families that improve tractability do no exist. Instead of assuming that clients' make a such a difficult calculation, we will instead assume that they use an econometric estimation approach that is consistent but not necessarily efficient, with the inefficiency coming from the incorporation of the information from the prior distribution in an approximate rather than a fully Bayesian way. We will describe an equlibrium in which clients do econometric estimation that anticipates consistent exaggeration and then show that consistent exaggeration is in fact optimal for the analysts.[4] This exercise can be viewed as the derivation of an Bayesian equilibrium in which clients are constrained by bounded rationality and thus use an unbiased and tractable but less efficient estimation approach. Alternatively, it can be viewed as merely an analysis of the incentives created for analysts if clients estimate

[3]If we relaxed this assumption, agents would face an additional incentive for limiting the uncertainty regarding their exaggeration strategy, since uncertainty about exaggeration creates a gap between $a = Var[E(y_j|s_j, C_j)]$ and $v = Var[E(y_j|x_j)]$. Relative to the solution described below, the agent would choose an exaggeration factor slightly closer to their clients' prior expectation of exaggeration.

[4]Actually, a consistent-exaggeration equilibrium will be the only equilibrium whenever $\lambda > 0$. To see this consider an alternative equilbrium where clients expect an analyst to exaggerate by $b \cdot f(j)$, where f varies predictably from observation to observation. In this case, the first-order condition in (12) below will be $b = [E(\widehat{\beta}_{CL}) + f^{-1}\lambda][E(\widehat{\beta}_{CL})^2 - \gamma\beta_0^2 + \lambda]^{-1}$, so the analyst will choose a lower b when f is high and vice versa, i.e. will choose a strategy closer to consistent exaggeration than they are expected to. It follows that a consistent exaggeration is the only equilibrium.

their ability using a particular econometric procedure.

We proceed by specifying the clients' estimator of analyst ability, solving the analyst's problem given the clients' valuation rule, and verifying that consistent-exaggeration forecasting is an equilibrium.

Clients' problem If analysts follow the consistent-exaggeration forecasting rule described above, they will issue forecasts such that:

$$\begin{aligned} E(y_j|s_j, C_j) &= \frac{p}{p+\Sigma}(s_j - C_j) \sim N(0, a) \\ x_j &= b \cdot \frac{p}{p+\Sigma}(s_j - C_j) \sim N(0, b^2 a) \\ y_j &= b^{-1} x_j + \varepsilon_j \\ \varepsilon_j &= y_j - E(y_j|s_j, C_j). \end{aligned}$$

As a result, x_j and y_j are distributed joint normally:

$$\begin{bmatrix} y_j \\ x_j \end{bmatrix} \sim N(0, \begin{bmatrix} a + V + (\Sigma + p)^{-1} & ba \\ ba & b^2 a \end{bmatrix}).$$

Note that a is the information content of the analyst's forecasts $Var[E(y_j|x_j)]$; clients are therefore trying to estimate a.

Given the regression-like setup, it will be convenient to discuss $\beta = b^{-1}$ as the change in the expectation of y for a given change in x. A natural set of estimators for $\beta = b^{-1}$ and a are the classical statistical estimators that are used to estimate exaggeration and forecast information content in Chapter 1:

$$\widehat{\beta}_{CL} = \frac{\sum_{j=1}^{J} x_j y_j}{\sum_{j=1}^{J} x_j^2} \tag{2.7}$$

$$\widehat{a}_{CL} = \widehat{\beta}_{CL}^2 \cdot \widehat{Var}(x_j) = \frac{(\sum_{j=1}^{J} x_j y_j)^2}{(J-1)\sum_{j=1}^{J} x_j^2}. \tag{2.8}$$

These estimators are consistent and unbiased, but they are inefficient if clients have prior information about a or $b(a, \lambda)$. A client can improve the efficiency of an estimate of a by averaging the observed $\widehat{a}_{CL}$ with the mean of her prior distribution. In addition, since the estimate $\widehat{\beta}_{CL}$ is likely to be noisier than the estimate $\widehat{Var}(x_j)$, especially when V is high, clients can improve on the efficiency of their estimate by constructing their $\widehat{a}$ with an average of the observed $\widehat{\beta}_{CL}$ and β_0, client's prior expectation of b^{-1} given the distribution $g(a, \lambda)$ and the function $b(a, \lambda)$. We therefore assume that clients estimate analysts' ability as:

$$\widehat{a}_P = \frac{(\widehat{\beta}_{CL}^2 + \gamma \cdot \beta_0^2) \cdot \widehat{Var}(x_j) + \delta \cdot a_0}{1 + \gamma + \delta}, \tag{2.9}$$

where δ is the weight given the prior expectation of ability and $\gamma > 0$ is the weight placed on β_0.

The γ term in (9) captures an important feature of any optimal estimator, namely that prior information about exaggeration should be relied on when estimates of exaggeration are noisy. Equation (9) is similar in structure to a maximum-likelihood estimator of ability; an analysis of the maximum likelihood estimator in Appendix A yields some intuitive predictions about the determinants of γ. The weight γ placed on β_0 should be higher when the estimate $\widehat{\beta}$ is noisier i.e. when earnings realizations are noisier (and V is higher) or when the number of observations J is low.[5]

Analyst's problem Analysts choose their x_j to maximize their expectation of $\widehat{a}_P - \lambda \cdot MSE$, their clients' estimation of their forecast value plus their incentive for absolute accuracy. If clients use the estimation approach outlined above, the analyst's problem is:

$$\max_{\mathbf{x}} E[\frac{(\sum_{j=1}^J x_j y_j)^2}{(J-1)\sum_{j=1}^J x_j^2}] + \gamma\beta_0^2 \frac{\sum_{j=1}^J x_j^2}{(J-1)} - \lambda E[\frac{\sum_{j=1}^J (y_j - x_j)^2}{(J-1)}], \tag{2.10}$$

[5]We can also think of γ as capturing the potential for exaggeration to signal high or low ability. When the distribution $g(a, \lambda)$ and the function $b(a, \lambda)$ are such that the priors on a and $b(a, \lambda)$ are positively (negatively) correlated, then exaggeration signals low (high) ability. Clients can account for this in their estimation by lowering (raising) γ relative to its value when the priors on a and $b(a, \lambda)$ are uncorrelated.

where the expectations are the analyst's before $\mathbf{y}$ is realized. The first-order condition for each x_j is:[6]

$$x_j = \frac{E(y_j\widehat{\beta}_{CL}) + E(y_j)\cdot\lambda}{E(\widehat{\beta}^2_{CL}) - \gamma\beta_0^2 + \lambda} = E(y_j)\cdot\frac{E(\widehat{\beta}_{CL}) + \lambda}{E(\widehat{\beta}_{CL})^2 - \gamma\beta_0^2 + \lambda}. \tag{2.11}$$

So a consistent-exaggeration strategy of the type assumed above is in fact optimal. The analyst chooses b such that:

$$\beta = b^{-1} = \frac{E(\widehat{\beta}_{CL})^2 - \gamma\beta_0^2 + \lambda}{\widehat{\beta}_{CL} + \lambda}. \tag{2.12}$$

From (7) above we can see that rational expectations on the part of the analyst imply that $E(\widehat{\beta}_{CL}) = \beta$. This condition together with (8) implies the following relationships between accuracy incentives (λ), the weight placed on β_0 (γ), and exaggeration (β):

- When $\gamma = 0$ (no prior information about β) and $\lambda = 0$ (no incentive for accuracy), any value of β is possible. This is a cheap talk result: if there is no incentive for absolute accuracy, any language is as good as the next so long as the clients do not have prior beliefs about β.

- When $\gamma = 0$ and $\lambda > 0$, $\beta = 1$. Adding even a small incentive for absolute accuracy to the cheap talk situation makes unbiased forecasting optimal.

- When $\gamma > 0$ and $\lambda \leq \gamma\beta_0^2$, $\beta = 0$ and agents exaggerate by an infinite factor. With no or a limited incentive for absolute accuracy and with clients placing some weight on their prior belief, analysts can always increase estimates of their ability by exaggerating more. Analysts essentially report a binary forecast (i.e., above or below the consensus) and cannot credibly communicate the strength of their beliefs.[7]

- When $\gamma > 0$ and $\lambda > \gamma\beta_0^2$, $\beta = \lambda^{-1}(\lambda - \gamma\beta_0^2) < 1$. Some exaggeration occurs, but it is limited to a finite amount by the incentive for absolute accuracy. As this incentive increases, the amount of exaggeration decreases. Likewise, as J decreases or random variable realizations become noisier and thus clients rely more on their prior beliefs about

[6]Although it might appear that this simplification was made using the incorrect assumption that $E(y_j\widehat{\beta}_{CL}) = E(y_j)\cdot\widehat{\beta}_{CL}$ and $E(\widehat{\beta}^2_{CL}) = E(\widehat{\beta}_{CL})^2$, actually, the two cross terms exactly cancel.

[7]This result is similar to the infinite exaggeration result in Ottaviani and Sorensen (2000).

β_0, exaggeration increases.[8]

2.2.2 Three-period model

In the two-period model above, the analyst makes all J forecasts before seeing any of the realizations. In this section, we analyze how an analyst's past forecasting performance affects her future exaggeration. We modify the model by assuming that agents observe the realizations of the first J variables and then forecast a second group of K variables. Clients expect consistent exaggeration within a group of random variables, but not necessarily across groups.

Clients estimate ability as before, except that they allow for different exaggeration in the two sets of observations:

$$\begin{aligned}
\widehat{a}_P &= (1+\gamma+\delta)^{-1}\frac{(\sum_{j=1}^{J} wx_jy_j + \sum_{j=J+1}^{J+K} x_jy_j)^2}{\sum_{j=1}^{J} w^2x_j^2 + \sum_{j=J+1}^{J+K} x_j^2} \\
&\quad + \frac{\gamma\beta_0^2}{1+\gamma+\delta}\frac{\sum_{j=1}^{J} x_j^2 + \sum_{j=J+1}^{J+K} x_j^2}{(J+K-1)} + \frac{\delta}{1+\gamma+\delta}\cdot a_0 \\
w &= \frac{\widehat{\beta}_J}{E(\beta_K|\widehat{\beta}_J)}
\end{aligned}$$

where β_J and β_K refer to the β for the first J and the second K random variables, respectively. The weight w is the ratio between the observed exaggeration in the first set and the clients' expectation of exaggeration in the second set of random variables, conditional on the observed $\widehat{\beta}_J$. The first order condition for the agent when forecasting the second set of variables reduces to:

$$\beta_K = \frac{wE(\widehat{\beta}_{JK}|\widehat{\beta}_J)^2 - \gamma\beta_0^2 + \lambda}{wE(\widehat{\beta}_{JK}|\widehat{\beta}_J) + \lambda}, \tag{2.13}$$

where $\widehat{\beta}_{JK}$ is the exaggeration factor estimated across both sets of observations, which will be an average of $w^{-1}\widehat{\beta}_J$ and β_K.

Proposition 1 *Equation (13) implies that agents will choose a β_K that is between the one-period optimal $\beta_1 = \lambda^{-1}(\lambda - \gamma\beta_0^2)$ and their client's expectation $E(\beta_K|\widehat{\beta}_J)$.*

[8] Notice that $b(a, \lambda)$ is a function of only λ. This implies that when clients' prior beliefs about a and λ are uncorrelated, then exaggeration will signal neither high or low ability. If instead clients' believe that high-ability agents face more (less) exogenous incentives to exaggerate, then exaggeration will signal high (low) ability. When ability (a) and exogenous incentives to exaggerate (λ) are more positively correlated, exaggeration signals high ability and γ and the equilibrium amount of exaggeration increase.

Proof. In Appendix B ∎

Agents who have had bad luck in the past and realized a lower $\widehat{\beta}_J$ than the β_J they intended will choose a lower β_K. This can be interpreted as the agents who have had bad luck in the past and are thus under-rated will exaggerate more in order to increase the relative weight of the later observations.[9]

2.3 Testing predictions of the model

The model in section 2 has three cross-sectional predictions about when we should expect more exaggeration. Agents should exaggerate more when they are underrated by their clients, when earnings realizations are expected to be noisy, and when they expect to make a limited number of future forecasts. In this section of the paper we test these predictions using the I/B/E/S analyst earnings forecast dataset and the methodology for measuring exaggeration outlined in Chapter 1. Specifically, we estimate the average exaggeration coefficient for a specific group of forecasts using the regression

$$A - C = \alpha + \beta(F - C) + \varepsilon \tag{2.14}$$

as in the classical estimator described in section 2.1.2, where A is the I/B/E/S actual earnings for a given firm-quarter combination, F is a forecast of earnings, and C is an econometric expectation of earnings based on prior forecasts for that firm-quarter.[10] We test the predictions for how exaggeration should vary with a specific variable by interacting the right-hand side of (14) with the variable of interest.

As we argue in Chapter 1, the regression in (14) produces an unbiased estimate of the inverse of the exaggeration factor, $\beta = b^{-1}$, because the error term is the analyst's expectational error at time of forecasting, $\varepsilon = A - E(A|s, C)$, and expectational errors must be mean zero with respect to all variables known at time of forecasting, including $F - C$. In order for interaction

[9] This prediction that under-rated agents should exaggerate more is also made by a different model in Graham (1999).

[10] The exaggeration measurement methodology, including the methodology for measuring C, is described in more detail in Zitzewitz (2001). All earnings variables are normalized by the share price.

versions of this regression to be valid, the analyst's expectational error must be mean zero with respect to the interaction variable as well. This must be true for all variables that are known at time of forecasting, but for variables that incorporate the econometricians knowledge of the future, we will need to verify that the orthogonality condition still holds.

2.3.1 Under-rated analysts

Since it is impossible to directly observe which analysts have true ability that is higher than their measured ability, we are forced to use our knowledge of the future to help identify under-rated analysts. In particular, we divide analysts with a given past forecast information content into those whose performance eventually rises and those whose performance falls and assume that, on average, the analysts whose performance rises were under-rated in the past.

Specifically, we rank analysts with at least 50 past forecasts based on two variables: their past forecast information content from observation 1 to $j-1$ and the difference between their past information content and their information content from observation $j+1$ to $j+50$ (or fewer if the analyst leaves the sample). We then interact these rankings with the right-hand side of equation (14).

Table 1 presents the results of such an interaction regression. The results suggest that under-rated analysts exaggerate more, whether or not past performance is controlled for. The results also do not change if we control for the analyst's career length or the size of their brokerage, both of which have significant positive effects on β.

In constructing this test, we took two steps to avoid violating the orthogonality condition discussed above. First, we used different observations to measure performance improvement (observations $j+1$ to $j+50$) and exaggeration (observation j). This is important since if an analyst "gets lucky" and gets surprised in the direction of their deviation from the consensus (i.e., $A-E$ and $F-C$ positively correlated), β will be overestimated, exaggeration will be underestimated, and analyst performance will be overestimated. Using different observations avoids this potential problem. Second, we used $\widehat{a}_{CL} = \beta^2 Var(x)$ as our performance measure, a measure that is robust to exaggeration, so even if exaggeration in observation j were correlated with exaggeration in observations $j+1$ to $j+50$ or 1 to $j-1$, this would not create a correlation with our measure of the change in performance.

2.3.2 Expected earnings uncertainty

We test for whether analysts exaggerate more when earnings are uncertain using a two-step process (Table 2). In the first step, we predict the average absolute earnings surprise (actual less consensus) for a particular firm-quarter based on market cap, the standard deviation of prior outstanding forecasts, and the prior average absolute earnings surprise for the firm in question. We hypothesize and find that average absolute earnings surprise is higher for small-cap firms, when past forecasts are dispersed, and for firms for which average earnings surprise has been large in the past. In the second step, we test the effect of expected earnings surprise on β using an interaction regression, finding that there is significantly more exaggeration when predicted absolute earnings surprise is higher. Notice that in this analysis all of the interaction variables are known at time of forecasting; thus the orthogonality condition should be satisfied.

2.3.3 Expected career length

The prediction that analysts should exaggerate less when they expect to make more future forecasts is more difficult to test. We can use the actual number of future forecasts as our interaction variable, and when we do this, we find less exaggeration by analysts who make more future forecasts (Table 3, Panel A). A problem with this analysis is that analysts who have good luck should both survive longer and have measured exaggeration that is less than what they intended.

An alternative possible approach is to use variables that are known at time of forecasting that predict an analyst's longevity. Probit regressions that predict an analyst's leaving the sample and not returning for at least 2 years after a given forecast find longer survival is expected for analysts who have made a large number of past forecasts, analysts who work at larger (usually the more prestigous) brokerages, and analysts who have had better forecast accuracy in the past (Table 3, Panel B).[11]

In Table 1, we found that analysts with more forecasting experience and analysts at larger

[11]Forecast information content, in turn, does not appear to play a role in predicting exits from the I/B/E/S sample. One potential explanation for this result is that analysts can leave the I/B/E/S sample for either good reasons (moving to lucrative proprietary researcg positions) or bad reasons (getting fired). We do find that for analysts who stay in the profession, forecast information content helps explain which analysts are ranked highly by Institutional Investor (Chapter 1, Table 7).

brokerage firms exaggerated less. The probit regressions suggest that one potential explanation for this result is that these analysts have longer expected careers, and the optimal exaggeration rate for these analysts is lower. Alternative explanations exist, however. Analysts may become less overconfident in their own information or better calibrated with experience. In the model we assumed that analysts' utility is linear in the market valuation of their forecasts; if the concavity of analyst's incentives varies with brokerage size or career length, this may also explain the results. Inexperienced analysts may face greater outside options and thus more convex incentives (i.e., they can gamble and then leave if it does work out), and this may explain their greater exaggeration. Analysts at larger firms may be given more concave incentives by their firm to reduce exaggeration, such as a risk of getting fired for deviating from the consensus and being wrong that is not fully compensated by the reward for deviating from the consensus and being right. A model in which firms have a collective reputation for exaggeration might predict this, since larger firms will make more forecasts in the future than smaller firms and thus would prefer that their analysts exaggerate less.

