Analysts' Learning and Herding:

Theory and Evidence

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Abstract

In this paper, we investigate the determinants of analysts' herding and learning. Using a simple construct whereby analysts only wish to minimize their forecasting error, we model forecasted earnings when firm characteristics and prior forecasts are public information and analysts may gain knowledge about the firm by either tapping directly into their own private channels or using consensus bias to reveal the collective wisdom. We show both theoretically and empirically that the degree of such learning is significantly influenced by analysts' expertise, the precision of common and analyst-specific signals, the characteristics of earnings, and the correlatedness of signals.

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Abstract

In this paper, we investigate the determinants of analysts' herding and learning. Using a simple construct whereby analysts only wish to minimize their forecasting error, we model forecasted earnings when firm characteristics and prior forecasts are public information and analysts may gain knowledge about the firm by either tapping directly into their own private channels or using consensus bias to reveal the collective wisdom. We show both theoretically and empirically that the degree of such learning is significantly influenced by analysts' expertise, the precision of common and analyst-specific signals, the characteristics of earnings, and the correlatedness of signals.

The question of whether analysts learn from each other or merely herd with each other has been the focal point of recent debates in the extant literature on analysts' forecasting. While proponents of herding and advocates of learning starkly disagree on whether and why analysts herd or learn, both lines of inquiry share one central theme: herders and learners, for whatever the reason, do not post unbiased estimates. Proponents of the herding theory, such as Scharfstein and Stein (1990), Trueman (1994), and Hong, Kubik, and Solomon (2000), argue that analysts, particularly less competent ones, simply herd with each other for reasons such as reputation or career concerns, to avoid making uncommon forecast errors and being singled out. Hence, these analysts posting only slightly biased estimates, making their forecasts more similar to the consensus, and simply neglecting their own beliefs about the firm. Advocates of the learning theory, such as Mikhail, Walther and Willis (1997), Clement (1999), and Bernhardt, Campello, and Kusoati (2004), posit that differentiating oneself from the crowd is the most important way a competent analyst can guarantee herself a long, successful career. A competent analyst then finds posting a largely biased estimate that is one substantially different from the consensus a better signal of her superior ability. In short, as Lim (2001) asserts, "the unbiasedness of forecasts need not mean they are best or most accurate."

Therein, we believe, lays the answer to the debate. Whether an analyst herds with or learns from the crowd seems merely to be a question of how the analyst should construct an optimal bias[1]; one that conforms to her objectives and helps to protect or promote her career. Such a bias, however, should account for an analyst's own information about the firm, as well as other relevant information, be it from public sources, private channels or other forecasters. In this paper, we pursue this question both theoretically and empirically: for an analyst with a given

level of experience and a unique private source who faces other analysts with different degrees of expertise and possibly their own private channels, what is the optimal bias?

We first model the interaction between two types of proper Bayesian analysts with different levels of expertise. These analysts have the ability to improve upon their common knowledge through accessing potentially different private channels and pursue a universal objective of making the least erroneous forecast. Such a construct permits the stylized features inherent in both the herding and learning literatures without making any supposition as to how an analyst should behave.[2] This framework allows us to combine elements from typical herding studies, which allow for analysts to update their beliefs [see, e.g., Trueman (1994) who allows Bayesian analyst to adjust their forecast to reflect their beliefs about accuracy of their own and other analysts' signals][3].

Our theoretical analysis shows that, even in the absence of complex objectives such as career aspirations or concerns, analysts follow either herding or learning strategies based on their levels of experience and expertise, We further show that when analysts can gain knowledge about the firm via tapping into private channels or reading into the consensus beliefs, the link between expertise and the degree of herding/learning is a direct result of information processing, and not necessarily an outcome of career aspirations or concerns. When an analyst observes the biased forecast of another analyst, particularly that of a more experienced analyst, she gains enough insight that she need not post a large bias, even though the precision of her private signal can improve with a positive bias. Put in a different way, if one analyst pays for the private information, others may not need to do the same. Not surprisingly, as the expertise of an analyst improves, she finds previously reported estimates less informative. Similarly, when the degree of informational asymmetry between the firm and the analyst declines, an average, novice

analyst finds a smaller bias to be optimal. However, faced with lower asymmetry of information simply because the existing forecasts by less competent analysts do not contain much hidden information, we find that seasoned analysts post larger biases. This is particularly the case when forecasts reflect information about an already transparent firm. An interesting implication of the model is the extent to which an analyst's expertise and informational asymmetry plays a role in determining the analyst's bias is directly impacted by how dispersed are the common and idiosyncratic signals of all analysts, as well as the extent of their correlation with each other. This highlights the influence and connectedness of both common and private signals, as well as the quality of private information channels and analysts' expertise, on how analysts construct and report their earnings forecast.

While elements of our theoretical predictions have already been shown by the literature[4], there does not exist a study that has analyzed whether an analyst's forecast error changes in the presence of a prior forecast, depending upon relative expertise and how earnings individually and industry-wide are connected.[5] Since an essential finding of our model is that the comparative expertise of analysts influences their forecast and the updates thereof, we delve further into said learning/herding to discern how learning changes when the information environment changes. One such change in the information environment is when a firm is included in the S&P 500. There is an increase in the number of analysts which follow a firm upon its inclusion into the S&P 500, thereby offering a change in the information environment which may facilitate learning across analysts as well as competition among them. Indeed, Denis, McConnell, Ovtchinnikov and Yu (2003) show that upon inclusion to S&P500 index, the information environment, as measured by analysts' earnings forecast errors, improves. Since, as noted by index sponsors, the index inclusion is merely a cosmetic change for the firm, we posit that an

event study of index inclusion would allow us to identify any firm-specific informational change that may impact our analysis. Utilizing the data that exists for companies before and after inclusion onto the S&P 500, we thus examine the learning environment surrounding the inclusion of the S&P500 index.

Our empirical evidence supports the analytical propositions set forth by our model.[6] As more analysts, or 'new followers,' begin covering these large firms, the opportunity for learning increases, both from experience and from each other.[7] This additional information provided to new followers offers them the possibility of higher accuracy depending on the relative quality of the signals they receive, their ability to recognize said worth and how dependent the analysts are upon that signal for information. Learning seems to be heavily dependent on the experience analysts have as well as their dependence on private channels of information.[8] For instance, we find that new followers, who are less experienced, post smaller biased forecasts, while existing, seasoned followers post larger positively biased estimates. Since both new and existing followers manage to reduce their forecasting error significantly, the disparity between biases posted by existing and new followers indicates first that only existing analysts can viably induce a firm to reveal more information by appealing to the management. Analysts with little to no experience then greatly benefit from the experience of the existing forecasting pool, diminishing the marginal value of their own experience. This disparity between existing and new analysts' experiences seems also to be influential with regard to the impact of the information asymmetry on forecasts. For instance, existing (new) analysts' degree of information asymmetry affects the forecast bias significantly positively (negatively).

Besides extending and bridging analyst learning and herding literatures, the implications of our research contribute significantly to a number of current lively debates. First and foremost,

our analysis sheds light on why analyst forecast error decreases upon exogenous changes in information environment, such as inclusion in S&P 500 index, (Harris and Gurel (1986), Lynch and Mendenhal (1997)). We show analytically that, as contended by Denis, McConnell, Ovtchinnikov and Yu (2003), an improvement in the overall earnings quality (i.e., less dispersed earnings) would lead to lower bias and forecast errors. However, we show that interactions among analysts can additionally influence the individual and collective knowledge of analysts about earnings. With better earnings characteristics, both old and new analysts find the smaller biases needed to discern private information. As such, less seasoned analysts find even less benefit in ascertaining information via private channels by posting large biases. Given the uncertainty of earnings a priori, inexperienced analysts find advantage in learning from the forecasts of their predecessors rather than pursuing private channels aggressively. This complementarity between earnings dispersion and the efficacy of analysts cross learning magnifies the impact of information enhancement on earnings forecasting. Our empirical examination further confirms that, even after controlling for the possible impact of more information generation by the firm, analysts' experience (as measured by the quarters following the firm or similar firms) and expertise (as measured by the information asymmetry) significantly affect the observed enhancement of the forecast error impact of index inclusion. This highlights the import of analysts' interaction in the development of both individual and collective beliefs about the firm's prospects.

Second, our analysis directly contributes to the recent debate on whether abundance and transparency in firm disclosure hinders information production. In light of recent regulatory developments, particularly the Regulation Fair Disclosure (Reg. FD) that requires firms to reveal any private communication with analysts immediately to public, a recent strand of academic

research has surged to study whether an increase in financial reporting affects the firm's information environment. Recent evidence on the effects of Reg. FD [see, e.g., Baily, Li, Mao, and Zhong (2003)] shows that in contrast to earlier findings, "forecast dispersion increase[d] significantly … [and] forecasting earnings beyond the current quarter has become more difficult after the imposition of Reg. FD". Our theoretical analysis is related intimately to this issue and shows exactly how even in the absence of more firm disclosure, mere analyst interaction and cross-learning among seasoned and less experienced analysts can improve the accuracy of forecasts. Since the efficacy of privately disseminated information to an analyst is manifested in the analyst's forecast error (Lim (2001)), each analyst's forecast error reveals privately obtained information. The value and impact of this implicit private information, however, is a function of differences in the expertise of analysts. We show that forecast error filtered through more seasoned and highly competent analysts affects the accuracy of consensus estimates as much as a firm's increases in accuracy. Indeed, as Baily et al (2003) suggest, if out of fear of prosecution, firms are forced to produce unrelated raw data with no or little contextual value, the role of analysts in processing information can be hindered severely. Our empirical evidence show that Reg. FD mostly benefits existing analyst as shown by the significant negative impact of Reg. FD dummy on both their bias and forecast error. The new analyst, however, gains no significant benefit from firms producing more information. Reg. FD has no marginal impact on the bias of new analyst, but makes their error worse.

The rest of the paper proceeds as follows. Section I describes in detail the model and its comparative statics used in our examination. Section II explains the empirical methodology and describes the data. Section III reports the results of our empirical examination of the competitive influences on analyst estimation. The paper concludes with section IV.

I. Model

In this section, we model analysts' earnings forecasting utilizing two components of earnings information, common and idiosyncratic, with some uncertainty about each component. We follow recent studies whereby earnings forecast accuracy is assumed to reflect market wide and analyst-specific components [see, e.g., Lim (2001) and Yao and Liu (2005)]. In doing so, we also assume like Lim (2001) that the idiosyncratic component directly relates to the private information that analysts can obtain from the firm by posting optimistic view of the firms prospect.[9] We differ from these studies in that our prototypical analyst also observes a previously posted forecast. As such, she can learn about both common and idiosyncratic components of earnings by incorporating previously revealed information. Since we assume analysts are proper Bayesians, they need not pursue the firm in obtaining private signals aggressively by posting largely positively biased estimates because they can simply learn almost as much from previous forecasts. Our analysts can also learn materially about the firm via evaluating the previously observed estimates. Since previously posted estimates partially reflect some private information, the analysts may weigh these estimates into their assessment heavily depending on how they value the expertise and experiences of the previous analysts.[10]

Assume one analyst exists who follows any stock in the index. Each stock's earnings is comprised of two components: 1) common component, $X_c \sim N(0, \sigma_c)$, and 2) idiosyncratic component, $X_i \sim N(0, \sigma_i)$. The analyst receives two noisy signals about each component: $\varepsilon_c \sim N(0, 1/\tau_c)$ with τ_c precision about the common component and $\varepsilon_i \sim N(0, 1/\tau_i)$ with τ_i precision about the idiosyncratic.

The analyst then constructs two forecasts: $F_c = X_c + \varepsilon_c$, about the common component of the firm's earnings and, $F_i = X_i + \varepsilon_i$, about the idiosyncratic component of the firm's earnings conditioned upon all available information. She then reports an aggregated forecasts, $F = F_c + F_i$, about the firm's earnings at time, $t = 0$.

