Available online at www.sciencedirect.com
SCIENCE DIRECT®
Journal of Financial Economics 80 (2006) 81–113
JOURNAL OF Financial ECONOMICS
www.elsevier.com/locate/jfec

Dynamic forecasting behavior by analysts: Theory and evidence☆

Jonathan Clarke[a], Ajay Subramanian[b,*]

[a]College of Management, Georgia Institute of Technology, Atlanta, GA 30332, USA
[b]J. Mack Robinson College of Business, Georgia State University, Atlanta, GA 30303, USA

Received 27 September 2004; received in revised form 31 January 2005; accepted 21 March 2005
Available online 12 October 2005

Abstract

We develop a multi-period learning model to examine the relation between analysts' forecasting behavior and their performance. In a competitive market for banking services, the surplus and the analyst's payoff, which is determined through bargaining, are convex in her reputation. The convexity of her payoff structure and the presence of employment risk lead to a U-shaped relation between the analyst's forecast boldness and prior performance and a positive relation between forecast boldness and experience. We find support for these predictions in our empirical analysis. Significant underperformers (outperformers) face higher (lower) employment risk and are more likely to issue bolder forecasts.

JEL classification: G24; D81; M52

Keywords: Analysts; Career concerns; Employment risk; Dynamic forecasting; Herding

☆We especially thank the anonymous referee and Harrison Hong for several insightful comments and suggestions that have significantly improved the paper. We also thank Vikas Agarwal, Naveen Daniel, John Graham, Jason Greene, Omesh Kini, Lalitha Naveen, Paul Oyer, Bill Schwert (the editor), Husayn Shahrur, Anand Venkateswaran, and seminar participants at the 2004 North American winter meetings of the Econometric Society, the Georgia Institute of Technology, and Georgia State University for valuable comments. We gratefully acknowledge the contribution of I/B/E/S International Inc. for providing earnings per share forecast data, available through the Brokers Estimate System. We are solely responsible for all errors.

*Corresponding author. Tel.: +1 404 651 4627; fax: +1 404 651 4219.
E-mail address: insasu@langate.gsu.edu (A. Subramanian).

0304-405X/$ - see front matter
doi:10.1016/j.jfineco.2005.03.008

1. Introduction

In markets where the average investor has incomplete information about a firm, earnings forecasts by security analysts play an important role in disseminating information. Analysts, as rational agents, are, however, affected by their incentives in their choices of earnings forecasts. The turmoil in financial markets that followed the bursting of the dot-com bubble has brought intense scrutiny upon analysts and has led to an examination of the perverse role of their incentives in misrepresenting information about firms. Therefore, the issue of how analysts' incentives influence their forecasting behavior is very important and relevant.

In this study, we propose a positive theory to examine the impact of incentives arising from compensation structures and reputation concerns on the dynamic forecasting behavior of security analysts. We show that the interplay between the convexity of an analyst's payoff in her perceived ability or reputation and the presence of employment risk leads to a non-monotonic (U-shaped) relation between the boldness of an analyst's forecast and her prior relative forecasting performance and a positive relation between boldness and experience. We find significant support for these predictions in our empirical analysis of analysts' forecasting behavior. Consistent with the predictions of our theory that emphasizes the importance of employment risk as a determinant of forecast boldness, we also find that analysts with high or low probabilities of future termination issue bolder forecasts than those with intermediate termination probabilities.

We develop and analyze a multi-period Bayesian learning model in which we focus on the group of analysts covering a particular firm. At the beginning of every period, each analyst issues her forecast of the firm's end-of-period earnings based on her noisy private information about the firm's earnings and the consensus forecast. The fundamental state variable that we model is the relative forecasting error of an individual, representative analyst; the difference between her cumulative forecasting error and the mean cumulative forecasting error of all analysts covering the firm over a prior time horizon. The analyst could issue forecasts of varying degrees of boldness represented by the standard deviations of the respective changes in the analyst's relative forecasting error. The expected change in the analyst's relative forecasting error under any forecast depends on her forecasting ability. There is incomplete, but symmetric information about an analyst's ability when she first enters the market. As in learning by doing models, the analyst's ability can change over time as she gains experience. All agents dynamically update their assessments of the analyst's ability based on her observed performance.

The analyst (directly and indirectly) affects the demand for the bank's services (business volume) through her perceived ability or reputation so that she has significant bargaining power with the bank. Hence, the analyst's compensation in each period is determined through ex post bilateral bargaining with the bank over the surplus that she generates. If the demand for investment banking services is perfectly competitive, and the bank's costs are increasing and convex in its business volume, we show that, consistent with prior evidence (Jackson, 2005), the bank's business volume and surplus at each date are increasing and convex in the analyst's average ability as perceived by the market (hereafter referred to as her average perceived ability). Assuming Nash bargaining between the bank and the analyst, we then show that the analyst's compensation, or share of the surplus, is also convex in her average perceived ability.

At any date, the analyst also faces employment risk because the bank could replace her with another analyst of higher perceived ability. However, if the bank incurs fixed costs in replacing the incumbent analyst and cannot find a replacement with certainty, we show that she could be fired only if her average perceived ability falls below a certain level (the termination threshold). At any date, the level of ex ante employment risk an analyst faces is, therefore, determined by her termination threshold, the probability that the bank finds a replacement (termination probability), and the proportional personal costs that she bears from being fired (termination costs). The convexity of an analyst's compensation in her perceived ability or reputation, and the presence of employment risk, is also consistent with existing empirical and anecdotal evidence.[1]

The analyst issues her forecast at each date to maximize her expected end-of-period compensation that depends on her end-of-period reputation.[2] We show that the boldness of the analyst's forecast varies non-monotonically with her prior forecasting performance. Specifically, she issues bolder forecasts when she significantly outperforms or under performs her peers than when she is an intermediate performer. The intuition for these results hinges on the interplay between the convexity of the analyst's payoff structure and her employment risk. When the analyst significantly outperforms her peers, her average perceived ability significantly exceeds the termination threshold. Because of the convexity of her payoff in her average perceived ability, she creates additional noise in the market's perception of her ability by issuing a bolder forecast. However, if she significantly underperforms her peers, she faces a substantial probability of being fired in the future so that she gambles by issuing bolder forecasts to increase the probability that her average perceived ability rises above the termination threshold. At intermediate performance levels, the proximity to the termination threshold could induce the analyst to herd by issuing more conservative forecasts, thereby reducing the deviation in her average perceived ability. Hence, employment risk is a crucial driving force for changes in the analyst's forecast boldness in response to her prior performance.

Next, we show that, ceteris paribus, the boldness of the analyst's forecast increases with time (in probability). The intuition for this result is that the growth in the analyst's forecasting ability with experience causes the ex ante employment risk she faces at each date to decline over time. The convexity of her payoff structure then induces her to issue bolder forecasts at each level of prior forecasting performance.

We also show that our results remain robust to a generalization of the model in which the analyst's effort in each period is also explicitly modeled. The analyst's unobservable effort affects her forecasting performance, and her ability grows with the effort that she exerts. The analyst's effort and forecast choices, and the market's assessment of the analyst's effort choices, are derived endogenously in equilibrium of a dynamic game between the analyst and the market.