In summary, the empirical evidence that is available is consistent with the prediction that analysts who expect to make more future forecasts should exaggerate less, but alternative explanations for the results exist.

2.4 Conclusion

The evidence presented in Chapter 1 suggests that there are persistent differences in analyst's exaggeration factors and forecast information content and that the best predictor of the future value of an analyst's forecasts is the value of her past forecasts. This suggests that potential clients should use an analyst's track record to determine how much to pay her. This paper investigates the incentives for exaggeration created by clients attempting to learn ability from forecasting record in a financial market environment where forecasts are valuable for their new information content.

We find that career concerns can create an incentive for agents to exaggerate, or overweight their private information. This incentive exists because high-ability analysts have viewpoints that are more different from the consensus on average and since potential clients learn more quickly about an analyst's average difference with the consensus than about whether she is exaggerating. The equilibrium exaggeration rate is finite so long as there is a sufficiently large external incentive for absolute forecast accuracy. The model also predicts that agents should exaggerate more when earnings are expected to be noisy, when they expect to make a limited number of future forecasts, or when they are under-rated by the market, and we find that these predictions are consistent with the equity analyst forecast data.

Although the evidence in the paper is for equity analysts, the issues examined in this paper potentially apply to other opinion-producing agents. A large number of agents produce opinions that can be thought of as forecasts of random variables. Especially when the actions taken based on the opinions are strategic substitutes, the value of privileged access to an opinion depends on its information content relative to the consensus. Whenever the realized values of random variables are noisy, agents will learn more quickly about the average difference between an agent's opinion and the consensus that they will about whether the agent is exaggerating, an the agent will be able to raise estimates of her ability by exaggerating. This incentive to exaggerate will be greater when the realization of the random variable is expected to be more noisy, which makes exaggeration harder to detect, when the agent expects to leave the profession soon, or when the agent perceives that she is under-rated by the market. These predictions, together with the empirical support for them in the analyst data, are potentially useful for consumers attempting to account for exaggerate in their interpretation of opinions or for firms attempting to reduce exaggeration in the incentives they design for opinion-producers.

Table 1. Exaggeration by under or over-rated analysts
Dependent variable: (ACT - CONS)

This table reports interaction coefficients from a version of equation (14) with the variables listed interacted with the right-hand side. Regressions also include (FOR - CONS) and the interaction variables. Regressions include forecasts made by analysts with at least 50 past forecasts in the 1993-99. The UNDER and INFO variables are rankings, scaled to 0 to 1, of the analyst based on past performance and performance change over the next 50 forecasts, respectively.

		Interactions with (FOR - CONS)							
		UNDER		INFO		FNUM/100		LN(BROKSIZE)	
Spec.	Obs.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
1	329,401	-0.458	0.141						
2	329,401	-0.503	0.133	-0.156	0.120				
3	329,401	-0.503	0.130	-0.140	0.117	0.048	0.016		
4	329,401	-0.519	0.133	-0.198	0.112	0.045	0.016	0.092	0.035
5	329,401			-0.029	0.136	0.046	0.018	0.084	0.038
6	329,401					0.046	0.018	0.082	0.041
7	329,401			-0.046	0.141			0.087	0.037
8	329,401							0.084	0.040

Variable defintions

ACT	Actual earnings per share
FOR	Analyst's forecast of earnings per share
CONS	Prior expectation of earnings per share, as estimated in Table 3
UNDER	Ranking based on change in analyst forecast value over the next 50 forecasts, scaled 0 to 1.
INFO	Ranking of analyst's historical forecast value, scaled 0 to 1.
FNUM	Forecast number in analyst's career
BROKSIZE	Number of analysts at analyst's brokerage

Notes:

1. Standard errors are heteroskedasticity robust and adjusted for clustering within firm-quarter combinations.

Table 2. Exaggeration and uncertainty

The effect of expected earnings uncertainty is examined by predicting the absolute earnings surprise for a firm-quarter combination based on its market cap, the standard deviation of price-normalized forecasts, and past earnings surprise for the firm, and average earnings surprise in the prior 90 days. We then interact predicted earnings surprise with the right-hand side of (2) to measure the effect on exaggeration. The negative interaction coefficient reported implies more exaggeration when expected earnings surprise is high.

	Coeff.	S.E.
First stage regression		
Dependent variable: Abs(ACT - CONS)		
Indepdent variables:		
Ln(Market Cap)	-0.0184	0.0009
Ln(SD-Price ratio)	0.0092	0.0004
Avg past abs(ACT - CONS) for firm	0.710	0.015
Avg abs(ACT - CONS) in quarter	0.136	0.007
Second stage		
Interaction coefficient from exaggeration regression		
Predicted abs. forecast error	-0.059	0.022

Notes:

1. Standard errors are heteroskedasticity robust and adjusted for clustering within firm-quarter combinations. Standard error in second stage is adjusted for the use of a predicted value on the right-hand side.

Table 3. Exaggeration and expected future forecasts

In panel A, the right hand side of (14) is interacted with the actual number of future forecasts an analyst makes between the current forecast and the end of 1999. Forecasts for the years 1993-97 and for analysts who have already made 50 forecasts are included in the sample. In Panel B, exit from the I/B/E/S sample (defined as making a final forecast and not reappearing in the sample for 2 years) is predicted for each forecast in the 1993-97 period. Past average relative forecast ranking is the average of a 0-1 ranking of analysts' relative forecast accuracy for each firm-quarter in which they forecast.

Panel A. Interaction regression with actual future forecasts
Dependent variable: actual earnings less consensus

	Coeff.	S.E.
Forecast less consensus	0.251	0.067
(FOR - CONS)*(Actual future forecasts/100)	0.117	0.037
Constant (in basis points)	-0.159	0.202
Actual future forecasts/100 (in basis points)	-0.134	0.140
Observations	198,909	

Panel B. Probit regression predicting exit from sample

	Coeff.	S.E.
Forecasts in career/100	-0.251	0.014
Ln(Analysts at brokerage)	-0.090	0.010
Ln(Forecast information content)	0.001	0.003
Observations	334,388	

Chapter 3

A Strategic Rationale for Imperfect Profit Measures

Summary 3 *In models by Fershtman and Judd (1987) and Sklivas (1987), firms competing in quantities benefit strategically from committing to managerial incentives that are biased toward revenue maximization. Little empirical evidence has been produced in support of these models, and their assumption that incentive contracts are observable has been criticized as unrealistic. Chapter 3 proposes an alternative model in which firms competing in strategic substitutes commit to using less precise profit measures, which biases the optimal unobservable contract towards revenue maximization. This model performs better empirically. Firms that compete in strategic substitutes choose less precise profit measures across six different measures. Firms with less precise profit measures in turn have stock returns and thus managerial incentives that are driven more by revenue growth. Controlling for this channel, firms that compete in strategic substitutes do not directly modify their managerial incentives in the direction predicted by observable-contract models; on the contrary, having committed to more revenue-driven stock returns, they actually undo part of the resulting incentive bias using their non-stock incentives, which is consistent with unobservable contracts.*

3.1 Introduction

Industries are said to compete in strategic substitutes if the optimal response to an aggressive action by one's competitor is passive.[1] In such industries, a firm finds it strategically valuable to commit in advance to aggressive action in order to encourage a passive response from its competitors (Fudenberg and Tirole, 1984). Likewise, in industries that compete in strategic complements, there is strategic value in committing to passive behavior in order to induce a passive response from one's competitors. In models by Fershtman (1985), Fershtman and Judd (1987) and Sklivas (1987) (hereafter, FJS), owners of firms that are competing in strategic substitutes commit to aggressive action by observably shifting their managerial incentives towards revenue maximization.[2]

A crucial assumption in the FJS model is that managerial incentives are fixed and observable. This assumption has been criticized as being unrealistic in a corporate setting because there many ways to secretly undo a bias in the publicly announced incentives (e.g., by Katz, 1991).[3] A firm in the FJS model would want to do exactly that: announce an incentive bias to induce passive behavior from its competitors, and then revert secretly to rewarding profit maximization.

This paper proposes a model in which a firm's owner can credibly alter the optimal *unobservable* managerial incentive contract by observably changing the precision of the profit measures on which the incentive contracts are based. In particular, when profit and revenue shocks are positively correlated, owners of firms competing in strategic substitutes can shift the optimal contract towards revenue maximization by reducing the precision of the profit measure, causing the optimal contract to rely on revenue to draw an inference about profit. Shifting the optimal contract towards revenue maximization induces a different mix of managerial actions that can be harmful to competitors and thus induce a passive response. For example, if an

[1] "Aggressive" and "passive" behavior is precisely defined throughout the paper as actions that reduce and increase competitors' profits, respectively. The terminology of strategic substitutes and complements is due to Bulow, Geanakopulous, and Klemperer (1985). Examples of competition in strategic substitutes include quantity (Cournot) competition and situations in which deterring participation is important; price (Bertrand) competition is an example of competition in strategic complements.

[2] In a related model by Vickers (1985), an owner achieves strategic commitment by appointing an agent with an observable taste for aggressive behavior.

[3] The observability assumption is less of a problem in a strategic trade context (e.g., Brander and Spencer, 1985; Maggi, 1996), where a government provides a revenue or export subsidy to shift home firms' incentives towards sales maximization, since it is harder for a government to secretly undo a subsidy.

agent can raise revenue by the same amount through either an easy but less profitable action (e.g., price cutting) or a difficult but more profitable action (e.g., improving the product), shifting incentives toward revenue maximization would induce more discounting and less product improvement. Owners of firms competing in strategic complements can likewise shift the optimal contract towards *profit* maximization and thus induce of mix of managerial actions that *increases* competitors' profits, inducing a passive response.

Whereas I am aware of no empirical evidence in support of the original FJS model,[4] this paper presents cross-sectional evidence consistent with an unobservable-contracts version of the model. In particular, I find that firms in industries that compete in strategic substitutes provide significantly less voluntary disclosure and less meaningful accounting profits across six different measures in both North American and non-North American samples. This result is even stronger when controlling for the factors found to affect disclosure policy in other studies. Firms with limited disclosure policies, in turn, have stock returns that depend on revenue growth in addition to earnings growth. Since managerial incentives are heavily influenced by stock returns, incentives are distorted toward revenue in industries that compete in strategic substitutes. Controlling for this channel, I find no evidence that firms in industries competing in strategic substitutes directly alter their managerial incentives in the direction predicted by an observable contracts model. On the contrary, I find evidence that these firms, having committed to a limited disclosure policy that biases their stock returns towards rewarding revenue growth, actually undo part (but only part) of the incentive bias using their non-stock incentives. This evidence is all consistent with the unobservable-contracts model in this paper and inconsistent with observable-contract models.

The evidence is thus that, controlling for other factors affecting optimal disclosure policy, firms competing in strategic substitutes choose a disclosure policy that causes their managerial incentives to be biased in a strategically advantageous way. This does not necessarily imply that the firms have consciously chosen their disclosure policies with the model in this paper

[4]This comment is based on a Social Sciences Citation Index search of all articles citing either Fershtman and Judd (1987) or Sklivas (1987) and on conversations with colleagues. The most closely related empirical papers test whether relative performance evaluation is more or less common in industries competing in strategic substitutes (Aggarwal and Samwick, 1999; Kedia, 1998) or whether vertical separation is more common among gas stations facing inelastic demand (Slade, 1998). The lack of empirical evidence supporting FJS is more striking given that it has been cited by over 100 theoretical papers in the journals covered by the SSCI.

in mind. Firms competing in strategic substitutes (complements) may as a general rule be uncooperative (cooperative) with their competitors, and may choose their disclosure policies accordingly. Alternatively, firms with limited (full) disclosure may have come to dominate industries competing in strategic substitutes (complements) through an evolutionary process. In a industry that competes in quantities, a limited disclosure policy will lead managers to increase and rivals to reduce quantities; firms with limited disclosure policy would tend to become more prominent and more emulated in such industries. Likewise, in a price-competition industry, a firm with limited disclosure might find itself in more frequent price wars, forcing it into bankruptcy or a change in tactics. Regardless of whether firms have chosen strategically optimal disclosure policies consciously, through an evolutionary process, or as part of a general rule of competitive conduct, the fact that they have done so remains interesting.

The remainder of the paper is divided into three sections. The next section presents a model in which strategic commitment considerations affect optimal disclosure policy. The third section presents the cross-sectional empirical evidence referred to above. A conclusion follows.

3.2 The model

3.2.1 Overview

The goal of the model is to analyze how strategic commitment considerations affect the optimal precision of the profit measure, which in practice a company affects through its voluntary disclosure and accounting policies. Using a less precise profit measure increases the costs related to managerial risk aversion and the deviation of managerial behavior from non-strategic profit maximization. These costs can be outweighed in industries which compete in strategic substitutes, since committing to less precise profit measurement, more revenue-oriented incentives, and thus more aggressive managerial behavior induces passive behavior or non-participation by competitors. For this to be the case, we need the actions taken when incentives shift from profit to revenue to decrease competitors profits (as with price cutting) rather than increase it (as with advertising that raises industry demand).

Precise profit measures also have costs and benefits less central to the model. Precise profit measures can lower reduce potential information asymmetry and thus lower the cost of equity and debt capital (Botosan, 1997; Sengupta, 1998) but the voluntary disclosure required to improve the precision of outsiders' understanding of a company's profitability can be costly to produce and can give valuable intelligence to competitors.[5] The combination of factors related and unrelated to strategic commitment produce an optimal profit measurement precision.

The model yields three testable predictions:

1. Less precise profit measures cause the optimal managerial contract to reward revenue more and profit less when profit and revenue shocks are positively correlated (Propositions 3).

2. All else equal, firms competing in strategic substitutes will choose less precise profit measurement since doing so reduces competitor's expected profits and encourages passive behavior and non-participation (Proposition 5).

3. Under certain conditions, firms competing in strategic substitutes will choose limited disclosure in order to commit to having their stock returns reward revenue growth but will then partially undo the incentive bias using their unobservable non-stock incentives (Proposition 4).

3.2.2 The model

Two firms compete in a industry.[6] In each firm, a long-run value maximizing board of directors acts as the principal, first choosing an observable precision for the profit measure, then making a participation decision based on expected profits and the realization of a random fixed cost, and then engaging in multi-action principal-agent contracting as in Holmstrom and Milgrom (1991). The timing of the model is as follows:

1. Both boards simultaneously decide how much noise (with variance n_i) to have in their

[5] For other costs of precise profit measures, see Barros (1997) for a model in which owners limit the collection of performance information in order to commit to lower bargaining power and thus less ability to extract surplus from employees making specific investments. See also Zabojnik (1998) for a model in which owners provide revenue maximization incentives to managers to reduce incentives for cost reduction in order to encourage specific investments by employees.

[6] We limit the analysis to the two-firm case for simplicity. In a model with more than two firms there could be higher-order effects of disclosure policy, e.g. a limited disclosure policy could encourage passive behavior by one competitor, but this could in turn encourage more aggressive behavior by another competitor.

measure of profits $\pi_i^* = \pi_i + \varepsilon_i$. Revenue is observed perfectly.[7] There is a cost $n(n_i)$ associated with this decision if they later choose to participate that captures the other costs and benefits of disclosure discussed above.

2. The boards observe the measurement choice of the other firm, learn the fixed cost f_i of participating in the industry (distributed F_i), and simultaneously decide whether to participate.[8]

3. The boards contract with their managers. Contracts are assumed to be linear[9] and of the form $w_i = \alpha_i + \beta_i \pi_i^* + \gamma_i r_i + \delta_i P_i$,[10] where w_i, π_i^*, r_i, and P_i are the managerial compensation, measured profits, revenue, and the market value of firm i. Using accounting-based measures carries a cost of $m_i(\beta_i, \gamma_i) = h(\beta_i^2 + \gamma_i^2)$, where h is a parameter indicating the severity of these costs.[11] Boards have complete bargaining power and set the agent's expected utility equal to her reservation utility.

4. The agents choose a vector of actions a_i.

5. Profit and revenue are realized. They are equal to $\begin{bmatrix} \pi \\ r \end{bmatrix} = \begin{bmatrix} \pi_e(a_i, a_{-i}) \\ r_e(a_i, a_{-i}) \end{bmatrix} + e$, where π_e and r_e are expected gross profit and revenue and $e \sim N(0, \Sigma)$ is a stochastic disturbance.

[7] This admittedly extreme assumption is made for simplicity; it would be sufficient to assume merely that the noise in the revenue is not infinite, so that revenue provides some information about true profitability when the profit measure is noisy.

[8] Having participation decisions made after the realization of a fixed cost causes the probability of participation to depend on expected profits, allowing a firm to reduce the likelihood of a competitor's participation by lowering their expected profits. This modelling device allows us to capture in a one-period model the participation-deterrence rationale for lowering competitor's expected profits; in a more complicated multi-period model, reducing future participation could also provide a rationale for lowering competitors' expected profits (e.g., long purse predation as in Bolton and Scharfstein, 1990).

[9] Linear contracts are optimal due to the assumption of constant absolute risk aversion utility and a joint normal error term if the single period in this model is viewed as the aggregation of several smaller periods (Holmstrom and Milgrom, 1987). Linear contracts can also be motivated by requiring that the agent not be able to gain by shifting profits or sales intertemporarly.

