“Lowballing” in Analysts’ Forecasts

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Abstract: We investigate the incentives for analysts to "lowball" (i.e., issue downward biased forecasts that are easy to meet or beat) and how this relates to the behavior of investors and managers. We find that downward biases in analyst forecasts are associated with lower volatility of forecast errors (i.e., more consistent errors) and that investors react more to biased but consistent forecasts. These more informative forecasts reduce information asymmetry in financial markets. Because "lowballing" implies forecasts that can be met or beat, meeting / beating signals a "lowballing" manager-analyst relationship, and precipitates a meet-or-beat price reaction premium due to the expected lower level of future information asymmetry in the financial markets. Investors implicitly reward analysts for consistency and managers for meeting or beating forecasts by reacting more strongly in both cases. This gives analysts an incentive to "lowball" if managers reciprocate by supplying information to analysts. We also find that both reactions are stronger when institutional ownership is larger because sophisticated investors can obtain more information out of biased but consistent forecasts.

"Lowballing" in Analysts' Forecasts

1. Introduction.

In this paper, we examine the link between analysts "lowballing" their forecasts and the behavior of investors and managers. Prior research on analyst forecasts has documented several empirical results. First, analysts appear to underreact to prior earnings announcements and fail to fully adjust to past forecast errors in their subsequent expectations (e.g., Abarbanell and Bernard (1992), Shane and Brous (2001)). More specifically, prior quarters forecast errors can predict current forecast errors. Second, analysts systematically produce biased estimates of quarterly forecasts that are, on average, lower than the realizations (e.g., Degeorge, Patel, and Zeckhauser (1999)). In addition, several studies (e.g., Bartov, Givoly, Hayn (2002) and Kaznik and McNichols (2002)) document that investors assign a valuation premium to firms that meet or beat expectations of earnings based on analysts forecasts.

In revisiting these issues, we propose the following explanations for these different findings. Given the positive market reaction around earnings announcements, managers prefer that analysts issue forecasts they can easily beat (i.e. "lowball" forecasts). To facilitate this, managers reward analysts that issue "lowball" forecasts with private information. Analysts can use that information to produce more useful, albeit biased, forecasts. These biased forecasts are more useful in the sense that, after removing the bias, the forecasts are closer to the firm's announced earnings than they would be without the private information supplied by managers. Sophisticated investors understand this arrangement between managers and analysts and can (at little or no cost) correct for the "lowball" bias. Because these "lowball" forecasts are more useful in predicting future realized earnings, they precipitate greater price reactions, particularly in firms with high sophisticated-investor ownership.

This explanation generates the following empirical predictions. First, because analysts base their forecasts on superior private information (from managers), their private (unreported) expectations tend to be closer to the firm's announced earnings. The forecast error is then largely driven by a stable systematic bias introduced by analysts instead of a random error component. Consequently, the forecast error for a given analyst should exhibit lower variance over different quarters. Second, if investors unravel this systematic bias, the biased forecasts are more informative. Thus, these forecasts induce greater price reactions than unbiased or optimistic forecasts. If sophisticated investors are better at unraveling systematic biases, the biased forecasts should engender a greater market reaction when the percentage of the firm held by sophisticated investors is higher. Third, because investors can extract more information from biased but consistent forecasts, the subsequent information asymmetry in the financial markets should be reduced for firms that meet or beat forecasts. Since sophisticated investors can extract more information from these forecasts, the reduction in information asymmetry should be stronger for firms with a greater proportion of institutional investors. Finally, because "lowballing" implies forecasts that can be met or beat, meeting / beating signals a "lowballing" manager-analyst relationship, and precipitates a meet-or-beat price reaction premium due to the expected higher level of transparency in the financial markets. Again, this is should be stronger when sophisticated investor ownership is higher.

Our results are consistent with these predictions. They indicate that analysts who have a propensity to "lowball" are more consistent in their forecast errors (i.e., the volatility of their forecast error is lower) than those who avoid "lowballing".[1] Although this higher consistency slightly increases their averaged forecast error, this small decrease in accuracy does not reduce the informativeness of their forecasts (i.e., their ability to move prices). Overall, we also find

[1] We explain in Section 2.5 in a game theoretical framework why analysts may choose not to "lowball".

that forecasts from analysts who "lowball" are more informative. These findings suggest that analysts strategically ignore past forecast errors when they issue new forecasts. We then turn our attention to the investors and we examine how they react to earnings forecasts. Hilary and Hsu (2007) find that more consistent forecasts move prices more. We find that analysts' consistency (but not accuracy) is more relevant to explain variations in forecasts informativeness when institutional ownership is greater, consistent with these sophisticated investors extracting more information from biased forecasts than naïve investors. We next examine the effects of "lowball" earnings forecasts on information asymmetry between informed and uninformed market participants. We find that the probability of informed trading when firms meet or beat analysts forecasts is reduced in the following quarter. The effect is stronger for firms with a greater proportion of institutional investors. This result reinforces that "lowball" forecasts improve transparency in financial markets. Finally, we find that the market reaction to meeting or beating analyst forecasts is positive, and particularly when institutional shareholding is larger, suggesting that investors who react more to pessimistic (but consistent) forecasts also react more when managers meet or beat forecasts. This behavior is rational for investors if meeting or beating earnings signals an improvement in future transparency of financial markets caused by the collaboration between managers and analysts.

In summary, our results indicate that analysts trade-off biases for consistency. Because *reported* forecasts are systematically below realization, they are slightly less accurate but more consistent, and ultimately more informative. This greater informativeness stems from more accurate (unreported) private analyst expectations. These informativeness increases the analysts capacity to move price. If analysts value this influence in financial markets, they have an incentive to exhibit systematic and persistent errors. Managers can help analysts to achieve greater consistency in their forecasts errors by providing relevant information. They have an incentive to do so if analysts reciprocate by "lowballing". In turn, investors, particularly the sophisticated ones, implicitly reward consistent analysts by reacting more to their forecasts and implicitly reward cooperative managers by reacting more positively to cases when firms meet or beat forecasts. Therefore, the positive reaction to earnings announcements of firms that meet or beat forecasts may not be (at least, not entirely) a reaction to news about earnings. Instead, the market may react positively to indications that analysts and managers are collaborating, which leads investors to rationally anticipate more informative analysts' forecasts and more transparent financial markets in the future. These different results suggest that the objectives and behavior of the analysts, investors, and managers are congruent. To the extent that analysts, investors, and managers do not deviate from a cooperating equilibrium, systematic biases improve transparency in financial markets, particularly when sophisticated investors hold larger equity stakes.

Our study contributes to the literature in several ways. First, we show that the main benefit for analysts associated with issuing pessimistic quarterly forecasts is not to increase the accuracy but rather the consistency of the reported forecasts. This finding is related to recent research as follows. Chen and Matsumoto (2006) report that favorable recommendations improve accuracy of analyst reported forecasts. In contrast to their study, we focus on favorable earnings forecasts instead of recommendations. Ke and Yu (2006) report that reported forecasts that are optimistic at the beginning of the period and pessimistic at the end are more accurate. In contrast to both studies, we focus on the effect of "lowballing" on forecast consistency. In addition, prior literature (e.g., Hilary and Hsu (2007)) suggests that consistency is more relevant than accuracy in determining forecasts informativeness of quarterly forecasts. Our results reveal that pessimistic forecasts are more informative than optimistic or unbiased forecasts. To the best of our knowledge, the effect of biases on informativeness of forecasts has not been directly studied in prior literature. Second, we show that these findings are conditional on the sophistication of the investors. We show that sophisticated investors react more than naïve investors to forecasts issued by analysts who were pessimistic in the past and to earnings announcements that meet or beat consensus forecasts. This provides additional understanding of the cross-sectional variations in the issuance of pessimistic forecasts by analysts. Finally, we study in an integrated approach the behavior of the analysts, investors, and managers and show how the different branches of literature can be reconciled. Our hypotheses link "lowballing", consistency, PIN, and the positive reaction around meeting and beating earnings forecasts in a coherent framework. We also discuss the role of investor sophistication in this framework. We provide empirical results that match our predictions.

The rest of the paper proceeds as follows. Section 2 develops our hypotheses. Section 3 describes our main empirical results. Section 4 presents some additional empirical analyses. Section 5 concludes.

2. Hypotheses development

We investigate the incentives faced by analysts, investors, and managers and we analyze them in a coherent framework. First, we motivate that analysts have incentives to bias their forecasts downward to increase their consistency and their informativeness (hypothesis H1). We then consider investors behavior and predict that sophisticated investors react more to consistently biased but informative forecasts than naïve investors (H2). We then argue that this "lowballing" activity should increase the transparency of financial market, particularly in the presence of more sophisticated investors (H3). Finally, we hypothesize that meeting or beating analysts' forecasts, the counter-part of "lowballing" forecasts, is more important for managers and investors when investors are more sophisticated (H4). We also explain in Section 2.5 why not all analysts and managers collaborate.

1) "Lowballing" and forecast properties.

Hilary and Hsu (2007) show that analysts who are more consistent in their forecast errors have a greater capacity to move equity prices with their forecasts, are less subject to post-forecast announcement drift, and have better career prospects. In addition, Hong and Kubik (2003) indicate that "brokerage house research directors […] point out that brokerage houses want analysts who are influential among the buy-side and that this influence is ultimately tied to making the right calls." If analysts want to maximize their capacity to influence financial markets, they may therefore have an incentive to minimize the variance of the forecast errors rather than to maximize the accuracy of their forecasts. Of course, accuracy and consistency are not necessarily mutually exclusive and analysts could still produce unbiased forecasts with minimum variance. By doing so, analysts could achieve both accuracy and consistency. However, this scenario is not necessarily descriptive of reality. One possibility is that analysts strategically induce a downward bias in their forecasts to curry favor with management that lead to better access to private information.