As in Lim (2001), the objective of the analyst is to minimize her squared difference error, or equivalently, to follow the quadratic objective function below:

$$\min_F \mathbf{E}\left[(F - X)^2 \mid \Omega\right] = \min_F \left\{(F - \mathbf{E}[X \mid \Omega])^2 + Var(X \mid \Omega)\right\} \tag{1}$$

where, E[· | Ω] is the conditional expectations operator, Ω is the information set available at the time of earnings estimation, and $X = X_c + X_i$.

Similar to Lim (2001), we can rewrite the objective function as a function of the analyst's forecast bias, or:

$$\min_b \left\{ b^2 + Var(X \mid \Omega) \right\} \tag{2}$$

For the case of only one analyst following the stock, we arrive at the exact same results as Lim (2001). However, we now assume that at time $t = 0^+$, a new analyst initiates following the stock. Since at this time, in addition to his private signals, the new analyst also knows the incumbent's forecast, his forecast should reflect this knowledge. Let's assume that the new analyst receives two noisy signals about each component of the earrings: $\varepsilon'_c \sim N(0, 1/\tau'_c)$ with τ'_c precision about the common component and $\varepsilon'_i \sim N(0, 1/\tau'_i)$ with τ'_i precision about the idiosyncratic. The new analyst then constructs two forecasts: $F'_c = X_c + \varepsilon'_c$, about the common component of the firm's earnings, and $F'_i = X_i + \varepsilon'_i$, about the idiosyncratic component of the

firm's earnings conditioned upon all available information. He then reports an aggregated forecasts, $F' = F'_c + F'_i$, about the firm's earnings at time, $t = 0^+$.

We further assume that the noises in the analysts' estimates of the idiosyncratic component of earnings are correlated. The intuition is that since private channels through which analysts gain access to hidden information are derived from the same firm, these channels reveal quite similar, if not identical, private information. We therefore assume that the idiosyncratic components of the analyst's signal are correlated: $\mathbf{E}[\varepsilon_i\ ,\ \varepsilon'_i] = \rho_i\,(\tau_i\ \tau'_i)^{-1}$. Likewise, since both analysts may have experience dealing with large, blue-chip firms, their errors in assessing the common component of earnings may well be highly positively correlated. Hence, we assume that common components of the analyst's signal are correlated: $\mathbf{E}[\varepsilon_c\ ,\ \varepsilon'_c] = \rho_c\,(\tau_c\ \tau'_c)^{-1}$.

The new analyst then faces a quadratic objective such as the following:

$$\min_{b'|b} \left\{ (b' \mid b)^2 + Var(X \mid \Omega) \right\} \tag{3}$$

or,

$$\min_{b'|b} \left\{ (b' \mid b)^2 + Var(X \mid F = X_c + \varepsilon_c + X_i + \varepsilon_i, F' = X'_c + \varepsilon'_c + X'_i + \varepsilon'_i) \right\} \tag{4}$$

Assuming that all common and idiosyncratic noises are independent of each other, the new analyst objective function can be expressed as:

$$\min_{b'|b} \left\{ (b' \mid b)^2 + Var(X) - \Theta \right\} \tag{5}$$

where,

$$\Theta = \begin{bmatrix} Cov(X,F) & Cov(X,F') \end{bmatrix} \times \begin{bmatrix} Var(F) & Cov(F,F') \\ Cov(F',F) & Var(F') \end{bmatrix}^{-1} \times \begin{bmatrix} Cov(X,F) \\ Cov(X,F') \end{bmatrix}$$

By way of assumptions, we know that

$$Var(X) = \sigma_c^2 + \sigma_i^2 = Cov(X,F) = Cov(X,F')$$

$$Cov(F,F') = Cov(F',F) = \sigma_c^2 + \sigma_i^2 + \rho_c \tau_c^{-1} \tau_c'^{-1} + \rho_i \tau_i^{-1} \tau_i'^{-1}$$

$$Var(F) = \sigma_c^2 + \tau_c^{-2} + \sigma_i^2 + \tau_i^{-2}$$

$$Var(F') = \sigma_c^2 + \tau_c'^{-2} + \sigma_i^2 + \tau_i'^{-2}$$

The new analyst quadratic objective function then can be expressed as [see Appendix for details]:

$$\min_{b'|b} \left\{ (b'|b)^2 + \left(\sigma_c^2 + \sigma_i^2\right) \times \right.$$
$$\left. \times \left(1 - \left[1 + \frac{\left(\tau_c^{-2} + \tau_i^{-2}\right)\left(\tau_c'^{-2} + \tau_i'^{-2}\right) - \left(\rho_c \tau_c^{-1} \tau_c'^{-1} + \rho_i \tau_i^{-1} \tau_i'^{-1}\right)^2}{\left(\sigma_c^2 + \sigma_i^2\right)\left[\tau_c^{-2} + \tau_i^{-2} + \tau_c'^{-2} + \tau_i'^{-2} - 2\left(\rho_c \tau_c^{-1} \tau_c'^{-1} + \rho_i \tau_i^{-1} \tau_i'^{-1}\right)\right]} \right]^{-1} \right) \right\} \tag{6}$$

As in Lim (2001), we further assume that analysts have access to private channels which improve their forecasts, or alternatively, $\tau_i(b)$ and $\tau'_i(b'|b)$. However, these private channels have diminishing returns. In other words, we assume that:

$$\frac{\partial \tau_i}{\partial b} > 0\,; \quad \frac{\partial^2 \tau_i}{\partial b^2} < 0; \quad \text{and} \quad \frac{\partial \tau_i'}{\partial (b'|b)} > 0\,; \quad \frac{\partial^2 \tau_i'}{\partial (b'|b)^2} < 0$$

Note that the objective for the new analyst is to minimize his squared error using his conditional bias. Unlike the case in Lim (2001), a new analyst chooses his bias conditioned upon old analyst's bias simply because he can learn from existing analyst estimation. In short, the new analyst has to set his bias such that:

$$
\begin{aligned}
(b'|b) = & \left[\left(\sigma_c^2+\sigma_i^2\right)V(b'|b)+U(b'|b)\right]^{-2} \times \frac{\partial \tau_i'(b'|b)}{\partial b'|b} \times \frac{1}{\tau_i \tau_i'^3(b'|b)} \times \left(\sigma_c^2+\sigma_i^2\right)^2 \times \\
& \Big\{ \left[\tau_i\left[\tau_c^{-2}+\tau_i^{-2}(b'|b)\right]-\rho_i\,\tau_i'(b'|b)\left[\rho_c\tau_c^{-1}\tau_c'^{-1}+\rho_i^2\tau_i^{-1}\tau_i'^{-1}(b'|b)\right]\right]\times V(b'|b) \\
& -\left[\tau_i-\rho_i\tau_i'\,(b'|b)\right]\times U(b'|b) \Big\}
\end{aligned} \tag{7}
$$

where,

$$
V(b'|b) = \left[\tau_c^{-2}+\tau_i^{-2}+\tau_c'^{-2}(b'|b)+\tau_i'^{-2}-2\left(\rho_c\tau_c^{-1}\tau_c'^{-1}+\rho_i\tau_i^{-1}\tau_i'^{-1}(b'|b)\right)\right]
$$

$$
U(b'|b) = \left(\tau_c^{-2}+\tau_i^{-2}\right)\left(\tau_c'^{-2}+\tau_i'^{-2}(b'|b)\right)-\left(\rho_c\tau_c^{-1}\tau_c'^{-1}+\rho_i\tau_i^{-1}\tau_i'^{-1}(b'|b)\right)^2
$$

In the following section we study the relationship between the original analyst's bias, b, and that of the new analyst, $(b'|b)$ in details. See Appendix for more details on derivation of (7).

A. Comparative Statics

Note that since equation (7) is a nonlinear function of bias, the solution for (7), and hence the comparative statics of the same, cannot be obtained analytically. To gain some insight into how characteristics of the firm's earnings and analysts' signals affect the new analyst's bias, we resort to simulation. We first need to make some assumptions about the fundamental relationship between analysts' bias and the accuracy of their estimates. As is evident from Figure 1 and for the sake of brevity, we choose the analyst's idiosyncratic precision to be a function of her or his bias as follows:

$$
\tau_i = K\left[\tanh\left(\frac{b-\alpha}{\beta}\right)+B\right] \quad \tau_i' = K'\left[\tanh\left(\frac{(b'|b)-\alpha'}{\beta'}\right)+B'\right] \tag{8}
$$

Note that as is shown in the aforementioned, the *tanh*(·) has two major appealing features: diminishing returns and symmetry. This means that if an analyst reports an unfavorable forecast, she looses accuracy. Further, the extent to which the analyst can improve her accuracy by tapping into private sources is limited (see Figure 1). Note that the parametric structure of the accuracy function determines 1) how sensitive the analyst's forecast is to private channels, and 2) how much of the analyst's forecast is due to the private signals.

Parameter α reflects how much of the precision is due to the firm's private information. As α increases, the precision becomes more dependent on the firm's private information. In other words, an analyst with high α has less ability to discern information on his own. Parameter β reflects at what speed the accuracy changes with bias. In other words, β reflects the information asymmetry between the analyst and the firm. Firms with lower β have heightened sensitivity to informational asymmetry and hence even small bias can largely improve the accuracy. Parameters K and B allow us to adjust how accuracy changes as bias goes from $-\infty$ to $+\infty$. For instance, by setting K to one and B to zero, we guarantee that the accuracy is between zero and two, or alternatively the dispersion of analyst signal is anywhere from half of the median earnings to infinity.

[Insert Figure 1 here]

The results of the numerical analysis, Tables I to III and Figures 2 and 3, indicate a number of interesting relationships between optimal bias for new analysts and the fundamental characteristics such as correlation between common errors, idiosyncratic errors, and original and new analysts' common errors. The most interesting and pronounced comparative static is an inverse relationship between original and new analysts' biases: as the original analyst's increases her bias, the new analyst's decreases his. Note that here an analyst can extract information about

the idiosyncratic signal by: 1) using her own knowledge of the firm and the industry, 2) utilizing available private sources, and 3) observing the previously posted forecast. Moreover, analysts are proper Bayesians who incorporate prior information in their estimates by weighting all signals according to their accuracies. As such, the new analyst will accordingly weight the old estimates to construct a posterior belief about the firm's earnings. However, in our setting, the extent to which an analyst can gain accuracy by using private channels homogeneous across all analysts, implying that the maximum precision obtainable with regard to idiosyncratic signals by either old or new analysts is same.

Since the analyst's objective is to forecast earnings with the least error, the new analyst need not overcompensate by posting a bias larger than the previous. Rather, she need only post a large enough bias to optimally extract valuable, undisclosed information from private channels. This, however, is more consistent with the idea that analysts learn from each other. Since in our model the bias is the difference between the forecasted and expected earnings, a new analyst posting a small bias after observing a large bias posted by an original analyst is tantamount to learning because the new analyst deviates from consensus by getting closer to the true earnings. This corresponds to the recent findings of Bernhardt, Campello and Kusoati (2004) which shows that, conditional on the expected earnings, subsequent revisions tend to deviate from the consensus. In fact, the overall direction of the revised estimates is in the opposite direction of the consensus movement.