[10] Relative performance evaluation (RPE) is assumed to be infeasible. If contracts were observable, principals could condition managerial wages on competitors' profits in order to commit to aggressive or passive actions (e.g., Aggarwal and Samwick, 1999; Joh, 1999). Even with unobservable contracts, a principal would want to use RPE to filter out common shocks to productivity (Holmstrom, 1979) and the amount of RPE used might increase with the variance of one's own profit measure if actions that decreased competitor's profits tended to increase own profits. This would provide another means through which an imprecise profit measure commits a firm to managerial incentives that reward aggressive actions. For simplicity, these effects are ruled out.

[11] One possible motivation for such an assumption is that the market valuation of a firm is harder to manipulate than accounting figures, and thus using accounting-based incentives leads to a certain amount of manipulation that is costly (due to the managerial effort expended, potential shareholder lawsuits, etc.).

We assume that profit and revenue shocks are positively but not perfectly correlated ($\sigma_\pi \sigma_r > \sigma_{\pi r} > 0$).

6. The market values the firm at $P = E(\pi \mid \pi^*, r)$, based on its inference about the true π from the observed π^* and r. The board maximizes expected long-run value (the true value of P), while managerial contracts can only be written on the near-term valuation inferred from π^* and r.

7. The agent receives w_i and experiences constant absolute risk aversion utility $U_i = -\exp\{-\rho[w_i - c(a_i)]\}$, where $c(a_i)$ is the private cost of the agent's actions and ρ is the risk aversion coefficient.

Firms are assumed to behave non-cooperatively and to reach a symmetric Nash equilibrium. The assumption of non-cooperative behavior is central to the prediction that firms choose less disclosure in industries that compete in strategic substitutes. If firms used disclosure policy as a means for making collusion more sustainable, we might expect them to agree on more disclosure in either type of industry depending on the benefits of sustaining collusion.[12] Focusing on a symmetric equilibrium is done partly for convenience and partly because the data on disclosure policy suggest a high degree of within-industry uniformity.[13]

3.2.3 Solution of model

The model is solved backwards by solving the market valuation, agents' action choice, principals' contracting, and principals' measurement choice problems in succession. To make the model more tractable, we make four assumptions:

Assumption 1 The Hessians of the private cost and the expected gross profit and revenue functions (given a set of actions by the other firm), C_{aa}, Π_{aa}, and R_{aa}, are positive definite, negative definite, and negative definite, respectively. This implies that the matrix $W_{aa} =$

[12] If sustaining collusion were the main strategic consideration affecting disclosure policy, we might expect to see maximum disclosure in industries with intermediate concentration levels. The fact that we do not see such a relationship in Section 3 increases our comfort in focusing on non-cooperative behavior.

[13] See Hermalin (1994) or Gal-Or (1999) for models in which the best response to weak incentives or delegation may be strong incentives or non-delegation.

$C_{aa} - \beta'\Pi_{aa} - \gamma' R_{aa}$ is positive definite for all $\beta', \gamma' \geq 0$, which ensures a unique solution to the agent's problem. The derivative of W_{aa} with respective to the action vector a is assumed to be small enough that it can be ignored.

Assumption 2 The matrix $(1-\beta')\Pi_{aa} - \gamma' R_{aa}$ is assumed to be negative definite for any combination of β', γ' chosen by the principal. This ensures a unique solution to the principal's contracting problem.

Assumption 3 While the net other costs of disclosure can be positive or negative ($n' \gtrless 0$), the function is assumed to be sufficiently convex to ensure a unique optimum disclosure policy ($n'' \gg 0$).

Assumption 4 In this paper, we are interested in the case where a shift toward revenue maximization and away from profit maximization decreases competitor's profits; we therefore assume that $(\frac{dV_{-i}^D}{da_i})'(a_\beta \cdot d\beta_i' + a_\gamma \cdot d\gamma_i') < 0$ if $d\beta_i' < 0$ and $d\gamma_i' > 0$.

Market valuation

The market values the firm at $E(\pi_i \mid \pi_i^*, r_i)$. The market's inference about true profitability is the average of measured profitability and the profitability implied by the revenue measure, weighted according to their variances:

$$E(\pi_i \mid \pi_i^*, r_i) = [\frac{\sigma_{\pi r}}{\sigma_r^2}(r_i - \widetilde{r}_e) + \widetilde{\pi}_e] \cdot \frac{n_i}{n_i + \sigma_\pi^2(1-R^2)} + \pi^* \cdot \frac{\sigma_\pi^2(1-R^2)}{n_i + \sigma_\pi^2(1-R^2)},$$

where $\widetilde{\pi}_e$ and $\widetilde{r}_e$ here refer to the market's rational expectations of π and r, which in equilibrium will always equal π_e and r_e, and R^2 refers to $\frac{(\sigma_{\pi r})^2}{\sigma_\pi^2 \sigma_r^2}$. Notice that increasing profit noise (n_i) causes the market to rely more on revenue for information about profits, and since revenue and profits positively covary ($\sigma_{\pi r} > 0$), higher revenue leads the market to infer higher profits. Substituting the market valuation equation into the managerial incentive contract yields the following reduced-form incentives for managers:

$$w = \alpha_i + \underbrace{(\beta_i + \delta_i \cdot \frac{\sigma_\pi^2(1-R^2)}{n_i + \sigma_\pi^2(1-R^2)})}_{\beta_i'} \cdot \pi_i + \underbrace{[\gamma_i + \delta_i(\frac{\sigma_{\pi r}}{\sigma_r^2} \frac{n_i}{n_i + \sigma_\pi^2(1-R^2)})]}_{\gamma_i'} \cdot r_i,$$

where β_i' and γ_i' are the manager's total incentives for profits and revenue, including direct incentives and the impact on the stock price.

Agent's problem

Agents, like firms, are assumed to reach a Nash Equilibrium, they therefore maximize utility given the actions of the other firm. The agent chooses actions to maximize her certainty equivalent utility:

$$\max_{a_i} \underbrace{\alpha + \beta_i' \cdot \pi_e(a_i, a_{-i}) + \gamma_i' \cdot r_e(a_i, a_{-i})}_{\text{Expected wage}} - \underbrace{t(\beta_i', \gamma_i')}_{\substack{\text{Risk}\\ \text{aversion}\\ \text{cost}}} - \underbrace{c(a_i)}_{\substack{\text{Effort}\\ \text{cost}}},$$

where the risk-aversion cost of using high-powered incentives $t(\beta_i', \gamma_i') = \frac{\rho}{2} \cdot (\beta_i'^2(\sigma_\pi^2 + n_i) + \beta_i'\gamma_i'\sigma_{\pi r} + \gamma_i'^2\sigma_r^2)$. The first-order condition is $c_a = \beta_i'\pi_a + \gamma_i' r_a$ where c_a, π_a, and r_a are the gradients of the private cost and the expected profit and revenue functions with respect to the agent's actions.

Principal's contracting problem

The principal chooses the incentive contract to maximize true, rather than inferred, expected firm value (excluding the predetermined fixed and net disclosure costs but including the accounting-based incentive cost). Firms are assumed to reach a Nash Equilibrium, and thus maximize value given the actions of the other firm:

$$\max_{\beta,\gamma,\delta} \pi_e(a_i^*(\beta_i', \gamma_i'), a_{-i}) - c(a_i^*(\beta_i', \gamma_i')) - t(\beta_i', \gamma_i') - m(\beta_i, \gamma_i).$$

This problem can be solved in two stages. In the first stage, we derive the lowest cost (i.e., lowest $m(\beta_i, \gamma_i)$) combination of $\beta_i, \gamma_i, \delta_i$ that achieves a given β_i' and γ_i'. In the second stage, we derive the optimal β_i' and γ_i'. The first-order conditions from the first problem can be combined to show that:

$$\frac{\beta_i}{\gamma_i} = -\frac{\sigma_\pi^2\sigma_r^2(1-R^2)}{\sigma_{\pi r}\cdot n_i} = -\mu < 0$$

This expression implies that β_i and γ_i have opposite signs. Given the costliness of accounting-based incentives, market-based incentives are used to get the correct power of incentives, and then the accounting-based incentives are used to fine tune the relative importance of profit and revenue.[14] The variable μ is the ratio of the stock price responses to an extra dollar of reported profits and revenue, respectively. The above expression, together with the definitions of β_i' and γ_i', can be used to express δ_i as a function of β_i' and γ_i':

$$\delta_i = \frac{\beta_i'}{2}\cdot\frac{n_i+\sigma_\pi^2(1-R^2)}{\sigma_\pi^2(1-R^2)} + \frac{\gamma_i'}{2}\cdot\frac{\sigma_r^2[n_i+\sigma_\pi^2(1-R^2)]}{\sigma_{\pi r}\cdot n_i}$$

Thus the minimum-cost β_i, γ_i, and δ_i can be expressed as a function of β_i' and γ_i' with $\beta_i = \frac{\beta_i'}{2} - \frac{\gamma_i'}{2}\mu_i$ and $\gamma_i = \frac{\gamma_i'}{2} - \frac{\beta_i'}{2\mu}$. The first-order conditions of the second-stage problem are:

$$\begin{aligned} m_\beta + t_{\beta'} &= (\pi_a' - c_a')\cdot a_{\beta'}^* \\ m_\gamma + t_{\gamma'} &= (\pi_a' - c_a')\cdot a_{\gamma'}^* \end{aligned}$$

To find $a_{\beta'}^*$ and $a_{\gamma'}^*$ we differentiate the agent's first order condition with respect to β_i' and γ_i'. This yields $a_{\beta'}^* = W^{-1}\pi_a$ and $a_{\gamma'}^* = W^{-1}r_a$. Substituting these expressions and the agent's first order condition into the principal's first order conditions yields

$$\begin{aligned} \pi_\beta &= [\pi_\beta + \rho\cdot(n_i+\sigma_\pi^2) + \frac{v}{\mu}]\cdot\beta_i' + (\pi_\gamma + \rho\cdot\sigma_{\pi r} - v)\cdot\gamma_i' \\ \pi_\gamma &= (\pi_\gamma + \rho\cdot\sigma_{\pi r} - v)\cdot\beta_i' + (r_\gamma + \rho\cdot\sigma_r^2 + v\mu)\cdot\gamma_i', \end{aligned}$$

where we define $v = h(\mu^{-1}+\mu)$, $\pi_\beta = \pi_a' W^{-1}\pi_a$, $\pi_\gamma = \pi_a' W^{-1} r_a$, $r_\beta = r_a' W^{-1}\pi_a$, and

[14] Market-based incentives providing the bulk of pay-for-performance incentives is consistent with the empirical evidence (Hall and Liebman, 1998, and Section 3). For a model in which the weights placed on performance measures by the market and by the optimal managerial contract differ, see Paul (1993).

$r_\gamma = r_a' W^{-1} r_a$. Notice that all of these expressions are scalars and that since W^{-1} is symmetric, $\pi_\gamma = r_\beta$. These simultaneous equations can be solved to yield expressions for β_i' and γ_i':

$$\beta_i' = \frac{\pi_\beta(r_\gamma + \rho \cdot \sigma_r^2 + v\mu) - \pi_\gamma(\pi_\gamma + \rho \cdot \sigma_{\pi r} - v)}{[\pi_\beta + \rho \cdot (n_i + \sigma_\pi^2) + \frac{v}{\mu}](r_\gamma + \rho \cdot \sigma_r^2 + v\mu) - (\pi_\gamma + \rho \cdot \sigma_{\pi r} - v)^2} \tag{3.1}$$

$$\gamma_i' = \frac{\pi_\gamma[\rho \cdot (n_i + \sigma_\pi^2) + \frac{v}{\mu}] - \pi_\beta(\rho \cdot \sigma_{\pi r} - v)}{[\pi_\beta + \rho \cdot (n_i + \sigma_\pi^2) + \frac{v}{\mu}](r_\gamma + \rho \cdot \sigma_r^2 + v\mu) - (\pi_\gamma + \rho \cdot \sigma_{\pi r} - v)^2}. \tag{3.2}$$

Intermediate results

Proposition 1 *The following intermediate results can be derived from equations (1) and (2):*

1. When accounting incentives are costless ($h = v = v\mu = \frac{v}{\mu} = 0$), if the agent is risk neutral ($\rho = 0$) the principal "sells the firm" to the agent, setting $\beta_i' = 1$ and $\gamma_i' = 0$.

2. An increase in the uncertainty affecting profits or revenue will reduce the power of the incentive for that measure (i.e., $\frac{\partial \beta'}{\partial \sigma_\pi^2}, \frac{\partial \gamma'}{\partial \sigma_r^2} < 0$).

3. When the agent is risk averse ($\rho > 0$), her earnings are increasing in both profit and revenue ($\beta_i', \gamma_i' > 0$).

Proof. The first two statements are immediate from (1) and (2). The third statement follows from the fact that the numerator and denominators of (1) and (2) are always positive since $\pi_\beta r_\gamma \geq \pi_\gamma^2$, $\sigma_r^2, \sigma_\pi^2 > \sigma_{\pi r}$, and $v, \mu \geq 0$. To see that the numerator of (2) is always positive, note from the Principal's first-order condition that $\frac{\pi_\beta}{\pi_\gamma}$ is a weighted average of $\frac{n_i+\sigma_\pi^2}{\sigma_{\pi r}}$, $\frac{\sigma_{\pi r}}{\sigma_r^2}$, and $-\mu$ with positive weights and is thus less than $\frac{n_i+\sigma_\pi^2}{\sigma_{\pi r}}$. ■

Proposition 2 *As the profit measurement noise rises to infinity $n_i \to \infty$, the optimal contract converges to a revenue-only contract with $\beta \to 0$ and $\gamma \to (r_a' W^{-1} r_a)^{-1} r_a' W^{-1} \pi_a \cdot \frac{r_\gamma}{r_\gamma + \rho \cdot \sigma_r^2}$.*

Proof. Take the limit of (1) and (2) and substitute in the definitions of π_β, π_γ, and r_γ. ■

The obvious analogy with weighted least squares regression is instructive. The principal sets γ_i' to approximate profit maximization, lowering the power of the incentive to accommodate the agent's risk aversion. If actions are uni-dimensional and risk aversion is very low, γ_i' reduces to π_a/r_a (the profit margin on the last dollar of revenue) and the revenue-only contract produces the same actions and profits as the full contract. If actions are multi-dimensional, however, revenue-only contracts produce only the best approximation of the full contract – with at least slightly lower powered incentives and a different mix of actions. It is how the mix of actions changes as profit measurement gets noisier and incentives shift toward revenue that determines whether imperfect profit measures have strategic value.[15]

The next proposition captures the impact of imperfect disclosure on managerial incentives. When profits are measured perfectly ($n_i = 0$) and revenues do not contain additional information about performance; the optimal contract places no weight on revenue. As profit noise increases, however, both market returns and managerial compensation under the optimal contract depend more on revenues and less on profits.

Proposition 3 *As profits are less perfectly measured, the optimal contract becomes less profit-based and more revenue-based* ($\frac{\partial \beta_i'}{\partial n_i} < 0, \frac{\partial \gamma_i'}{\partial n_i} > 0$).

Proof. In Appendix C. ■

Under certain conditions, an increase in profit noise will cause the market to shift more towards rewarding revenue than the optimal managerial. In this case, some of this shift toward revenue in market returns will be undone in the unobservable managerial contract using the accounting-based incentives.