Prior literature suggests that managers derive benefits out of reporting earnings that are higher than the analysts' forecasts and reward analysts who facilitate this pattern with information (e.g., Brown and Caylor (2005)). Research also has found that managers are in position where they can help analysts to form more accurate expectations of earnings realizations. For example, Bowen, Davis, and Matsumoto (2002) find that analyst forecast accuracy increases when firms host conference calls in conjunction with their earnings announcement. These findings suggest that company-provided information improves an analyst's ability to accurately forecast a firm's earnings. Prior research (e.g., Francis and Philbrick (1993), Lim (2001), Matsumoto (2002)) has found that analysts are willing to accommodate managers' demands to curry their favors. Chen and Matsumoto (2006) find that analysts who issue more favorable recommendations experience a greater increase in their relative forecast accuracy compared with analysts with less favorable recommendations.[2] Ke and Yu (2006) show that the trend in forecasts of annual earnings influences the accuracy.[3] These results are consistent with the hypothesis that analysts rely on biased reports to appease executives in order to obtain better access to management's private information. In this context, the difference between reported forecasts and earnings is not due to a random component but rather to a predictable systematic bias introduced by analysts. This should generate a greater consistency in the errors of their reported forecasts. This discussion motivates our first hypothesis:

H1a: The forecast consistency is greater for analysts who "lowball" than for the ones who do not.

[2] Chen and Matsumoto (2006) focus on the effect of buy-sell recommendations. We focus on the effect of biases in quarterly earnings forecasts.
[3] Our study is different from Ke and Yu (2006) in several respects. First, we focus on forecast error consistency instead of forecast error accuracy. Hilary and Hsu (2007) suggest that consistency is more relevant for the informativeness of analyst forecasts and for analyst careers than forecast accuracy. Second, we consider the behavior of the analysts, investors, and managers in an integrated framework instead of focusing on analyst behavior. Third, we consider how the degree of investor sophistication affects the behavior of the analysts. Finally, Ke and Yu (2006) consider the evolution of the bias from initially optimistic to finally pessimistic. We focus quarterly forecasts and we concentrate on the bias at the end of the quarter. An advantage of focusing on quarterly forecasts instead of yearly forecasts is that the sample size is significantly larger. A drawback is that it is difficult to estimate any time trend within a quarter. We therefore focus on the bias in the last forecast for the quarter.

If investors can unravel at little cost the systematic biases in earnings forecasts, the "lowballing" forecasts should be more informative because they are based on more accurate (unreported) analyst expectations. Consistent with this view, Hilary and Hsu (2007) note that forecasts issued by more consistent analysts affect price more and that, controlling for the level of consistency, accuracy of *reported* forecast does not significantly affect informativeness. To the extent that "lowballing" increases forecast consistency, we expect that it should also increase forecast informativeness:[4]

H1b: The informativeness of forecasts is greater for analysts who "lowball" than for the ones who do not.

2) Investors behavior vis-à-vis earnings forecasts.

We then examine if all types of investors similarly value consistency in forecast errors. We expect that sophisticated investors are better able to unravel systematic biases than naïve investors. Thus, sophisticated investors should prefer forecasts with biases if these biases reduce random errors, even if they also reduce accuracy. This proposition relates to the findings of Hand (1990) and Collins, Gong, and Hribar (2003), among others. Hand (1990) finds that institutional investors are less fixated on reported earnings and are able to identify systematic biases in reported earnings caused by debt-equity swaps. Collins, Gong, and Hribar (2003) show that sophisticated investors can better price accruals than naïve investors and that institutional

[4] Note, however, that that link between "lowballing" and informativeness is fairly complex because investors do not observe the true consistency of the analyst but only a noisy estimation. Some analysts may appear to be consistent in sample just by chance. For these analysts, past consistency should not be an indicator of future consistency and should not lead to a higher market reaction to their forecasts. It is obviously difficult for investors to distinguish between analysts that are truly consistent and those that merely appear to be consistent. However, to the extent that analysts who "lowball" are more likely to be consistent, investors may use the degree of "lowballing" to filter the noise in the estimation of analyst consistency and give more weight to analysts who lowball, even after controlling for the degree of apparent consistency.

investors have greater resources for gathering and processing information contained in financial reports. If institutional investors are better at processing information (as suggested by prior literature), they should be better at unraveling systematic biases in analyst forecasts and should value consistency more than individual investors, motivating our next hypotheses:

H2: Consistency is more important for the informativeness of forecasts when there are more institutional investors among shareholders than in firms when there are fewer institutional investors.

H2 focuses on the relative importance of consistency conditional on investor sophistication. Investors who are totally unable to unravel biases and want to form accurate earnings expectations should only value accuracy. However, to the extent that even naïve investors can partially unravel biases, they should also value consistency. It is therefore likely that consistency will be relevant for both naïve and sophisticated investors but as hypothesized in H2, the relative importance should vary.

3) Institutional investors and managerial incentives.

We then consider the effect of investor clientele on the managers' incentives. Prior literature suggests that meeting or beating analysts forecasts (MBE) is important for managers. For example, Degeorge, Patel, and Zeckhauser (1999), Brown (2001) and Matsumoto (2002) find a disproportionate number of cases in recent years where earnings per share are slightly (by a few cents) above analysts' forecasts. Prior literature also suggests that financial markets assign a higher value to firms that meet expectations, controlling for an estimate of the firm's fundamental value. For example, Brown and Caylor (2005) find that the market reward to MBE is greater than meeting other earnings thresholds examined by Degeorge, Patel, and Zeckhauser (1999) and Burgstahler and Dichev (1997). Given the importance of MBE, managers prefer forecasts that are easier to meet or beat.

These findings can be related to our prior hypotheses. Specifically, our first hypothesis H1b suggests that investors extract more information from forecasts that are easier to meet or beat. This should make financial markets more transparent and trading on private information will be less common.[5] If meeting or beating earnings in a given period signals that "lowballing" is more likely in the future,[6] then more informative forecasts are also more likely in the future. If informative forecasts increase transparency, then meeting or beating analyst forecasts can be interpreted as a signal that markets will be more transparent in the future. Prior literature (e.g., Easley, Hvidkjaer, and O'Hara. (2002), Easley and O'Hara. (2004)) has shown that a reduction in information asymmetry should have a positive effect on equity price. We therefore expect that meeting and beating analyst forecasts should be associated with a positive market reaction. More importantly for our purposes, our second hypothesis H2 suggests that sophisticated investors are able to extract more information from consistent forecasts. If "lowball" forecasts increase consistency and informativeness, H2 also suggests that "lowball" forecasts should be more informative when there is greater institutional ownership. This implies that the effect of "lowballing" on market transparency should be larger in this case, leading to a more positive price reaction for firms that meet or beat forecasts.

This discussion generates several hypotheses. First, meeting and beating earnings should be associated with a reduction in the future information asymmetry between informed and

[5] We empirically investigate this assumption in Section 4.
[6] We empirically investigate this assumption in Section 4.

uninformed market participants. This prediction is consistent with the empirical findings of Brown, Hillegeist and Lo (2007). More importantly for our purposes, this effect should be stronger when institutional ownership is greater:

H3: Meeting and beating forecasts should be associated with a greater decrease in information asymmetry between informed and uninformed market participants when there are more institutional investors among shareholders than in firms when there are fewer institutional investors.

Relatedly, there should be a positive reaction when firms meet or beat earnings. The market reaction to meeting and beating the forecast should then be more positive when institutional ownership is larger than when it is smaller.

H4: The market reaction to meeting or beating analysts' forecasts should be greater for firms when there are more institutional investors among shareholders than in firms when there are fewer institutional investors.

4) Summary

If these different predictions are valid, the different incentives among managers, investors, and managers are congruent. Investors, particularly the sophisticated ones, should be able to extract more information from consistent forecasts. Hence, they should react more to these forecasts, which should reduce the future information asymmetry in the financial markets. To the extent that analysts value their capacity to move prices, they should issue more of these consistent forecasts when investors react more to consistent forecasts, for example, when investors are more sophisticated. One way to achieve this consistency is by accommodating managers by issuing forecasts that are easy to meet or beat. In return for this "lowballing", analysts may expect additional information that can help them improve consistency. Investors should react positively to signs of this collaboration and thus provide implicit incentives for both managers and analysts to collaborate. Specifically, we expect that more sophisticated investors should react more positively to cases when managers meet or beat forecasts because it provides evidence of a more valuable future collaboration between analysts and managers. This may explain why investors keep reacting positively to firms that meet or beat earnings forecasts. It may not be that investors are repeatedly surprised by earnings realizations but rather that they take the fact that a firm can meet or beat forecasts as an indication that managers and investors are collaborating to make financial markets more transparent. These different incentives may also explain why analysts appear to refuse to learn from past errors and why forecast errors appear to be persistent. Figure 1 provides a summary of our different predictions.

5) An illustrative game theoretical example

Our different hypotheses can be understood in a game theoretical framework. Suppose that analysts and managers interact (investors react to the outcome of the game played by analysts and managers). Managers can either disclose information to analysts or refuse to disclose any information. If managers disclose information, analysts can form more consistent forecasts. Investors always reward analysts for issuing consistent forecasts but sophisticated investors value consistent forecasts more than naïve investors. Therefore, the reward is greater when investors are more sophisticated. Analysts can either "lowball" or refuse to "lowball". To simplify the setting, we can assume that managers meet or beat analyst forecasts if and only if analysts "lowball". Investors always reward managers for meeting or beating the forecast but sophisticated investors value meeting or beating forecasts more than naïve investors. Therefore, the reward is greater when investors are more sophisticated. This reward is assumed to be exogenous for simplicity but we justify this assumption below. There is a small penalty incurred by the analyst if she "lowballs" and there is a small penalty incurred by the manager if she discloses the information to the analysts. For example, Hong and Kubik (2003) and Ke and Yu (2006) suggest the existence of psychic costs associated with biased forecasts. The cost for the manager can be motivated, for example, by the possibility that the disclosure may help a competitor in the product market. Figure 2 shows examples of such pay-off functions.