[Insert Table I here]

[Insert Table II here]

[Insert Table III here]

[Insert Figure 2 here]

[Insert Figure 3 here]

An interesting feature of our model is that it can isolate the effect of cross-sectional differences in forecast ability; hence, it permits one to focus on the interaction between the analyst and her private information channel. Our results indicate that factors such as the analysts' expertise, quality of private channels, and correlation of signals significantly affect the way the learning process works. The interactions between these factors and the consensus bias shed light as to when and for whom herding and learning are optimal strategies. For instance, we find partial support for the herding literature when analyst expertise is considered. We show that young, inexperience analysts tend to post larger biases, i.e., follow the crowd more closely. Note that since we define bias to be the difference between the analyst's own unconditional expectation of earnings and her posted forecast, any large bias implies that the analyst is moving away from her own beliefs and conforming more with the crowd. As is shown in Table I and Figure 1, when α rises, i.e., the analyst efficacy deteriorates and his reliance on the firm increases, the optimal bias rises significantly. The association between analyst expertise and optimal bias, however, is not linear. At very high levels of α, when an analyst almost exclusively has to rely on the firm to improve the accuracy of his estimates, the costs, or squared error, become so large that the analyst decides to stay with his own beliefs. It is important to note that the degree to which an inexperienced analyst decreases his bias is a direct function of the observed bias. In other words, when older estimates seem to be highly positive, the inexperienced analyst can easily rely on the consensus to gain insight into the hidden piece of information because favorable older estimates should contain highly precise information.

Another interesting comparative static is that information asymmetry between the firm and the analyst affects the optimal bias considerably (see Table I and Figure 2). When both new

and old analysts are equally talented, the new analyst tends to post a lower bias as the degree of information asymmetry, as inversely measured by β, decreases. This is not surprising because the new analyst finds both the gathering and processing of information about such firms easier. This is particularly true when the previously reported consensus is known to be equally (or more) accurate and, hence, the reasonably accurate information can then be deduced without appeasing management too much. Results in Table I, however, show that when the new analyst is more competent than the old analyst, as the degree of information asymmetry between firm and analyst declines, the optimal bias increases. This seems counterintuitive only if we do not consider the old analyst's comparative lack of expertise. Note that when the new analyst can better forecast the firm's performance, the bias of the old analyst does not appear to have much validity in that large biases in this scenario solely compensate for lack of competence. This bias, however, is less informative for the more competent analyst simply because she could have easily achieved most of the resulting precision without any bias. The more competent new analyst hence has to increase her bias to guarantee that privately acquired information is truly unique and hence enhances precision. Indeed, this is consistent with the main conjecture and principle finding of Bernhardt, Campello and Kusoati (2004) which shows that more competent analysts deviate from the consensus more to signal their own ability more clearly.

Our results also indicate that the correlation of the signals of old and new analysts influences the magnitude of optimal bias significantly. Both correlations between common components and correlation between idiosyncratic components have a positive impact on the new analyst's conditional bias: as either of the common or idiosyncratic components of analysts' forecasts become more interlinked, the new analyst is less likely to post a non-positive bias. The overall intuition is rather simple: the more positively correlated signals become, the less

informative the resulting bias becomes for other analysts because embedded uniqueness vanishes. When the idiosyncratic signals become more positively correlated across analysts, the forecasting analyst learns to find less unique, untapped information in other analysts' forecasts, therefore keeping her bias positive so that she can increase her overall accuracy by tapping into private channels. When the common signals become more positively correlated across analysts, the two analysts become more equally able to discern and incorporate publicly available information in constructing their estimates and thus, they learn less about the common components from each other's biases.

Interestingly, while an increase in the correlation of the idiosyncratic components increases the bias of the new analyst's estimate moderately, an increase in the correlation of the common components across analysts increases the bias of the new analyst's estimate sharply. The main reason for the difference in the degree of sensitivity between the common and idiosyncratic components of earnings lies in the extent to which an analyst perceives previous forecasts to be related to diligent private channeling. Note that an analyst improves her overall forecast accuracy by increasing the precision of both the common and idiosyncratic signals. This, however, means that whichever signal has the higher precision plays a more significant role in the overall accuracy of a forecast.[11] When an analyst finds her common signal comparatively more accurate than her private signal, her overall forecast simply reflects her own expertise in discerning and understanding the common factor. Private channels in such a case remain unexplored. This leaves, therefore, any successor to doubt that any reasonable amount of private information is being reflected in the consensus. The new analyst then has to appease management more than usual, i.e., post a larger bias, to be able to extract private information. In doing so however, her overall forecast would be highly accurate - not only due to her large bias

increasing the accuracy of private signals tremendously, but also due to the observed consensus helping to improve the common signal accuracy as well. Our results support this contention. In the case where previous analysts have a more accurate common signal, the bias of the new analyst is larger while her forecast error is small.

Lastly, our results in Table IV, indicate that the dispersion of the different components of earnings themselves affect analyst forecast error as well as bias. Interestingly, the impact of a reduction in the dispersion of the idiosyncratic component of earnings is more economically pronounced than a reduction in the common components of earnings. This is because while a reduction in the dispersion of any component makes forecasting easier, a less disperse idiosyncratic component means that there is little information left unrevealed that private channels can possibly unravel. Indeed, while a less dispersed common component makes forecasting easier, it does not entirely eliminates the possibility that considerable information can be ascertained from the firm by utilizing one's private sources.

[Insert Table IV here]

II. Empirical Tests and Methodology

While not all of our earlier comparative statics can be tested empirically, we believe that the most pertinent elements can. As noted earlier, the most prominent comparative static of our model is that the negative association between an analyst's optimal bias and her forecast's error is greatly influenced by her relative degree of expertise. We also find that the degree of information asymmetry between the firm and the analyst affects the optimal bias and forecast errors. These implications underline our main contentions that the degree of learning and herding is primarily a function of the information environment and how analysts process relevant information. We empirically test the importance of experience and information asymmetry in

determining forecast error and bias, controlling for such things as industry dynamics, information asymmetry, earnings smoothing and regulatory effects.

To test our analytical predictions, we resort to the experiment of index inclusion. Since sponsors such as Standard and Poor's explicitly cite inclusion of a stock in their indices as a non-informationally motivated action, this allows us to focus on cases whereby the information liquidity environment changes due to some exogenous event, and due to increased following. While newly included firms may improve the information environment by enhancing publicly available related data, as suggested by Denis, McConnell, Ovtchinnikov and Yu (2003), contemporaneously a host of new analysts joins the forecasting pool, potentially changing the information environment by providing additional sources of private and public information processing. This, in turn, provides us with a perfect setting to investigate how learning and herding among analysts changes when the information environment changes.

As noted earlier, we show the extent to which forecasting can improve with changes in the information environment (i.e. index inclusion), depending on the analysts' ability and the expertise. Our analysis shows that as the analyst discerns private information more effectively, whether due to superior ability or a lower level of firm-analyst information asymmetry, her forecast bias decreases. We first test if analyst experience affects her forecast bias, controlling for index inclusion. Our contention is that experience materially captures analyst's efficacy in information processing. In short, we suggest that in the following model, the sign of experience should be significantly negative:

$$Error_t^i = \alpha_0 + \eta\, Expertise_t^i + \beta_0\, Inclusion_t + \beta_1\, Accrual_t^i + \beta_2\, RegFD_t^i + \mathbf{\Phi}\, \mathbf{SICs} + \varepsilon \qquad (9)$$

where, t is the quarter in which we measure bias/forecast error and i denotes the ith analyst. We measure expertise in two ways, the first of which is more of an absolute measure and the second of which is relative in nature: 1) quarters of experience, and 2) quarters of experience divided by the average quarters of consensus analysts, respectively. If the implications set forth by our theoretical model are correct, these proxies to be negatively related to the analyst's forecast error, as measured by the difference between the firm's actual earnings and the analyst forecast, as well as the analyst bias, as measured by the difference between analyst forecast and the aggregate consensus. Note that we control for the impact of inclusion by using a dummy variable indicating whether the forecast was made after the index inclusion. We also control for industry fixed effects by including industry (two digit SIC code) dummies, earnings smoothing by employing accruals, and regulations by using a RegFD dummy, which describes whether the time period falls before or after the Fair Disclosure Regulation went into effect (August 2000).

Interestingly, our theoretical analysis also shows that the impact of the degree of information asymmetry between the firm and analyst on forecast error can also be influenced by the analyst's expertise. This predicted relationship can be found in Figure 4. For inexperienced analysts, as the degree of asymmetry of information declines so too does the analyst's bias and forecast error. For experienced analysts, however, a decline in the information asymmetry does not necessarily reduce the analyst's forecast error. We contend that in the eye of a competent analyst, existing forecasts (i.e., consensus earning forecast) are not important because she cannot rely on the word of her perceived "less competent" peers. This mistrust of consensus lends to an increased bias in order to extract private information effectively. We thus test this phenomenon by estimating the following model for two subsets of firms: high and low asymmetry firms. The resulting empirical equation is the following:

$$Error_t^i = \alpha_0 + \gamma\ Information\ Asymmetry_t^i + \beta_0\ Inclusion_t^i + \beta_1 Accrual_t^i + \beta_2 \mathrm{Reg}FD_t^i + \mathbf{\Phi}\ \mathbf{SICs} + \varepsilon \tag{10}$$

where, t is the quarter in which we measure bias and forecast error and i denotes the ith analyst. We measure the degree of information asymmetry between the analyst and the firm by measuring the difference between forecast error from estimates at least 360 days (4 quarters) before the actual earnings realization date to forecasts that are estimated within 90 days (same earnings quarter).

[Insert Figure 4 here]

Lastly, our numerical results indicate that characteristics of earnings also affect the analyst's bias. We find that as the uncertainty of the common and idiosyncratic components rises, the bias increases. We posit that the common component's uncertainty can be proxied by the standard deviation of the 2-digit SIC industry's earnings while the idiosyncratic uncertainty can be proxied by the ratio of the standard deviation of firm's earnings to the standard deviation of the 2-digit SIC industry's earnings. We hence test this phenomenon by estimating the following:

$$Error_t^i = \alpha_0 + \psi'\ Uncertainty_t^i + \beta_0\ Inclusion_t^i + \beta_1 Accrual_t^i + \beta_2 \mathrm{Reg}FD_t^i + \beta_3 NumAnalysts + \mathbf{\Phi}\ \mathbf{SICs} + \varepsilon \tag{11}$$

A. Data

Changes in the Standard and Poor's 500 list are usually made when a company is involved in a merger, corporate restructure, or bankruptcy. When a company is removed, it is normally replaced by the largest firm in its particular industry. Changes are also made to the index when Standard & Poor's wants the index to be more representative of the U.S. stock

market as a whole. We collect all of the firms added to the S&P 500 from 1988 to 2003. There are 324 additions during this period. After making deletions for insufficient data for the relevant time needed for our empirical examination, we are left with 157 companies. We collect the earnings estimates, as well as actual earnings, for twelve quarters before and twelve quarters beyond the addition onto the S&P 500. Each analyst for each firm gives several estimates for each quarter due to revisions, and we include all of the revisions in our analysis. We are interested in the bias that arises from increased coverage that occurs over time rather than the level of accuracy so this resolution remains acceptable. We utilize the data from 197 analysts whose earnings estimates are listed in the FIRST CALL database. Our dataset is based on the analyst. Each entry includes the firm being covered, both their actual and estimated quarterly earnings per share as well as the industry of the firm being followed, the number of quarters the analyst has been following the firm/industry, the number of analysts (out of the 197) following the relevant firm in that quarter and the relevant quarter. An entry exists for each of the 197 analysts covered for each of the 157 relevant firms (new additions to the S&P 500) that they cover. The entries total 118,248. All analyst information is collected from the FIRST CALL database.

Consistent with Brown and Sivakumar (2001), Bradshaw and Sloan (2002), and Doyle, Lundholm, and Soliman (2003), and Johnson and Schwartz (2001) we define earnings as the IBES reported actual earnings per share. As discussed in the above papers, the IBES actual EPS is a good proxy for what a firm reports in its quarterly earnings announcement.

Companies that consistently manage their earnings are much easier to forecast thus we control for this phenomena by using accruals as a proxy for earnings management behavior. We define accruals as GAAP earnings less pro-forma earnings, as defined by Doyle, Lundholm, and

Soliman (2003). Dechow (1994), Dechow (1998), and Barth et al. (2001) show the current period accruals predict future cash flows.