Proposition 4 *Under certain conditions, the firm will use the accounting-based incentives in the unobservable managerial contract to undo part of the revenue-bias in market valuations caused by profit noise (i.e., will set $\beta_i > 0$ and $\gamma_i < 0$). A sufficient condition is that the correlation between profit-motivated and revenue-motivated managerial actions (which affects*

[15]Notice also that as the optimal power of incentives rises as the correlation between the actions induced by rewarding measured output (revenue) and true output (profits) increases. It is the correlation *between the actions induced* by rewarding an imperfect and the ideal measure of profits that affects the optimal power of incentives, not the correlation between the measures themselves. Feltham and Xie (1994) and Baker (1999) also make this point, and they derive measures that are similar to but arguably less intuitive than the weighted least-squares regression of the actions motivated by a perfect measures on those motivated by an imperfect measure derived in Proposition 2.

the weight placed on revenue by optimal managerial incentives) be sufficiently low relative to the correlation between revenue and profit shocks (which affects the weight placed on revenue by the market), i.e. that $\frac{r_\beta}{\pi_\beta} = (\pi_a' W^{-1}\pi_a)^{-1}\pi_a' W^{-1} r_a \leq \frac{\sigma_{\pi r}}{\sigma_\pi^2}$.[16]

Proof. Note that $\beta_i > 0 \Leftrightarrow \gamma_i < 0 \Leftrightarrow \beta_i' > \delta_i \cdot \frac{\sigma_\pi^2(1-R^2)}{n_i+\sigma_\pi^2(1-R^2)} = \frac{1}{2}(\beta_i' + \gamma_i' \cdot \mu) \Leftrightarrow \beta_i' > \gamma_i' \cdot \mu$. Substitute for β_i' and γ_i' and reduce to get condition in footnote. Note that under the conditions in the proposition this condition is satisfied, since $\pi_\beta r_\gamma - \pi_\gamma^2 > 0$. ∎

Principal's profit noise selection and participation problem

The final step in solving the model is to calculate the effect of added profit noise on expected profits taking into account the effect on competitor's actions and participation. The effect of an increase in profit noise depends on how it affects a firm's own and its competitor's actions and on how actions affect expected profit. Define $a_n^i = (a_\beta \cdot \frac{d\beta'}{dn_i} + a_\gamma \cdot \frac{d\gamma'}{dn_i})$ to be the impact of added profit noise on a firm's own actions. Also define $A_{jk} = \frac{da_j^{-i}}{da_k^i}$ to be the matrix of one firm's best responses to the other's actions. By the envelope theorem, the impact of added profit noise on own and competitor's net profits assuming both enter is:

$$\frac{\partial V_i^D}{\partial n_i} = (\frac{\partial V_i^D}{\partial a_{-i}})'(A a_n^i) - \beta^2 \cdot \frac{\rho}{2}$$

$$\frac{\partial V_{-i}^D}{\partial n_i} = (\frac{\partial V_{-i}^D}{\partial a_i})'(a_n^i)$$

Firms participate if their expected profits are greater than the realization of their fixed cost $V_i > f_i$. Expected profits conditional on participation are given by:

$$E(V_i|V_i > f_i) = V_i^M(n_i) + F_{-i}\{E[V_{-i}(n_i, n_{-i})]\} \cdot [V_i^D(n_i, n_{-i}) - V_i^M(n_i)]$$

Unconditional expected profits are a monotonically increasing function of conditional expected profits, so n_i is chosen by maximizing the above expression. The solution concept is again Nash equilibrium, so expected profits are maximized taking n_{-i} as given. The first order condition is:

[16] *The exact condition for* $\beta_i > 0$ *is that* $\pi_\beta r_\gamma - \pi_\gamma^2 > \rho\{\pi_\gamma[(n_i + \sigma_\pi^2)\mu + \sigma_{\pi r}] - \pi_\beta(\sigma_{\pi r}\mu + \sigma_r^2)\}$.

$$\frac{\partial V_i^M}{\partial n_i} \cdot (1 - F_{-i}) + \frac{\partial V_i^D}{\partial n_i} \cdot F_{-i} - \frac{dF_{-i}}{dEV_{-i}} \cdot (\frac{\partial V_{-i}^D}{\partial n_i} \cdot F_i) \cdot (V_i^M - V_i^D) = 0$$

substituting for $\frac{\partial V_i^D}{\partial n_i}$ and including net disclosure costs yields an expression with four distinct effects:

$$\underbrace{F_{-i} \cdot (\frac{\partial V_i^D}{\partial a_{-i}})' A a_n^i}_{\substack{\text{Strategic} \\ \text{response of} \\ \text{competitor}}} \underbrace{- \frac{dF_{-i}}{dEV_{-i}} \cdot \frac{\partial V_{-i}^D}{\partial n_i} \cdot F_i \cdot (V_i^M - V_i^D)}_{\text{Participation deterrence}} - \underbrace{\beta^2 \cdot \frac{\rho}{2}}_{\substack{\text{Risk} \\ \text{aversion} \\ \text{cost}}} = \underbrace{n'(n_i)}_{\substack{\text{Net} \\ \text{disclosure} \\ \text{cost}}}$$

Proposition 5 *Given our assumption that $n(n)$ is convex enough to ensure an optimal solution, we know that any increase (decrease) in one of the effects on the left-hand side will increase (decrease) the optimal profit noise. When a shift in managerial incentives toward revenue and away from profit reduces competitors' profit (as in Assumption 4):*

1. The participation deterrence effect is positive.

2. The strategic response effect is positive (negative) when actions are strategic substitutes (complements), i.e. when the reaction matrix A is negative (positive) definite.

Proof. The first statement follows from Assumption 4 and Proposition 3. The proof of the second is in Appendix C. ■

Propositions 3, 4, and 5 give us three predictions that we can test in the next section, namely, that firms in industries that compete in strategic substitutes should have less precise profit measures (Proposition 5), that less precise profit measures should shift market returns and managerial incentives toward rewarding revenue when profit and revenue shocks are positively correlated (Proposition 3), and that firms may use their accounting-based incentives to undo some of the incentives created by market returns (Proposition 4).

3.3 Empirical evidence

This section presents three findings that coincide with the three main predictions from the model above:

1. Firms that compete in strategic substitutes provide less voluntary disclosure and less meaningful profit figures.

2. Both firms that provide less disclosure and those that compete in strategic substitutes have shareholder returns that depend more on revenue growth and less on profit growth. Shareholder returns play a large enough role in determining managerial compensation (both explicitly and by affecting bonuses and other incentive plans) that these firms also have managerial incentives that depend more on sales growth and less on profit growth.

3. Controlling for the effects of shareholder returns, firms that compete in strategic substitutes have incentives that are biased *away from* revenue growth. This bias is only large enough to partially undo the bias towards revenue created by shareholder returns. It is consistent with firms choosing a limited disclosure policy to commit to bias their incentives towards revenue and then attempting to secretly undo part of this bias.[17]

Of these three findings, the most attention is devoted to the first. That firms should pursue a different disclosure policy based whether their industry more closely resembles Cournot or Bertrand competition is the most unique theoretical prediction and empirical finding of this paper, therefore deserving the most attention. The first part of the second finding, that firms competing in strategic substitutes have revenue-biased managerial incentives, is predicted by both this paper and by observable-contract FJS models. The second part of the second finding, that profits play a greater role stock returns and incentives for firms that provide better profit measures, is a prediction of many models but is important because firms would not reduce disclosure for the reasons modelled above if it made managerial incentives depend less on revenue. The final finding, that firms appear to undo part of the disclosure-related incentive bias, is also a unique prediction of the model in this paper. Given that believing the third finding requires believing the first two, however, this finding receives the least attention of the three.

[17] When we say that firms' accounting-based incentives are secret, we mean that they are not credibly observed by the other firm. The accounting-biased incentives are fully anticipated in a rational-expectations equilibrium, and, in practice, they are often observed in proxy statements. By claiming that they are not credibly observed, however, we are saying that a firm would not achieve a commitment by distorting them away from the non-strategic best response, since the firm could always be undoing the distortion with unobserved relational contracts.

The character of the evidence in this section is necessarily cross-sectional. Firms and industries rarely shift suddenly from quantity to price competition.[18] Firms and industries do sometimes shift from a non-competitive (and thus non-strategic) environment to a competitive one, but these shifts tend to either happen in countries in which managerial compensation data is unavailable or involve regulatory changes that also affect disclosure directly.[19] Given the need to rely on cross-sectional evidence, particular care must be taken to identify and control for omitted variables that also affect disclosure policy or managerial incentives and could be correlated with an industry's strategic environment; this will be done as each finding is discussed below.

3.3.1 Strategic environment and disclosure policy

Measurement choices and data sources

The first step in testing whether firms competing in strategic substitutes provide less voluntary disclosure is developing measures of an industry's strategic environment and a firm's disclosure policy. The more difficult measurement issue is determining whether an industry competes in strategic substitutes or complements. Almost all industries actually make both types of competitive choices; they make participation and investment decisions that are strategic substitutes and then pricing decisions that are strategic complements. An industry more closely resembles pure quantity competition as its initial capacity decisions become more important. In a strategic trade model by Maggi (1996), firms choose capacities that they can later exceed by paying an additional marginal cost. The size of this additional marginal cost provides an index of the strategic nature of competition; when it is infinite, competition reduces to pure quantity competition; when it is zero, competition reduces to pure price competition. Empirically, this metric of the importance of the capacity decision is most naturally proxied by the capital intensity of the industry; in capital-intensive industries, capacity is expensive to build and difficult to exceed, while this is less the case in labor-intensive industries. The capital-output ratio is thus my main proxy for the strategic nature of competition.

[18] An exception is a capital-intensive industry that passes from a capacity-building phase to having persistent overcapacity (e.g., steel), although such changes are hardly ever sudden.

[19] Examples that were considered and rejected include the opening up of the South African economy to trade after the end of apartheid-era sanctions and the introduction of competition into electricity generation.

In addition to using measured capital intensity as a proxy, I also performed an *ad hoc* classification of two-digit industries according to the perceived importance of capacity decisions and thus the degree to which an industry resembles pure quantity rather than differentiated price competition. Agriculture, mining, air transportation, and telecommunications, and certain capital-intensive manufacturing sectors are classified as quantity competition while construction, wholesale and retail trade, services, and certain light manufacturing industries are classified as price competition (Table 1). These judgements can be debated, of course, but they are consistent with how the industries are usually approached in single-industry models and are in any case highly correlated with capital intensity.

Other proxies for the strategic nature of competition are also considered. Investments in cost-reducing technology are strategic substitutes in many oligopoly models; the average total factor productivity growth in an industry might therefore be considered a proxy for the importance of cost reducing investments and thus the strategic nature of competition. Aggarwal and Samwick (1999) use the Herfindahl index as a proxy, arguing that "a firm in a more concentrated industry will have fewer close substitutes for its products" (p. 26) and thus less resemble differentiated price competition. To provide a link with the limited prior literature in this area, this variable was also considered.[20]

The measurement of voluntary disclosure is more straightforward. Two samples of firms are used in the analysis: a North American sample of firms from the Standard & Poors COMPUSTAT database and a World sample of firms from S&P's Global Vantage database. The primary disclosure measure for the North American sample was the voluntary disclosure scores given to 415 North American industrial firms by the American Institute of Management Research (AIMR).[21] In addition, binary indicators of specific disclosure policies are also used. For the

[20]One approach that was considered and not adopted is that of Kedia (1998). Kedia attempts to directly estimate the sign of the effect of a competitor's action on the marginal profitability of one's own action, using an firms' sales as the proxy for its action. Unfortunately, this approach does not perform well empirically. Kedia classifies industries if a regression coefficient is significant at the 10% level and yet classifies only 13% of the industries. Kedia also allows the strategic nature of competition to vary by year; 30% of industries are classified as substitutes in one year and complements in another, a hard-to-interpret result. Furthermore, although Kedia mentions a few classifications that make intuitive sense, my own attempts to replicate her classifications suggest that they are not generally intuitive.

[21]See Lang and Lundholm (1993) for a description of this data. The scores were normalized to a percentage of points possible. Scores were not used for firms in excluded industries (Annex Table 1) and a few scores for non-North American firms or which could not be matched with COMPUSTAT.

North American sample, variables are also available for whether a firm held a conference call in March, April, or May 1997, whether a firm achieved an unqualified audit opinion, and whether a firm engaged a "Big-Six" auditor.[22] For the World sample, variables for whether a firm reported fully consolidated results and whether a firm published results using U.S. Generally Accepted Accounting Principals (GAAP) were used in addition to the unqualified opinion and Big Six auditor variables.[23]

The North American and World samples were drawn from the publicly traded firms included in the COMPUSTAT and Global Vantage datasets, respectively. For most measures, data from the years 1987-98 was used, but AIMR data was only available from 1987-95. Financial firms (SIC 6), non-market services such as health, legal, and educational services (SIC 8 and 9), and utilities and non-air transportation were excluded from the sample. Firms with missing asset data or less than $1 million in assets were excluded; this reduced the North American sample significantly. A small number of observations with very large financial ratios were also excluded (Annex Table 1). This yielded a sample of 4,596 North American and 9,262 World firms with asset data and 3,570 North American and 8,370 World firms with all financial variables. AIMR scores were available for 368 of the North American firms with asset data and for 257 of those with all financial variables.[24]

Summary statistics and results

Tables 2 and 3 provide summary statistics by strategic category for the variables mentioned above plus other firm and industry characteristics that may influence disclosure. In North America, firms that compete in strategic substitutes have lower disclosure scores, were less likely to hold a conference call, less likely to obtain an unqualified audit opinion, but were slightly

[22]The conference call variable was collected from the First Call database; the audit opinion and auditor variables are from COMPUSTAT. Achieving an unqualified audit opinion is interpreted as a disclosure policy choice since companies can almost always achieve an unqualified opinion by complying with the requests of their auditors for information.

[23]The literature provides some motivation for using these measures. Alford, et. al. (1993) finds that firms reporting non-consolidated earnings have lower earnings-response coefficients. Leuz and Verrecchia (1999) find that bid-ask spreads decline when German firms adopt U.S. GAAP. Becker, et. al. (1998) find that firms with non-big 6 auditors report higher and more variable discretionary accurals.

[24]The number of firms is focused on as the relevant measure of sample size as the within-firm variation in disclosure policy is very low (Annex Table 2).

more likely to use a Big-Six auditor.[25] In the World sample, firms competing in strategic substitutes were less likely to obtain an unqualified audit opinion, report consolidated results, or use a Big Six auditor but more likely to use U.S. GAAP.

As discussed above, firms' optimal disclosure policy can also be affected by non-strategic factors which should be controlled for. Disclosure can reduce asymmetric information and thus lower the costs of equity and debt capital (Lang and Lundholm, 1996; Botosan, 1997; Sengupta, 1998), and firms that are raising capital have been found to choose higher levels of disclosure (Lang and Lundholm, 1993; Frankel, et. al., 1995; Tasker, 1997). Larger firms have also been found to provide higher levels of disclosure, which is logical since the benefits of higher valuations rise directly in proportion to a firm's size while the costs of disclosure probably do not. More profitable firms have likewise been found to provide more disclosure, although theoretically the direction of the relationship is ambiguous.[26]

Taking these factors into account, the net benefits ($NETBEN$) of adopting a specific disclosure policy can be expressed as:

$$\begin{aligned} NETBEN &= a \cdot NEWEQ + b \cdot NEWDT + c \cdot PROFIT + \\ &\quad [d(STRAT) - e] \cdot ASSETS - f \cdot (ASSETS)^{\xi} + g, \end{aligned}$$

where a and b are the cost of capital benefits of disclosure per unit of new equity and debt capital raised ($NEWEQ$ and $NEWDT$) , c is the benefit of a higher valuation multiple for earnings ($PROFIT$), $d(STRAT)$ is the strategic benefit modelled in this paper, e is the cost of disclosing information to competitors, $f \cdot (ASSETS)^{\xi}$ is the actual cost of providing the information, and g is an error term. Normalizing this equation by assets yields:

[25] Throughout the paper, firms are classified according to their primary SIC industry, as reported in COMPUSTAT or Global Vantage. I also used the Segments data to construct a weighted average of the characteristics of the industries in which each firm competed, but results were very similar.

[26] On the one hand, share-owning managers may be more interested in ensuring that good news is fully reflected in valuations than bad news. On the other hand, poor performing firms may want to disclose more to protect themselves from shareholder lawsuits, while high performing firms may want to keep their success a secret for competitive reasons.

$$\frac{NETBEN}{ASSETS} = [d(STRAT) - e] + a \cdot \frac{NEWEQ}{ASSETS} + b \cdot \frac{NEWDT}{ASSETS} + c \cdot \frac{EBIT}{ASSETS} - f \cdot (ASSETS)^{\xi - 1} + g'$$

using operating profit ($EBIT$) as the measure of profits and replacing the error term with a normalized one which in practice is less heteroskedastic. This expression can be naturally used in a probit model of the adoption of discrete disclosure policies (e.g., using a Big Six auditor). It can also be applied to a continuous measure of disclosure policy like the AIMR rating by interpreting $NETBEN$ and the letters as the benefit from a incremental increase in disclosure, assuming that g' decreases with disclosure, and rewriting the above expression to solve for the level of disclosure at which the net incremental benefit is zero.

Tables 4 and 5 summarize the results from estimations of the above model using different disclosure measures and different proxies for the strategic nature of competition.[27] Firm size is significant in every regression, but the other financial control variables are not jointly significant in about half the specifications,[28] and therefore results are presented both with and without financial controls. Firms that compete in strategic substitutes are found to have significantly lower AIMR scores and be significantly less likely to hold conference calls regardless of the proxy chosen for strategic environment. These firms are also less likely to obtain an unqualified audit opinion, report consolidated results, or use U.S. GAAP (in the countries where they have a choice). In contrast, there does not appear to be a significant relationship between strategic environment and using a Big-Six auditor.

The AIMR scores are constructed by committees of financial analysts that are specialists in a particular industry sector and often use rating criteria that are specific to each sector. Most researchers that have used the AIMR scores have therefore limited themselves to using the within-sector information. Since this paper is interested is how disclosure varies with an

[27]The individual regressions for each disclosure variable are presented in Annex Tables 2 and 3. Given the presence of random effects in the models, to simplify the estimation procedure, the parameter ξ was estimated first to be about 0.8 in a non-linear least squares regression and then this value was used in subsequent regressions. Although this procedure is not ideal, it was viewed as adequate given that the results were very similar when parameters of 0.5 or 0.9 were used instead.

[28]In particular, they are never significant at the 10% level in regressions with the AIMR score as the dependent variable and are not significant in 25% of the probit regressions.

industry's strategic environment, however, the between-sector information in the AIMR scores is particularly important. In Table 4, cross-sector differences in AIMR scores are allowed for by including AIMR-sector random effects in the regression. This approach assumes that any cross-sector differences in AIMR scoring criteria are not related to the strategic environment of the industry, in other words, that analysts in strategic complements industries like retail do not have lower rating standards than analysts in strategic substitutes industries like mining. It is not possible to test this assumption using the entire dataset since most AIMR sectors do not have sufficient variation in capital intensity, but we can examine the limited number of sectors that do have such variation. Table 6 replicates the analysis in the first column for the six sectors with the most within-sector variation in capital intensity and finds a similar relationship between disclosure and our proxy for the strategic nature of competition.

Table 7 compares the results for the capital intensity and strategic classification proxies with those for the other proxies, total factor productivity growth and the Herfindahl index, and examines the effect of controlling for unionization. Unionization is positively correlated with capital intensity and negatively correlated with disclosure; including it in regressions reduces the size of the coefficients for the proxies for strategic substitutes by about 30-40 percent but, with the exception of the Herfindahl, does not remove their significance. With the exception of the Herfindahl when unionization is included, similar results are obtained for the other proxies. Given that including all of proxies at once raises the explanatory power of the model only slightly, focusing on the capital intensity and the strategic classification seems appropriate.