Analysts and managers play this game an infinite number of times (but we can allow that the game to end in each period with a constant probability without loss of generality). This framework is commonly described as a repeated prisoner's dilemma. It is well-known (e.g., Gibbons (1992)) that a "trigger-strategy" is a sub-game perfect Nash equilibrium if the discount rate for both the manager and the analyst is sufficiently low relative to the pay-offs. A "trigger-strategy" is one where a player cooperates until the other player fails to cooperate, which triggers a switch to non-cooperation afterwards. Everything else equal, the discount rate is more likely to be below to the cut-off point for collaboration if the pay-off is greater. In other words, assuming that discount rates are randomly distributed, we should observe a greater number of analysts and managers having sufficiently low discount rate when the pay-off is greater. This can explain why many analysts "lowball" and obtain more information from managers but some do not. We therefore expect that collaboration should occur more often when investors are more sophisticated than when they are naive. The reward implicitly received by managers who meet or beat forecast can then be motivated either as positive reaction of investors who see that analysts and managers are collaborating or alternatively as a strategic decisions made by investors to encourage managers to collaborate with analysts.

In this framework, H1a hypothesizes that the collaboration between analysts and managers is mutually beneficial (i.e., forecasts that "lowball" are more consistent). H1b hypothesizes that analysts are implicitly rewarded for issuing consistent forecasts and H2 that the implicit reward received by analysts for issuing consistent forecasts is greater in the presence of sophisticated investors than in the presence of naïve investors. H3 provides a rationale for investors to implicitly reward managers and investors for their collaboration and for sophisticated investors to do so more than naïve investors. H4 hypothesizes that managers are implicitly rewarded for meeting and beating forecasts and that the reward is greater in the presence of sophisticated investors than in the presence of naïve investors. In other words, our different hypotheses and tests examine either the assumption or the predictions of our simple game theoretical analysis.

3. Empirical results

1) Sample.

We obtain actual earnings and analyst forecast data from the I/B/E/S Detail History tapes over the period 1983 – 2005. We focus on quarterly forecasts. To obtain meaningful estimates of consistency for each firm-analyst, we drop firms with less than 5 analysts covering the firm and analysts with less than 12 prior quarter experience. For each firm-analyst, we use the last forecast issued by the analyst prior to earnings announcement and following previous earnings announcement. To test the market reaction to earnings announcements, we use all observations for which actual earnings and consensus analyst forecasts are available in I/B/E/S. Accounting data and stock price are from Compustat quarterly data files and stock return data are from CRSP daily files. We obtain data about institutional ownership from the Forms 13F as reported in Thomson Financial database. Except for binary and ranking variables, all data are winsorized at the 1% level.

We do not partition our tests between the pre- and post-Reg FD periods for several reasons. First, Reg FD was introduced in late 2000. Given that we need 12 quarters to estimate our measure of consistency, we could only obtain data for a couple of years. This largely precludes tests based on the post-regulation period. The implementation of the tests would also be complicated by the fact that several of our specifications already have multiple interactions. Second, it is not clear what the effect of this regulation should be in our context, even if the amount of information privately communicated to analysts is reduced. For example, managers could still selectively help analysts by accepting or refusing to answer certain questions. Alternatively, if the amount of publicly available information is really reduced, the relatively more rare cases when analysts obtain private information might have a greater impact on prices. In other words, even if the "quantity" of information has been reduced, the "price" might have increased, in which case the net effect is not determinable *ex ante*.

2) The effect of "lowballing" on consistency

To investigate hypothesis H1a, we consider the effect of "lowballing" on consistency. To do so, we estimate the following two models for analyst i, firm j and quarter t:

$$Cons_{i,j} = \alpha_0 + \alpha_1\, Lowball_{i,j} + \alpha_k\, X^k_{i,j} + e_{i,j} \qquad (1)$$

$$Cons_{i,j,t} = \alpha_0 + \alpha_1\, Lowball_{i,j,t} + \alpha_k\, X^k_{i,j,t} + \gamma_{ij}\, F_{i,j} + e_{i,j,t} \tag{2}$$

The two models are very similar but the first one is purely cross-sectional whereas the second is a panel specification with analyst-firm fixed effects. The variables are similarly defined but they are not calculated over the same period. In the cross-sectional model, they are calculated over the entire sample whereas they are calculated over a rolling window based on the last 12 quarters for the panel specification. To simplify the notation, we use the same name for the variables in the cross-sectional and panel specifications, even though the variables are calculated over different periods. This second approach is more appropriate than the first one if the analysts' characteristics are changing over time. The addition of such fixed effects is demanding for the data, but it minimizes the risk that a cross-sectional omitted variable may be driving our results. We therefore expect our results to be weaker in our panel specifications than in our cross-sectional ones.

Cons, our measure of consistency, is calculated in the following steps. First, we estimate the forecast error for analyst i following firm j in quarter t as I/B/E/S actual earnings minus forecast. Second, we calculate the standard deviation of forecast errors over all quarters he/she covered the firm. Third, we rank all the analysts who cover firm j in quarter t based on the standard deviation of forecast errors. Similarly, in cross-sectional tests, we rank all the analysts over the entire sample period. We then obtain the consistency ranking score similar to prior literature (e.g., Hong, Kubik and Solomon (2000), Hong and Kubik (2003), Ke and Yu (2006), Hilary and Hsu (2007)) using the following formula:

$$Cons = 1\text{-(rank-1) / (number of analysts in the quarter -1)}$$

Using rank variables is useful because this approach implicitly controls for the shocks that affect the firm and, therefore, all the analysts who cover it.

Lowball is calculated in the following steps. First, we estimate the forecast error for analyst i following firm j in quarter t as IBES actual earnings minus forecast. If this error is positive, we consider that the analyst has "lowballed" in this quarter. If the error is negative, we consider that the analyst has "high-balled". Forecasts that are perfectly accurate remain unclassified. Second, we calculate the frequency of "lowballing" as the difference between the number of pessimistic and optimistic forecasts, scaled by the total number of forecasts. *Lowball* therefore ranges between -1 and +1.

X^k represents a vector of K control variables. *Bold* represents the distance from the consensus, measured as the absolute value of the distance between the forecast and the consensus forecast (defined as the average forecasts from other analysts).[7] *Horizon* is the number of days between forecast date and earnings announcement date.[8] *Exp* is the number of quarters the analyst has followed the firm. *Breadth* is the number of firms followed by the analyst in a given quarter. Because we measure accuracy and consistency in terms of ranking, we also create similar ranking variables for *Bold*, *Horizon*, *Exp*, and *Breadth*. *Brokersize* is the log of number of analysts employed by brokerage house in the year when the forecast was issued. Finally, $F_{i,j}$ represents a vector of analyst-firm fixed effects.

We present some descriptive statistics in Table 1. As expected, the mean and median value of *Cons* is close to 0.5 since it represents normalized rankings between 0 and 1. Consistent with the idea that analysts tend to "lowball", 68% of earnings are meeting or beating the previous

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[7] We use the first forecast issued after the earnings announcement for quarter t -1 to define *Bold*. Specifically, we calculate the distance from consensus as: abs($forecast_{i,j,t}$ - (Σ $forecasts_{j,t}$ - $forecast_{i,j,t}$) / (number of analysts – 1)).

[8] Since we rank variable, *Horizon* also represents the rank of the forecasts among the different forecasts issued during the forecast.

forecast. The average value of *Lowball* is 0.28. Since the value range of *Lowball* between – 1 and + 1, a positive value indicate that analyst "lowball" more frequently than not. We also present the correlations between our main variables in Table 2. Consistent with H1a, the univariate correlation between *Lowball* and *Cons* is significantly positive (p-value equal 0.00). The correlations between the different control variables are low, suggesting that multicollinearity is not a major problem in our setting.

We tabulate the results from models (1) and (2) in Table 3. Column 1 reports the results from our cross-sectional specifications. Standard errors are corrected for heteroskedasticity using the Huber-White correction and clustering of observations by analyst. Results from our fixed-effect specifications are reported in columns 2. Standard errors are corrected for heteroskedasticity and clustering of observations by firm-analyst. Correcting for clustering by period does not change our conclusions. Consistent with H1a, results indicate that analysts who "lowball" are more consistent. The statistical significance of the relation is very high in all our models. The t-statistics are 24.51 in the cross-sectional specification and 10.92 in the panel one. Our cross-sectional results (untabulated) hold if we include either a firm fixed effect or an analyst fixed effect. The economic significance is such that increasing *Lowball* by one standard deviation increases consistency by approximately 10% of its mean value in the cross-sectional model or 8% in the panel one.[9] The results are similar but more significant if we remove the different control variables. The average Variance Inflation Factor (VIF) is only 1.03 in both models (the maximum is 1.05). This suggests that multicollinearity is not an issue in our sample. These results are consistent with H1a.

3) The effect of "lowballing" on accuracy.

[9] 0.154 * 0.341/0.503 = 10% and 0.101 * 0.379/0.500 = 8%

For completeness, we consider the effect of "lowballing" on forecast accuracy. However, in this case, we are unable to predict the direction of the effect. To understand this point, we can decompose the forecast error e for firm i, analyst j and time t as a systematic bias (b) and a random component (ε):

$$e_{i,,j,t} = b_{i,j} + \varepsilon_{i,j,t} \qquad (3)$$

where we assume (for convenience) that ε follow a normal distribution with mean zero and standard deviation $\sigma_{e,i,j}$. There is a potential trade-off between the bias and the magnitude of the random component. Everything else equal and absent any strategic game, increasing the absolute value of b will lead to a greater expected error (in absolute value). In other words, the absolute value of e in equation (3) should be greater for analysts who consistently "lowball". However, results in Table 3 suggest that analysts may be able to access better information. If true, this could reduce σ_e and improve the accuracy of the forecasts. The net effect is therefore undermined *ex ante*.