III. Empirical Findings

A. Univariate Results

Looking generally at the univariate results, we find evidence of both herding and learning. Comparing the errors, both forecast and aggregate, of 'new guys' versus 'old guys,' it is clear that overall the old guys do better than the new (Table V). From Table V, it is also clear that new followers are less seasoned analysts: they have almost one fourth of the old followers experience in following similar firms. As noted by earlier research [see, e.g., Bernhardt, Campello and Kusoati (2004) and Clement and Tse (2005)], these less experienced analysts tend to be herders (i.e., post zero or negative biases and forecast closer to the consensus) and make larger forecast errors. The new analysts also tend to suffer from a larger degree of information asymmetry as compared to more experienced analysts.

[Insert Table V here]

At first glance, it appears that biases and forecast errors of both new and old analysts decrease after the inclusion occurs. While this seems to support the notion that inclusions are not entirely information neutral and firms possibly produce more and better information in such an event, a closer look at the evolution of bias and the error across new and old analysts paints a much more interesting picture.

Table VI shows the breakout of summary statistics by relative quarters around inclusion. Looking to relative quarter average biases and forecast errors for quarters pre- and post-inclusion, we find that while eventually biases become smaller for new and old analysts, initially following inclusion, old analysts actually post much larger biases ($0.6523 versus $0.1559 for

old analysts versus new analysts respectively). We also find that inclusion improves forecast errors for all analysts regardless of experience. As noted in Table VI, while the pre- and post-inclusion twelve-quarter average biases for old analysts are $0.0588 and $0.0160, respectively, the pre- and post-inclusion four-quarter average biases are -$0.0044 and $0.1054. In fact, looking at the relative quarters -4 to +4, we find that the distinction between pre- and post-inclusion over short and long run is mainly due the substantially larger bias in the first post-inclusion quarter. The large bias by experienced analysts after inclusion, coupled with the entrance of new analysts to the forecasting pool, confirms our earlier prediction. The results suggest that seasoned analysts, when joined by less experience peers, need to post large positive biases to discern reliable information from the firm. This is quite interesting because despite the so-called improved information environment, as contended by Denise et al (2003), old analysts find themselves in need of aggressive information acquisition when consensus information becomes less reliable due to uncertain forecasts made by new analysts whose talent at estimating earnings of the newly listed firm has not yet been revealed.

[Insert Table VI here]

Notably, however, both the cross learning of analysts and the gradual seasoning of new analysts over time help old analysts to reduce their biases to even smaller levels than those of pre-inclusion. While average post-inclusion bias for old analysts stands at $0.1054 in the first four quarters, after twelve quarter past inclusion, the average bias drops by almost ten fold to $0.01060. Interestingly, while old analysts' bias decreases precipitously after inclusion, the new analysts' bias remains almost intact. The average four-quarter post inclusion bias for new analysts stands at -$0.0845 as opposed to an average twelve-quarter post inclusion bias for new analysts of -$0.0659. This reveals an interesting dynamic in the learning process of different

analysts. Our results suggest that initially when faced with unknown new comers, old analysts 'play it safe' by ascertaining as much information from the firm as possible. As time passes, however, old analysts are able to 'measure up' the competition by observing the quality of their forecast. This dynamic, while not modeled directly, in fact can be deduced from our model as well. Since in the repeated game, large biases will be followed by small ones and vice versa, we can see that high levels of information efficiency can be achieved quickly while old and new analysts interchange the role of the dominant information producer.

To test whether analysts change roles as main information processors, we examine the correlations and autocorrelations of old and new analysts' biases and errors. As noted in Table VII, we see that the correlation between the bias of old and new analyst as well as the correlation between the change in bias for old and new analysts are strongly negative while the correlation between their forecast errors is strongly positive. The initial four-quarter correlation of biases and quarterly change in biases are -0.4417 and -0.6979. This implies that analysts interchangeably take on the role of main information processors, i.e., one analyst posts the larger, more optimistic bias while the other follows suit with a smaller bias. Moreover, the rapid decline of quarterly autocorrelation of old analysts from -0.3578 in the first four quarters to 0.0366 in the first twelve quarters as opposed to a gradual decline of quarterly autocorrelation of new analysts from -0.7699 in the first four quarters to -0.5007 in the first twelve quarters indicates that more seasoned analysts learn about the changes in the information environment at a faster pace, including the quality of the forecasting pool, and hence they can achieve low levels of error more quickly.

[Insert Table VII here]

B. Multivariate Results

The results from the multivariate analysis support our univariate findings concerning the relationship between old and new analysts and the resulting herding versus learning behavior. Table VIII shows the estimation results from equations (9) and (10) controlling for the impact of experience, changes in the information environment, regulatory constraints, and firm specific variables on analyst expertise. Both definitions of experience, the number of quarters of company-related experience and the relative experience of the analyst are negative for both forecast error and bias. This implies that as the analyst discerns private information more effectively, her forecast error decreases, as previously posited. Also in support of our theoretical findings, we find that experience leads to an increase in bias. The impact of the change in the information environment (alternatively the information component of the shadow cost – see Chen et al., 2003) is irrefutable when looking at Table VIII. Inclusion, which is a dummy variable taking on a value of one when the covered firm has been included in the S&P 500 Index and zero otherwise, is negative and highly statistically significant across all estimations. When a company is added to the index, the increased coverage and increased publicity improves the information environment which improves all analysts' accuracy. This leads to a decrease in both forecasting error, and bias, regardless of experience. The economic significance ranges from $0.03 drop in forecast error to an $0.082 decrease in bias. However, by looking at the interaction between experience and inclusion, we find that inclusion impacts forecast error and bias in different ways, controlling for experience. This interaction variable is not significant for the forecast error estimates, which suggests that experience and not the act of inclusion, is relevant in the deduction in the forecast error, supporting the literature in declaring inclusion as an information-neutral event and our supposition that it is the information pool as well as analyst

interaction that is important in enhancing the information environment to the point of increased analyst accuracy across the board. In contrast to forecast error regressions, when regressing the same interactive variables (along with the same control variables) on bias we see that inclusion along with its interactive term with experience is significant. This delineation lends support to the model prediction as well as univariate analysis that old analysts aggressively seek out firm information, as seen by the increased bias, when new inexperienced analysts first join the team and decrease the faith that old analysts have in the information provided in the consensus estimate. The cumulative impact of experience on bias is a $0.01 increase when defining experience by number of quarters following the firm or $0.02 increase when defining experience relative to the analyst pool. Reg F.D. leads to a reduction of forecast errors and bias. The public information pool is now richer since companies have to report the same information to all analysts, which leads to a reduction in information asymmetry. We do not find evidence that Reg F.D. leads to excessive noise from companies relaying uninformative information. Accruals lead to more positive forecast errors. These results might explain why companies engaged in earnings management always consistently beat analysts' estimates (Brown and Caylor (2005)). However, earnings management leads to a decrease in analyst biases.

[Insert Table VIII here]

In addition to analyst experience, our theoretical model predicted that information asymmetry between the firm and the analyst also affects analyst's forecasting. In support of our these predictions, the results in Table IX demonstrate nicely that information asymmetry is positively related to forecast error. Empirically, this translates into a positive and significant value for all estimations using the measures of information asymmetry (from a $0.139 to a $0.209 increase in forecast error). We also look at the impact of information asymmetry

controlling for index inclusion, and find that even after inclusion, information asymmetry still leads to a $0.097 increase in forecast error. Experience itself is once again negatively related to the forecast error indicating that the sensitivity of the private channel accuracy decreases over time (with experience). Interestingly enough, once including information asymmetry, the overall impact of experience is still positively related to bias, implying that once analysts account for the level of private information available, they will continue to strive to distinguish themselves from their peers. Information asymmetry, however, is negatively related to bias, resulting in a range of a $0.002 to a $0.017 decrease in bias. When there is high information asymmetry, the cost of purchasing information would be prohibitively high so an analyst would post a lower bias, resorting instead to gaining as much information as she can from the consensus.

[Insert Table IX here]

The impact of the level of certainty of signals seems to be relevant as well with regard to estimation error as shown in Table X. An increase in the level of industry uncertainty, which is analogous to the common component of the signal, is positively associated with forecast error (bias), resulting in a $0.072 ($0.269) increase in forecast error (bias). This implies that when uncertainty decreases, so too does the error or bias. The company-level uncertainty, analogous instead to the idiosyncratic component, is also positively association with forecast error (bias), resulting in a $0.036 ($0.126) increase in forecast error (bias). Interestingly, the magnitude of the impact seems to be greater at the industry level for forecast error and at the company level for the bias. This implies that perhaps idiosyncratic uncertainty, relative to common, impels more dependence on the channel efficacy mentioned in the results above. Full results are seen in Table X.

[Insert Table X here]

IV. Conclusions

Despite apparent differences, both the 'learning' and the 'herding' lines of literature underlie the fact that the optimal strategy of an analyst with regard to achieving a minimum forecast error is not to post unbiased estimates. Determining the optimal bias and achieving a minimum forecast error is not as easily achieved as previously thought. Both the 'learning' and the 'herding' lines of literature in analyst estimation place rigid assumptions in model or empirical specifications (i.e. linearity in the relationship between analyst expertise and bias) which destroys variation in optimization resulting in misspecification. Lifting these restricting assumptions enables a more realistic optimization wherein two optimal strategies emerge. Given differences in information asymmetry between the firm and analyst, analyst expertise and precision, either learning or herding may be optimal strategies. We find that the extent to which analyst's expertise and informational asymmetry play a role in determining the analyst's bias is directly impacted by how dispersed are the common and idiosyncratic signals of all analysts as well as the extent of their correlation with each other. We further find that such things as expertise, quality of private channels and the correlation of signals impact how efficiently an analyst can learn, implying that there are situations wherein analysts may be unable to learn and conversely that there are situations which are conducive to learning. The implications of our results can help to reconcile the seemingly contrasting views in the literature and the true information content of analyst estimation.

Appendix

A. The Objective Function:

Analyst objective function can be expressed as:

$$\min_{b'|b} \left\{ (b' \mid b)^2 + Var(X) - \Theta \right\} \tag{A1}$$

where,

$$\Theta = \begin{bmatrix} Cov(X,F) & Cov(X,F') \end{bmatrix} \times \begin{bmatrix} Var(F) & Cov(F,F') \\ Cov(F',F) & Var(F') \end{bmatrix}^{-1} \times \begin{bmatrix} Cov(X,F) \\ Cov(X,F') \end{bmatrix}$$

However, we know that:

$$Var(X) = \sigma_c^2 + \sigma_i^2 = Cov(X,F) = Cov(X,F')$$

$$Cov(F,F') = Cov(F',F) = \sigma_c^2 + \sigma_i^2 + \rho_c \tau_c^{-1} \tau_c'^{-1} + \rho_i \tau_i^{-1} \tau_i'^{-1}$$

$$Var(F) = \sigma_c^2 + \tau_c^{-2} + \sigma_i^2 + \tau_i^{-2}$$

$$Var(F') = \sigma_c^2 + \tau_c'^{-2} + \sigma_i^2 + \tau_i'^{-2}$$

by substation the relevant terms in (A1), we then have:

$$\min_{b'|b} \left\{ (b' \mid b)^2 + \left(\sigma_c^2 + \sigma_i^2\right) \times \right.$$
$$\left. \times \left(1 - \left[1 + \frac{\left(\tau_c^{-2} + \tau_i^{-2}\right)\left(\tau_c'^{-2} + \tau_i'^{-2}\right) - \left(\rho_c \tau_c^{-1} \tau_c'^{-1} + \rho_i \tau_i^{-1} \tau_i'^{-1}\right)^2}{\left(\sigma_c^2 + \sigma_i^2\right)\left[\tau_c^{-2} + \tau_i^{-2} + \tau_c'^{-2} + \tau_i'^{-2} - 2\left(\rho_c \tau_c^{-1} \tau_c'^{-1} + \rho_i \tau_i^{-1} \tau_i'^{-1}\right)\right]} \right]^{-1} \right) \right\} \tag{A2}$$