Finally, we empirically test the predictions of our model using earnings forecast data from I/B/E/S over the period 1988 and 2000 for a sample of firms with significant analyst

[1]Although precise data on analysts' compensation are not available, there is anecdotal evidence to suggest that large pay discrepancies exist between analysts being named to *Institutional Investor's* All-America research team and those that do not make the team. Given that Leone and Wu (2002) find that *Institutional Investor* all-stars have superior performance to non-star analysts, this would imply significant convexity in the compensation structures for analysts. Mikhail et al. (1999) find that an analyst is more likely to be fired if her forecast accuracy declines relative to her peers.

[2]All of our results hold for a risk-averse analyst with Constant Relative Risk Aversion (CRRA) preferences.

coverage. We show, for the first time, strong evidence of a statistically and economically significant U-shaped relation between analysts' future boldness and prior relative forecasting performance as predicted by the model. By demonstrating the propensity of both outperforming and under performing analysts to issue bolder forecasts, we supplement the findings of prior studies that find that outperforming analysts issue bolder forecasts (Hilary and Menzly, 2001; Clement and Tse, 2005) (Because these studies estimate a linear relation between boldness and prior performance, they cannot detect a non-monotonic relation). We also extend earlier research (Hong et al., 2000) by documenting a positive relation between boldness and experience controlling for the U-shaped relation between boldness and prior performance (Chevalier and Ellison, 1999; Lamont, 2002, document findings similar to those of Hong et al., 2000 in their empirical investigations of mutual fund managers and macroeconomic forecasters, respectively).

We then directly test the importance of employment risk in driving variations in forecast boldness by examining the relationship between the boldness of an analyst's forecast and her probability of termination, that is, the probability that the brokerage house removes the analyst from covering the stock. To the best of our knowledge, this is the first study to empirically examine the relation between an analyst's employment risk and her *future* forecast boldness (Hong et al., 2000; Hong and Kubik, 2003 examine the relation between an analyst's *prior* forecast boldness and the probability of termination). Consistent with Hong and Kubik (2003), we document a negative relation between the probability of termination and prior relative performance. We then document a significant U-shaped relation between an analyst's future forecast boldness and her probability of termination. As predicted by our theory, these results imply that significant underperformers (outperformers) are more (less) likely to be fired and are also more likely to issue bolder forecasts.

From a theoretical standpoint, our study contributes to the rapidly growing literature that examines the impact of reputation concerns on the behavior of economic agents in different settings (other theories of herding that are not based on reputation or compensation include Banerjee, 1992; Bikhchandani et al., 1992; see Bikhchandani and Sharma, 2001 for a survey of this literature). Scharfstein and Stein (1990) and Avery and Chevalier (1999) examine two-period models of sequential investment by two types of corporate managers and provide conditions for managers to ignore their private information and either herd or deviate. Trueman (1994) uses a model similar in spirit to that of Scharfstein and Stein (1990) to investigate the forecasting behavior of analysts and also shows that analysts can have incentives to ignore their private information and herd. However, these studies analyze two-period models that restrict agents to be of two types. Hence, in contrast with our study, they are not designed to explain why analysts choose to issue forecasts that deviate to varying extents from the consensus over time and in response to their prior performance; that is, cross-sectional and temporal variations in the forecasting behavior of analysts (see also the discussion in Welch, 2000).[3] Further, because these models do not incorporate employment risk, they cannot explain the empirical evidence presented by Hong et al. (2000) and our study on the effect of employment risk on analysts' forecasting behavior.

[3]Graham (1999) investigates the herding behavior of investment newsletters and also predicts that the incentive to "herd" increases with reputation. He finds significant support for his predictions in his empirical analysis. Moreover, he develops an empirical test of herding that is directly based on his theory.

Zwiebel (1995) models the propensity of corporate managers to undertake innovations in a two-period setting. He shows that average managers prefer the industry standard while high or low ability managers undertake innovations. There are several important distinctions between Zwiebel's (1995) framework and ours leading to different implications for analysts' forecasting behavior. First, the effect of prior performance, rather than ability, on agents' actions is unclear in his model. In contrast with our model, an agent of given ability in his framework always either innovates or adopts the industry standard regardless of prior performance. Second, in his general analysis, the proportion of agents who can innovate must be below an exogenous, sufficiently low, threshold.[4] Third, Zwiebel (1995) analyzes a two-period model where agents differ in their choice of action only in the first period. Hence, the extensions of his results to a multi-period setting, and the implications for the effect of experience on the choice of action, are unclear. (The effect of experience on agents' actions is not obvious in multi-period settings. In the model of Prendergast and Stole (1996) for example, agents become more conservative over time). Fourth, in our model, agents also have imperfect information about their own abilities, and their abilities grow over time as a result of learning by doing.

We contribute to the career concerns literature by theoretically and empirically examining the impact of incentives arising from compensation structures and career concerns, especially employment risk, on the dynamic forecasting behavior of analysts. In particular, we endogenously derive the incentive structure of the analyst by modeling the demand for investment banking services and the bargaining between the investment bank and the analyst over the surplus that she generates. We show that implicit incentives arising from the presence of employment risk play a crucial role in driving cross-sectional and temporal variations in the boldness of analyst's forecasts. Our empirical analysis shows, for the first time, the propensity for both outperforming and underperforming analysts to issue bold forecasts and the positive relation between boldness and experience controlling for the predicted non-monotonic relation between boldness and prior performance. We also highlight the importance of employment risk in driving variations in analysts' forecast boldness, by showing that analysts with low or high employment risk are more likely to issue bolder forecasts than those with intermediate employment risk.

The plan for the paper is as follows. In Section 2 we present the model. In Section 3, we derive the analyst's optimal forecasting policy. In Section 4, we present our empirical analysis. Section 5 concludes and all proofs are in Appendices A and B. In Appendix C, we describe a generalization of the model in which the analyst's effort is explicitly modeled.

2. The Model

We focus on the group of analysts covering a particular firm. We examine the scenario in which there are a large number of such analysts (this is true for prominent firms) so that a particular analyst's forecast choice does not affect the benchmark with respect to which an analyst's forecasting performance is evaluated. Hence, without loss of generality, we focus on an individual, representative analyst who dynamically issues forecasts in response to her incentives. We consider an infinite time horizon with forecasting dates $\Gamma \equiv (0\Delta, 2\Delta, 3\Delta, \ldots)$. The representative analyst begins covering the firm at date 0. Analysts issue forecasts of the

[4] Zwiebel (1995) presents a specific example in Section IV of his paper that relaxes this assumption. However, the generality of his results in the absence of this assumption is unclear.

firm's earnings at the beginning of each forecasting period $[i\Delta, (i+1)\Delta]; i \geqslant 0$, and the firm announces its earnings at the end of the period.