To empirically investigate this question, we repeat the analysis of the previous section but we substitute *Accu,* a measure of accuracy, as a dependent variable. We estimate two models very similar to (1) and (2).

$$Accu_{i,j} = \alpha_0 + \alpha_1\, Lowball_{i,j} + \alpha_k\, X^k_{i,j} + e_{i,j} \qquad (4)$$

$$Accu_{i,j,t} = \alpha_0 + \alpha_1\, Lowball_{i,j,t} + \alpha_k\, X^k_{i,j,t} + \gamma_m\, F_{ij} + e_{i,j,t} \qquad (5)$$

We define *Accu* similarly to *Cons*. First, we calculate accuracy as the absolute value of forecast errors for analyst i following firm j in quarter t. Second, in panel regressions, we rank all the analysts who cover firm j based on the accuracy. Third, we calculate the mean of the ranking scores. In panel regressions, we use the twelve prior quarters. In cross-sectional regressions, we use the entire sample period.

We report the results in Table 4. They suggest that there is a negative relation between "lowballing" and accuracy. *Lowball* is negative and significant in our two specifications (with t-statistics equal to -4.60 and -5.48 respectively). However, the economic effect is such that increasing *Lowball* by one standard deviation decreases accuracy by only 1% (using either the cross-sectional or the panel specifications), which is lower magnitude than the effect of *Lowball* on *Con*s.[10] The economic magnitude of the effect of "lowballing" on accuracy is therefore more limited than on consistency. As in Section 4.2, the VIF are well below the conventional threshold for multicollinerity and results hold when *Lowball* is the only independent variable.

4) The effect of "lowballing" on informativeness

Given that "lowballing" has a positive effect on consistency and only a limited effect on accuracy and given that consistency is more important for analysts forecasts informativeness (Hilary and Hsu (2007)), we expect that "lowballing" has a positive effect on analysts forecast informativeness (H1b). To investigate this prediction, we estimate two models similar to the one we use for consistency and accuracy.

The first one is the cross-sectional approach that we used above but we substitute $Beta_{i,j}$ a measure of informativeness as the dependent variable. To calculate $Beta_{i,j}$, we first estimate a regression of the buy-and-hold market-adjusted three-day return around forecast revision date *(Bhr3d)* on the earning forecast minus the prior consensus deflated by price two days prior to the forecast *(Rev)*. The consensus is calculated using the mean of the last three forecasts issued by other analysts. We obtain $Beta_{i,j}$, the coefficient associated with *Rev*, from this regression. We

[10] -0.011 * 0.341 / 0.505 = 1%, 0.016 * 0.379 / 0.512 = 1%

then regress $Beta_{i,j}$ on $Lowball_{i,j}$ and different control variables. Aside from the control variables that we use in Tables 3 and 4, we also include a vector (Y) of five firm-specific variables. We did not previously include these variables previously because our dependent variables were based on the ranks of analysts for a given firm and a given quarter. Firm-level variables should not affect these ranks. These 5 variables are *Coverage*, *Size*, *Mkt-to-Bk*, *Debt-ratio*, and *Stdroa*. *Coverage* is the log of number of analysts following the firm in a given quarter. *Size* is the log of market value of equity. *Mkt-to-Bk* is the ratio of the market value of equity over book value of equity. *Debt-ratio* is the debt to equity ratio. In the panel regressions, control variables are the average value over the previous twelve quarters. *Stdroa* is the log of the standard deviation of firm's return on asset over the previous twelve quarters. In the cross-sectional model, we use the average values of our different control variables for a given analyst over the entire periods of their respective variables and *Stdroa* is the log of the standard deviation of firm's return on asset over the entire sample.

$$Beta_{i,j} = \alpha_0 + \alpha_1\, Lowball_{i,j} + \alpha_k\, X^k_{i,j} + \beta_k\, Y^k_{i,j} + e_{i,j} \tag{6}$$

We also use a panel specification where we interact *Rev* with *Lowball* and include firm-analyst fixed effects:

$$Bhr3d_{i,j,t} = \alpha_0 + \alpha_1\, Lowball_{i,j,t} + \alpha_2\, Rev_{i,j,t} + \alpha_3\, Lowball{*}Rev_{i,j,t} + \alpha_k\, X^k_{i,j,t} + \beta_k\, Y^k_{i,j,t} + \gamma_{ij}\, F_{ij} + e_{i,j,t} \tag{7}$$

The key variable for our purpose in equation (7) is the interaction between *Lowball* and *Rev*. We expect *Lowball* in (6) and *Lowball*Rev* in (7) to be both significantly positive if "lowballing" increases forecast informativeness.

Results reported in Table 5 are consistent with our prediction. We find a positive effect of "lowballing" on analyst forecast informativeness. The corrected t-statistics are 21.71 and 8.02 respectively. Our cross-sectional results (untabulated) hold if we include either a firm fixed effect or an analyst fixed effect. The economic effect is such that increasing *Lowball* by one standard deviation increase *Beta* by approximately 15% in the cross-sectional specification[11]. As in the previous two sections, the VIF are well below the conventional threshold for multicollinerity (the highest value is 2.14) and results hold when *Lowball* is the only independent variable. These results are consistent with H1b.

Results from Sections 3.2 to 3.4 summarize the incentives for the analysts. Analysts who consistently "lowball" enjoy a greater consistency although their accuracy is marginally lower. The net effect is a greater informativeness of the forecasts they issue. This suggests that analysts strategically issue forecasts that can please managers.[12]

5) The effect of institutional ownership on the relation between consistency and informativeness.

Our next hypothesis is that consistency should be relatively more important for sophisticated investors than for naïve investors (Hypothesis H2). To test H2, we partition our sample based on the whether the firm has a high or low institutional ownership. To do so, we calculate *Inst* as the ratio of shares owned by an institution scaled by the shares outstanding. We

[11] 6.924 * 0.341 / 15.443 = 15%.
[12] We revisit this last issue in Section 4.

form *DInst*, an indicator variable that takes the value of one if *Inst* is above the median value in the sample, zero otherwise. To avoid multiple interaction terms, we focus on our cross-sectional model. We estimate model (8) for both sub-samples.

$$Beta_{i,j} = \alpha_0 + \alpha_1\, Cons_{i,j} + \alpha_k\, X^k_{i,j} + \beta_k\, Y^k_{i,j} + e_{i,j} \qquad (8)$$

Results for model (8) are reported in Columns 1 (low institutional ownership) and 2 (high institutional ownership) of Table 6. *Cons* is significant in both sub-samples with t-statistics of 8.57 and 11.02 respectively but, as expected, we find that the coefficient associated with *Cons* is 45% larger in the sample of higher institutional ownership than in the sample of low institutional ownership (5.513 versus 3.793). A chi-square test indicates that the difference is statistically significant with a p-value of 0.01. For completeness, we repeat our analysis using model (8) but we substitute *Lowball* and *Accu* for *Cons* in the regression. Results for *Lowball*, reported in Columns 3 and 4, are consistent with our prior findings. The magnitude and the statistical significance of the coefficients associated with *Lowball* are higher in the sample of with a high institutional ownership (7.73 with a t-statistic equal to 16.52 versus 6.41 with a t-statistic equal to 15.66). The difference in coefficients associated with *Lowball* in columns 3 and 4 is statistically different from zero (p-value equals 0.03). These results are consistent with H2. On the other hand, untabulated results indicate that *Accu* does not have a statistically different effect on informativeness conditional on institutional ownership.

6) The effect of institutional ownership on the relation between meeting and beating earnings forecasts and probability of informed trading (PIN).

Brown, Hillegeist, and Lo (2007) indicate that the probability of informed trading (PIN) is reduced when firms meet or beat consensus forecasts. If, as our hypothesis H2 suggests, institutional investors are able to extract more information when analyst forecasts are easier to beat and if institutional investors react more to earnings announcements when they are above analyst forecasts, price should be closer to intrinsic value for firms that meet or beat consensus forecasts when institutional ownership is greater. In this case, the probability of informed trading in the subsequent period should be reduced. To examine this prediction, we estimate models (9) and (10):

$$\Delta PIN_{i,j,\,t+1} = \alpha_0 + \alpha_1\, MBE_{i,j,t} + \alpha_2\, \Delta Size_{i,t} + \alpha_3\, \Delta Coverage_{\,i,t} + e_{i,t} \qquad (9)$$

$$PIN_{i,t} = \alpha_0 + \alpha_1\, MBC_{i,t} + \alpha_k\, Y^{k}_{i,j} + \varphi_j\, FF_j + e_{i,j} \qquad (10)$$

PIN represents the probability of informed trading in the quarter t+1. Brown, Hillegeist, and Lo (2007) describe PIN as the unconditional expectation of the fraction of total daily trades that are based on private information. We obtain the quarterly estimates from Stephen Brown's website.[13] *ΔPIN* represents the change in *PIN* from the quarter prior to earnings announcement to the subsequent one. Model (9) is similar to the specification in changes used in Brown, Hillegeist, and Lo (2007). It includes a control for change in firm size (*ΔSize*) and change in analyst coverage (*ΔCoverage*). Model (10) is a level specification. Our treatment variable, *MBC*, represents the number of times that a firm meets or beats earnings consensus forecasts in the last 12 quarter. Y^K is a vector of control variables that includes the five firm specific variables that we used in our previous regressions: *Coverage*, *Size*, *Market-to-Book*, *Leverage*, and *StdRoa*. *FF* is a vector of firm fixed effects. We first estimate model (9) and (10) for the

[13] http://userwww.service.emory.edu/~sbrow22/

overall sample. We then estimate both models in samples of firms that have either low or high institutional ownership (using the median of *Inst* as a cut-off point).