B. Solving for Optimal Bias:

In equation (6), the objective function is

$$(b'|b)^2+\left(\sigma_c^2+\sigma_i^2\right)\times\left(1-\left[1+\frac{\left(\tau_c^{-2}+\tau_i^{-2}\right)\left(\tau_c'^{-2}+\tau_i'^{-2}\right)-\left(\rho_c\tau_c^{-1}\tau_c'^{-1}+\rho_i\tau_i^{-1}\tau_i'^{-1}\right)^2}{\left(\sigma_c^2+\sigma_i^2\right)\left[\tau_c^{-2}+\tau_i^{-2}+\tau_c'^{-2}+\tau_i'^{-2}-2\left(\rho_c\tau_c^{-1}\tau_c'^{-1}+\rho_i\tau_i^{-1}\tau_i'^{-1}\right)\right]}\right]^{-1}\right)$$

Let us assume that,

$$V(b'|b)=\left[\tau_c^{-2}+\tau_i^{-2}+\tau_c'^{-2}(b'|b)+\tau_i'^{-2}-2\left(\rho_c\tau_c^{-1}\tau_c'^{-1}+\rho_i\tau_i^{-1}\tau_i'^{-1}(b'|b)\right)\right]$$

$$U(b'|b)=\left(\tau_c^{-2}+\tau_i^{-2}\right)\left(\tau_c'^{-2}+\tau_i'^{-2}(b'|b)\right)-\left(\rho_c\tau_c^{-1}\tau_c'^{-1}+\rho_i\tau_i^{-1}\tau_i'^{-1}(b'|b)\right)^2$$

the objective function then can be rewritten as:

$$(b'|b)^2+\left(\sigma_c^2+\sigma_i^2\right)\times\left(1-\left[1+\frac{U(b'|b)}{\left(\sigma_c^2+\sigma_i^2\right)V(b'|b)}\right]^{-1}\right)$$

By taking the first derivative of with respect to $b'|b$, then we have:

$$2\,(b'|b)+\left(\sigma_c^2+\sigma_i^2\right)\times$$

$$\left\{\left[\tau_i\left[\tau_c^{-2}+\tau_i^{-2}(b'|b)\right]-\rho_i\,\tau_i'(b'|b)\left[\rho_c\tau_c^{-1}\tau_c'^{-1}+\rho_i^2\tau_i^{-1}\tau_i'^{-1}(b'|b)\right]\right]\times\frac{1}{\left(\sigma_c^2+\sigma_i^2\right)V(b'|b)}\right.$$

$$\left.-\left[\tau_i-\rho_i\tau_i'\,(b'|b)\right]\times\frac{U(b'|b)}{\left(\sigma_c^2+\sigma_i^2\right)V^2(b'|b)}\right\}\times\left[1+\frac{U(b'|b)}{\left(\sigma_c^2+\sigma_i^2\right)V(b'|b)}\right]^{-2}\times\frac{\partial\tau_i'(b'|b)}{\partial b'|b}$$

After some algebra and rearranging terms, we then have:

$$(b'|b)=\left[\left(\sigma_c^2+\sigma_i^2\right)V(b'|b)+U(b'|b)\right]^{-2}\times\frac{\partial\tau_i'(b'|b)}{\partial b'|b}\times\frac{1}{\tau_i\tau_i'^3(b'|b)}\times\left(\sigma_c^2+\sigma_i^2\right)^2\times$$

$$\left\{\left[\tau_i\left[\tau_c^{-2}+\tau_i^{-2}(b'|b)\right]-\rho_i\,\tau_i'(b'|b)\left[\rho_c\tau_c^{-1}\tau_c'^{-1}+\rho_i^2\tau_i^{-1}\tau_i'^{-1}(b'|b)\right]\right]\times V(b'|b)\right.$$

$$\left.-\left[\tau_i-\rho_i\tau_i'\,(b'|b)\right]\times U(b'|b)\right\}$$

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Table I

Model Comparative Statics

This table reports the comparative statics of the new analyst's conditional bias with respect to previously reported forecast, analyst's expertise, characteristics of private informational channel, characteristics of the common and idiosyncratic component signals, characteristics of earnings, and correlation between signals. The impact of the private informational channel on the analyst's bias is represented by a functional relationship as $\tau'_i = K' [\tanh((b - \alpha')/\beta') + B']$. Parameters B' and K' govern the magnitude of accuracy obtainable through utilizing the private channel. Parameter α' determines how much of the precision is due to firm's private information. As α' increases, the precision becomes more dependent on the firm's private information. In other words, an analyst with high α' has less ability to discern information on his own. Parameter β' determines at what speed the accuracy changes with bias. In other words, β' reflects the severity of the asymmetry of information between analyst and the firm. Firms with higher β' have lower levels of informational asymmetry and hence any minimal positive bias can largely improve the accuracy. We assume that $B = 1$ and $K = 1$ so that the analyst's precision about idiosyncratic noise is equally related to his/her ability as well as the firm's privately revealed information. For old analyst, we assume that precision is governed by $\tau = [\tanh(b) + 1]$.

	Impact on New Analyst's Conditional Bias, $b'\|b$	Impact on New Analyst's Forecast Error
Old Analyst's Bias, b	−	−
New Analyst's Inexperience , α'	+	+
New analyst and Firm Information Asymmetry , $1/\beta'$	−, when $\alpha' < 0$ + , when $\alpha' \geq 0$	−, when $\alpha' < 0$ −, when $\alpha' \geq 0$
Old Analyst's Common Signal's Precision, τ_c	+	+
New Analyst's Common Signal's Precision, τ'_c	−	−
Correlation between common components of signals, ρ_c	−	−
Correlation between idiosyncratic components of signals, ρ_i	+	+
Earning's common component's dispersion, σ_c	+	+
Earning's idiosyncratic component's dispersion, σ_i	+	+

Table II

Comparative Statics of the New Analyst's Conditional Bias: Impact of Characteristics of Private Informational Channels

This table reports the comparative statics of the new analyst's conditional bias with respect to characteristics of private informational channel. The impact of the private informational channel on the analyst's bias is represented by a functional relationship as $\tau'_i = K' [\tanh((b - \alpha')/\beta') + B']$. Parameters B' and K' govern the magnitude of accuracy obtainable through utilizing the private channel. Parameter α' determines how much of the precision is due to firm's private information. As α' increases, the precision becomes more dependent on the firm's private information. In other words, an analyst with high has less ability to discern information on his own. Parameter β' determines at what speed the accuracy changes with bias. In other words, β' reflects the severity of the asymmetry of information between analyst and the firm. Firms with higher β' have lower levels of informational asymmetry and hence any minimal positive bias can largely improve the accuracy. We assume that $B = 1$ and $K = 1$ so that the analyst's precision about idiosyncratic noise is equally related to his/her ability as well as the firm's privately revealed information. For old analyst, we assume that precision is governed by $\tau = [\tanh(b) + 1]$. As for other parameters of interests, we assume that $\sigma_c = 1.0$, $\sigma_i = 1.5$, $\tau_c = 1.0$, and $\tau'_c = 1.0$.

Panel A. $\alpha' = -1.0$ and $\beta' = 1$

	$\rho_c = 0.0$ and $\rho_i = 0.0$		$\rho_c = 1.0$ and $\rho_i = 0.0$		$\rho_c = 0.0$ and $\rho_i = 1.0$		$\rho_c = 1.0$ and $\rho_i = 1.0$	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.014007	0.573	0.014060	0.871	0.025258	0.685	0.045507	0.934
1.0	0.012908	0.549	0.010000	0.855	0.022400	0.645	0.018676	0.931
1.5	0.012534	0.541	0.008778	0.849	0.021351	0.631	0.004159	0.916

Panel B. $\alpha' = 0.0$ and $\beta' = 1$

	$\rho_c = 0.0$ and $\rho_i = 0.0$		$\rho_c = 1.0$ and $\rho_i = 0.0$		$\rho_c = 0.0$ and $\rho_i = 1.0$		$\rho_c = 1.0$ and $\rho_i = 1.0$	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.095677	0.661	0.050614	0.935	0.134751	0.824	0.116489	0.953
1.0	0.088079	0.630	0.031082	0.899	0.120020	0.769	0.064230	0.874
1.5	0.085482	0.620	0.024788	0.884	0.114922	0.749	0.048724	0.851

Panel C. $\alpha' = -1.0$ and $\beta' = 2$

	$\rho_c = 0.0$ and $\rho_i = 0.0$		$\rho_c = 1.0$ and $\rho_i = 0.0$		$\rho_c = 0.0$ and $\rho_i = 1.0$		$\rho_c = 1.0$ and $\rho_i = 1.0$	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.020900	0.598	0.016334	0.894	0.034705	0.731	0.030039	0.999
1.0	0.018793	0.573	0.011134	0.871	0.030591	0.685	0.013344	0.936
1.5	0.018222	0.564	0.009100	0.862	0.029124	0.668	0.017787	0.904

Panel D. $\alpha' = 0.0$ and $\beta' = 2$

	$\rho_c = 0.0$ and $\rho_i = 0.0$		$\rho_c = 1.0$ and $\rho_i = 0.0$		$\rho_c = 0.0$ and $\rho_i = 1.0$		$\rho_c = 1.0$ and $\rho_i = 1.0$	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.053865	0.669	0.025629	0.937	0.076310	0.840	0.058843	0.963
1.0	0.049063	0.637	0.015541	0.899	0.066914	0.781	0.033634	0.877
1.5	0.047445	0.626	0.012367	0.885	0.063773	0.760	0.025310	0.853

Table III

Comparative Statics of the New Analyst's Conditional Bias: Impact of Distributional Characteristics of Common Signals

This table reports the comparative statics of the new analyst's conditional bias with respect to precision of private signals about common and idiosyncratic components of earnings across different levels of correlations between old and new analysts' private signals about common and idiosyncratic components of earnings. Here, we assume that $\tau_i = [\tanh(b) + 1]$ and that $\tau'_i = [\tanh(b'|b) + 1]$. We assume that $\sigma_c = 1.0$ and $\sigma_i = 1.5$.

Panel A. $\tau_c = 0.5$ and $\tau'_c = 0.5$

	$\rho_c = 0.0$ and $\rho_i = 0.0$		$\rho_c = 1.0$ and $\rho_i = 0.0$		$\rho_c = 0.0$ and $\rho_i = 1.0$		$\rho_c = 1.0$ and $\rho_i = 1.0$	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.095677	0.661	0.050614	0.935	0.134751	0.824	0.116489	0.953
1.0	0.088079	0.630	0.031082	0.899	0.120020	0.769	0.064230	0.874
1.5	0.085482	0.620	0.024788	0.884	0.114922	0.749	0.048724	0.851

Panel B. $\tau_c = 0.5$ and $\tau'_c = 1.0$

	$\rho_c = 0.0$ and $\rho_i = 0.0$		$\rho_c = 1.0$ and $\rho_i = 0.0$		$\rho_c = 0.0$ and $\rho_i = 1.0$		$\rho_c = 1.0$ and $\rho_i = 1.0$	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.048008	0.452	0.010900	0.569	0.033918	0.582	0.154740	0.319
1.0	0.036343	0.390	0.001528	0.484	0.016960	0.485	0.065224	0.203
1.5	0.032502	0.368	0.000000	0.452	0.013458	0.451	0.036060	0.170

Panel C. $\tau_c = 1.0$ and $\tau'_c = 0.5$

	$\rho_c = 0.0$ and $\rho_i = 0.0$		$\rho_c = 1.0$ and $\rho_i = 0.0$		$\rho_c = 0.0$ and $\rho_i = 1.0$		$\rho_c = 1.0$ and $\rho_i = 1.0$	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.159632	0.527	0.172454	0.685	0.219658	0.689	0.368181	0.729
1.0	0.150296	0.509	0.156807	0.673	0.199504	0.653	0.310928	0.760
1.5	0.147012	0.502	0.150902	0.669	0.192742	0.639	0.283596	0.763

Panel D. $\tau_c = 1.0$ and $\tau'_c = 1.0$

	$\rho_c = 0.0$ and $\rho_i = 0.0$		$\rho_c = 1.0$ and $\rho_i = 0.0$		$\rho_c = 0.0$ and $\rho_i = 1.0$		$\rho_c = 1.0$ and $\rho_i = 1.0$	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.093323	0.390	0.071882	0.479	0.087433	0.573	0.160702	0.497
1.0	0.073823	0.344	0.044732	0.427	0.039337	0.482	0.091053	0.389
1.5	0.067052	0.327	0.035829	0.406	0.029990	0.449	0.069127	0.358

Table IV

Comparative Statics of the New Analyst's Conditional Bias: Impact of Distributional Characteristics of Earnings

This table reports the comparative statics of the new analyst's conditional bias with respect to dispersions of common and idiosyncratic components of earnings across different levels of correlations between old and new analysts' private signals about common and idiosyncratic components of earnings. Here, we assume that τ_i = [tanh(b) + 1] and that τ'_i = [tanh($b'|b$) + 1]. We assume that τ_c = 1.0 and τ'_c = 1.0.