Potential biases

Omitted variables Given that proxies for the major determinants of disclosure policy that have been mentioned in the literature were included in the models above, the main potential source of omitted variable bias would be if these proxies were imperfect. We should be particularly worried about those variables for which omitted variable bias causes an overestimate of the effect of the strategic nature of competition on disclosure policy, i.e. those variables which are correlated with capital intensity and disclosure in opposite directions. If the proxies for these variables were imperfect in this way, then some of the results reported above could be due to omited variable bias.

Table 8 reports the correlation of the control variables with disclosure measures, while Tables 2 and 3 report how they vary with strategic environment. Firm size is the only control variable that is consistently significant, but it is positively correlated with both capital intensity and disclosure, so imperfectly controlling for it should not be contributing to the results.[29] The two variables with opposite signed correlations are profitability and new debt capital; both are positively correlated with disclosure and negatively correlated with capital intensity. The negative correlations between capital intensity and both new debt raised and profitability are a surprise and may be related to the use of assets in the denominator of both measures. In any case, the role of the control variables other than firm size in the regressions in Tables 4 and 5 is very limited; even with better proxies their role is likely to remain limited.

Endogeneity The results in Tables 4-7 would be biased if the independent variables themselves depended on a firm's (perceived or actual) disclosure policy. For example, if a firm that was exogenously regarded by the market as having a good disclosure policy faced lower capital costs and thus decided to raise more capital, this could induce an upward correlation between disclosure and capital raised, firm size, and capital intensity. In the case of capital intensity, this would bias the coefficient on capital intensity positively toward zero. Positively biasing the coefficients on the control variables firm size and capital raised could also affect the estimated coefficient on capital intensity; in particular, a positive bias to the firm size coefficient would negatively bias the coefficient on capital intensity.

I am not very worried about this type of endogeneity for two reasons. First, the effect of disclosure policy on capital costs is estimated to be very small (under 100 basis points) relative to the role of technology in determining the optimal firm size and capital intensity of an industry. Second, it is doubtful that all of the positive correlation between firm size and disclosure is due to endogeneity, since disclosure is obviously relatively cheaper for a larger firm, but even if it were, the correct specification would be to leave out the control for firm size. Even in this specification, the coefficients on capital intensity are negative and significant (See Annex Tables 2 and 3).

[29] Furthermore, using an alternative proxy, such as EBITDA, only increases the magnitude of the coefficients on capital intensity.

3.3.2 Disclosure and the revenue bias in stock returns and managerial incentives

The second prediction of the model to be tested is whether a limited disclosure policy causes stock returns and managerial incentives to place greater weight on revenue growth. In addition, we would like to know whether firms competing in strategic substitutes have stock returns and managerial incentives that place greater weight on revenue growth as the model predicts.

Measurement and data sources

The two major measurement choices in this section are how to measure executive compensation and thus managerial incentives and how to determine whether the stock returns or managerial incentives of certain firms are biased away from profits and towards revenue. Top executives receive pay-for-performance incentives through salary increases, bonuses, long-term incentive plans, and their option and stock holdings. Hall and Liebman (1998) report that the last two sources of incentives have become especially important in the last decade. The COMPUSTAT Executive Compensation data on these components of compensation for 14,324 executives from 1,913 North American firms from 1993-97 are summarized in Table 9.

The naive comparison of the relative size of executive compensation and the increase in the value of stock and option holding in Table 9 suggests that the latter dwarfs the former in providing managerial incentives. Adding the compensation and the nominal increase in the value of an executive's assets is problematic for several reasons. First, whereas asset values follow a random walk, compensation is persistent from year to year; a $100,000 raise represents a greater increase in an executive's total wealth than a $100,000 increase in the value of stock holdings. Second, assets are expected to increase in nominal value, especially in bull markets like the 1993-97 period. The difference between the performance of an executive's firm-related assets and a comparably leveraged market portfolio is a better indicator of the contribution of a firm's stock performance to an executive's wealth. Labelling the natural increase in the value of stock holdings during a bull market as compensation overstates the role of stock returns in total compensation. Third, nominal compensation increases are also expected. The difference between the actual and expected raises is more relevant than the nominal raise as a measure of the change in an executive's wealth.

Table 9 constructs a measure of an executive's firm-related wealth, which is the sum of the permanent income value of compensation and the value of stock and option holdings. The annual change in an executive's firm-related wealth is a function of the relative performance of her stock and option holdings and the difference between her actual and expected compensation increase. Using this measure, the relative roles of compensation and the change in value of stock and option holdings in providing managerial incentives is much more equal.

The revenue and profit weights in stock returns, compensation, and managerial incentives are measured using a common specification from the executive compensation literature:

$$d\ln(Y) = a \cdot d\ln(Sales) + b \cdot d\ln(Ebitda) \tag{3.3}$$

where Y is either a shareholder returns index, compensation, or the firm-related managerial wealth measure in Table 9. The first differences specification removes firm fixed effects in the level of managerial compensation as recommended by Murphy (1985). Three different measures of profit are included since all three are used by practitioners as indicators of firm value.[30]

Results

Tables 10 presents estimations of (3) for different subsamples of firms. The left-hand panel reveals that revenue growth has a greater weight and profit growth a smaller weight in industries classified as strategic substitutes or with high capital intensity; the right-hand panel reveals that the same is true for industries with limited disclosure. The results are more pronounced for shareholder returns and total managerial wealth than for compensation, suggesting that any incentive bias towards or away from revenue comes from manager's shareholdings rather than their compensation.

The regressions in Table 11 test the statistical significance of the differences observed in Tables 10 by interacting (3) with strategic environment proxies and disclosure measures. In almost all cases the conclusions drawn above are statistically significant, although again the results are less significant for compensation than for shareholder returns or managerial wealth.

[30] Alternative measures of profitability that were considered include earnings including and excluding extraordinary items. Regressions including all three earnings items showed that stock returns were more responsive to *Ebitda* than to the other two measures, and so *Ebitda* was used as the single proxy for accounting profit.

Potential biases

The biggest potential concern with the above results is that shareholder returns could be biased towards sales in capital-intensive industries for reasons having nothing to do with disclosure policy. For example, if sales are indicative of future earnings, then for firms where future earnings are a larger component of value (i.e., those with high price-earnings ratios) sales will be more value relevant. If capital-intensive firms also have high PE ratios, this could explain the results above. Likewise, since capital-intensive firms are larger, if larger or more unionized firms had returns that were more dependent on sales growth, the results above might be biased. Annex Table 4 replicates some of the results in Table 12 and adds controls for PE ratio and firm size (measured using assets) and finds that the results are not sensitive to including these controls.

3.3.3 The partial undoing of incentive biases through non-stock compensation

Compensation is both mechanically and implicitly related to stock returns. Part of compensation takes the form of options and stock grants, long-term incentive plans and bonuses are often explicitly tied to stock returns, and higher compensation is easier to justify when stock returns are high. If a limited disclosure policy causes stock returns to be biased toward sales, the relationship between compensation and stock returns will cause compensation to also be biased towards sales.

The question this section asks is whether firms that compete in strategic substitutes augment or partially reverse the incentive biases in stock returns using non-stock compensation. If observable contracts are used to achieve strategic commitment as in the FJS models, we might expect to see firms augmenting the incentive bias in their stock returns with non-stock incentives, in part because the bias towards revenue in stock returns is inherently limited by the fact that investors ultimately value profits and reward revenue only to the extent that it is informative about profits. On the contrary, if contracts are unobservable as in the model above, we might under certain conditions expect to see firms partially undo incentive biases through non-stock compensation.

Table 12 presents interactions of (3) with cash and non-stock compensation as the dependent variables and shareholder returns added as an independent variable. The results for the interactions with strategic environment proxies suggest that firms competing in strategic substitutes do undo part of the incentive bias towards revenue with their non-stock compensation; these results are consistent with our observation above that the biases toward revenue were smaller for compensation than for stock returns and managerial wealth. The results for the interactions with the disclosure measures, however, suggest that firms with limited disclosure augment the resulting bias towards revenue. Taken together, these results are consistent with firms that limit disclosure for strategic reasons undoing part of the resulting incentive bias while firms that limit disclosure for other reasons do not.[31]

3.4 Conclusion

This paper has argued theoretically and documented empirically that firms competing in strategic substitutes pursue more limited disclosure policies and that these firms' choice of disclosure policy biases their managerial incentives in a strategically advantageous way. The paper offers no evidence on whether firms are consciously taking account of strategic concerns or have arrived at an advantageous disclosure policy through an evolutionary process or as part of a general rule of competitive conduct. Even given that caveat, the idea that strategic concerns might affect disclosure policy has more far reaching implications than the cross-sectional patterns presented above. In particular, the model and evidence in this paper can help us think more broadly about strategy and disclosure in three very different environments.

1. *The U.S.-Japan managerial "myopia" debate.* In the late 1980s, it was often argued that Japanese firms derived a strategic advantage from their less meaningful quarterly earnings figures[32] and their larger, more involved equity and debt holders (e.g., Jacobs, 1991). Less focus on quarterly earnings figures was argued to give Japanese firms two strategic advantages, by allowing them to make investments in intangibles and to focus on increasing market share. Stein (1989) provided a model of the first advantage in which

[31] We know that firms competing in strategic substitutes are only partially undoing the incentive bias because non-stock compensation is included in the managerial wealth measures which we found to be significantly biased towards revenue above.

[32] For example, in the late 1980s, Japanese firms were not required to report consolidated earnings statements; reporting only parent company results allowed them to use transfer pricing to hide profits or losses in subsidiaries.

less precise profit measures encourage greater investment intangibles that are unobserved by the market. This paper can be viewed as a model of the second advantage. Using less meaningful profit measures acts as a commitment to reward Japanese managers based on market share growth, encouraging aggressive behavior by Japanese managers and passive behavior by their U.S. rivals.

2. *The Korean crisis.* In Baily and Zitzewitz (1998), we argued that the recent crisis in Korea was largely due overinvestment by Korean firms in heavy manufacturing industries[33] and that this overinvestment could be traced to the absence within Korean firms of measures of the economic profitability (i.e., profits net of capital costs) of divisions or products. We attributed the absence of these measures in part to the fact that they were less relevant for Korean firms historically given that access to capital was limited and that interest subsidies, low labor costs, and less intense competition in domestic and international markets helped ensure the profitability of investments. An alternative explanation suggested by the model in this paper is that Korean firms in capital intensive industries were cultivating a reputation for aggressive behavior in order to encourage exit and discourage investment by their foreign competitors and that eschewing profitability measures was part of building this reputation. It is certainly true that Korean firms had developed a reputation for destroying the global profitability of industries they entered (e.g., textiles, shipbuilding, DRAMs, volume autos), that this reputation had some strategic benefits, and that their apparent disregard for earning high returns on capital contributed to this reputation. It is less clear, however, whether not adopting economic profit measures was a conscious decision made with this reputation in mind.

3. *Newly public e-commerce firms.* E-commerce firms are notorious for earnings figures that are difficult to interpret. A typical problem is that selling, general, and administrative (SG&A) expenses are greater than gross margins, but SG&A includes recurring expenses, one-time expenses, and investments (e.g., in marketing) that cannot be credibly separated.

[33] By 1995, Korean firms in autos, steel minimills, DRAMs, and most of food processing had invested to 100 percent of U.S. capital intensity (comapred with an economy average of 33 percent) despite achieving only 50 percent of U.S. total factor productivity. Low returns were an inevitable result. Baily and Zitzewitz (1998) was based heavily on work we while at the McKinsey Global Institute (1998).

As a result, the stock market often responds to revenue growth as well as or instead of earnings growth. Managers interested in medium-term valuations therefore have an incentive to increase revenue as well as profits. These incentives may be partly responsible for promotions that often look more revenue than profit maximizing.[34] The model in this paper suggests that the imperfect profit figures and the aggressive managerial behavior that they promise may be strategically valuable in deterring participation or investment by competitors.

In summary, this paper shows that by relaxing the assumption that contracts are observable, one can find evidence that managerial incentives are important for strategic as well as organizational efficiency reasons. The paper also provides evidence that accounting and disclosure policies are affected and should be affected by strategic concerns as well as more common considerations such as the cost of capital and the cost of information provision. These two broad findings have implications for management and future research alike.

[34]Examples include the 20-40% off discounts offered to *existing* customers by Peapod, an online grocery delivery service, and the $75-400 new account bonuses offered by online brokerages and banks, sometimes without requiring an initial deposit. These promotions could also be motivated by switching costs (Klemperer, 1987) or a desire to develop a reputation for low pricing (Bagwell, Ramey, and Spulber, 1997).

Table 1. Summary statistics of industries by strategic classification

SIC	Industry	Firms	Firms with disclosure score	Ad hoc Strat Subs./ Comps.	Capital-value added ratio	AIMR disclosure score	Assets ($ millions)
01-09	Agriculture	43	3	SS	3.0	60	515
10-14	Mining	738	38	SS	5.0	62	623
15-17	Construction	126	13	SC	0.3	75	654
20-39	Manufacturing	2,880	230		1.3	71	2,611
	"Heavy" Manufacturing (SIC 22, 26, 28, 29, 33, 34, 37)	1,074	134	SS	1.7	70	3,901
	"Light" manufacturing (SIC 23, 27, 31)	243	18	SC	0.6	70	873
	"Other" manufacturing (SIC 20, 21, 24, 25, 30, 32, 35, 36, 38 , 39)	1,563	78		1.0	72	1,903
45	Air transport	27	10	SS	2.1	74	4,649
48	Communication	133	11	SS	2.8	62	9,323
50-51	Wholesale trade	141	9	SC	0.7	74	1,042
52-59	Retail trade	212	32	SC	0.8	90	2,101
70-79	Other services	275	27	SC	0.6	61	1,698
	All Strategic substitutes	2,100	191	SS	2.8	69.3	3,183
	All Strategic complements	1,105	99	SC	0.6	76.9	1,408
	All industries	4,768	368		1.7	72.0	2,336

Notes:

1. Transportation and utilities (except air transportation), finance, insurance, real estate, health care, legal services, and education are excluded from this study.
2. Firms are number of publically traded firms listed in COMPUSTAT, capital-output ratios are the average net reproducible wealth at original cost divided by gross product originating in a sector in 1997. Unionization rate is calculated from the Current Population Survey.

Table 2. Summary statistics for North American and World sample

		Mean	Std. Dev	Obs.	Firms	Obs./Firm
North American sample						
Disclosure measures						
AIMR disclosure score	Percent	72	14	1,958	415	4.7
Held conference call from 3/97-5/97	Percent	6.1	24	9,825	9,825	1
Unqualified audit opinion with no explanatory notes	Percent	74	44	42,143	6,813	6.2
Unqualified audit opinion	Percent	97	16	42,143	6,813	6.2
Big 6 auditor	Percent	87	34	41,852	6,787	6.2
Firm characteristics						
Assets	$ millions	2,336	10,279	31,880	4,596	6.9
ROIC (measured as EBIT/Assets)	Percent	6.5	14.1	31,498	4,570	6.9
New equity-assets	Percent	2.7	10.3	18,457	3,692	5.0
New debt-assets	Percent	5.3	16.3	17,614	3,629	4.9
Short-term debt-assets	Percent	2.4	5.4	30,826	4,540	6.8
Log assets-sales ratio		0.06	0.86	30,990	4,467	6.9
Industry characteristics (whole economy)						
Strategic substitutes dummy	Percent	0.50	0.50	79,205	7,055	11.2
Log capital-value added ratio (NIPA data)		1.5	1.4	112,977	10,090	11.2
Unionization rate 1995	Percent	13	10	112,977	10,090	11.2
Industry characteristics (manufacturing only)						
Log capital-value added ratio (NBER data) 1992		0.89	0.56	56,839	5,079	11.2
Average total factor productivity growth 1987-97	Percent	1.5	2.8	56,839	5,079	11.2
Herfindahl index 1992		601	471	56,381	5,039	11.2
Unionization rate 1995	Percent	17	11	55,411	4,948	11.2
World sample						
Disclosure measures						
Unqualified audit opinion with no explanatory notes	Percent	82	38	50,958	8,671	5.9
Unqualified audit opinion	Percent	98	13	50,958	8,671	5.9
Reported consolidated results	Percent	95	22	50,958	8,671	5.9
Used U.S. GAAP	Percent	1.0	10.0	50,958	8,671	5.9
Big 6 auditor	Percent	71	45	50,958	8,671	5.9
Firm characteristics						
Assets	$ millions	2,131	8,256	50,957	8,671	5.9
ROIC (measured as EBIT/Assets)	Percent	12.0	11.5	47,937	8,379	5.7
New equity-assets	Percent	1.6	8.4	50,958	8,671	5.9
New debt-assets	Percent	3.5	12.5	50,958	8,671	5.9
Short-term debt-assets	Percent	39	18	50,958	8,671	5.9
Log assets-sales ratio		0.03	0.75	50,672	8,615	5.9

Table 3. Summary statistics for North American and World sample by strategic classificatior