The fundamental state variable that we model is the relative forecasting error of the representative analyst at any date $t \in \Gamma$ over a prior horizon $[t-T,t]$, where $T \geqslant \Delta$. This is the difference between the analyst's cumulative forecasting error for the period $[t-T,t]$ and the mean cumulative forecasting error for the entire group of analysts over the same period. The actual value of T does not play an important role in our theoretical analysis. In our empirical analysis, however, we allow for the fact that it could take different values such as one quarter, six months, or one year.

If $e(t)$ denotes the cumulative forecasting error of the analyst at date $t \in \Gamma$ over the prior time horizon T, and $e_m(t)$ denotes the mean forecasting error for all analysts covering the firm over the same time period, then the analyst's relative forecasting error is a stochastic process given by

$$r(t) = e(t) - e_m(t)^5. \tag{1}$$

Analysts possess differing forecasting abilities that affect the evolutions of their relative forecasting errors. The representative analyst's forecasting ability at any date is described by $l(t) \in R$. The analyst's ability can change over time as she gains more experience. Although our results hold in the more general scenario in which the analyst's ability can vary stochastically over time, we simplify the analysis and notation by assuming that the representative analyst's ability changes deterministically with time.[6]

$$l(t) = l(0) + \zeta t. \tag{2}$$

For simplicity, we assume that the growth rate ζ is publicly observable. The growth of analysts' abilities over time is consistent with prior empirical evidence that analysts become better forecasters with experience (for example, Mikhail et al., 2003). From a theoretical standpoint this can be justified, for example, by the fact that the analyst acquires human capital through the effort she exerts in each period. In Appendix C, we generalize our framework to also model the analyst's unobservable effort choices. In this framework, the analyst's effort and forecast choices in each period, the market's assessment of her effort in each period, and the growth of her ability (that depends on her effort and is, therefore, unobservable) are determined endogenously. The implications for the analyst's forecasting behavior are not qualitatively different from those derived from the analysis of the simpler model presented here, where effort is not explicitly modeled and the analyst's ability grows as in Eq. (2).

There is incomplete, but symmetric, information about the analyst's initial ability $l(0)$ when she first enters the market (we can allow for beliefs about the analyst's ability to be asymmetric without altering any of our results qualitatively). The analyst and the market update their assessments of this initial ability in a Bayesian manner based on the analyst's relative forecasting performance. The analyst affects the demand for the investment bank's services (the business volume) through her perceived ability or reputation. Therefore, she

[5]Because the actual choice of the benchmark is not crucial to our analysis, we use the mean forecasting error purely for concreteness. Our empirical results hold if the benchmark is chosen to be the mean as well as the median.

[6]Specifically, we can generalize the model to allow for the analyst's ability to evolve as a normal or Gaussian process without altering the implications of our analysis (details available).

has significant bargaining power vis-à-vis the bank so that her compensation in each period is determined by ex post bargaining over the surplus she generates instead of explicit contracts. Hence, we adopt the perspective of several studies in the incomplete contracting literature (for example, Stole and Zwiebel, 1996), where explicit contracts between agents are not enforceable and their payoffs are determined through bargaining.[7]

2.1. The analyst's private information and possible forecasts

At the beginning of each period, the analyst issues a forecast based on the noisy private information that she gathers about the firm's earnings as well as the consensus forecast. In general, the information the analyst possesses about the consensus forecast is also noisy because it is revealed only after all analysts have issued their final forecasts for the period. For simplicity, we model only the final forecast that an analyst issues for a forecasting period and assume that all analysts issue their forecasts simultaneously.[8]

We directly model the changes in the representative analyst's relative forecasting error under the set of possible forecasts that she could issue. At each date t, the analyst's private information on the basis of which she issues a forecast is described by the uniformly bounded interval $[\sigma_{\min}(t), \sigma_{\max}(t)] \subseteq R_+$. If the analyst issues a forecast corresponding to $\sigma(t) \in [\sigma_{\min}(t), \sigma_{\max}(t)]$, then the change in her relative forecasting error over the following period is a normally distributed random variable with mean $-l(t)$ and standard deviation $\sqrt{\Delta}\sigma(t)$. Therefore,

$$r_l(t+\Delta) - r_l(t) = -l(t)\Delta + \sigma(t)\sqrt{\Delta}N(t), \tag{3}$$

where the subscript on the relative forecasting error indicates its dependence on the analyst's ability. In Eq. (3), $N(\cdot)$ is a standard normal random variable that can vary with the analyst's forecast (we do not explicitly indicate this dependence for notational simplicity).

The analyst's relative forecasting error is observable ex post to all market participants. From Eq. (3), the analyst's expected relative forecasting error declines with her forecasting ability $l(t)$ implying that, on average, she is a better forecaster relative to her peers as her ability improves. The interval $[\sigma_{\min}(t),\sigma_{\max}(t)]$ characterizes the range of possible forecasts that the analyst could issue when she can deviate to varying extents from the consensus. The left (right) endpoint $\sigma_{\min}(t)$ ($\sigma_{\max}(t)$) corresponds to her most conservative (boldest) forecast in which her deviation from the consensus forecast is minimized (maximized) in probability so that the absolute change in her relative forecasting error is also minimized (maximized) in probability.

[7] As discussed in this literature, explicit contracts between the bank and the analyst could be impossible to enforce for several reasons including (but not limited to) non-verifiability of the analyst's relative forecasting error, reputation, and the business volume that she generates; the possibility of hold-up by either party arising from the inalienability of human capital and the fact that both have bargaining power vis-à-vis each other; and the possibility of the bank replacing the analyst with another of superior perceived ability at any date.

[8] Bernhardt and Kutsoati (2000) incorporate the timing of forecasts in a model of sequential forecasting. See Holden and Stuerke (2000) for a model of analysts' forecast revisions. Our model focuses on the dynamic forecasting behavior of analysts, and we test its predictions using quarterly forecast data. Analysts rarely update their quarterly earnings forecasts. The median number of quarterly forecasts issued by an analyst is one (see Table 1).

The interval $[\sigma_{\min}(t),\sigma_{\max}(t)]$ and the analyst's actual choice $\sigma(t) \in [\sigma_{\min}(t), \sigma_{\max}(t)]$ are unobservable to all other market participants. Given that the firm's earnings process and the consensus forecasts can evolve stochastically over time, both $\sigma_{\min}(\cdot)$ and $\sigma_{\max}(\cdot)$ are stochastic processes that could vary across analysts. We assume it is common knowledge that $\sigma_{\min}(\cdot)$ and $\sigma_{\max}(\cdot)$ are independently and identically distributed across time with $mean(\sigma_{\min}(t)^2) = mean(\sigma_{\max}(t)^2) = \sigma_0^2 > 0$ at each date t. However, the actual distributions of $\sigma_{\min}(\cdot)$ and $\sigma_{\max}(\cdot)$ are unknown to all market participants.[9] The unobservability of the analyst's forecast boldness choice $\sigma(t) \in [\sigma_{\min}(t), \sigma_{\max}(t)]$ and the convexity of her payoff in her perceived ability provide an incentive for the analyst to create noise in her perceived ability by issuing bolder forecasts. The interplay between this incentive and the effect of employment risk leads to the U-shaped relation between the analyst's forecast boldness and her prior relative performance that we empirically document.[10]

For simplicity, we analyze the special case of the more general model in which, at any date t, the analyst either issues her boldest forecast corresponding to $\sigma_{\max}(t)$ *or* her most conservative forecast corresponding to $\sigma_{\min}(t)$. To simplify the exposition, we refer to these as her bold and conservative forecasts, respectively. All our results are valid in the more general setting in which the analyst could issue a forecast corresponding to any $\sigma(t) \in [\sigma_{\min}(t), \sigma_{\max}(t)]$.