Panel A. σ_c = 1.0 and σ_i = 1.5

	ρ_c = 0.0 and ρ_i = 0.0		ρ_c = 1.0 and ρ_i = 0.0		ρ_c = 0.0 and ρ_i = 1.0		ρ_c = 1.0 and ρ_i = 1.0	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.095677	0.661	0.050614	0.935	0.134751	0.824	0.116489	0.953
1.0	0.088079	0.630	0.031082	0.899	0.120020	0.769	0.064230	0.874
1.5	0.085482	0.620	0.024788	0.884	0.114922	0.749	0.048724	0.851

Panel B. σ_c = 0.5 and σ_i = 1.5

	ρ_c = 0.0 and ρ_i = 0.0		ρ_c = 1.0 and ρ_i = 0.0		ρ_c = 0.0 and ρ_i = 1.0		ρ_c = 1.0 and ρ_i = 1.0	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.086443	0.624	0.043038	0.861	0.119135	0.768	0.099094	0.877
1.0	0.079830	0.597	0.026514	0.830	0.106696	0.720	0.055595	0.809
1.5	0.077565	0.587	0.021182	0.818	0.102393	0.702	0.042185	0.790

Panel C. σ_c = 1.0 and σ_i = 0.5

	ρ_c = 0.0 and ρ_i = 0.0		ρ_c = 1.0 and ρ_i = 0.0		ρ_c = 0.0 and ρ_i = 1.0		ρ_c = 1.0 and ρ_i = 1.0	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.058146	0.501	0.023958	0.641	0.073997	0.591	0.054705	0.652
1.0	0.054366	0.483	0.014945	0.623	0.067694	0.562	0.032423	0.612
1.5	0.053058	0.477	0.012015	0.616	0.065512	0.551	0.024828	0.601

Panel D. σ_c = 0.5 and σ_i = 0.5

	ρ_c = 0.0 and ρ_i = 0.0		ρ_c = 1.0 and ρ_i = 0.0		ρ_c = 0.0 and ρ_i = 1.0		ρ_c = 1.0 and ρ_i = 1.0	
b	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*	*b'|b*	*Error*
0.5	0.023919	0.314	0.007672	0.362	0.026473	0.347	0.016948	0.366
1.0	0.022867	0.307	0.004887	0.357	0.025138	0.337	0.010953	0.353
1.5	0.022495	0.304	0.003965	0.354	0.024687	0.333	0.008510	0.349

Table V

Sample Statistics

This table reports mean and standard deviation of variables of interest for the entire sample, new analysts and old analysts across for entire period, periods prior to and after the S&P500 inclusion. Bias is the forecast minus consensus. Forecast Error is the actual earnings minus forecast. Relative experience is the quarters of experience following same 2-digit SIC firms as the included firm as compared to the average number of quarters of experience of other analysts following the newly included firm. IAB, the biased-based information asymmetry proxy, is defined as the average forecast bias using forecasts created at least 360 days (4 quarters) prior to the earnings realization date minus the average forecast bias using forecasts created less than or equal to 90 days (one quarter) prior to the earnings realization date. IAE is an analogous measure to IAB using forecast error instead of bias. Old analysts are defined as analysts with more than 1 quarter of experience. New analysts are defined as analysts with no experience following the firm (this is the first quarter of following). Mean equality test for differences between new and old analysts for the entire period as well as for before and after inclusion periods are all significant at 5% level.

	Entire Period			Before Inclusion			After Inclusion		
Variable	Obs	Mean	Std.	Obs	Mean	Std.	Obs	Mean	Std.
Panel A. All Analysts									
Bias	104296	0.01436	2.67268	42119	0.04359	2.33941	56809	-0.00140	3.00381
Forecast Error (FE)	106503	0.10532	0.65046	42361	0.14082	0.53420	58704	0.07848	0.71091
Relative Experience	106503	1.00000	0.59482	42361	0.94571	0.58719	58704	1.04129	0.59761
IAB	88930	1.18292	3.68478	34713	0.77394	2.58798	49567	1.48374	4.28463
IAE	88942	0.42571	0.74515	34856	0.37241	0.67676	49418	0.45940	0.77787
Panel B. Old Analysts									
Bias	100976	0.01629	2.69837	40267	0.04664	2.34796	55520	0.00042	3.03505
Forecast Error (FE)	103117	0.10429	0.65494	40471	0.14019	0.53690	57387	0.07782	0.71447
Relative Experience	103117	1.02684	0.58468	40471	0.98129	0.57578	57387	1.06128	0.58891
IAB	86611	1.19444	3.70799	33371	0.77763	2.58660	48734	1.49387	4.30426
IAE	86638	0.42681	0.74703	33519	0.37212	0.67583	48592	0.46054	0.78005
Panel C. New Analysts									
Bias	3320	-0.04430	1.71574	1852	-0.02275	2.14459	1289	-0.07969	0.94393
Forecast Error (FE)	3386	0.13667	0.49409	1890	0.15448	0.47269	1317	0.10712	0.53240
Relative Experience	3386	0.18262	0.16699	1890	0.18378	0.14590	1317	0.17058	0.17690
IAB	2304	0.38443	0.66950	1337	0.37953	0.69981	826	0.39252	0.63361
IAE	2319	0.75258	2.64254	1342	0.68221	2.62146	833	0.89115	2.85424

Table VI

Time Series Summary Statistics of Bias and Forecast Error For Old and New Analysts

This table reports mean bias and mean forecast error for an inclusion event window of (-4,+4) for both new and old analysts. The tables also reports summary information for windows of twelve, eight, and four quarters prior to and after the inclusion. Mean equality test for differences between new and old analysts are significant at 5% level.

		All Analysts		Old Analysts		New Analysts		Old minus New	
Relative Quarter	Num. Analysts	Bias	Forecast Error	Bias	Forecast Error	Bias	Forecast Error	Bias	Forecast Error
-4	19	-0.2704	0.1218	-0.2765	0.1220	-0.0176	0.1149	-0.2589	0.0071
-3	19	-0.0078	0.3857	0.0014	0.3780	-0.2189	0.5613	0.2203	-0.1833
-2	19	0.0538	0.1322	0.0466	0.1326	0.2577	0.1196	-0.2111	0.0130
-1	20	0.2017	0.0145	0.2066	0.0138	0.0478	0.0354	0.1588	-0.0216
0	21	-0.0482	0.1184	-0.0494	0.1168	-0.0124	0.1660	-0.0370	-0.0492
1	21	0.6302	0.1256	0.6523	0.1284	-0.1559	0.0316	0.8082	0.0968
2	21	-0.1500	0.0202	-0.1567	0.0164	0.0733	0.1458	-0.2300	-0.1294
3	23	-0.0288	-0.0304	-0.0246	-0.0312	-0.2431	0.0093	0.2185	-0.0405
4	23	-0.1845	0.0306	-0.1863	0.0273	-0.0668	0.2436	-0.1195	-0.2163
Avg [-4,-1]	19	-0.0045	0.1308	-0.0044	0.1293	0.0138	0.1662	-0.0182	-0.0369
Avg [0, +4]	22	0.1008	0.0585	0.1054	0.0576	-0.0845	0.0882	0.1899	-0.0306
Avg [-8,-1]	19	0.0248	0.1327	0.0283	0.1314	-0.0252	0.1615	0.0535	-0.0301
Avg [0, +8]	22	-0.0263	0.0478	-0.0247	0.0464	-0.0896	0.1057	0.0649	-0.0593
Avg [-12,-1]	19	0.0530	0.1427	0.0588	0.1429	-0.0180	0.1445	0.0768	-0.0016
Avg [0, +12]	23	0.0139	0.0906	0.0160	0.0900	-0.0659	0.1038	0.0819	-0.0138

Table VII

Correlation Analysis of Old and New Analysts' Biases and Forecast Errors

This table reports correlations and one-period lagged auto-correlations of old and new analysts' biases and forecast error for windows of twelve, eight, and four quarters after the inclusion.

	Biases	Forecast Errors	Quarterly Change in Biases	Quarterly Change in Forecast Errors
Correlations:				
$\rho_{old, new}$ [0, +12]	-0.1341	0.1092	-0.5191	0.0421
$\rho_{old, new}$ [0, +8]	-0.2733	0.1159	-0.6215	0.1242
$\rho_{old, new}$ [0, +4]	-0.4417	0.0547	-0.6979	0.3278
	Old Analyst's Bias	Old Analyst's Error	New Analyst's Bias	New Analyst's Error
One-period Autocorrelations:				
$\rho_{Q, Q-1}$ [0, +12]	0.0366	0.0404	-0.5007	-0.3557
$\rho_{Q, Q-1}$ [0, +8]	-0.0468	0.1987	-0.6153	-0.7449
$\rho_{Q, Q-1}$ [0, +4]	-0.3578	0.4875	-0.7699	-0.9485

Table VIII
Impact of Competency (i.e., Experience) on Analysts Forecasting

The following OLS regression is specified: $BIAS_{it}$ ($ERROR_{it}$)= $\alpha_0 + \eta$ $Expertise_{i,t} + \beta_0 Inclusion_{it} + \beta_1 Accruals_{it} + \beta_2 RegFD_t + \Phi$ SICs + ε. The dependent variable refers to the analyst's bias (forecast error) for the new or old analyst with term as specified. Expertise is measured by experience or relative experience. Experience is the number of quarters the analyst has followed the firm for which forecast error is calculated. Relative Experience is experience divided by average experience of the sample of analysts in the relevant industry for that quarter. Included is a dummy variable indicating if the firm is included in the S&P500. Accruals accounts for accounting accrued revenue/liabilities utilized for earnings smoothing. RegFD is a dummy variable which takes on a value of 1 if RegFD is in effect and 0 otherwise. Coefficients on 2-digit SIC code dummies are not reported for brevity. The absolute values of t-statistics are reported in brackets. *, **, *** indicate significance levels of 10, 5, and 1 percent respectively.