Results for model (9) are reported in Column 1 (overall sample), Column 2 (low institutional ownership) and 3 (high institutional ownership) of Table 7. *MBE* is negative but weakly significant in the overall sample (with a t-statistic slightly below 10%). *MBE* is strongly significant in the sub-sample of firms with high level of institutional ownership but insignificant in the sample of low institutional ownership (with t-statistic equal to 0.26 and -2.77 in Columns 2 and 3, respectively). The difference between the coefficients associated with *MBE* in Columns 2 and 3 is statistically significant with a p-value slightly above 5%. We obtain comparable results when we examine model (10). *MBC* is negative in all three samples (Columns 4, 5 and 6). However, both the magnitude and the statistical significance are larger in the sub-sample of firms with a larger institutional ownership. The coefficient and the t-statistic associated with *MBC* are -0.013 and -3.13 in the sub-sample of low institutional ownership and -0.023 and -8.58 in the sample of high institutional ownership. The difference in coefficient is statistically significant at the 3% level. These different results are consistent with the idea that equity price is closer to the intrinsic value when firms are able to meet and beat analyst forecasts and have a large institutional ownership. These results are consistent with H3.

7) The effect of institutional ownership on the reaction to meeting or beating analyst forecasts

We then examine if the market reaction to meeting or beating analyst forecasts is greater when firms have a greater institutional ownership (H4). To this end, we estimate the following model:

$$CAR_{i,t} = \alpha_0 + \alpha_1\, CFE_{i,t} + \alpha_2\, MBE_{i,t} + \alpha_3\, CFE{*}MBE_{i,t} + \alpha_k\, Y^k_{i,j} + \varphi_j\, FF_j + \varepsilon_{i,t} \qquad (11)$$

CAR represents the previously defined firm-return around earnings announcement. *CFE* represent the consensus forecast error (the actual earnings minus *CF*). *MBE* is a dummy variable that takes the value of one if realized earnings are greater than or equal to the consensus forecast, zero otherwise. *CFE*MBE* is the interaction between the two. Y^K is a vector of control variables that includes the five firm specific variables that we used in our previous regressions: *Coverage, Size*, *Market-to-Book*, *Leverage*, and *StdRoa*. *FF* is a vector of firm fixed effects. We estimate model (11) for firms that have either low or high institutional ownership (using the median of *Inst* as a cut-off point).

Results are reported in Table 8. Consistent with prior literature, both *MBE* and *CFE*MBE* are highly significant (with t-statistics ranging between 11.79 and 33.43). Consistent with H4, we find that both *MBE* and *CFE*MBE* are significantly greater in the sample of high institutional ownership (0.023 versus 0.025 for *MBE*, 1.343 versus 2.364 for *CFE*MBE*). The differences between the coefficients are statistically significant with p-values equal to 0.03 and 0.00. On the other hand, the coefficient associated with *CFE* is statistically identical in both samples (with a p-value of 0.87). We obtain comparable result (untabulated) if we use an indicator variable for firms that strictly beet analyst forecasts (instead of meet or beat them). We also obtain similar results (untabulated) if we use the percentage of forecasts that are below the earnings realization instead of using *MBE*. This last result is perhaps not surprising given that *MBE* is the analog of analysts issuing “lowballing:” forecasts. The economic significance is such that the effect of *MBE* is 10% larger in the sample of firms with high institutional ownership and the effect of the interaction between *CFE* and *MBE* is more than twice as large. In other words, we find that investors who react more to consistent forecasts are also the ones who react more when managers meet or beat forecasts. Although there could be additional reasons for the positive market reactions when firms meet or beat forecast earnings (e.g., MBE could signal positive news about future earnings), our empirical results are consistent with our hypothesis H4. Brown, Hillegeist, and Lo (2007) interpret *PIN* as a measure of the cost of capital. If this interpretation is correct, this would also justify the positive market reaction by institutional investors when firms meet or beat earnings and results in section 3.6 would also be consistent with H4.

4. Additional empirical analysis

1) The effect of institutional ownership on the consistency and "lowballing"

As noted above, we find that "lowballing" helps with consistency and that consistency has a greater effect on informativeness when institutional ownership is high. If analysts value their capacity to influence financial markets, analysts should "lowball" more and be more consistent when there is a higher institutional ownership. In addition, results in Table 8 indicate that managers have incentives to collaborate with analysts if this collaboration helps managers to meet or beat forecasts. This collaboration makes it easier for the analyst to issue the biased but consistent forecasts. We therefore expect that analysts following firms with a larger institutional ownership should "lowball" more and should be more consistent than analysts following firms with lower institutional ownership.

To investigate these predictions, we estimate the following models (using both a cross-sectional and a panel setting):

$$Lowball_{j,t} = \alpha_0 + \alpha_1\, Inst_{j,t} + \alpha_k\, X^k_{j,t} + \beta_k\, Y^K_{i,j} + e_{j,t} \quad (12a)$$

$$\sigma_{\varepsilon\, j,t} = \alpha_0 + \alpha_1\, Inst_{j,t} + \alpha_k\, X^k_{j,t} + \beta_k\, Y^K_{i,j} + e_{j,t} \quad (12b)$$

Lowball is previously defined in section 3.2 and σ_ε is the log of the standard deviation forecast error for analyst i and firm j. In the panel specification, we calculate the standard deviation over the twelve quarters prior to quarter t. In the cross-sectional regressions, we calculate the standard deviation using the overall sample period. *Inst* is the average percentage of institutional ownership of firm j. We use the entire sample period to calculate the average *Inst,* X^k, and Y^k in our cross-sectional setting and the prior three years in the panel specification.

Results in Table 9 are consistent with our predictions. We report the results for model (12a) in columns 1 (cross-sectional model) and 2 (panel model). The t-statistic associated with the percentage of institutional ownership is high both in the cross-sectional model (14.41) and in the panel specification (4.05). The economic effect is such that increasing institutional ownership by one standard deviation increases *Lowballing* by 15% of its mean value in the cross-sectional model and 25% in the fixed effect one.[14] When we turn our attention to the control variables, we observe that more experienced analysts, those working for larger brokerage houses and those following firms that have less stable earnings tend to "lowball" more. This suggests that analysts that have a greater incentives to "lowball" (because they follow firms that harder to predict) or those that have a greater capacity to obtain information from manager (because they are more experienced, are working for bigger employers or are following smaller firms) tend to "lowball" more. These results are generally consistent with Ke and Yu (2006). We then report the results for model (12b) in Columns 3 and 4. Also consistent with our

[14] 0.236 * 0.171/ 0.263 = 15% and 0.479 * 0.149 /0.280 = 25%

predictions, *Inst* is significantly positive in both the cross-sectional and panel models (t-statistic equals -12.79 and -3.96 respectively).

2) Informative forecast and PIN

We have assumed throughout the paper that more informative forecasts can reduce information asymmetry between informed and uninformed market participants. To empirically investigate this assumption, we estimate models (13a) and (13b):

$$PIN_{i,t} = \alpha_0 + \alpha_1\, Inform_{i,t} + \alpha_k\, Y^k_{i,j} + \varphi_j\, FF_j + \varepsilon_{i,t} \quad (13a)$$

$$PIN_{i,t+1} = \alpha_0 + \alpha_1\, Inform_{i,t} + \alpha_k\, Y^k_{i,j} + \varphi_j\, FF_j + \varepsilon_{i,t} \quad (13b)$$

where *Inform* is a measure of analyst forecast informativeness. We calculate *Inform* as the average over the last 12 quarters of the ratio of 3-day market-adjusted returns scaled by earnings forecast revision. Y^K is our previously defined vector of firm-level control variables and *FF* represents a vector of firm fixed-effects.

Results are reported in Table 10. Consistent with the idea that more informative forecasts improves the transparency in financial markets, the coefficient associated with *Inform* is negative both when PIN_t (Column 1) and PIN_{t+1} (Column 2) is the dependent variable (with p-values equal to 0.00 and 0.01 respectively). This relation holds after controlling for firm fixed effects.

3) Meeting and beating consensus as signal of future "lowballing"

We have assumed in our motivation of H4 that meeting and beating earnings forecasts is a signal that analysts will issue "lowball" (and therefore informative) forecasts in the future. To empirically validate this assumption, we regress either *MBE* or the percentage of analysts who “lowball” in the quarter t+1 on *MBE* in quarter t, our five usual firm level control variables, and a vector of firm fixed effects. We use a logit specification in the first case and an OLS specification in the second. Untabulated results indicates that the coefficient associated with *MBE* is positive and highly significant (with t-statistics approximately equal to 36) in both cases. Meeting and beating consensus forecast is therefore a strong signal that analyst will lowball in the future, even after controlling for firm fixed effects.

4) The effect of consistency and “lowballing” on persistency.

Before concluding the paper, we note that our findings above could also explain why analysts do not seem to learn and fail to incorporate the effect of their prior forecast errors in their current forecast. Prior literature (e.g., Abarbanell and Bernard (1992), Shane and Brous (2001)) has shown that when current forecast errors are regressed on prior forecast errors, there is a positive relation. In other words, β is positive if we estimate the following regression:

$$e_{i,t} = \alpha + \beta\, e_{i,t-1} + \eta_{i,t} \qquad (14)$$

If we assume that $e_{i,t} = b + \varepsilon_{i,t}$ (i.e., the forecast error can be decomposed between a systematic bias and a random error), the variance of e and the variance of ε are the same (since b is constant). Estimating equation (14) becomes:

$$(b + \varepsilon_{i,t}) = \alpha + \beta\,(b + \varepsilon_{i,t-1}) + \eta_{i,t} \qquad (15)$$

Absent any ε, we would simply observe a constant relation between the forecast errors over time and β would be equal to one. However, the presence of ε biases β toward zero due to the well-known noise-in-variable problem. In this framework, it is not surprising to observe a positive value for β in (14). In addition, we should observe a stronger relation between forecast errors for analysts who have a more systematic bias and a greater precision in their expectation (i.e., a lower variance in their ε). Forecast errors should appear to be more "persistent" in these cases. Note that in this context consistency and persistency are two related but different notions. Persistency refers to the notion that the forecast error is serially correlated, whereas the consistency refers to the stability of the forecast error. In other words, persistency refers to the coefficient β in model (14), whereas consistency refers to the volatility of η.