The changes in the analyst's relative forecasting error under her bold and conservative forecasts, respectively, are given by Eq. (3) with $\sigma(t) = \sigma_{\max}(t), \sigma(t) = \sigma_{\min}(t)$, respectively. The parameters $\sigma_{\min}(),\sigma_{\max}()$ and the normal random variable $N(t)$ can differ, in general, across analysts. Because we focus on the forecasting behavior of a representative analyst, we simplify the notation by not explicitly indicating the variation of these parameters across analysts.

2.2. Learning about ability by the market and the analyst

For convenience, we hereafter refer to market participants other than the analyst as the market. The analyst's and the market's symmetric priors on her initial ability $l(0)$are normally distributed with mean 0 and variance $\sigma^2_{\text{initial}}$. Given that $\sigma_{\min}()^2,\sigma_{\max}()^2$ are independently and identically distributed over time with $mean(\sigma^2_{\min}(t)) = mean(\sigma^2_{\max}(t)) = \sigma_0^2$, the sample variance of the analyst's relative forecasting errors converges to σ_0^2 after a sufficiently large number of observations. Because the parameters $\sigma_{\min}(),\sigma_{\max}()$ are unobservable to the market, are i.i.d. over time, and have unknown distributions, it is, therefore, reasonable to suppose that the market's assessment of the analyst's choice of forecast boldness in each period is σ_0.[11]

Purely for notational convenience, we assume that Δ is small relative to the time horizon under consideration. Making the continuous time approximation as in Oksendal (2001), we can then show that the analyst's average ability as perceived by the market at a date t is

[9]The analyst's private information cannot be elicited through contracts because they are not enforceable. Chen and Jiang (2005) also propose a herding model in which analysts receive private, noisy signals about the firm's earnings and the consensus. In contrast with our model, however, theirs is a static model.

[10]Hu et al. (2005) find a similar U-shaped relation between the relative risk choices of mutual fund managers and their prior relative performance.

[11]Because the parameters $\sigma_{\min}(),\sigma_{\max}()$ are i.i.d. over time with unknown distributions, and the drift of the evolution of the analyst's relative forecasting error (the analyst's forecasting ability) is also unknown, the market does not alter its assessment σ_0 of the analyst's forecast boldness (see Bensoussan, 1992).

given by

$$\widehat{l}(t) = \frac{\sigma^2_{\text{initial}}\left(-r_l(t) + \zeta t^2/2\right) + \sigma_0^2\zeta t}{\sigma^2_{\text{initial}} t + \sigma_0^2}. \tag{4}$$

The analyst, however, updates her assessment of her own ability by incorporating her choices of forecast boldness $\sigma_{\min}(\cdot)$ or $\sigma_{\max}(\cdot)$. At any date t, the analyst's assessment of her own ability is path-dependent; that is, it depends on her past history of forecast choices and relative forecasting performance. Suppose $\{\sigma^*(s); s<t\}$ represents the analyst's prior forecast choices, where $\sigma^*(s) \in \{\sigma_{\max}(s), \sigma_{\min}(s)\}$. We can use the analysis in Section 6.2 of Oksendal (2001) to show that the analyst's posterior assessment of her own ability at any date is normally distributed with variance $\sigma_a(t)$ and mean $\mu_a(t)$ given by

$$\sigma_a(t)^2 = \left(1/\sigma^2_{\text{initial}} + \int_0^t (1/\sigma^*(s)^2)\,\mathrm{d}s\right)^{-1} \tag{5}$$

and

$$\mathrm{d}\mu_a(t) = \zeta\,\mathrm{d}t + \frac{\sigma_a(t)^2}{\sigma^*(t)^2}[\mathrm{d}r_l(t) - (\zeta + \mu_a(t))\,\mathrm{d}t] = \zeta\,\mathrm{d}t + \frac{\sigma_a(t)^2}{\sigma^*(t)^2}\,\mathrm{d}W(t). \tag{6}$$

In the above, $W(\cdot)$ is a Brownian motion adapted to the filtration $\{F_t\}$ of the underlying probability space generated by the processes $r_1(\cdot)$ and $\sigma^*(\cdot)$. Hereafter, we refer to the analyst's average ability as perceived by the market as the analyst's average perceived ability.

3. The analyst's optimal forecasting policy

In this section, we derive the analyst's optimal forecasting policy in response to her incentive structure, that is, her compensation in each period and her employment risk. In Appendix A, we endogenously derive the analyst's compensation structure as well as her employment risk by analyzing the bargaining game between the investment bank and the analyst and the incentives of the bank to replace the analyst with another of superior perceived ability at any date. Proposition 1 describes the results of this analysis.

Proposition 1. (a) *The analyst's compensation at date t if she is employed by the investment bank for the period* $[t, t+\Delta]$ *is given by*

$$ge^{c\hat{l}(t)} \text{ at date } t \text{ where } 0<c<\infty, g>0. \tag{7}$$

(b) *At any date, there exists a threshold* l_b *such that the incumbent analyst can be replaced with nonzero probability if and only if her average perceived ability* $\widehat{l}(t) \leqslant l_b$. *Moreover, she is not replaced with certainty even if her average perceived ability is below this threshold.*

Proof. See Appendix A.

If the analyst is fired, she bears significant personal costs (termination costs), which are a proportion $\delta \in (0, 1]$ of her payoff at date t. Because the analyst could be fired in each successive period in which her performance is below the termination threshold, persistent underperformance increases the likelihood that the analyst will be fired.

The analyst chooses her forecast (bold or conservative) at the beginning of each forecasting period to maximize her discounted expected compensation at the end of the period.[12] From Eq. (7), her end-of-period compensation depends on her perceived ability or reputation at the end of the period. We normalize the analyst's discount rate to zero.[13] From Eq. (7), the analyst's objective at date t is to choose her forecast to maximize

$$\mathrm{E}\left[ge^{c\hat{l}(t+\Delta)} - \delta\left(1_{\text{fired}=1} 1_{\widehat{l}(t+\Delta)\leqslant l_b}\left(ge^{c\hat{l}(t+\Delta)}\right)\middle| F_t\right].\tag{8}$$

In the above, $\mathrm{E}[\cdot|F_t]$ denotes conditional expectation, $\{F_t\}$ is the analyst's information filtration that is generated by the processes $r_1(\cdot)$ and $\sigma^*(\cdot)$. The variable *fired* is a binary random variable representing the event that the analyst is fired. Henceforth, we normalize units so that $g = 1$.