	FE		Bias	
Experience	-0.005*		-0.010**	
	[0.003]		[0.005]	
InclExp	0.002		0.021***	
	[0.003]		[0.006]	
InclRelExp		0.005		0.036***
		[0.004]		[0.008]
Relative Experience		-0.011***		-0.016***
		[0.003]		[0.006]
Included	-0.030***	-0.030***	-0.082***	-0.071***
	[0.008]	[0.005]	[0.014]	[0.009]
accruals	0.267***	0.267***	-0.018***	-0.017***
	[0.002]	[0.002]	[0.003]	[0.003]
RegFD	-0.049***	-0.050***	-0.050***	-0.049***
	[0.003]	[0.003]	[0.005]	[0.005]
Constant	0.046**	0.047**	0.070*	0.065*
	[0.020]	[0.019]	[0.036]	[0.035]
Observations	105774	105774	104568	104568
R-squared	0.28	0.28	0.01	0.01
F-test	928.41	928.8	16.93	17.18

Table IX

Impact of Information Asymmetry on Analysts Forecasting

The following OLS regression is specified: $BIAS_{it}\ (ERROR_{it}) = a_0 + \gamma\ Information\ Asymmetry_t + \beta_0\ Included_t + \beta_1 Accruals_t + \beta_2 RegFD_t + \beta_3 Expertise_{i,t} + \boldsymbol{\Phi}\ \boldsymbol{SICs} + \varepsilon$. The dependent variable refers to the analyst's bias (forecast error) for the new or old analyst with term as specified. Included is a dummy variable indicating if the firm is included in the S&P500. Information asymmetry is error-based; defined as the forecast error when forecast was made three quarters prior to the current quarter minus the forecast error when forecast was made one quarter prior to the current quarter. Expertise is measured by experience or relative experience. Experience is the number of quarters the analyst has followed the firm for which forecast error is calculated. Relative Experience is experience divided by average experience of the sample of analysts in the relevant industry for that quarter. Included is a dummy variable indicating if the firm is included in the S&P500. Accruals accounts for accounting accrued revenue/liabilities utilized for earnings smoothing. RegFD is a dummy variable which takes on a value of 1 if RegFD is in effect and 0 otherwise. Coefficients on 2-digit SIC code dummies are not reported for brevity. The absolute values of t-statistics are reported in brackets. *, **, *** indicate significance levels of 10, 5, and 1 percent respectively.

	FE				Bias			
Experience	-0.012***		-0.013***		-0.010*		-0.010*	
	[0.003]		[0.003]		[0.006]		[0.006]	
InclExp	0.002		0.003		0.022***		0.023***	
	[0.004]		[0.004]		[0.008]		[0.008]	
Relative Experience		-0.014***		-0.014***		-0.014**		-0.014**
		[0.004]		[0.004]		[0.007]		[0.007]
InclRelExp		0.001		0		0.034***		0.034***
		[0.005]		[0.005]		[0.009]		[0.009]
Included	-0.030***	-0.028***	0.008	0.013**	-0.085***	-0.070***	-0.072***	-0.056***
	[0.010]	[0.006]	[0.010]	[0.007]	[0.018]	[0.011]	[0.018]	[0.012]
IAIncl			-0.112***	-0.112***			-0.039***	-0.039***
			[0.006]	[0.006]			[0.011]	[0.011]
IA	0.139***	0.139***	0.209***	0.209***	-0.002	-0.002	0.022**	0.022**
	[0.003]	[0.003]	[0.005]	[0.005]	[0.006]	[0.006]	[0.009]	[0.009]
accruals	0.239***	0.239***	0.240***	0.240***	-0.016***	-0.015***	-0.015***	-0.015***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.004]	[0.004]	[0.004]	[0.004]
RegFD	-0.066***	-0.068***	-0.067***	-0.069***	-0.056***	-0.056***	-0.056***	-0.056***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.007]	[0.007]	[0.007]	[0.007]
Constant	0.065*	0.052	0.039	0.023	0.086	0.08	0.077	0.07
	[0.038]	[0.038]	[0.038]	[0.037]	[0.069]	[0.068]	[0.069]	[0.068]
Observations	75655	75655	75655	75655	74861	74861	74861	74861
R-squared	0.3	0.3	0.3	0.3	0.01	0.01	0.01	0.01
F-test	736.36	736.44	731.29	731.34	11.33	11.47	11.37	11.49

Table X

Impact of Uncertainty of Signals on Analysts Forecasting

The following OLS regression is specified: $BIAS_{it}$ $(ERROR_{it})$ $= a_0 + \beta_0\ Uncertainty_t + \beta_0\ Included + \beta_1 Accruals + \beta_2\ NumAnalysts + \beta_3 RegFD + \boldsymbol{\Phi}\ \mathbf{SICs} + \varepsilon$. The dependent variable refers to the bias/forecast error for the new or old analyst with term as specified. StdDev Industry is the quarterly standard deviation of actual quarterly earnings computed at the 2-digit SIC level, and StdDev Company / StdDev Industry, the standard deviation of actual earnings computed at the company level and scaled by industry-level standard deviation. Included is a dummy variable indicating if the firm is included in the S&P500. Accruals accounts for accounting accrued revenue/liabilities utilized for earnings smoothing. RegFD is a dummy variable which takes on a value of 1 if RegFD is in effect and 0 otherwise. Observations are analyst-year specific. Coefficients on 2-digit SIC code dummies are not reported for brevity. Standard errors are reported in brackets. *, **, *** indicate significance levels of 10, 5, and 1 percent respectively.

	Bias	Bias	Forecast Error	Forecast Error
StdDev Industry	0.269***		0.072***	
	[0.005]		[0.011]	
StdDev Company / StdDev Industry		0.126***		0.036***
		[0.005]		[0.011]
Included	-0.049***	-0.032***	-0.037***	-0.035***
	[0.004]	[0.004]	[0.010]	[0.010]
Accruals	0.302***	0.345***	-0.029***	-0.018***
	[0.002]	[0.002]	[0.006]	[0.005]
NumAnalysts	-0.001***	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]
RegFD	-0.118***	-0.102***	-0.090***	-0.090***
	[0.004]	[0.004]	[0.009]	[0.010]
Constant	0.048***	0.045***	0.127***	0.126***
	[0.003]	[0.004]	[0.008]	[0.009]
Observations	105767	103521	104561	102332
R-squared	0.21	0.19	0.01	0.01
F-statistics	5748.32	5006.66	133.95	126.53

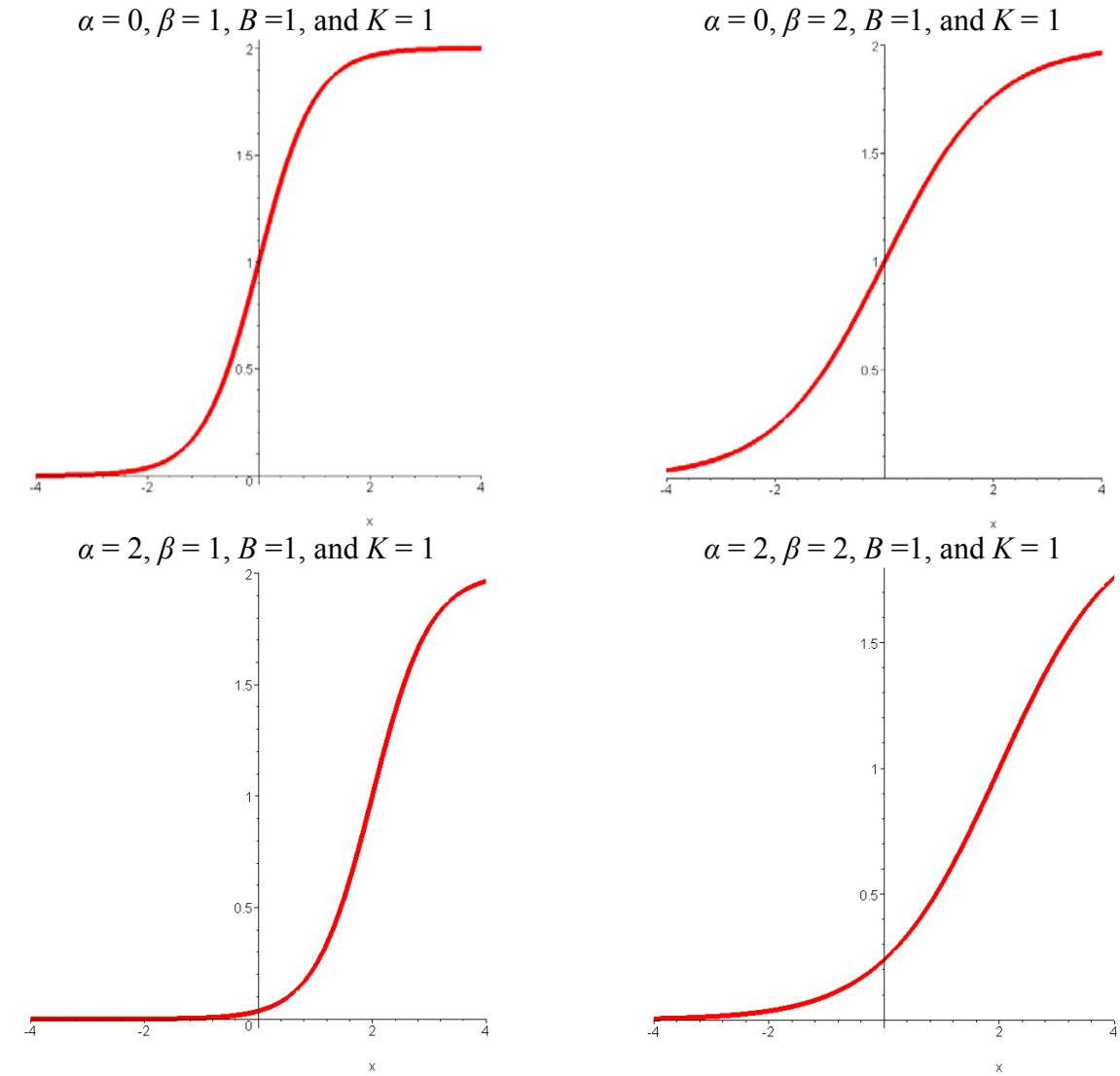
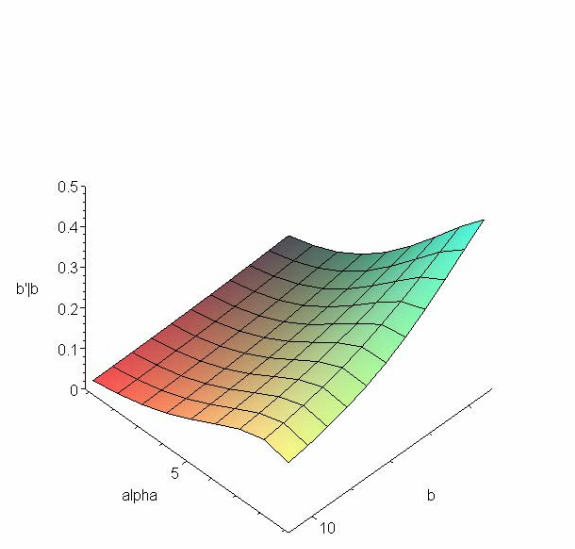
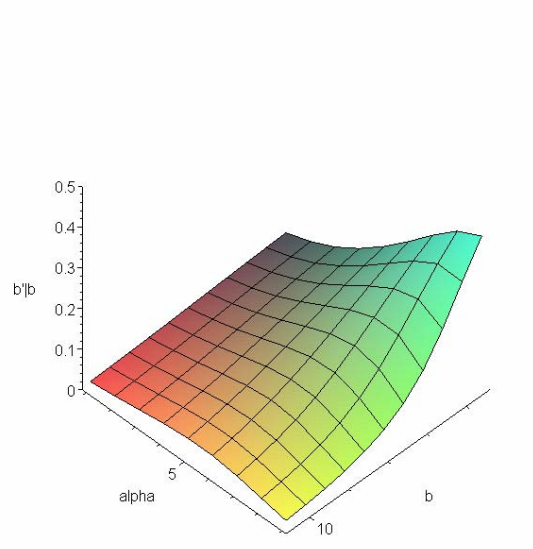


Figure 1. This plot demonstrates the relationship between the accuracy (vertical axis) and bias (horizontal axis). The accuracy increases with bias when analyst's bias is positive; however, this relationship is not monotonically increasing: there are diminishing returns to making a positive bias. In addition, a negative bias worsens the analyst's access to private channels, hence reduces her accuracy. The negative impact of a negative bias is also decreasingly diminishing. This reflects the intuition that not all pertinent information is private and that markets, analysts included, do provide additional outside information about the firm. The functional relationship plotted here are $\tau = K$ $[\tanh((b - \alpha)/\beta) + B]$. By adjusting parameters B and, we assure that accuracy is bounded when bias goes from $-\infty$ to $+\infty$. Parameter α inversely measures the analyst's efficacy, i.e., how much of the precision is due to firm's private information. As α increases, the precision becomes more dependent on the firm's private information. In other words, an analyst with high has less ability to discern information on his own. Parameter β determines at what speed the accuracy changes with bias. In other words, β reflects the severity of the asymmetry of information between analyst and the firm. Firms with higher β have lower levels of informational asymmetry and hence any minimal positive bias can largely improve the accuracy.