	All observations			Disclosure score available		
	All	Subs.	Comps.	All	Subs.	Comps.
North American sample						
Observations	31,880	13,755	7,671	1,798	931	482
Firms	4,596	2,036	997	368	191	99
Disclosure measures						
AIMR disclosure score	72.0	69.3	76.9	72.0	69.3	76.9
Held conference call from 3/97-5/97	16.6	14.7	20.2	40.5	40.4	42.3
Unqualified audit opinion with no explanatory notes	76.5	74.6	79.6	65.7	64.6	72.0
Unqualified audit opinion	98.3	97.9	99.0	99.7	99.7	99.8
Big 6 auditor	88.8	89.0	88.5	98.8	98.9	97.9
Firm characteristics						
Assets	2,336	3,183	1,408	7,589	8,324	5,644
ROIC (measured as EBIT/Assets)	6.5	4.7	8.7	11.9	11.0	13.1
New equity-assets	2.7	3.1	2.4	-0.3	0.0	0.2
New debt-assets	5.3	4.2	7.5	6.6	5.5	8.2
Short-term debt-assets	2.4	2.3	2.4	1.5	1.5	1.2
Log assets-sales ratio	0.06	0.41	-0.24	-0.04	0.12	-0.27
Industry characteristics (whole economy)						
Log capital-value added ratio (NIPA data)	1.71	2.85	0.62	1.55	2.22	0.66
Unionization rate 1995	14.9	18.8	7.4	17.3	22.9	6.8
Industry characteristics (manufacturing only)						
Log capital-value added ratio (NBER data) 1992	1.00	1.33	0.49	1.21	1.50	0.52
Average total factor productivity growth 1987-97	1.3	0.6	-0.4	0.1	-0.1	-1.5
Herfindahl index 1992	621	683	440	632	647	315
Unionization rate 1995	18.6	24.2	11.5	21.1	23.8	10.6
World sample						
Observations	50,957	15,711	16,208			
Firms	8,671	3,051	3,077			
Disclosure measures						
Unqualified audit opinion with no explanatory notes	82.4	81.6	84.5			
Unqualified audit opinion	98.2	96.7	98.8			
Reported consolidated results	95.1	92.5	96.3			
Used U.S. GAAP	1.0	1.0	0.7			
Big 6 auditor	71.3	67.1	72.4			
Firm characteristics						
Assets	2,131	2,302	1,618			
ROIC (measured as EBIT/Assets)	12.0	10.6	12.4			
New equity-assets	1.6	2.4	1.3			
New debt-assets	3.5	3.8	3.8			
Short-term debt-assets	39.1	35.8	42.1			
Log assets-sales ratio	0.03	0.39	-0.26			

Table 4. Overview of effect of industry strategic nature on disclosure policy
Coefficients on variable proxying for strategic nature of industry

		Dependent variable					
		AIMR score	Conf. Call	Unqual. opin. no notes	Unqual. opin.	Big 6 auditor	# neg. & sign.
Independent varaible	Financial controls	Continuous	Probit	Probit	Probit	Probit	(out of 5)
Strategic substitutes dummy	Yes	-8.867***	-0.206***	-0.199***	0.064	0.242**	3
		(1.736)	(0.082)	(0.043)	(0.172)	(0.094)	
	No	-8.450***	-0.258***	-0.152***	-0.206**	0.111*	4
		(1.444)	(0.075)	(0.034)	(0.082)	(0.068)	
Industry capital-output ratio (NIPA)	Yes	-3.564***	-0.127***	-0.046**	-0.015	0.039	3
		(0.899)	(0.042)	(0.019)	(0.061)	(0.032)	
	No	-4.046***	-0.172***	-0.018	-0.073***	-0.012	3
		(0.662)	(0.036)	(0.014)	(0.024)	(0.022)	
Industry capital-output ratio (NBER)	Yes	-2.461***	-0.075*	-0.060***	-0.026	0.028	3
		(0.774)	(0.043)	(0.022)	(0.098)	(0.069)	
	No	-2.765***	-0.085**	-0.062***	-0.155***	0.010	4
		(0.614)	(0.037)	(0.019)	(0.034)	(0.046)	
Firm capital-output ratio	Yes	-5.409***	-0.149***	-0.003	-0.006	0.047	2
		(1.159)	(0.043)	(0.019)	(0.050)	(0.032)	
	No	-4.196***	-0.229***	-0.034***	-0.113***	-0.024	4
		(0.713)	(0.036)	(0.012)	(0.018)	(0.019)	
Industry capital-output ratio (firm data)	Yes	-3.590***	-0.085***	-0.044**	-0.042	0.086**	3
		(0.702)	(0.032)	(0.018)	(0.071)	(0.038)	
	No	-4.013***	-0.129***	-0.025*	-0.082***	0.004	4
		(0.493)	(0.028)	(0.013)	(0.029)	(0.027)	
# Negative & Significant (out of 10)		10	10	8	5	0	32/50

Notes:
1. All regressions include year fixed effects. Continuous variable regressions include firm and industry random effects, probit regressions use standard errors adjusted for clustering within firms and industries.
2. "Demeaned" AIMR score is a firm's AIMR score less the mean for its AIMR category/
3. The capital intensity variables are normalized to a mean of zero and a standard deviation of one.
4. Significance at the (two-tailed) 10%, 5%, and 1% level is indicated by one, two, and three asterisks.
5. All regressions control for firm size, which is significant in every regression.

Table 5. Effect of industry strategic nature on disclosure policy -- World sample

	Financial controls	Consolidated results	Unqualified opinion, no explan. notes	Unqualified opinion	US GAAP	Big 6 auditor	# neg. & sign. (out of 5)
Strategic substitutes dummy	Yes	-0.043	-0.279***	-0.413***	-0.034	0.025	2
		(0.073)	(0.030)	(0.063)	(0.172)	(0.046)	
	No	-0.034	-0.225***	-0.398***	0.033	0.011	2
		(0.070)	(0.029)	(0.060)	(0.155)	(0.045)	
Industry capital-output ratio (NBER)	Yes	-0.178***	-0.121***	-0.103*	-0.132	-0.048	3
		(0.067)	(0.024)	(0.058)	(0.111)	(0.039)	
	No	-0.188***	-0.115***	-0.085	-0.170	-0.049	2
		(0.065)	(0.023)	(0.055)	(0.109)	(0.039)	
Firm capital-output ratio	Yes	-0.220***	-0.132***	-0.130***	-0.346***	-0.049**	5
		(0.045)	(0.015)	(0.025)	(0.088)	(0.022)	
	No	-0.213***	-0.072***	-0.101***	-0.227***	-0.049**	5
		(0.041)	(0.014)	(0.022)	(0.079)	(0.019)	
Industry capital-output ratio (NIPA)	Yes	-0.040*	-0.070***	-0.067***	-0.059*	0.008	4
		(0.023)	(0.008)	(0.012)	(0.036)	(0.012)	
	No	-0.025	-0.055***	-0.065***	-0.049*	0.006	3
		(0.020)	(0.007)	(0.011)	(0.028)	(0.012)	
# Negative & Significant (out of 8)		5	8	7	4	2	26/40

Notes:

1. All regressions include year and country fixed effects. Probit coefficients are scaled to represent the change in probability of policy's adoption from a infinitesimal change in the independent variable. Standard errors are robust to clustering within firms.
2. The capital intensity variables are normalized to a mean of zero and standard deviation of one.
3. Significance at the (two-tailed) 10%, 5%, and 1% level is indicated by one, two, and three asterisks.
4. All regressions control for firm size, which is significant in almost every regression.

Table 6. Variation of disclosure and capital intensity within AIMR sectors
Dependent variable: AIMR score

Coefficients on capital-output ratio for specific sectors

					Sample industries	
AIMR sector	Obs.	Firms	Coeff.	S.E.	High CI	Low CI
All	1162	190	-2.8***	0.6		
Food processing	137	21	-10.8**	5.0	Milling (2070), Beer (2082)	Poultry (2015), Spirits (2085)
Packaging	37	9	-8.8*	4.7	Metal Cans (3411)	Paper packagings (2670)
Construction	25	8	-7.4**	2.9	Cement (1400)	Construction (1500), Building materials (Various SICs)
Paper products	156	20	-5.7*	3.1	Paper products (2600), Wood products (2400)	Printing and Stationery (5110)
Non-ferrous metals	21	7	-4.4**	1.8	Primary and secondary smelting (3330 & 3340)	Non-ferrous metal products (3350)
Specialty chemicals	85	19	1.1	2.2	Dyes (2860)	Soap and detergent (2040), Paints (2050)

Notes:
1. Regressions include assets^-0.2, year fixed effects, and firm and industry random effects.
2. Capital intensity variable is normalized to a mean of zero and standard deviation of one.
3. Capital intensity variable is the NBER capital-output ratio, except for construction and paper products (which have sectors outside manufacturing) which use the industry average assets-sales ratio.
4. Significance at the (two-tailed) 10%, 5%, and 1% level is indicated by one, two, and three asterisks.
5. Coefficients are comparable to coefficients in Table 4.

Table 7. Alternative proxies for strategic nature of competition
Dependent variable: AIMR score

Obs.	1413	1413	1798	1798	1413	1413
Firms	290	290	368	368	290	290
R-sq.	0.16	0.18	0.16	0.18	0.18	0.20
Strategic substitutes dummy	-8.450***	-6.139***			-5.058***	-2.494
	(1.444)	(1.723)			(1.757)	(1.996)
Capital-output ratio (NIPA)			-3.827***	-3.112***	-2.616***	-2.699***
			(0.626)	(0.643)	(0.796)	(0.785)
Unionization rate		-1.678***		-2.125***		-1.782***
		(0.700)		(0.570)		(0.687)
Assets ^ -0.2	-9.148***	-9.445***	-7.326***	-8.092***	-8.628***	-8.926***
	(1.475)	(1.464)	(1.304)	(1.298)	(1.467)	(1.454)

Manufacturing only

Obs.	1230	1225	1230	1225	1208	1203	1203	1203
Firms	229	227	229	227	225	223	223	223
R-sq.	0.10	0.13	0.05	0.12	0.04	0.11	0.12	0.13
Capital-output ratio (NBER)	-2.361***	-1.409**					-2.242***	-1.716***
	(0.524)	(0.614)					(0.530)	(0.661)
Average TFPG 1987-97			-4.295***	-2.974**			-3.060**	-2.773**
			(1.223)	(1.202)			(1.238)	(1.223)
Herfindahl index					-1.294**	-0.334	-1.123*	-0.752
					(0.631)	(0.641)	(0.612)	(0.677)
Unionization rate		-2.140***		-2.707***		-2.961***		-1.166
		(0.779)		(0.669)		(0.706)		(0.904)
Assets ^ -0.2	-5.380***	-5.603***	-2.453	-4.011**	-4.076**	-4.981***	-4.839***	-4.771***
	(1.745)	(1.707)	(1.786)	(1.760)	(1.812)	(1.745)	(1.842)	(1.808)

Notes:
1. All regressions include year fixed effects and firm random effects.
2. Significance at the (two-tailed) 10%, 5%, and 1% level is indicated by one, two, and three asterisks.

Table 8. Correlation matrixes for the North American sample

Correlation among disclosure measures and between disclosure measures and firm characteristics

	AIMR score	Conf. Call	Unqual opin., no notes	Unqual opin.	Big 6
Disclosure measures					
Held conference call from 3/97-5/97	0.26				
Unqualified audit opinion with no explanatory notes	0.05	-0.05			
Unqualified audit opinion	NA	0.02	0.08		
Big 6 auditor	0.05	0.11	-0.01	0.05	
Firm characteristics					
Assets	0.03	0.09	-0.05	0.01	0.06
ROIC (measured as EBIT/Assets)	0.12	0.14	0.11	0.10	0.11
New equity-assets	-0.02	-0.07	0.06	-0.01	-0.05
New debt-assets	0.10	0.08	0.09	0.06	0.05
Short-term debt-assets	-0.06	-0.07	-0.10	-0.06	-0.09
Log assets-sales ratio	-0.28	-0.05	-0.02	-0.02	0.01

Correlation among industry characteristics and between industry and firm characteristics

	SS dummy	NIPA Cap/VA	Union 95	NBER Cap/VA	TFPG	Herf.
Industry characteristics (whole economy)						
Strategic substitutes dummy						
Log capital-value added ratio (NIPA data) 1992	0.63					
Unionization rate 1995	0.48	0.36				
Industry characteristics (manufacturing only)						
Log capital-value added ratio (NBER data) 1992	0.37	0.70	0.56			
Average total factor productivity growth 1987-97	0.17	-0.04	-0.11	0.03		
Herfindahl index 1992	0.22	0.07	0.23	0.09	0.07	
Disclosure measures						
AIMR disclosure score	-0.24	0.06	0.00	-0.21	-0.17	-0.10
Held conference call from 3/97-5/97	-0.06	-0.05	-0.01	0.05	0.04	0.03
Unqualified audit opinion with no explanatory notes	-0.06	-0.02	-0.05	-0.04	0.01	-0.02
Firm characteristics						
Assets	0.08	0.01	0.01	0.12	-0.03	0.20
Log assets-sales ratio	0.33	0.38	-0.09	0.03	-0.03	0.02

Table 9. Executive compensation summary statistics, 1993-98
Thousands of dollars

	Mean	P10	P25	Percentiles Median	P75	P90	Obs.	Execs.	Firms
Total compensation	1,294	220	353	648	1,299	2,634	42,699	14,324	1,913
Cash compensation	568	169	245	385	650	1,078			
Salary	317	135	180	258	366	550			
Bonus	251	0	32	105	389	585			
Long-term and non-cash compensation	726	6	48	204	628	1,599			
Black-Scholes value of options granted	492	0	0	105	382	1,049			
Restricted stock grants	90	0	0	0	0	137			
Long-term incentive plan payouts	62	0	0	0	0	98			
Other non-salary compensation	19	0	0	0	1	32			
All other total compensation	63	0	3	10	31	85			
Shares/options owned by executive*market price	19,347	401	1,101	3,065	9,222	26,520	39,990	13,906	1,912
Exercisable options	3,031	0	114	670	2,333	6,544			
Unexercisable options	2,671	0	158	735	2,179	5,808			
Shares owned	13,645	3	95	571	2,511	10,888			
Firm-related managerial wealth	28,132	2,557	4,317	8,618	19,569	45,282	38,740	13,906	1,912
Permanent income value of compensation	11,235	2,001	3,149	5,694	11,280	22,805			
Value of shares owned	14,149	10	120	642	2,721	11,464			
Value of in-the-money options held	2,748	0	41	470	1,945	5,977			
Change in firm-related managerial wealth	-237	-5,594	-1,434	-98	1,029	4,537	30,285	11,205	1,868
Change in value of shares/options (relative to market performance)	-384	-3,621	-809	-44	421	2,307			
Estimated change in permanent income	146	-2,245	-586	-36	655	2,620			
Memo items:									
Change in value of shares/options (In absolute terms)	4,129	-1,049	-64	273	1,644	6,104			
Increase in total compensation	214	-437	-59	56	306	950			
Log percent change in firm-related wealth	-5.5	-37.5	-16.5	-2.1	10.2	23.7	30,285	11,205	1,868
Percentage change in value of shares/options (relative to market performance)	-21.4	-102.3	-41.4	-6.6	17.1	43.1			
Percentage change in permanent income	-4.1	-31.5	-10.8	-1.0	9.8	22.9			
Memo items:									
Shareholder returns (abolsute terms)	12.5	-26.9	-5.1	14.0	32.9	50.8			
Percent change in total compensation	13.7	-49.7	-10.4	11.1	38.5	80.3			

Notes:
1. The Permanent income value of compensation is calculated assuming a discount rate of 25% (the 18% value-weighted average shareholder return during the period studied plus the 7% retirement/death rate for executives) and an average compensation growth rate of 13.7%.
2. The estimated change in permanent income reflects an estimated "decay rate" of 14% for annual changes in compensation.
3. The average change in the vaue of managerial shares and options relative to market performance is the difference between the value of the manager's stock and options and what the value would be if the firm's shareholder returns had been the same as the value-weighted average for all firms in the sample.
4. The mean change in the relative value of shares and options is slightly negative since small capitalization firms (of which manager's tend to own a larger percentage) had lower returns than large capitalization firms during the period studied.
5. The mean change in permanent income is positive since permanent income is calculated assuming that managers' will receive the (unweighted) average raise and since during the period studied, higher-paid managers received higher percentage increases in compensation.