We now derive the analyst's optimal dynamic forecasting policy, that is, her choice of forecast, bold or conservative, at each date. We first note from Eq. (4) that, at any date $t = i\Delta; i > 0$, the analyst can be fired if and only if her relative forecasting error $r_1(t)$ is greater than $r_b(t)$, where

$$r_b(t) = -\left[\left(\sigma^2_{\text{initial}}t + \sigma^2_0\right)l_b - \sigma^2_0\zeta t\right]/\sigma^2_{\text{initial}} + \tfrac{1}{2}\zeta t^2.\tag{9}$$

From Eq. (9), if $\zeta > 0$, so that the analyst's ability improves with experience as in learning by doing models, then beyond a threshold value of t, $r_b(\cdot)$ is an increasing function. In other words, the termination threshold expressed in terms of relative forecasting error increases with time beyond this threshold so that the analyst's ex ante employment risk declines. From Eq. (8) (with $g = 1$), the analyst's conditional expected end-of-period payoff at date t can be expressed as

$$U(t) = \mathrm{E}\left[\exp\left(c\hat{l}(t+\Delta)\right) + 1_{r_l(t+\Delta)\geqslant r_b(t+\Delta)} 1_{\text{fired}=1}(-\delta)\exp\left(c\hat{l}(t+\Delta)\right)\middle| F_t\right].\tag{10}$$

Proposition 2. (a) *At each date t, and for given $\mu_a(t)$,$\sigma_a(t)$, there exist thresholds $r_{\text{low}}(t)$, $r_{\text{high}}(t)$ with $-\infty < r_{\text{low}}(t) \leqslant r_{\text{high}}(t) < \infty$ such that, if $r_l(t) \leqslant r_{\text{low}}(t)$ or $r_l(t) \geqslant r_{\text{high}}(t)$, the analyst issues the bold forecast. If $r_l(t) \in (r_{\text{low}}(t), r_{\text{high}}(t))$, the analyst issues the conservative forecast.*

(b) *A necessary condition for the existence of a nonempty interval $(r_{\text{low}}(t), r_{\text{high}}(t))$ is*

$$\left[\frac{1}{2}c^2\left(\frac{\sigma^2_{\text{initial}}}{\sigma^2_{\text{initial}}(t+\Delta)+\sigma^2_0}\right)^2\left(\sigma_{\max}(t)^2 - \sigma_{\min}(t)^2\right)\right]\Delta < \ln\left(\frac{1}{1-\alpha\delta}\right).$$

Proof. See Appendix B.

The results of the above propositions imply that, in general, the analyst issues the bold forecast when she significantly outperforms or underperforms her peers and the conservative forecast if she is an intermediate performer. The underlying intuition for these results is that, when the analyst's relative performance is superior, it follows from

[12]We have also numerically analyzed the scenario in which the analyst chooses her forecast in each period to maximize her discounted expected stream of future compensation payments. The results of all our simulations for various choices of underlying parameter values reveal that the primary positive implications of our analysis when the analyst has the objective function given by Eq. (8) are qualitatively unaltered. This is not surprising because the intuition underlying our results remains unaltered even if the analyst has long-term objectives (details of this analysis are available upon request).

[13]The analyst is assumed to be risk-neutral to simplify the analysis. Our results are qualitatively unaltered in the scenario where the analyst is risk-averse and has CRRA preferences (details available upon request).

Eq. (4) that her average perceived ability significantly exceeds the termination threshold l_b so that her probability of being fired in the future is low. Because her end-of-period payoff is convex in her end-of-period average perceived ability, she prefers to increase the uncertainty in her end-of-period perceived ability by issuing the bold forecast. However, if her relative performance is poor so that her average perceived ability is close to or below the termination threshold l_b, she has little to lose and, therefore, gambles by issuing the bold forecast. At intermediate levels of relative performance, the possibility that her perceived ability could fall below the termination threshold induces her to herd by issuing the conservative forecast, thereby reducing the deviation in her average perceived ability.

In general, the analyst issues a conservative forecast over some region of prior forecasting performance if and only if her ex ante employment risk, characterized by the parameters $r_b(t+\Delta), \alpha, \delta$, is sufficiently high. The fact that the analyst with little or no ex ante employment risk always issues a bold forecast implies that the crucial factor driving the temporal and cross-sectional variation in her forecasting behavior, bold or conservative, is the presence of employment risk. Proposition 3 demonstrates that the likelihood of issuing a bold forecast, ceteris paribus, increases with experience beyond a threshold.

Proposition 3. *Given any $\varepsilon > 0$ and $r \in R$, there exists $t_* > 0$ such that, for all $t > t_*$,* $\text{Prob}[r < r_{\text{low}}(t)] > 1 - \varepsilon$. *By the result of Proposition 1, this result implies that the probability that the analyst with relative performance $r(t) = r$ issues a conservative forecast is less than ε for $t > t_*$.*

Proof. See Appendix B.

The above result follows from the fact that, as the analyst's experience increases, the growth in her ability causes her employment risk to decline, thereby increasing her incentive to exploit the convexity in her payoff structure by issuing bold forecasts.

4. Empirical analysis

Given that our model focuses on the group of analysts covering a particular firm, our empirical tests examine the model's predictions at the firm level, that is, we focus on analysts' earnings forecasts and their relative performance at the individual firm level. In our first set of tests, we investigate the relationship between an analyst's forecast boldness and her prior relative forecasting performance, and we confirm our prediction that this relation is approximately U-shaped. In our second set of tests, we examine the link between an analyst's forecasting behavior and her underlying incentives, specifically those arising from her employment risk. Employment risk plays a crucial role in driving variations in analysts' forecasting behavior. Analysts with high and low employment risk are more likely to issue bolder forecasts than those with intermediate employment risk. We directly test these predictions by investigating the relation between an analyst's forecast boldness and her probability of termination. Consistent with the theory, we demonstrate that significant underperformers (outperformers) are more (less) likely to be terminated. Further, analysts with low or high probabilities of termination are more likely to issue bolder forecasts.

4.1. Data description

We collect individual analysts' forecasts of quarterly earnings per share (EPS) from the I/B/E/S Detailed History database over the period 1988–2000. The Detailed History database tracks the identity of the analyst issuing the forecast, her employer, the date the forecast was issued, and the actual forecast. Because our theory pertains to the dynamic forecasting behavior of analysts, we focus on forecasts of end-of-quarter earnings per share. We restrict consideration to stocks in our sample that have at least 12 analysts providing coverage in a given quarter. We impose this filter to focus on high-profile stocks. As argued by Hong and Kubik (2003), such stocks are covered each quarter by brokerage houses and are also sought after by analysts. Therefore, dropping coverage on these stocks is likely to be a negative career event for an analyst instead of a voluntary decision (we try different cutoffs such as ten and 15 with qualitatively similar results). Our final sample contains quarterly earnings forecasts on 1,091 firms from 4,185 unique analysts at 256 brokerage houses.