We investigate this idea in Table 11 by regressing contemporary forecast errors on prior errors. We examine if the forecast error is more persistent for analysts who are more consistent or who "lowball" more frequently. In Columns 1 and 2, we partition the sample based on the median value of *Cons*. In Columns 3 and 4, we partition the sample based on the median value of *Lowball.* Standard errors are corrected for heteroskedasticity and for clustering of observations by analyst-firm in all four columns.

Consistent with prior research, we find that analysts do not fully adjust and that forecast errors are persistent. The relation is highly significant (t-statistic for *FE* in Table 10 range between 20.13 and 28.19). More importantly for our purpose, results in Columns 1 and 2 indicate that persistency is higher for more consistent firms. The coefficient associate with *FE* is approximately 31% greater in Column 2 than in Column 1. The difference between the coefficients in Columns 1 and 2 is statistically significantly different from zero (p-value=0.00). Results in Columns 3 and 4 focus on "lowballing". We find that analysts who "lowball" more consistently have a more persistent forecast error. The coefficient associated with *FE* is approximately 24% larger in Column 4 than in Column 3. The difference is statistically different from zero (p-value=0.00).

5) Summary.

Our hypotheses have linked “lowballing” and consistency, consistency and informativeness, informativeness and PIN, as well as PIN and the positive reaction around meeting and beating earnings forecasts. These different predictions are matched by the appropriate empirical results. Table 3 links “lowballing” and consistency, Table 6 links consistency and informativeness, Table 10 links informativeness and PIN, and Table 8 links the positive reaction around meeting and beating earnings forecasts and PIN. In addition, Table 5 directly links “lowballing” and informativeness. Finally, we have shown that these effects are stronger when institutional ownership is greater in Tables 3, 5, 6, 7 and 8.

5. Conclusion.

This study investigates the incentives for analysts to “lowball” and how this relates to the behavior of investors and managers. We find that analysts who repeatedly “lowball” are more consistent in their forecast errors than the ones who chose not to “lowball”. This higher consistency slightly increases their forecast errors but this small decrease in accuracy does not reduce the informativeness of the analysts. Overall, we find that analysts who “lowball” are more informative. These findings suggest that analysts strategically ignore past forecast errors when they issue new forecasts. Consistent with this idea, we find that forecast errors are significantly more persistent if the analysts are more consistent or if they “lowball” more. In addition, we find that more sophisticated investors extract more information from biased but consistent forecasts than naïve investors. Analysts tend to "lowball" more when institutional ownership is higher. The probability of informed trading is reduced in the following quarter when firms meet or beat analyst forecasts. We also find that this effect is stronger for firms with a greater proportion of institutional investors. This result is consistent with the idea that "lowball" forecasts improves the transparency in financial markets. Finally, we find that the market reaction to meeting or beating analyst forecasts is positive, and more so when institutional shareholding is larger, suggesting that investors who react more to pessimistic (but consistent) forecasts also react more when managers meet or beat forecasts.

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Figure 1. Summary of the relations

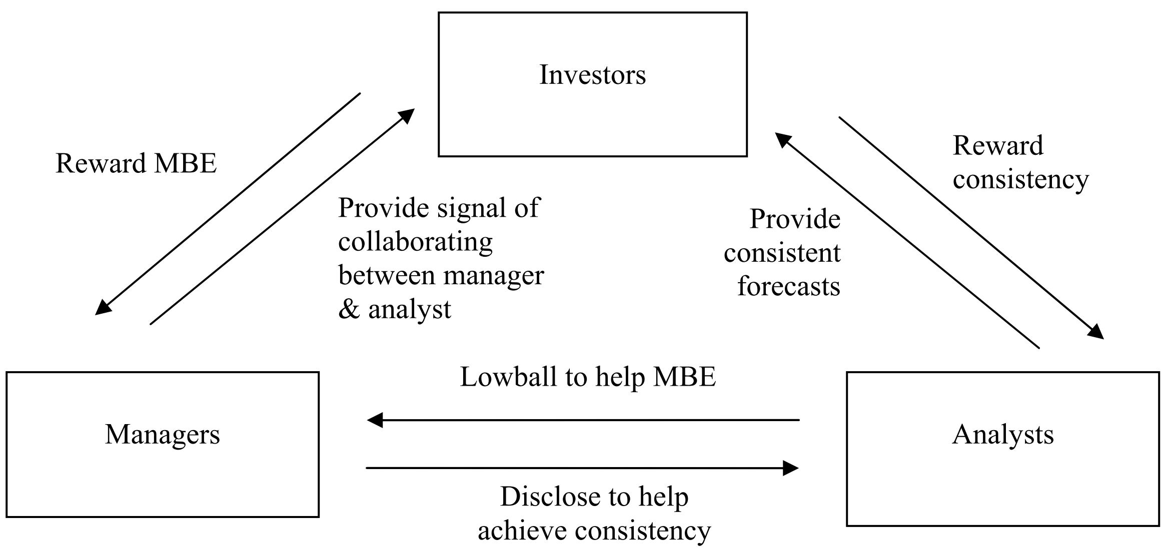

Figure 2. Examples of pay-off functions in a game theoretical framework

With Naïve investors

		Analyst	
		L	NL
Mgr	D	(5,5)	(0,6)
	ND	(6,0)	(1,1)

with sophisticated investors

		Analyst	
		L	NL
Mgr	D	(10,10)	(0,11)
	ND	(11,0)	(1,1)

D represents the strategy of manager to disclose information. ND represents the strategy of not disclosing. L represents the strategy of the analyst to "lowball". NL represents the strategy of not "lowballing". (.,.) represents the pay-off for the manager and the analyst. For example, (6,0) indicates a pay-off of six for the manager and zero for the analyst.

Table 1: Descriptive statistics on some key variables.

Variable	N	Mean	Std Dev	Median
Cons	103,364	0.500	0.329	0.500
Accu	103,364	0.514	0.099	0.512
Lowball	103,364	0.282	0.378	0.333
Beta	22,400	6.842	14.908	2.526
Inst	90,728	0.645	0.162	0.648
Bhr3d	103,364	-0.001	0.044	-0.000
FE	160,288	0.000	0.004	0.000
BM	111,267	0.682	0.465	1.000

Table 2: Correlation table.

	Cons	*Accu*	*Lowball*	*Horizon*	*Bold*	*Broker Size*	*Exp*
Accu	**0.43**	1.00					
Lowball	**0.10**	**-0.04**	1.00				
Horizon	**-0.06**	**-0.13**	**-0.01**	1.00			
Bold	**-0.12**	**-0.18**	**-0.04**	**-0.07**	1.00		
BrokerSize	**0.08**	**0.08**	**0.11**	**0.16**	**-0.07**	1.00	
Exp	**0.04**	**0.04**	**0.02**	**0.10**	**-0.03**	**0.09**	1.00
Breadth	**-0.04**	**-0.05**	**0.00**	0.00	0.00	**-0.05**	**0.13**

Cons is a measure of consistency based on the rank of the standard deviation of forecast error. *Accu* is a measure of accuracy based on the rank of the absolute value of forecast errors. *Bold* represents the distance from the consensus, measured as the absolute value of the distance between the forecast and the consensus forecast (defined as the average forecasts from other analysts). *Lowball* is the difference between the number of pessimistic and optimistic forecasts scaled by the total number of forecasts. *Horizon* is number of days between forecast date and earnings announcement date. *Exp* is log of number of quarters the analyst has followed the firm. *Breadth* is the number of firms followed by the analyst the year the forecast was issued. *Bold*, *Horizon*, *Exp*, and *Breadth* are rank variables similar to *Cons* and *Accu*. *Brokersize* is the log of number of analysts employed by brokerage house in the year when the forecast was issued. All variables in Panel B (except *Cons* and *StdROA*) are the average values in the previous twelve quarters. Correlations in bold are significantly different from zero at least at the 5% level.

Table 3: The effect of "lowballing" on consistency

Variable	*Cons*	*Cons*
	1	2
Intercept	0.723	0.636
	(31.73)	(14.83)
Lowball	**0.154**	**0.101**
	(24.51)	**(10.92)**
Horizon	-0.130	-0.233
	(-5.67)	(-8.33)
Boldness	-0.261	-0.270
	(-10.26)	(-8.84)
BrokerSize	0.029	0.030
	(8.51)	(2.99)
Experience	-0.277	-0.036
	(-20.70)	(-1.79)
Breadth	0.032	-0.016
	(-2.92)	(-0.68)
N	23,829	105,994
R^2	7.82	51.00

Cons is calculated in the following steps. First, we estimate the forecast error for analyst i following firm j in quarter t as IBES actual earnings minus forecast. Second, in Column 2, we calculate the standard deviation of analyst i' forecast errors for firm j over the twelve quarters prior to quarter q. In Column 1, we calculate the standard deviation over all quarters he/she covered the firm. Third, in column 2, we rank all the analysts who cover firm j in quarter t based on the standard deviation of forecast errors. In Column 1, we rank all the analysts over the entire sample period. We then obtain the consistency ranking score using the following formula:

Cons = 1-(rank-1)/(number of analysts in the quarter -1)

Lowball is based on the difference between the number of pessimistic and optimistic forecasts scaled by the total number of forecasts. We use the entire sample period in Column 1 and a rolling twelve quarter window in Column 2. *Bold* represents the distance from the consensus, measured as the absolute value of the distance between the forecast and the consensus forecast. *Horizon* is number of days between forecast date and earnings announcement date. *Exp* is log of number of quarters the analyst has followed the firm. *Breadth* is the number of firms followed by the analyst in a given quarter. *Bold*, *Horizon*, *Exp*, and *Breadth* are all ranked variables. *Brokersize* is the log of number of analysts employed by brokerage house in the year when the forecast was issued. In Column 1, we use the average values of our different control variables for a given analyst over the entire periods of their respective variables (i.e., *Bold, Horizon, Exp, Breadth*, *Brokersiz, Cover, Size, Mkt-to-Bk* and *Debt-ratio).* In column 1, *Stdroa* is the log of the standard deviation of firm's return on asset over the entire sample. In column 2, *Stdroa* is the log of the standard deviation of firm's return on asset over the previous twelve quarters. Analyst-firm fixed effects are included but not tabulated. Standard errors are corrected for heteroskedasticity using the Huber-White correction and clustering of observations by analyst in Column 1. Analyst-firm fixed effects are included but not tabulated in columns 2. Standard errors are corrected for heteroskedasticity and clustering of observations by firm-analyst in Column 2.