Table 10. Influence of accounting variables by strategic nature of competition and disclosure policy

	Full sample	By strategic classification		By capital intensity (NIPA)		Firms with disclosure score			Conference call	
		Substitutes	Complements	High (> 1.5)	Low (< 0.75)	All	Score < 65	Score > 75	No	Yes
Dependent variable: Shareholder returns										
Obs.	3535	1323	1131	665	1190	1573	448	706	3405	2857
Firms	973	368	309	197	322	406	120	175	930	781
R-sq.	0.18	0.08	0.23	0.09	0.22	0.07	0.06	0.11	0.13	0.19
d ln(Sales)	-0.110***	-0.005	-0.300***	0.117	-0.273***	0.084**	0.087	0.005	0.081***	0.021
	(0.038)	(0.060)	(0.066)	(0.081)	(0.066)	(0.041)	(0.062)	(0.079)	(0.032)	(0.042)
d ln(Ebitda)	0.436***	0.223***	0.632***	0.136**	0.607***	0.131***	0.063**	0.352***	0.193***	0.337***
	(0.029)	(0.043)	(0.056)	(0.060)	(0.053)	(0.024)	(0.029)	(0.058)	(0.022)	(0.027)
Dependent variable: Log percentage change in managerial compensation										
Obs.	13810	5408	4273	2709	4496	6663	1930	2981	13612	10863
Firms	955	362	304	192	316	402	119	174	912	762
R-sq.	0.02	0.03	0.01	0.04	0.01	0.01	0.01	0.02	0.02	0.02
d ln(Sales)	0.118***	0.130**	0.037	0.414***	-0.036	0.249***	0.336***	-0.101	0.197***	0.206***
	(0.047)	(0.067)	(0.088)	(0.087)	(0.088)	(0.053)	(0.075)	(0.109)	(0.036)	(0.048)
d ln(Ebitda)	0.257***	0.290***	0.114*	0.119**	0.193***	0.057**	0.023	0.384***	0.127***	0.104***
	(0.033)	(0.046)	(0.068)	(0.062)	(0.065)	(0.026)	(0.029)	(0.075)	(0.021)	(0.028)
Dependent variable: Log percentage change in firm-related managerial wealth										
Obs.	13114	5112	4062	2544	4259	6353	1811	2898	12793	10370
Firms	952	362	303	192	315	402	119	174	908	762
R-sq.	0.10	0.08	0.10	0.07	0.10	0.05	0.04	0.09	0.06	0.10
d ln(Sales)	-0.055***	0.033	-0.179***	0.161***	-0.203***	0.131***	0.155***	0.006	0.065***	0.086***
	(0.020)	(0.030)	(0.036)	(0.041)	(0.037)	(0.021)	(0.030)	(0.041)	(0.015)	(0.021)
d ln(Ebitda)	0.267***	0.188***	0.320***	0.071***	0.329***	0.044***	0.005	0.251***	0.091***	0.146***
	(0.014)	(0.020)	(0.027)	(0.028)	(0.027)	(0.010)	(0.011)	(0.027)	(0.009)	(0.012)

Notes:
1. Regressions include firm random effects.

Table 11. Interaction of financial variables with strategic nature proxies and disclosure policies

	Strategic nature of competition proxies					Disclosure measures			Memo:
Interaction variable	Strat. Subs.	Capital-output (NIPA)	Capital-output (NBER)	TFP growth	Herfindahl	AIMR score	Conf. Calls .	Unqualified opinion	Unionization
Unionization controls	No	No	Yes	Yes	Yes	No	No	No	No
Dependent variable: Shareholder returns									
d Sales	0.294***	0.080**	0.087	-0.180***	-0.083	0.012	-0.060	-0.277***	-0.169***
	(0.089)	(0.037)	(0.059)	(0.047)	(0.054)	(0.039)	(0.052)	(0.063)	(0.047)
d Ebitda	-0.401***	-0.114***	-0.091***	0.136***	0.016	0.079***	0.145***	0.265***	0.075***
	(0.070)	(0.027)	(0.036)	(0.026)	(0.033)	(0.014)	(0.035)	(0.043)	(0.029)
Dependent variable: Change in compensation									
d Sales	0.104	0.105**	-0.103*	-0.153***	0.330***	-0.077	0.017	-0.352***	-0.172***
	(0.109)	(0.045)	(0.061)	(0.057)	(0.062)	(0.052)	(0.059)	(0.076)	(0.047)
d Ebitda	0.177**	-0.023	0.045	0.153***	-0.068**	0.070***	-0.023	0.287**	0.104***
	(0.080)	(0.031)	(0.035)	(0.028)	(0.033)	(0.017)	(0.034)	(0.047)	(0.027)
Dependent variable: Change in firm-related executive wealth									
d Sales	0.213***	0.084***	-0.020	-0.141***	0.050*	-0.016	0.023	-0.185***	-0.150***
	(0.046)	(0.019)	(0.027)	(0.025)	(0.028)	(0.021)	(0.025)	(0.031)	(0.021)
d Ebitda	-0.133***	-0.072***	-0.049***	0.097***	-0.020	0.057***	0.054***	0.235***	0.061***
	(0.033)	(0.013)	(0.015)	(0.012)	(0.014)	(0.006)	(0.014)	(0.019)	(0.012)

Notes:
1. Coefficients displayed are from interactions of accounting variables and strategic nature or disclosure policy proxies in regressions which also contain the uninteracted accounting variables and interactions variable.
2. All regressions contain firm random effects

Table 12. Determinants of compensation controlling for shareholder returns

Dependent variable: Log percent change in total compensation less option grants

Interaction variable	Strat. Subs.	Capital-output (NIPA)	Capital-output (NBER)	TFPG	Herfindahl	AIMR score	Conf. Calls	Unqualified opinion
Obs.	12655	18252	14291	14291	14218	8572	31813	20038
Firms	676	970	749	749	746	406	1706	984
R-sq.	0.07	0.07	0.09	0.09	0.09	0.07	0.08	0.07
d ln(Sales)	-0.230**	-0.078*	-0.169***	-0.023	-0.022	0.024	-0.076	-0.119*
	(0.108)	(0.045)	(0.049)	(0.052)	(0.056)	(0.050)	(0.056)	(0.074)
d ln(Ebitda)	0.078	0.015	0.081***	0.080***	0.114***	0.053***	0.067*	0.113**
	(0.082)	(0.032)	(0.026)	(0.028)	(0.029)	(0.017)	(0.035)	(0.050)
Shareholder returns	0.229***	0.083***	-0.054**	-0.074***	-0.024	0.078***	-0.018	-0.022
	(0.046)	(0.018)	(0.025)	(0.016)	(0.020)	(0.030)	(0.026)	(0.041)

Notes:

1. Coefficients displayed are from interactions of accounting variables and strategic nature or disclosure policy proxies in regressions that also contain the uninteracted accounting variables and interaction variables.
2. All regressions contain firm random effects.

Annex Table 1. Outliers excluded from the analysis

	North American sample				World sample	
	Total		With AIMR data			
	Obs.	Firms	Obs.	Firms	Obs.	Firms
Total observations with disclosure data	60,206	9,325	2,615	536	75,105	10,458
Excluding:						
Finance; health, legal, and educational services; transport (except air); utilities	44,973	6,988	1,968	416	65,521	9,410
Assets > $1 million or missing	34,114	4,706	1,808	369	63,528	9,325
Short-term debt-to-assets > 100%	34,060	4,705	1,808	369	62,878	9,297
No prior year financial information	32,954	4,652	1,805	369	61,578	9,282
Abs(New equity-to-assets) > 50%	32,002	4,626	1,799	368	60,513	9,274
Abs(New debt-to-assets) > 50%	31,880	4,596	1,798	368	60,457	9,262
Short-term debt, new equity, new debt, or ROIC missing	17,105	3,570	793	257	47,907	8,370
Sample for regressions including assets	31,880	4,596	1,798	368	60,457	9,262
Sample for regressions including financial variables	17,105	3,570	793	257	47,907	8,370

Annex Table 2. Effect of industry strategic nature on disclosure policy -- North American sample

The regressions that are summarized in Table 4 are reported in their entirety. Sets of regressions using different measures of the nature of industry competition are reported in each panel. Each panel contains three specifications for each dependent variable that include different controls. The regressions using the NBER industry capital-output ratio include only manufacturing firms. The notes on Table 4 apply here as well.

	AIMR score	Conf. Call	Unqual. opin. no notes	Unqual. opin.	Big 6 auditor
Dep. variable type	Continuous	Probit	Probit	Probit	Probit
Obs.	597	1494	11106	8368	11069
Firms	193	1494	2310	2061	2302
R-sq.	0.19	0.15	0.12	0.33	0.21
Dep. variable mean		0.19	0.73	0.99	0.91
Strategic substitutes dummy	-8.867***	-0.206**	-0.199***	0.064	0.242***
	(1.736)	(0.082)	(0.043)	(0.172)	(0.094)
Assets ^ -0.2	-11.661***	-0.874***	0.194***	-0.427***	-0.688***
	(2.429)	(0.091)	(0.027)	(0.086)	(0.047)
New equity-to-assets	-0.462	-0.172***	0.117***	0.097**	-0.022
	(0.559)	(0.047)	(0.017)	(0.041)	(0.020)
New debt-to-assets	0.200	0.008	0.076***	0.117**	-0.033
	(0.590)	(0.044)	(0.017)	(0.055)	(0.023)
Short-term debt-to-assets	-2.465**	-0.007	-0.142***	-0.128***	-0.024
	(1.195)	(0.070)	(0.017)	(0.026)	(0.027)
ROIC	0.745	0.122	0.149***	0.074	-0.054
	(0.961)	(0.092)	(0.024)	(0.051)	(0.035)
Strategic substitutes dummy	-8.450***	-0.258***	-0.152***	-0.206**	0.111
	(1.444)	(0.075)	(0.034)	(0.082)	(0.068)
Assets ^ -0.2	-9.148***	-0.839***	0.060***	-0.335***	-0.559***
	(1.475)	(0.074)	(0.018)	(0.033)	(0.027)
Strategic substitutes dummy	-7.068***	-0.126*	-0.152***	-0.231***	0.048
	(1.520)	(0.070)	(0.034)	(0.081)	(0.063)

	AIMR score	Conf. Call	Unqual. opin. no notes	Unqual. opin.	Big 6 auditor
Dep. variable type	Continuous	Probit	Probit	Probit	Probit
Obs.	793	2171	17102	13147	17041
Firms	257	2171	3569	3252	3558
R-sq.	0.10	0.15	0.12	0.32	0.19
Dep. variable mean		0.20	0.74	0.99	0.90
Industry capital-output ratio (NIPA)	-3.564***	-0.127***	-0.046*	-0.015	0.039
	(0.899)	(0.042)	(0.019)	(0.061)	(0.032)
Assets ^ -0.2	-7.814***	-0.860***	0.178***	-0.417***	-0.661***
	(2.126)	(0.069)	(0.021)	(0.069)	(0.037)
New equity-to-assets	-0.279	-0.139***	0.124***	0.062	-0.020
	(0.472)	(0.039)	(0.014)	(0.039)	(0.016)
New debt-to-assets	-0.316	0.037	0.070***	0.007	-0.042**
	(0.474)	(0.038)	(0.014)	(0.049)	(0.018)
Short-term debt-to-assets	-1.404**	-0.032	-0.144***	-0.112***	-0.042**
	(0.663)	(0.061)	(0.013)	(0.020)	(0.019)
ROIC	0.249	0.051	0.187***	0.162***	-0.025
	(0.896)	(0.066)	(0.021)	(0.046)	(0.025)
Industry capital-output ratio (NIPA)	-4.046***	-0.172***	-0.018	-0.073***	-0.012
	(0.662)	(0.036)	(0.014)	(0.024)	(0.022)
Assets ^ -0.2	-7.326***	-0.788***	0.043***	-0.330***	-0.559***
	(1.304)	(0.056)	(0.014)	(0.028)	(0.022)
Industry capital-output ratio (NIPA)	-4.096***	-0.141***	-0.014	-0.117***	-0.078***
	(0.685)	(0.030)	(0.014)	(0.025)	(0.022)

	AIMR score	Conf. Call	Unqual. opin. no notes	Unqual. opin.	Big 6 auditor
Dep. variable type	Continuous	Probit	Probit	Probit	Probit
Obs.	559	1292	11266	8937	11230
Firms	174	1292	2268	2135	2264
R-sq.	0.12	0.12	0.14	0.30	0.19
Dep. variable mean		0.21	0.72	0.99	0.90
Industry capital-output ratio (NBER)	-2.461***	-0.075*	-0.060***	-0.026	0.028
	(0.774)	(0.043)	(0.022)	(0.098)	(0.069)
Assets ^ -0.2	-7.63***	-0.811***	0.161***	-0.391***	-0.668***
	(2.448)	(0.082)	(0.026)	(0.080)	(0.046)
New equity-to-assets	0.273	-0.112*	0.116***	0.023	-0.005
	(0.579)	(0.058)	(0.018)	(0.051)	(0.021)
New debt-to-assets	-0.462	0.059	0.056***	-0.022	-0.041*
	(0.571)	(0.050)	(0.018)	(0.064)	(0.022)
Short-term debt-to-assets	-0.951	-0.100	-0.144***	-0.097***	-0.032
	(0.726)	(0.087)	(0.017)	(0.027)	(0.023)
ROIC	0.586	-0.049	0.185***	0.167***	-0.065**
	(1.130)	(0.076)	(0.025)	(0.052)	(0.029)
Industry capital-output ratio (NBER)	-2.765***	-0.085**	-0.062***	-0.155***	0.010
	(0.614)	(0.037)	(0.019)	(0.034)	(0.046)
Assets ^ -0.2	-5.380***	-0.722***	0.012	-0.340***	-0.569***
	(1.745)	(0.066)	(0.019)	(0.038)	(0.030)
Industry capital-output ratio (NBER)	-2.397***	0.027	-0.066***	-0.027	0.176***
	(0.620)	(0.034)	(0.018)	(0.031)	(0.043)

	AIMR score	Conf. Call	Unqual. opin. no notes	Unqual. opin.	Big 6 auditor
Dep. variable type	Continuous	Probit	Probit	Probit	Probit
Obs.	793	2133	16863	12965	16817
Firms	257	2133	3504	3200	3495
R-sq.	0.13	0.14	0.13	0.33	0.18
Dep. variable mean		0.20	0.74	0.99	0.91
Firm capital-output ratio	-5.409***	-0.149***	-0.003	-0.006	0.047
	(1.159)	(0.043)	(0.019)	(0.050)	(0.032)
Assets ^ -0.2	-9.89***	-0.872***	0.185***	-0.385***	-0.642***
	(2.120)	(0.071)	(0.022)	(0.075)	(0.037)
New equity-to-assets	-0.059	-0.127***	0.122***	0.012	-0.016
	(0.477)	(0.039)	(0.014)	(0.040)	(0.017)
New debt-to-assets	0.078	0.049*	0.073***	0.056	-0.051***
	(0.481)	(0.038)	(0.015)	(0.049)	(0.018)
Short-term debt-to-assets	-1.26*	-0.027	-0.141***	-0.109***	-0.047***
	(0.662)	(0.060)	(0.014)	(0.020)	(0.019)
ROIC	-0.601	0.022	0.203***	0.166***	-0.017
	(0.943)	(0.070)	(0.023)	(0.053)	(0.028)
Firm capital-output ratio	-4.196***	-0.229***	-0.034***	-0.113***	-0.024
	(0.713)	(0.036)	(0.012)	(0.018)	(0.019)
Assets ^ -0.2	-8.967***	-0.799***	0.050***	-0.306***	-0.555***
	(1.327)	(0.058)	(0.015)	(0.030)	(0.023)
Firm capital-output ratio	-3.066***	-0.147***	-0.031***	-0.162***	-0.072***
	(0.717)	(0.027)	(0.012)	(0.019)	(0.020)

	AIMR score	Conf. Call	Unqual. opin. no notes	Unqual. opin.	Big 6 auditor
Dep. variable type	Continuous	Probit	Probit	Probit	Probit
Obs.	793	2171	17102	13147	17041
Firms	257	2171	3569	3252	3558
R-sq.	0.16	0.15	0.12	0.32	0.20
Dep. variable mean		0.20	0.74	0.99	0.90
Industry capital-output	-3.590***	-0.085***	-0.044**	-0.042	0.086**
ratio (firm data)	(0.702)	(0.032)	(0.018)	(0.071)	(0.038)
Assets ^ -0.2	-7.73***	-0.847***	0.180***	-0.415***	-0.670***
	(2.066)	(0.069)	(0.021)	(0.069)	(0.037)
New equity-to-assets	-0.247	-0.141***	0.123***	0.063*	-0.023
	(0.473)	(0.039)	(0.014)	(0.039)	(0.016)
New debt-to-assets	-0.313	0.034	0.070***	0.006	-0.042***
	(0.475)	(0.038)	(0.014)	(0.049)	(0.018)
Short-term debt-to-assets	-1.307**	-0.026	-0.143***	-0.112***	-0.043***
	(0.663)	(0.060)	(0.013)	(0.020)	(0.019)
ROIC	0.296	0.071	0.190***	0.161***	-0.021
	(0.879)	(0.067)	(0.021)	(0.046)	(0.026)
Industry capital-output	-4.013***	-0.129***	-0.025*	-0.082***	0.004
ratio (firm data)	(0.493)	(0.028)	(0.013)	(0.029)	(0.027)
Assets ^ -0.2	-7.180***	-0.780***	0.044***	-0.329***	-0.561***
	(1.267)	(0.056)	(0.014)	(0.028)	(0.022)
Industry capital-output	-4.045***	-0.124***	-0.020	-0.137***	-0.067***
ratio (firm data)	(0.505)	(0.027)	(0.013)	(0.029)	(0.026)

Annex Table 3. Effect of industry strategic nature on disclosure policy -- World sample

The regressions that are summarized in Table 5 are reported in their entirety. Sets of regressions using different measures of the nature of industry competition are reported in each panel. Each panel contains three specifications for each dependent variable that include different controls. The regressions using th NBER industry capital-output ratio include only manufacturing firms. The notes on Table 5 apply here as well.