4.2. Description of variables

For our empirical analysis, we follow Hong et al. (2000) in constructing measures of future and past relative forecast error, future and past boldness, and experience. We denote $E_{i,j,t}$ as the forecast error of analyst i for firm j at date t for the previous quarter. This is the absolute difference between the analyst's forecast issued at date $t-\Delta$ of the firm's earnings that are announced at date t and the firm's actual earnings. We then sort the analysts who cover firm j based on their forecast errors and assign a ranking based on this sorting, with the most accurate analyst receiving a rank of one. In the case of ties, each analyst is assigned the mean value of the ranks that they take up (alternative procedures for handling ties, such as assigning the median value of the ranks they take up or the highest value of the ranks they take up, produce similar results). Because the maximum rank an analyst can receive for a firm depends on the number of analysts who cover the firm, we scale an analyst's rank by the number of analysts who cover the firm. The prior relative forecast error score is then given by

$$\mathit{prior\ relative\ forecast\ error\ score}_{i,j,t} = 100 - \left[\frac{\mathit{Accuracy\ rank}_{i,j,t} - 1}{\mathit{number\ of\ analysts}_{j,t} - 1}\right] \times 100, \qquad (11)$$

where $\mathit{number\ of\ analysts}_{j,t}$ is the number of analysts who cover the firm over the quarter. The prior relative forecast error score ranges from zero for the least accurate analyst covering a firm to a score of one hundred for the most accurate analyst covering the firm. We are also interested in the future relative forecast error score of each analyst i who covers firm j at date t. This is constructed as in Eq. (11) from the future forecast error of analyst i for firm j, which is the analyst's forecast error over the subsequent quarter $[t,t+\Delta]$.

Our measure of forecast boldness is constructed as follows. Let $F_{i,j,t}$ denote analyst i's forecast of firm j's earnings for the period $[t-\Delta,t]$. Let $\overline{F}_{-i,j,t} = 1/n\sum_{m\in\{-i\}}F_{m,j,t}$, where $\{-i\}$ is the set of all analysts other than analyst i who produce an earnings per share estimate for firm j in period $[t-\Delta,t]$, and n is the number of analysts in $\{-i\}$. Hence, $\overline{F}_{-i,j,t}$ is a measure of the consensus forecast made by all other analysts. We define boldness as

$$prior\ boldness_{i,j,t} = \left|F_{i,j,t} - \overline{F}_{-i,j,t}\right|. \tag{12}$$

We measure *prior boldness*$_{i,j,t}$ in hundredths of a cent. We then replicate the previous ranking methodology (for constructing the prior relative forecast error score) to arrive at a prior boldness score, which is defined as

$$prior\ boldness\ score_{i,j,t} = 100 - \left[\frac{Boldness\ rank_{i,j,t} - 1}{number\ analysts_{j,t} - 1}\right] \times 100. \tag{13}$$

The prior boldness score ranges from zero for the least bold analyst covering a firm to a score of one hundred for the boldest analyst covering the firm in a given quarter. We construct a future boldness score for analyst i covering firm j at date t as in Eqs. (12) and (13) from the future boldness of the analyst, that is, the boldness of the analyst's forecast for the period $[t,t+\Delta]$.

We also construct a measure of an analyst's experience based on the number of years that the analyst has been following a particular security. We define an indicator variable, *high experience*, which takes the value of one if an analyst has covered a security for more than five years. This is approximately the mean experience of analysts. Our results are robust to alternative cutoffs for the *high experience* variable. Because the thrust of our theoretical and empirical analysis is at the firm level, we focus on stock-specific experience.

4.3. Sample descriptive statistics

Table 1 presents descriptive statistics for our sample. The mean forecast boldness is 3.06 cents and the median value is 1.14 cents. The mean and median relative forecast error values are 8.17 and 2.50 cents, respectively. Analysts cover each security for an average of 5.49 years with a median of five years. Using our definition of *high experience*, approximately 53% of the earnings forecasts are issued by experienced analysts. The average boldness score and average relative forecast error score are 47.14 and 52.75, respectively. Analysts rarely update their quarterly forecasts of earnings per share. The median number of forecasts issued by an analyst per stock per quarter is 1.00.

4.4. Empirical tests

We now describe the results of our empirical analysis.

4.4.1. Empirical relation between future boldness and prior relative forecasting performance boldness and relative forecast error transition matrices

We first examine temporal variations in analysts' forecast boldness and relative forecasting performance. In each quarter, we rank analysts into quartiles based on their prior (future) forecast boldness and relative forecast error, respectively. We then examine the proportions of analysts in a given quartile of prior boldness (relative forecast error) appearing in various quartiles of future boldness (relative forecast error). The results displayed in Fig 1a and b suggest that analysts' boldness and relative forecast error vary significantly over time. However, consistent with the theory, there is some evidence of persistence in analysts' boldness as well as relative forecast error. Analysts who are bold (conservative) in the past are more likely to be bold (conservative) in the future. Similarly,

Table 1
Descriptive statistics for our sample of quarterly forecasts of earnings per share over the period 1988 to 2000

Quarterly forecasts are obtained from the I/B/E/S Detailed History file. Boldness is a measure of the extent to which an analyst deviates from the consensus as described in the text. Forecast error is defined as the absolute value of the difference between an analyst's forecast of earnings per share and the actual value of earnings per share. Both boldness and forecast error are measured in hundredths of a cent. Relative forecast error score ranges from zero to one hundred, with higher scores indicating more accurate forecasts. Similarly, the boldness score ranges from zero to one hundred, with higher scores indicating bolder forecasts. Both measures are calculated each quarter. Experience is the number of years for which an analyst has been following a security. High experience is an indicator variable that takes the value one if experience is greater than five years (approximately the mean and median experience of analysts in the sample) and zero otherwise. Standard deviations are reported in parentheses.

Variable	Number of observations	Mean	10th percentile	50th percentile	90th percentile
Boldness (in hundredths of a cent)	182,188	306.24 (505.60)	10.71	114.29	814.71
Forecast error (in hundredths of a cent)	182,188	816.79 (21.63)	12.00	250.00	2000.00
Boldness score	182,188	47.14 (28.26)	9.52	45.45	87.50
Relative forecast error score	182,188	52.75 (28.18)	13.33	53.85	90.91
Experience	182,188	5.49 (3.87)	1.00	5.00	11.00
High experience indicator	182,188	0.53 (0.50)	0.00	1.00	1.00

analysts with superior (inferior) prior relative forecasting performance are more likely to have superior (inferior) future relative forecasting performance.

4.4.2. Univariate tests of the relationship between future boldness and prior relative forecasting performance

Table 2 presents a preliminary examination of the relationship between future boldness and prior relative forecasting performance. Each quarter, we rank analysts into deciles based on their prior relative forecast error score. We then compute mean and median future boldness for each of these deciles over the subsequent quarter. To test for a U-shaped relation, we compute the median future boldness within past performance deciles five and six and then test to see whether median boldness in each decile is different from this value. Our results support the existence of a U-shaped relation. The mean (median) future boldness score is 49.93 (50.00) for the worst prior relative forecast error decile, falls to 46.29 (43.75) for the intermediate deciles five and six, and then rises to 48.19 (47.06) for the best prior relative forecast error decile. These differences are statistically significant, suggesting the presence of a U-shaped relation. Moreover, the results represent economically important deviations from the consensus. The mean (median) future boldness is 3.09 cents (1.26) for the worst relative forecast error decile. At deciles five and six, the mean and median future boldness values are approximately 2.81 and 1.00 cent, respectively. At the best-performing deciles, the mean and median values are 3.56 and 1.44 cents, respectively.