Table 4: The effect of "lowballing" on accuracy

Variable	*Accu*	*Accu*
	1	2
Intercept	0.616	0.562
	(93.15)	(21.36)
Lowball	**-0.011**	**-0.016**
	(-4.60)	**(-5.48)**
Horizon	-0.101	-0.118
	(-13.23)	(-13.48)
Boldness	-0.191	-0.132
	(-20.91)	(-13.71)
BrokerSize	0.009	0.008
	(8.03)	(2.19)
Experience	0.024	0.012
	(6.46)	(1.80)
Breadth	-0.021	-0.012
	(-5.73)	(-1.66)
N	23,829	105,994
R^2	6.01	68.57

Accu is calculated in the following steps. First, we calculate absolute value of forecast errors for analyst i who following firm j in quarter q. Second, in panel regressions, we rank all the analysts who cover firm j based on the accuracy. Third, we calculate the mean of the ranking scores. In panel regressions, we use the twelve prior quarters. In cross-sectional regressions, we use the entire sample period. *Lowball* is based on the difference between the number of pessimistic and optimistic forecasts scaled by the total number of forecasts. We use the entire sample period in Column 1 and a rolling twelve quarter window in Column 2. *Bold* represents the distance from the consensus, measured as the absolute value of the distance between the forecast and the consensus forecast (defined as the average forecasts from other analysts). *Horizon* is number of days between forecast date and earnings announcement date. *Exp* is log of number of quarters the analyst has followed the firm. *Breadth* is the number of firms followed by the analyst in a given quarter. *Bold*, *Horizon*, *Exp*, and *Breadth* are all ranked variables. *Brokersize* is the log of number of analysts employed by brokerage house in the year when the forecast was issued. Analyst-firm fixed effects are included but not tabulated. Standard errors are corrected for heteroskedasticity using the Huber-White correction and clustering of observations by analyst in Column 1. Standard errors are corrected for heteroskedasticity and clustering of observations by firm-analyst in Column 2.

Table 5: The effect of "lowballing" on analyst forecast informativeness

Variable	*Beta*	*Bhr3d*
	1	2
Intercept	-12.423	-0.012
	(-9.68)	(-1.78)
Lowball	**6.924**	-0.001
	(21.71)	(-1.13)
Rev		2.323
		(27.29)
*Lowball*Rev*		**1.657**
		(8.02)
Horizon	6.027	-0.003
	(5.97)	(-1.51)
Bold	-3.551	-0.004
	(-2.89)	(-1.70)
BrokerSize	0.638	-0.001
	(4.00)	(-1.64)
Exp	-0.734	-0.003
	(-1.32)	(-1.73)
Breadth	-0.039	0.001
	(-0.07)	(0.63)
Cover	0.231	0.003
	(7.51)	(1.91)
Size	-0.364	0.001
	(-3.03)	(2.28)
Mkt-to-Book	1.442	0.001
	(22.99)	(6.64)
Lev	-0.714	-0.000
	(-21.55)	(-1.36)
StdRoa	-2.565	0.000
	(-18.45)	(1.32)
N	22,819	96,180
R^2	13.01	17.86

Bhr3d is buy-and-hold market-adjusted three-day return around forecast revision date. *Rev* is the forecast minus the prior consensus, which is calculated using the mean of the last three forecasts, deflated by price two days prior to the forecast. To calculate *Beta*, we first estimate a regression of *Bhr3d* on *Rev*. We obtain *Beta* is the coefficient associated with *Rev* obtained from this regression. *Lowball* is based on the difference between the number of pessimistic and optimistic forecasts scaled by the total number of forecasts. We use the entire sample period in Column 1 and a rolling twelve quarter window in Column 2. *Bold* represents the distance from the consensus, measured as the absolute value of the distance between the forecast and the

consensus forecast. *Horizon* is number of days between forecast date and earnings announcement date. *Exp* is log of number of quarters the analyst has followed the firm. *Breadth* is the number of firms followed by the analyst in a given quarter. *Bold*, *Horizon*, *Exp*, and *Breadth* are all ranked variables. *Brokersize* is the log of number of analysts employed by brokerage house in the year when the forecast was issued. *Cover* is the number of analysts following the firm in a given quarter. *Size* is the log of market value of equity. *Mkt-to-Bk* is the ratio of the market value of equity over book value of equity. *Debt-ratio* is the debt to equity ratio. In Column 1, we use the average values of our different control variables for a given analyst over the entire periods of their respective variables (i.e., *Bold, Horizon, Exp, Breadth*, *Brokersize, Cover, Size, Mkt-to-Bk* and *Debt-ratio).* In column 1, *Stdroa* is the log of the standard deviation of firm's return on asset over the entire sample. In column 2, *Stdroa* is the log of the standard deviation of firm's return on asset over the previous twelve quarters. Standard errors are corrected for heteroskedasticity using the Huber-White correction and clustering of observations by analyst in Column 1. Standard errors are corrected for heteroskedasticity and clustering of observations by firm-analyst in Column 2.

Table 6: The effect of consistency on analyst forecast informativeness conditional on ownership

Dependent Variable	*Beta*	*Beta*	*Beta*	*Beta*
	1	*2*	*3*	*4*
	Low *Inst*	High *Inst*	Low *Inst*	High *Inst*
Intercept	-15.773	-17.092	-9.857	-14.520
	(-10.08)	(-9.09)	(-6.26)	(-7.84)
Cons	**3.793**	**5.53**		
	(8.57)	**(11.02)**		
Lowball			**6.412**	**7.735**
			(15.66)	**(16.52)**
Horizon	4.625	8.956	4.086	8.354
	(3.61)	(6.01)	(3.29)	(5.79)
Boldness	-4.810	-1.959	-5.195	-2.271
	(-2.94)	(-1.09)	(-3.24)	(-1.28)
BrokerSize	0.821	0.696	0.675	0.522
	(4.02)	(3.17)	(3.35)	(2.47)
Experience	0.981	0.956	-0.296	-0.100
	(1.42)	(1.11)	(-0.44)	(-0.12)
Breadth	0.491	0.063	0.317	-0.280
	(0.77)	(0.08)	(0.52)	(-0.39)
Coverage	0.384	0.257	0.312	0.153
	(9.91)	(5.73)	(8.28)	(3.54)
Size	-0.578	-0.488	-0.460	-0.372
	(-4.02)	(-2.51)	(-3.28)	(-1.97)
Mkt-to-Book	1.360	1.706	1.256	1.685
	(17.37)	(16.97)	(16.55)	(17.05)
Lev	-0.601	-0.751	-0.599	-0.806
	(-15.00)	(-15.32)	(-15.50)	(-16.39)
StdRoa	-2.337	-2.721	-2.228	-2.842
	(-13.30)	(-12.78)	(-13.01)	(-13.57)
N	11,231	11,230	11,231	11,230
R^2	12.09	11.35	13.49	12.79

Bhr3d is buy-and-hold market-adjusted three-day return around forecast revision date. *Rev* is the forecast minus the prior consensus, which is calculated using the mean of the last three forecasts, deflated by price two days prior to the forecast. To calculate *Beta*, we first estimate a regression of *Bhr3d* on *Rev*. We obtain *Beta* is the coefficient associated with *Rev* obtained from this regression. *Cons* is calculated in the following steps. First, we estimate the forecast error for analyst i following firm j in quarter t as IBES actual earnings minus forecast. Second, in Column

2, we calculate the standard deviation of analyst i' forecast errors for firm j over the twelve quarters prior to quarter q. In Column 1, we calculate the standard deviation over all quarters he/she covered the firm. Third, in column 2, we rank all the analysts who cover firm j in quarter t based on the standard deviation of forecast errors. In Column 1, we rank all the analysts over the entire sample period. We then obtain the consistency ranking score using the following formula:

$$Cons = 1-(rank-1)/(number\ of\ analysts\ in\ the\ quarter\ -1)$$

Lowball is the difference between the number of pessimistic and optimistic forecasts scaled by the total number of forecasts. *Bold* represents the distance from the consensus, measured as the absolute value of the distance between the forecast and the consensus forecast. *Horizon* is number of days between forecast date and earnings announcement date. *Exp* is log of number of quarters the analyst has followed the firm. *Breadth* is the number of firms followed by the analyst in a given quarter. *Bold*, *Horizon*, *Exp*, and *Breadth* are all ranked variables. *Brokersize* is the log of number of analysts employed by brokerage house in the year when the forecast was issued. *Cover* is the number of analysts following the firm in a given quarter. *Size* is the log of market value of equity. *Mkt-to-Bk* is the ratio of the market value of equity over book value of equity. *Debt-ratio* is the debt to equity ratio. *Stdroa* is the log of the standard deviation of firm's return on asset over the previous twelve quarters. We use the average values of our different control variables for a given analyst over the entire periods of their respective variables (i.e., *Bold, Horizon, Exp, Breadth*, *Brokersiz, Cover, Size, Mkt-to-Bk* and *Debt-ratio).* In column 1, *Stdroa* is the log of the standard deviation of firm's return on asset over the entire sample. In column 2, *Stdroa* is the log of the standard deviation of firm's return on asset over the previous twelve quarters.