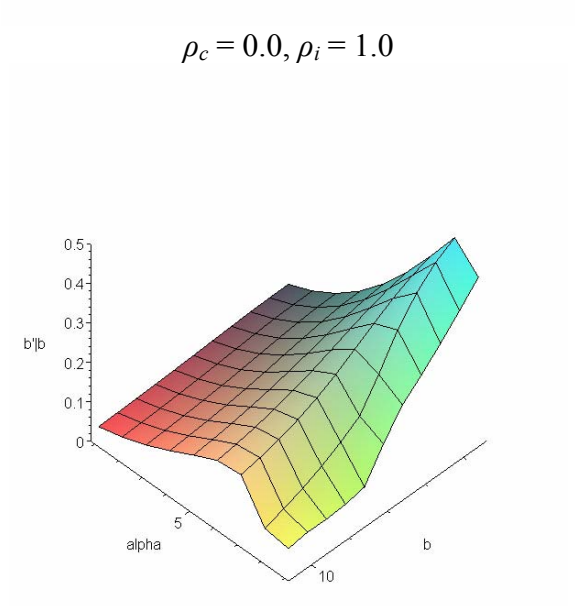
$\rho_c = 0.0, \rho_i = 0.0$



$\rho_c = 1.0, \rho_i = 0.0$



$\rho_c = 0.0, \rho_i = 1.0$



$\rho_c = 1.0, \rho_i = 1.0$

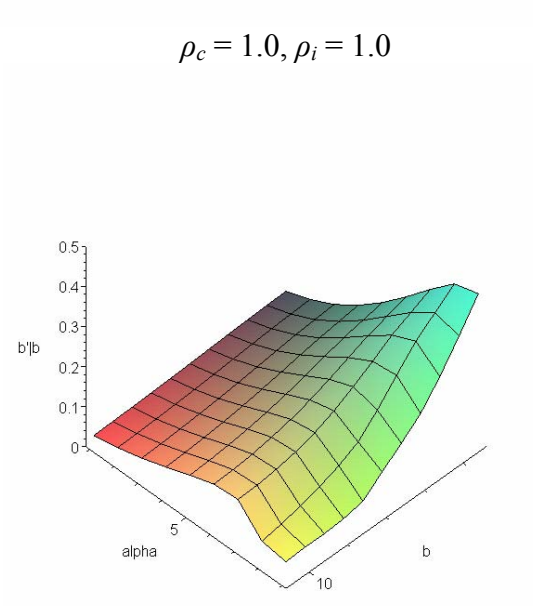
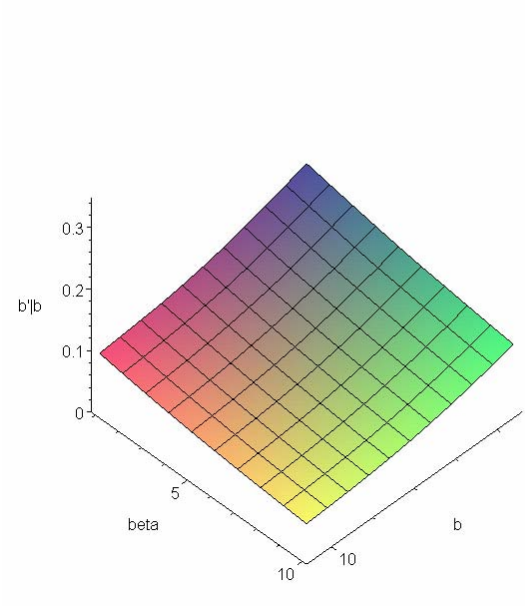
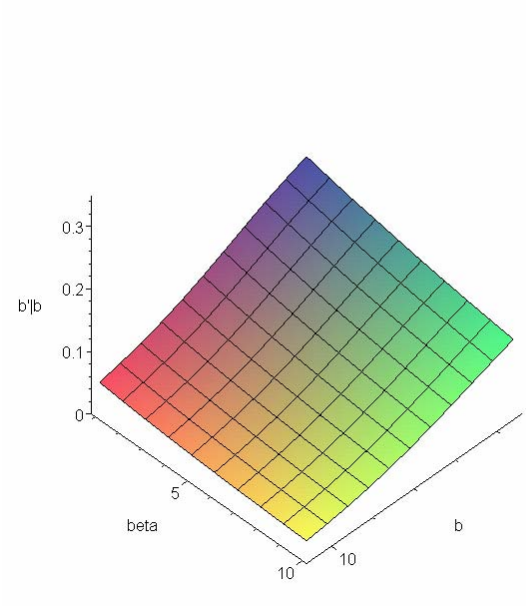


Figure 2. Comparative statics with respect to the analyst's expertise, *α*: Aforementioned plots depict the relationship between new and old analyst's bias for different degrees of analyst's expertise across different correlation structures. ρ_c is the correlation between both analysts' common errors and ρ_i the correlation between both analysts' idiosyncratic errors. The original analyst's common signal's precision, σ_c, is 1.0 and the new analyst's common signal's precision, σ_i, is 1.50. Earning's common component's dispersion, τ_c, is 1.0 and idiosyncratic component's dispersion, τ'_c, is 1.0.

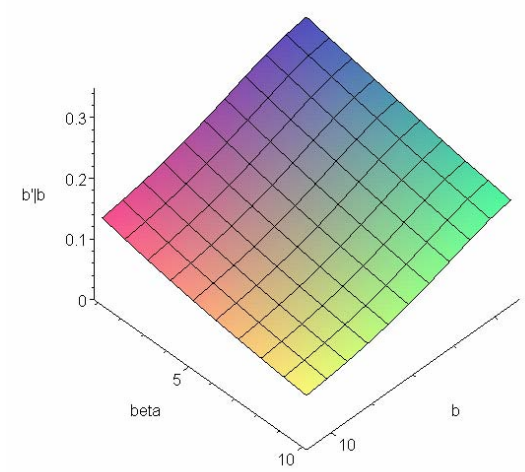
$\rho_c = 0.0, \rho_i = 0.0$



$\rho_c = 1.0, \rho_i = 0.0$



$\rho_c = 0.0, \rho_i = 1.0$



$\rho_c = 1.0, \rho_i = 1.0$

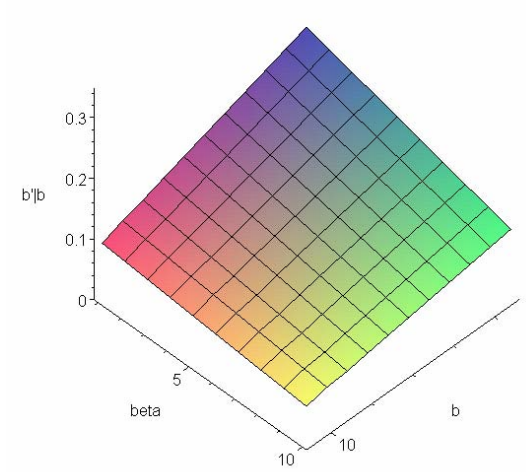


Figure 3. Comparative statics with respect to the information asymmetry, β: Aforementioned plots depict the relationship between new and old analyst's bias for different degrees of analyst-firm degree of information asymmetry across different correlation structures. ρ_c is the correlation between both analysts' common errors and ρ_i the correlation between both analysts' idiosyncratic errors. The original analyst's common signal's precision, σ_c, is 1.0 and the new analyst's common signal's precision, σ_i, is 1.50. Earning's common component's dispersion, τ_c, is 1.0 and idiosyncratic component's dispersion, τ'_c, is 1.0.

[1] The theoretical bias denotes the difference between the analysts' forecast and mean of the earnings distribution. Empirically, extant studies define bias to be the difference between an analyst's forecast and the consensus forecast. We follow these conventions throughout the paper. Our theoretical and empirical bias are same as the literature.

[2] As far as the general construct of the model goes, we are partly motivated by Bernhardt, Campello and Kusoati (2004) who argue that when analysts, as proper Bayesians, incorporate all information in their forecasts, and when private sources of information are common, the forecast clustering, which is often seen as an evidence of herding, can be the natural outcome of a learning process through which analysts reflect their own and others' information.

[3] Some learning studies that permit analysts to improve estimates by utilizing public and private sources [see, e.g., Lim (2001) who shows that a positive bias serves to appease to managers in order to gain access to private information].

[4] Our analytical findings are partly supported by the existing evidence. For instance, Trueman (1994) shows that less competent analysts discount their own estimates and report an estimate, which is consistent with what other analysts propose to avoid dire career consequences. Bernhardt, Campello and Kusoati (2004) finds that analyst with greater experience and more firms followed tend to consistently and significantly differ from consensus estimates.

[5] Both learning and herding strands of literature reflect extreme examples of Bayesian updating when analysts assume the precision of their signals are infinitely large or small. Typical herding studies such as Trueman (1994) assume that analysts without expertise essentially disregard their own estimates fearing to stand out in the analyst crowd. Learning papers like Bernhardt, Campello and Kusoati (2004), however, assume that expert analysts confidently rely on their own estimates. We differ from these studies in that we believe that only through the window of a proper Bayesian, one that incorporates all types of information without any predisposed belief about the validity of the information source, we can accurately model the analyst forecasting problem.

[6] Our analytical findings are partly supported by the existing evidence. For instance, Trueman (1994) shows that less competent analysts discount their own estimates and report an estimate, which is consistent with what other analysts propose to avoid dire career consequences. Bernhardt, Campello and Kusoati (2004) finds that analyst with greater experience and more firms followed tend to consistently and significantly differ from consensus estimates.

[7] Experience is defined by the number of quarters an analyst follows a firm. We define new analysts as analysts with less than 3 quarters experience.

[8] The relationship between learning/herding and experience is noted by some of the recent studies such as Bernhardt, Campello and Kusoati (2004) and Clement and Tse (2005). Both of these papers show that more seasoned analysts tend to post "bold" estimates; forecasts substantially different from consensus.

[9] Existing evidence indicates that analysts rarely post sell recommendation for a stock suggesting that losing a the firm's favor can be viewed as a costly proposition. In extremes, firms even pursue legal ramification for an analyst's unfavorable recommendations. In a 2001 congressional hearing, president and chief executive officer of the Association for Investment Management and Research told the U.S. House of Representatives Committee on Financial Services, Capital Markets Subcommittee, that "…In addition to pressures within their firms, analysts can also be, and have been, pressured by the executives of corporate issuers to issue favorable reports and recommendations. Regulation Fair Disclosure notwithstanding, recent history, supported by the results of a research study issued by Reuters, has shown that companies retaliate against analysts who issue 'negative' recommendations by denying them direct access to company executives and to company-sponsored events that are important research tools. Companies have also sued analysts personally, and their firms, for negative coverage. Such actions create a climate of fear that does not foster independence and objectivity."

[10] Essentially, we also extend existing studies such as Lim (2001) by allowing stylized facts such as the correlatedness of analysts' information, the efficacy of private information channels, and analysts' expertise to play a central role in the analyst's decisions making process. In particular, while we follow Lim (2001) in that we assume an analyst's objective function as a mean square error reduction problem in which a positive bias can improve quality of private signal, we extend Lim (2001) by allowing for interactions between different analysts, correlated information, and common wide spread shocks.

[11] Note that here we assume that the common component's signal is more accurate than the idiosyncratic component's signal. We have experimented with alternative case where the idiosyncratic signal is more precise and found that results, as expected, is reversed.