Prior boldness score	Future boldness score: Least bold	2	3	Most bold
Least bold	26.71%	24.48%	25.65%	23.16%
2	24.37%	27.61%	24.48%	23.53%
3	25.53%	24.47%	25.29%	24.71%
Most bold	23.62%	23.3%	24.51%	28.58%

(a)

Prior relative forecast error score	Future relative forecast error score: Least accurate	2	3	Most accurate
Least accurate	28.27%	24.67%	23.34%	23.72%
2	25.02%	25.63%	25.35%	24.00%
3	23.13%	25.83%	25.99%	25.05%
Most accurate	23.57%	24.13%	25.18%	27.12%

(b)

Fig. 1. The transition matrices relating the past boldness and relative forecast error scores to the future boldness and relative forecast error scores. The prior (future) boldness score measures the extent of deviation of the analyst's forecast from the consensus over the previous (following) quarter and ranges from zero to one hundred. The prior (future) relative forecast error score measures the relative accuracy of the analyst's forecast over the previous (following) quarter and also ranges from zero to one hundred.

4.4.3. Multivariate tests of the relation between future boldness on prior relative forecasting performance

In Table 3, we more rigorously examine the relationship between future boldness and prior relative forecasting performance using multivariate ordinary least squares regressions. The dependent variable in each specification is *future boldness* (measured in hundredths of a cent). At any date *t*, this is the boldness of analyst *i*'s forecast of firm *j*'s

Table 2
The univariate relation between future boldness and prior performance

Quarterly forecasts are obtained from the I/B/E/S Detailed History file. Prior relative forecast error score measures the relative accuracy of the analyst's forecast over the previous quarter and ranges from zero to one hundred, with higher scores indicating more accurate forecasts. Future boldness is a measure of the extent to which an analyst deviates from the consensus over the subsequent quarter, and is measured in hundredths of a cent. The future boldness score measures the deviation of the forecast from the consensus and ranges from zero to one hundred. Analysts are ranked into deciles each quarter based on their prior relative forecast error score. Decile one contains analysts with the lowest relative forecast error scores and decile ten contains the highest relative forecast error scores. We then compute mean and median future boldness for each decile. The *p*-value reported for each decile corresponds to a sign rank test of the hypothesis that the median future boldness in the decile is statistically different from the median future boldness of quartiles five and six. Median values are reported in parentheses.

Prior relative forecast error decile	Prior relative forecast error score	Future boldness	Future boldness score	Number of observations	*P*-value
Least accurate	6.57	309.31	49.93	15,789	0.000
	(7.50)	(126.46)	(50.00)		
2	18.87	302.46	47.99	15,718	0.000
	(18.75)	(118.11)	(46.15)		
3	29.38	304.21	47.33	15,752	0.000
	(29.17)	(112.50)	(45.45)		
4	39.37	289.92	46.17	15,513	0.000
	(39.29)	(106.67)	(43.75)		
5	48.89	280.43	46.41	15,683	0.873
	(50.00)	(100.00)	(43.75)		
6	58.09	281.45	46.16	15,847	0.378
	(58.33)	(100.00)	(43.75)		
7	67.35	288.03	46.02	15,382	0.000
	(67.50)	(106.67)	(43.33)		
8	76.66	291.91	46.56	15,349	0.000
	(76.92)	(105.00)	(44.12)		
9	86.20	294.00	47.15	16,218	0.000
	(86.36)	(110.82)	(45.65)		
Most accurate	96.18	355.72	48.19	15,733	0.000
	(96.00)	(144.44)	(47.06)		

earnings for the following quarter $[t, t+\Delta]$.[14] The main independent variable of interest is *prior relative forecast error score*, as defined in Eq. (11). Our theory predicts a positive coefficient on *prior relative forecast error score*^{2}. In each specification, we also include dummy indicator variables for firm, quarter, and brokerage house effects. As discussed in Section 3, the model predicts significant persistence in the forecast boldness of analysts. Therefore, we also control for the prior boldness of the analyst by including a *prior boldness indicator* variable that takes the value one if her prior boldness score as defined in

[14]We choose *boldness* defined in Eq. (8) (measured in hundredths of a cent) instead of the boldness score defined in Eq. (9) as our dependent variable, to be able to evaluate the economic significance of forecast deviations. We have also run regressions using boldness scores as the dependent variable and the results are similar.

Table 3
The results of ordinary least squares regressions of future boldness on experience and prior relative forecasting performance

Future boldness is a measure of the deviation of an analyst's forecast from the consensus forecast over the subsequent quarter and is measured in hundredths of a cent. Prior (future) relative forecast error score is the forecasting accuracy score measured over the previous (next) quarter, and ranges from zero to one hundred, with higher values corresponding to more accurate forecasts. Prior two quarters' average relative forecast error score is the average relative forecast error score over the previous two quarters. Prior (two quarters' average) boldness indicator is an indicator variable that takes the value one if the prior (two quarters' average) boldness score of the analyst over the previous quarter (two quarters) exceeds fifty, and zero otherwise. High experience is an indicator variable that takes the value of one if the analyst has covered a security for more than five years and zero otherwise. In each specification, we include indicator variables for the quarter of the forecast, the brokerage house the analyst works for in the quarter of the forecast, and the firm the forecast is issued on. *P*-values are reported in parentheses.

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Prior relative forecast error score	−1.069	−0.772	−0.233			
	(0.000)	(0.000)	(0.160)			
Prior relative forecast error score^2	0.009	0.007	0.003			
	(0.000)	(0.000)	(0.086)			
Prior two quarters' average relative forecast error score				−1.68	−1.19	−0.582
				(0.001)	(0.000)	(0.001)
Prior two quarters' average relative forecast error score^2				0.015	0.011	0.007
				(0.001)	(0.000)	(0.001)
Prior boldness indicator		6.947	3.04			
		(0.006)	(0.197)			
Prior two quarters' average boldness indicator					13.38	6.006
					(0.000)	(0.001)
High experience		3.334	2.223		4.733	2.98
		(0.138)	(0.289)		(0.048)	(0.186)
Future relative forecast error score			−20.06			−20.01
			(0.000)			(0.000)
Future relative forecast error score^2			0.176			0.175
			(0.000)			(0.000)
Quarter effects	Yes	Yes	Yes	Yes	Yes	Yes
Brokerage house effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.380	0.380	0.462	0.380	0.380	0.457
Number of observations	156,984	156,984	156,984	136,613	136,613	136,613

Eq. (13) exceeds fifty and zero otherwise, as an additional control variable. We also control for the experience of the analyst by including the *high experience* indicator variable.