Table 7: The effect of meeting and beating consensus forecast on PIN conditional on ownership

Dependent Variable	ΔPIN_{t+1}	ΔPIN_{t+1}	ΔPIN_{t+1}	PIN_{t+1}	PIN_{t+1}	PIN_{t+1}
	1	2	3	4	5	6
	Overall	Low *Inst*	High *Inst*	Overall	Low *Inst*	High *Inst*
Intercept	-0.493 (-2.14)	-0.186 (-0.53)	-1.082 (-3.90)	0.368 (79.12)	0.362 (46.75)	0.372 (58.06)
MBE	-0.547 (-1.66)	0.137 (0.26)	-1.049 (-2.77)			
MBC				-0.022 (-9.82)	-0.013 (-3.13)	-0.023 (-8.58)
ΔSize	-8.630 (-13.97)	-11.841 (-13.47)	-3.614 (-4.43)			
ΔCoverage	-1.398 (-3.87)	-1.587 (-2.88)	-1.113 (-2.48)			
Size				-0.029 (-42.51)	-0.027 (-21.93)	-0.030 (-33.36)
Coverage				-0.006 (-11.74)	-0.006 (-8.33)	-0.005 (-7.80)
Mkt-to-Book				0.002 (11.93)	0.001 (5.27)	0.002 (9.91)
Lev				-0.002 (-10.10)	-0.001 (-4.47)	-0.002 (-8.98)
StdRoa				-0.005 (-8.69)	-0.004 (-4.02)	-0.004 (-6.12)
N	146,215	73,108	73,107	102,133	40,841	61,292
R^2	0.16	0.24	0.06	59.81	56.47	59.70

PIN is the probability of informed trading. *Coverage* is the log of number of analysts following the firm in a given quarter. *Size* is the log of market value of equity. *Mkt-to-Bk* is the ratio of the market value of equity over book value of equity. *Debt-ratio* is the debt to equity ratio. *Stdroa* is the log of the standard deviation of firm's return on asset over the previous twelve quarters. *ΔPIN*, *ΔSize*, and *ΔCoverage* are the change in PIN, size, and analyst coverage. Firm fixed effects are included but not tabulated in Columns 4 to 6. Standard errors are corrected for heteroskedasticity and clustering of observations by firm. Coefficients in columns 1 to 3 are multiplied by 1,000.

Table 8: Market reaction to firms meeting or beating analyst forecasts

	Low institutional ownership (*DInst=0)*	High institutional ownership *(Dinst=1)*	p-value of the difference
	1	2	3
Intercept	0.030	0.030	
	(6.37)	(7.08)	
CFE	0.155	0.166	0.87
	(3.85)	(2.92)	
MBE	**0.023**	**0.025**	**0.03**
	(31.62)	**(33.43)**	
*CFE*MBE*	**1.343**	**2.364**	**0.00**
	(11.79)	**(14.17)**	
Coverage	0.001	-0.001	0.10
	1.19	-1.12	
Size	-0.008	-0.007	0.07
	(-11.79)	(-11.57)	
Mkt-to-Book	-0.001	-0.001	0.51
	(-2.66)	(-4.32)	
Lev	0.001	0.001	0.50
	(2.02)	(3.42)	
StdROA	-0.001	-0.001	0.94
	(-0.95)	(-1.23)	
R^2	15.36	11.93	
Nobs	66,756	66,696	

CAR represent the previously define firm-return around earnings announcement. *CFE* represent the consensus forecast error (the actual earnings minus *CF*). *MBE* is a dummy variable that takes the value of one if realized earnings are greater than or equal to the consensus forecast, zero otherwise. *CFE*MBE* is the interaction between the two. *Size* is the log of market value of equity. *Mkt-to-Bk* is the ratio of the market value of equity over book value of equity. *Debt-ratio* is the debt to equity ratio. *Stdroa* is log of the standard deviation of firm's return on asset over the previous twelve quarters. *DInst* is an indicator variable that equals one if the firm has a greater proportion of institutional investors among its shareholders, zero otherwise. Standard errors are corrected for heteroskedasticity and clustering of observations by firm. Firm fixed effects are included but not tabulated.

Table 9: The effect of ownership on "lowballing"

Variable	*Lowball*	*Lowball*	σ_ε	σ_ε
	1	2	3	4
Intercept	-0.789	-0.949	-0.907	-0.487
	(-11.45)	(-9.62)	(-4.70)	(-2.45)
Inst	**0.236**	**0.479**	**-0.595**	**-0.439**
	(14.41)	**(7.94)**	**(-12.79)**	**(-3.96)**
Horizon	-0.030	-0.095	0.166	0.172
	(-1.04)	(-2.85)	(2.14)	(2.92)
Boldness	-0.073	-0.105	0.103	0.298
	(-2.50)	(-2.89)	(1.38)	(4.43)
BrokerSize	0.109	0.047	-0.018	0.011
	(6.40)	(3.53)	(-2.49)	(0.43)
Experience	0.108	0.123	0.029	0.171
	(6.56)	(4.34)	(0.67)	(3.17)
Breadth	0.124	0.029	-0.172	-0.153
	(5.04)	(1.06)	(-2.53)	(-3.01)
Coverage	0.005	-0.144	0.008	0.513
	(6.38)	(-5.95)	(3.51)	(11.06)
Size	0.017	0.112	-0.231	-0.676
	(5.95)	(13.74)	(-29.01)	(-41.38)
Mkt-to-Book	0.012	0.002	-0.138	-0.030
	(10.64)	(1.64)	(-37.68)	(-9.69)
Lev	-0.001	-0.003	0.124	0.007
	(-1.39)	(-2.09)	(38.00)	(2.34)
StdRoa	-0.041	-0.026	0.530	0.268
	(-11.92)	(-5.24)	(51.02)	(22.78)
N	22,461	92,655	22,461	92,417
R^2	39.88	72.15	63.92	87.79

Lowball is the difference between the number of pessimistic and optimistic forecasts scaled by the total number of forecasts. We use the entire sample period in Column 1 and a rolling twelve quarter window in Column 2. *Inst* is the average percentage of institutional ownership of firm j. We use the entire sample period to calculate this average in our cross-sectional setting and the prior three years in the panel specification. σ_ε is the log of the standard deviation forecast error for analyst i and firm j. In the panel specification, we calculate the standard deviation over the twelve quarters prior to quarter t. In the cross-sectional regressions, we calculate the standard deviation using the overall sample period. *Bold* represents the distance from the consensus, measured as the absolute value of the distance between the forecast and the consensus forecast. *Horizon* is number of days between forecast date and earnings announcement date. *Exp* is log of number of quarters the analyst has followed the firm. *Breadth* is the number of firms followed by the analyst in a given quarter. *Bold*, *Horizon*, *Exp*, and *Breadth* are all ranked variables.

Brokersize is the log of number of analysts employed by brokerage house in the year when the forecast was issued. *Cover* is the number of analysts following the firm in a given quarter. *Mkt-to-Bk* is the ratio of the market value of equity over book value of equity. *Debt-ratio* is the debt to equity ratio. In Columns 1 and 3, we use the average values of our different control variables for a given analyst over the entire periods of their respective variables (i.e., *Bold, Horizon, Exp, Breadth*, *Brokersize, Cover, Size, Mkt-to-Bk* and *Debt-ratio).* In column 1, *Stdroa* is the log of the standard deviation of firm's return on asset over the entire sample. In column 2, *Stdroa* is the log of the standard deviation of firm's return on asset over the previous twelve quarters. Analysts fixed effect are included in column 2 but not tabulated. Analysts fixed effects and analysts-firm fixed effects are included in columns 1 and 2 respectively but are not tabulated

Table 10: The effect of forecast informativeness on PIN

	PIN_t	PIN_{t+1}
	1	2
Intercept	363.480	377.674
	(55.62)	(58.10)
Inform	-0.059	-0.053
	(-2.97)	(-2.65)
Coverage	-4.861	-3.247
	(-7.99)	(-5.19)
Size	-31.177	-33.000
	(-35.84)	(-38.04)
Mkt-to-Book	2.737	2.319
	(11.51)	(9.92
Lev	2.497	2.243
	(-10.93)	(-9.79)
StdROA	-4.834	-4.205
	(-7.65)	(-6.71)
R^2	55.39	56.74
Nobs	69,463	67,075

Inform is the mean value of the ratio of *Bhr3d* divided by *Rev* over the last 12 quarters. *Size* is the log of market value of equity. *Mkt-to-Bk* is the ratio of the market value of equity over book value of equity. *Debt-ratio* is the debt to equity ratio. *Stdroa* is log of the standard deviation of firm's return on asset over the previous twelve quarters. Standard errors are corrected for heteroskedasticity and clustering of observations by firm. Firm fixed effects are included but not tabulated. Coefficients have been multiplied by 1,000.

Table 11: The effect of consistency and "lowballing" on persistency

<u>*Variable*</u>	FE_{t+1} 1 Low *Cons*	FE_{t+1} 2 High *Cons*	FE_{t+1} 3 Low *Lowball*	FE_{t+1} 4 High *Lowball*
Intercept	0.000 (14.06)	0.000 (15.68)	0.000 (3.91)	0.000 (24.14)
FE_t	**0.220** **(28.19)**	**0.288** **(21.46)**	**0.201** **(22.62)**	**0.249** **(20.13)**
N	78,132	79,186	85,944	71,374
R^2	6.72	5.56	5.74	6.84

FE is forecast error in quarter q. Standard errors are adjusted for heteroskedasticity and clustering f observations by firm-analyst.