	Consolidated	Unqualified opinion, no explan. notes	Unqualified opinion	US GAAP	Big 6 auditor
Obs.	15339	30533	30348	11300	30525
Firms	3226	5656	5594	2380	5657
Pseudo R-sq.	0.323	0.182	0.200	0.317	0.398
Dep. variable mean	0.913	0.822	0.978	0.023	0.740
Strategic substitutes dummy	-0.043	-0.279***	-0.413***	-0.034	0.025
	(0.073)	(0.030)	(0.063)	(0.172)	(0.046)
Assets ^ -.2	-3.215***	0.426***	-0.348	-9.627***	-2.818***
	(0.457)	(0.135)	(0.239)	(1.623)	(0.176)
New equity-to-assets	0.666*	0.344***	-0.090	0.882	0.201
	(0.343)	(0.125)	(0.298)	(0.833)	(0.135)
New debt-to-assets	0.442***	0.288***	0.068	-0.059	-0.235***
	(0.163)	(0.079)	(0.146)	(0.399)	(0.084)
Short-term debt-to-assets	0.558**	-1.063***	-0.656***	-0.802	0.197
	(0.255)	(0.087)	(0.175)	(0.488)	(0.122)
ROIC	0.340	1.132***	0.853***	0.842	0.086
	(0.374)	(0.125)	(0.158)	(1.143)	(0.130)
Strategic substitutes dummy	-0.034	-0.225***	-0.398***	0.033	0.011
	(0.070)	(0.029)	(0.060)	(0.155)	(0.045)
Assets ^ -0.2	-3.101***	0.337**	-0.491**	-9.558***	-2.793***
	(0.406)	(0.132)	(0.226)	(1.653)	(0.176)
Strategic substitutes dummy	-0.048	-0.228***	-0.396***	0.122	0.020
	(0.066)	(0.029)	(0.060)	(0.140)	(0.044)

Obs.	11598	26948	26142	7475	26938
Firms	2670	4887	4703	1731	4889
Pseudo R-sq.	0.422	0.221	0.230	0.264	0.388
Dep. variable mean	0.894	0.806	0.985	0.048	0.750
Industry capital-output	-0.178***	-0.121***	-0.103*	-0.132	-0.048
ratio (NBER)	(0.067)	(0.024)	(0.058)	(0.111)	(0.039)
Assets ^ -.2	-3.597***	0.536***	-0.501	-9.227***	-3.427***
	(0.556)	(0.141)	(0.329)	(1.435)	(0.207)
New equity-to-assets	0.850**	0.703***	-0.226	0.746	0.182
	(0.365)	(0.150)	(0.482)	(0.978)	(0.163)
New debt-to-assets	0.638***	0.061	-0.039	0.392	-0.241***
	(0.182)	(0.094)	(0.202)	(0.349)	(0.088)
Short-term debt-to-assets	1.176***	-1.425***	-0.599**	-0.977**	0.051
	(0.322)	(0.101)	(0.262)	(0.490)	(0.145)
ROIC	0.340	1.078***	0.804***	1.903	-0.245*
	(0.400)	(0.132)	(0.199)	(1.259)	(0.141)
Industry capital-output	-0.188***	-0.115***	-0.085	-0.170	-0.049
ratio (NBER)	(0.065)	(0.023)	(0.055)	(0.109)	(0.039)
Assets ^ -0.2	-3.571***	0.520***	-0.523*	-9.174***	-3.344***
	(0.505)	(0.138)	(0.300)	(1.472)	(0.198)
Industry capital-output	-0.101	-0.138***	-0.067	0.009	0.084**
ratio (NBER)	(0.062)	(0.023)	(0.053)	(0.095)	(0.036)

Obs.	26760	54861	54500	22141	54846
Firms	5368	9393	9291	4393	9395
Pseudo R-sq.	0.419	0.194	0.154	0.306	0.376
Dep. variable mean	0.904	0.810	0.981	0.024	0.757
Firm capital-output ratio	-0.220***	-0.132***	-0.130***	-0.346***	-0.049**
	(0.045)	(0.015)	(0.025)	(0.088)	(0.022)
Assets ^ -.2	-3.210***	0.557***	0.006	-8.825***	-2.968***
	(0.328)	(0.100)	(0.184)	(1.094)	(0.137)
New equity-to-assets	0.646**	0.564***	0.185	1.112*	0.227**
	(0.262)	(0.095)	(0.203)	(0.611)	(0.102)
New debt-to-assets	0.659***	0.220***	0.011	0.079	-0.169***
	(0.129)	(0.061)	(0.111)	(0.282)	(0.063)
Short-term debt-to-assets	0.377**	-1.237***	-0.543***	-1.243***	-0.018
	(0.193)	(0.072)	(0.141)	(0.346)	(0.100)
ROIC	-0.525**	0.991***	0.559***	0.959	0.040
	(0.240)	(0.102)	(0.133)	(0.785)	(0.108)
Firm capital-output ratio	-0.213***	-0.072***	-0.101***	-0.227***	-0.049**
	(0.041)	(0.014)	(0.022)	(0.079)	(0.019)
Assets ^ -0.2	-3.028***	0.563***	-0.028	-8.534***	-2.960***
	(0.291)	(0.098)	(0.180)	(1.092)	(0.133)
Firm capital-output ratio	-0.169***	-0.083***	-0.101***	-0.064	-0.011
	(0.040)	(0.013)	(0.022)	(0.056)	(0.020)

Obs.	24440	50160	49815	20598	50128
Firms	4966	8733	8631	4107	8729
Pseudo R-sq.	0.422	0.188	0.187	0.309	0.384
Dep. variable mean	0.901	0.816	0.982	0.025	0.753
Industry capital-output	-0.040*	-0.070***	-0.067***	-0.059*	0.008
ratio (NIPA)	(0.023)	(0.008)	(0.012)	(0.036)	(0.012)
Assets ^ -.2	-3.335***	0.499***	-0.410**	-8.652***	-3.027***
	(0.371)	(0.104)	(0.206)	(1.095)	(0.144)
New equity-to-assets	0.696**	0.476***	0.033	0.973	0.202*
	(0.279)	(0.100)	(0.252)	(0.609)	(0.108)
New debt-to-assets	0.526***	0.160**	-0.060	-0.091	-0.236***
	(0.131)	(0.063)	(0.124)	(0.286)	(0.065)
Short-term debt-to-assets	0.630***	-1.112***	-0.495***	-0.794**	0.097
	(0.211)	(0.072)	(0.159)	(0.338)	(0.097)
ROIC	0.245	1.178***	0.844***	1.654***	0.134
	(0.321)	(0.102)	(0.142)	(0.549)	(0.105)
Industry capital-output	-0.025	-0.055***	-0.065***	-0.049*	0.006
ratio (NIPA)	(0.020)	(0.007)	(0.011)	(0.028)	(0.012)
Assets ^ -0.2	-3.193***	0.411***	-0.486**	-8.702***	-3.011***
	(0.331)	(0.102)	(0.196)	(1.114)	(0.143)
Industry capital-output	-0.015	-0.058***	-0.062***	-0.005	0.016
ratio (NIPA)	(0.019)	(0.007)	(0.010)	(0.026)	(0.011)

Appendix A

Maximum likelihood estimation for Chapter 2

In this appendix we assume that rather than calculating expectations for a and b, clients calculate maximum likelihood estimates. We can think about combining the prior distribution $g(a, \lambda)$ and the function $b(a, \lambda)$ into a prior on a and $\beta = b^{-1}$, which we will call $f(a, \beta)$. For tractability, we will also assume that the prior distribution $g(a, \lambda)$ is such that the distribution $f(a, \beta)$ is concave in logs for both variables, i.e. $\frac{d^2 \ln f(a,\beta)}{da^2} \leq 0$ and $\frac{d^2 \ln f(a,\beta)}{d\beta^2} \leq 0 \, \forall x$, a condition that is satisfied by the normal and chi-squared distributions, for example. We also assume that $V = Var(y_j | x_j)$ is known.

Given these assumptions, the log likelihood function is:

$$\ln L(x, y, a, \beta) = \sum_{j=1}^{J} \ln \phi(\frac{\beta x_j}{a^{1/2}}) + \sum_{j=1}^{J} \ln \phi(\frac{y_j - x_j \beta}{V^{1/2}}) + \ln[f(a, \beta)],$$

where $\phi(\cdot)$ is the standard normal p.d.f. The maximum likelihood estimators of a and b satisfy the conditions:

$$\begin{aligned}
\widehat{a}_{MLE} &= \widehat{\beta}_{MLE}^2 \frac{\sum_{j=1}^{J} x_j^2}{J} + \frac{f_a(\widehat{a}_{MLE}, \widehat{\beta}_{MLE})}{f(\widehat{a}_{MLE}, \widehat{\beta}_{MLE})} \cdot \frac{\widehat{a}_{MLE}^{3/2}}{J} \\
\widehat{\beta}_{MLE} &= (1 + \frac{V}{\widehat{a}_{MLE}})^{-1} [\frac{\sum_{j=1}^{J} x_j y_j}{\sum_{j=1}^{J} x_j^2} + \frac{f_\beta(\widehat{a}_{MLE}, \widehat{\beta}_{MLE})}{f(\widehat{a}_{MLE}, \widehat{\beta}_{MLE})} \cdot \frac{V}{\sum_{j=1}^{J} x_j^2}].
\end{aligned}$$

We have assumed that $\frac{f_a}{f}$ is monotonically decreasing in a, so the second term in the expression for a will be positive (negative) when a is less (greater) than the mode of the prior distribution. The maximum likelihood estimate of a will thus be between $\widehat{\beta}^2_{MLE}\widehat{Var}(x_j)$ and the mode of the prior. The first factor in the maximum likelihood estimate of β induces a bias toward zero that is a artifact of our taking a maximum likelihood approach to estimation. Ignoring this factor, the maximum likelihood estimate of β will be between $\widehat{\beta}_{OLS}$ and the mode of the prior, with more weight being placed on the prior when V is large.

Thus the MLE is similar in structure to the estimating approach assumed in (9):

$$\widehat{a}_P = \frac{(\widehat{\beta}^2_{CL} + \gamma \cdot \beta_0^2) \cdot \widehat{Var}(x_j) + \delta \cdot a_0}{1 + \gamma + \delta}.$$

The estimate of β is some weighted average of the observed β_{CL} and the mean of the prior distribution β_0. Ability is estimated in turn as some weighted average of $\widehat{\beta}^2_{MLE}\widehat{Var}(x_j)$ and the mean of the prior distribution. The weight placed on the prior belief about exaggeration, γ, is increasing in V and decreasing in J, i.e. it is higher when realizations are noisy or when the number of observations is small.

Appendix B

Proof of Proposition 1 in Chapter 2

We know that $E(\widehat{\beta}_{JK}|\widehat{\beta}_J)$ is between $w^{-1}\widehat{\beta}_J$ and β_K. Since $w^{-1}\widehat{\beta}_J = E(\beta_K|\widehat{\beta}_J)$, this implies that β_K will be above $E(\widehat{\beta}_{JK}|\widehat{\beta}_J)$ when it is above client's expectation based on the observed $\widehat{\beta}_J$. If we define $\triangle\beta = \beta_K - E(\widehat{\beta}_{JK}|\widehat{\beta}_J)$, we can rewrite the first order condition as

$$\begin{aligned} E(\widehat{\beta}_{JK}|\widehat{\beta}_J) + \triangle\beta &= \frac{wE(\widehat{\beta}_{JK}|\widehat{\beta}_J)^2 - \gamma\beta_0^2 + \lambda}{wE(\widehat{\beta}_{JK}|\widehat{\beta}_J) + \lambda} \\ E(\widehat{\beta}_{JK}|\widehat{\beta}_J) &= \frac{\lambda(1-\triangle\beta) - \gamma\beta_0^2}{\lambda + w\cdot\triangle\beta} \\ \beta_K &= E(\widehat{\beta}_{JK}|\widehat{\beta}_J) + \triangle\beta = \frac{\lambda - \gamma\beta_0^2 + w(\triangle\beta)^2}{\lambda + w\cdot\triangle\beta} \\ \beta_K &= \beta_1 - \frac{wE(\widehat{\beta}_{JK}|\widehat{\beta}_J)\cdot\triangle\beta}{\lambda}. \end{aligned}$$

If we define $\beta_1 = \lambda^{-1}(\lambda - \gamma\beta_0^2)$ to be the optimal one-period beta, we can multiply both sides of the above expression by $\lambda^{-1}(\lambda + w\cdot\triangle\beta)$to get:

$$\beta_K = \beta_1 - \frac{wE(\widehat{\beta}_{JK}|\widehat{\beta}_J)\cdot\triangle\beta}{\lambda}$$

This implies that β_K is less than β_1 if and only if it is greater than $E(\widehat{\beta}_{JK}|\widehat{\beta}_J)$ and $E(\beta_K|\widehat{\beta}_J)$.

Appendix C

Proof of Propositions 3 and 5 in Chpater 3

C.1 Proposition 3

If we call $m = \begin{bmatrix} \beta_i' \\ \gamma_i' \end{bmatrix}$ the vector of incentives, we can write the first order condition to the principal's contracting problem as $V_m = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$. If we take the total differential of this first order condition with respect to profit noise, we get that:

$$\begin{aligned} V_{mm}\frac{dm}{dn_i} + \frac{dV_m}{dn_i} &= V_{mm}\begin{bmatrix} \frac{d\beta_i'}{dn_i} \\ \frac{d\gamma_i'}{dn_i} \end{bmatrix} + \begin{bmatrix} -\rho\beta_i' - h\frac{\mu}{n_i}\gamma_i' \\ \frac{h}{\mu n_i}\beta_i' \end{bmatrix} = 0 \Rightarrow \\ \begin{bmatrix} \frac{d\beta_i'}{dn_i} \\ \frac{d\gamma_i'}{dn_i} \end{bmatrix} &= V_{mm}^{-1}\begin{bmatrix} \rho\beta_i' + h\frac{\mu}{n_i}\gamma_i' \\ -\frac{h}{\mu n_i}\beta_i' \end{bmatrix}. \end{aligned}$$

The conditions for $\frac{d\beta_i'}{dn_i} < 0, \frac{d\gamma_i'}{dn_i} > 0$ are respectively (using the fact that the determinant of V_{mm} is positive at an optimum):

$$V_{\beta\gamma} < -\frac{\frac{h}{\mu n_i}\beta_i'}{\rho\beta_i' + h\frac{\mu}{n_i}\gamma_i'} V_{\gamma\gamma} \tag{C.1}$$

$$V_{\beta\gamma} < -\frac{\rho\beta_i' + h\frac{\mu}{n_i}\gamma_i'}{\frac{h}{\mu n_i}\beta_i'} V_{\beta\beta}. \tag{C.2}$$

Taking the derivative of the principal's first order condition yields the following expressions for $V_{\beta\beta}, V_{\beta\gamma} = V_{\gamma\beta}, V_{\gamma\gamma}$:

$$\begin{aligned} V_{\beta\beta} &= \pi_{\beta\beta}(1-\beta_i') - \pi_{\gamma\beta}\cdot\gamma_i' - \rho(n_i + \sigma_\pi^2) - \frac{v}{\mu} \\ V_{\beta\gamma} &= \pi_{\beta\gamma}(1-\beta_i') - \pi_{\gamma\gamma}\cdot\gamma_i' - \rho\sigma_{\pi r} + v \\ V_{\gamma\gamma} &= \pi_{\gamma\gamma}(1-\beta_i') - r_{\gamma\gamma}\cdot\gamma_i' - \rho\sigma_r^2 - v\mu, \end{aligned}$$

where $\pi_{\beta\beta} = \frac{\partial\pi_\beta}{\partial\beta} = 2\pi_a' W^{-1}\Pi_{aa}W^{-1}\pi_a$, $\pi_{\beta\gamma} = 2\pi_a' W^{-1}\Pi_{aa}W^{-1}r_a = \pi_{\gamma\beta} = \pi_a' W^{-1}R_{aa}W^{-1}\pi_a + r_a' W^{-1}\Pi_{aa}W^{-1}\pi_a$, $\pi_{\gamma\gamma} = r_a' W^{-1}\Pi_{aa}W^{-1}r_a + \pi_a' W^{-1}R_{aa}W^{-1}r_a = r_{\beta\gamma} = \pi_a' W^{-1}R_{aa}W^{-1}r_a + r_a' W^{-1}\Pi_{aa}W^{-1}r_a$, $r_{\gamma\gamma} = 2r_a' W^{-1}R_{aa}W^{-1}r_a$ (ignoring any terms involving W_{aaa} since we assumed these third-order effects would be small).

We know that all these terms are negative since W^{-1} is positive definite and Π_{aa}, R_{aa} are negative definite (since this implies that the symmetrical expressions are negative, which together with the $\pi_{\beta\gamma} = \pi_{\gamma\beta}$ and $r_{\beta\gamma} = \pi_{\gamma\gamma}$ identities, implies that the non-symmetrical terms are). The terms involving ρ are all positive when $\sigma_{\pi r} > 0$. We know that when accounting incentives are costless ($h = v = 0$), conditions (4) and (5) are satisfied since $V_{\beta\beta}, V_{\beta\gamma}, V_{\gamma\gamma} < 0$. We also know that when accounting incentives are very costly ($h \to \infty$), conditions (4) and (5) converge to $V_{\beta\gamma} < -V_{\beta\beta}\cdot\mu$, and $V_{\beta\gamma} < -V_{\beta\beta} \div \mu$ since $\frac{\beta_i'}{\gamma_i'} \to \mu$. Since conditions (4) and (5) hold for the two extreme values of h, they also hold for intermediate values.

C.2 Proposition 5

The first statement follows from Assumption 4 and Proposition 3. The second follows from the fact that $[(a_n^i)'\frac{\partial V_{-i}^D}{\partial a_i}][\frac{\partial V_{-i}^{D}}{\partial a_i}' A a_n^i]$ is positive (negative) when A is negative (positive) definite, since $\frac{\partial V_{-i}^D}{\partial a_i}\frac{\partial V_{-i}^D}{\partial a_i}'$ is positive definite (like all outer products of a vector). Since the participation deterrence effect, $(a_n^i)'\frac{\partial V_{-i}^D}{\partial a_i}$, is always negative, the strategic response effect, $\frac{\partial V_{-i}^D}{\partial a_i}' A a_n^i$, is positive (negative) when A is negative (positive) definite.

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