In Specification 1 of Table 3, we examine the relation between *future boldness*, *prior relative forecast error score,* and *prior relative forecast error score^2*. Consistent with the predictions of the model, we find strong evidence of a non-monotonic, U-shaped relation between boldness and prior relative forecast performance. The coefficient on *prior relative forecast error score^2* is positive and highly significant. In Specification 2, we add controls for prior boldness and experience by including the *prior boldness indicator* and *high experience* as additional explanatory variables. The coefficient on *prior relative forecast error score^2* is again positive and significant. Consistent with the model's predictions, the coefficient on *prior boldness indicator* is positive and significant, indicating that analysts who are bold in the past are more likely to issue a bold forecast in the future quarter. Finally, in conformity with our theory and the findings of prior studies (for example, Hong et al., 2000), the coefficient on *high experience* is positive and marginally significant.

From the coefficients in Specification 2, the boldness of an analyst attains a minimum at a prior relative forecast error score of (approximately) 58, ceteris paribus. The boldness increases by approximately 0.21 cents when the prior relative forecast error score decreases from 58 to 0 and increases by approximately 0.14 cents when it increases from 58 to 100. These represent approximate increases of 7% (18%) and 5% (12%) percent, respectively, as a proportion of the mean (median) forecast boldness of 3.00 (1.13) cents reported in Table 1.

Recent empirical evidence suggests that future boldness and future relative forecast accuracy might be positively correlated (Clement and Tse, 2005). For example, as discussed in Appendix C, an analyst's effort could vary with her prior performance thereby affecting her choice of forecast and her future performance. Therefore, in Specification 3 of Table 3, we include *future relative forecast error score* and *future relative forecast error score*^{2} as additional explanatory variables. At any date, the *future relative forecast error score* is the analyst's forecast accuracy measure over the subsequent quarter, that is, the same quarter as one over which *future boldness* is measured. We include *future relative forecast error score*^{2} as an explanatory variable to incorporate the possibility of a nonlinear relationship between future boldness and future relative forecast accuracy.

We continue to find the predicted positive and significant coefficient on *prior relative forecast error score*^{2} (We also run the tests controlling for deciles of future relative forecast accuracy. The results are qualitatively similar.) The coefficient on *future relative forecast error score* is negative and significant while the coefficient on *future relative forecast error score*^{2} is positive and significant. These findings extend those of Clement and Tse (2005) as they imply that bolder forecasts are either very accurate or very inaccurate. This evidence is also consistent with bolder forecasts being riskier.

Next, we examine the relation between future boldness and prior relative forecasting performance measured over time horizons of six months and one year, respectively. For brevity, we report the results for a six-month evaluation horizon. In Specifications 4, 5, and 6 of Table 3, at each date, and for each analyst, we compute the *average prior relative forecast error score* over the previous two quarters; that is, the analyst's *prior relative forecast error score* defined in Eq. (11) averaged over the previous two quarters. The U-shaped relation between future boldness and prior relative forecasting performance is significant in all three specifications. Consistent with the theory, the coefficient on *high experience* is positive and significant in Specification 5, and marginally significant in Specification 6.

From the coefficients in Specification 5 the boldness of an analyst attains a minimum at a prior two quarters' average relative forecast error score of (approximately) 54, ceteris paribus. The boldness increases by approximately 0.32 cents when the prior two quarters' average relative forecast error score decreases from 54 to zero and increases by approximately 0.23 cents when it increases from 54 to one hundred. These represent approximate increases of 10% (33%) and 8% (20%) percent, respectively, as a proportion of the mean (median) forecast boldness of 3.00 (1.13) cents as reported in Table 1. [15]

[15]The results of tests of the relation between future boldness and prior forecasting performance measured over one year are qualitatively similar (these are not reported for brevity). For robustness, we have also examined the relation between future boldness and prior forecasting performance using Fama-Macbeth pooled regressions. Because the results are unchanged, these tests are not reported.

4.4.4. Empirical relation between future boldness and employment risk

We now empirically analyze the relation between an analyst's future forecast boldness and her employment risk.

Relation between future forecast boldness and the probability of termination. We now directly test the importance of incentives, specifically, employment risk, in driving variations in analysts' forecast boldness. Our theory predicts that analysts with low (high) average perceived abilities face high (low) employment risk and that these analysts are more likely to issue bolder forecasts. An analyst's perceived ability or employment risk at any date can be represented by her probability of termination. Because our theoretical and empirical analyses focus on analysts' forecasting behavior at the individual firm level, we consider turnover in stock coverage as in Section V of Hong and Kubik (2003). We restrict consideration to high-profile stocks that are covered by at least 12 analysts in each quarter. As argued by Hong and Kubik (2003), dropping coverage on such stocks is likely to be a significant negative career event instead of a voluntary decision by an analyst. Similar to Section V in Hong and Kubik (2003), we restrict consideration to events in which an analyst drops coverage on a stock but continues to work for the brokerage house so that the dropping of coverage is not the result of the analyst leaving the brokerage house for alternative employment. To further increase the likelihood that these are negative career events, we impose an additional filter by restricting consideration to turnover events in which an analyst drops coverage on a stock, and the total coverage of the stocks in the analyst's entire portfolio also declines. We have run our tests with and without this additional filter, and our results are qualitatively unchanged. In our subsequent analysis, we empirically examine the relation between an analyst's future forecast boldness and the probability that she is forced to drop coverage on the stock by her employer. Consistent with our theory, we show that analysts with very low or high termination probabilities are more likely to issue bolder forecasts.

Our empirical strategy is to use logit analysis to estimate the probability of termination of an analyst following a procedure similar to that in Hong and Kubik (2003). We then examine the relation between an analyst's future forecast boldness and her probability of termination. To obtain accurate statistical confidence levels on parameter estimates (especially in the estimation of the relationship between future boldness and the probability of termination), we use bootstrap inference (see, for example, MacKinnon, 2002). We use our original sample to generate 250 random samples using bootstrapping (with replacement) and use the results of our tests on each bootstrapped sample to determine statistical confidence levels for parameter estimates (see Section 7 of MacKinnon, 2002).[16]

At the beginning of any quarter, we use logit analysis to estimate the probability that an analyst is terminated in the quarter, that is, she drops coverage on the stock. We estimate this probability as a function of the analyst's prior relative performance and prior boldness. As in Hong and Kubik (2003), we also include indicators for each year of experience of the analyst and a set of dummies for the brokerage house, quarter, and the

[16]The results of direct tests on the original sample (without bootstrapping) yield similar confidence levels on the parameter estimates. They are not reported for brevity.

number of firms the analyst follows.[17] More precisely, we estimate

$$\begin{aligned}&\Pr\left(Coverage\ Dropped_{i,j,[t,t+\Delta]}\right)\\&= F(\alpha + \beta * prior\ Relative\ Performance_{i,j,t} + \gamma * Prior\ Boldness_{i,j.t}\\&\quad + \delta * Experience\ Effects + \chi * Quarter\ Effects\\&\quad + v * Brokerage\ House\ Effects + \phi * Number\ of\ Firms\ Covered\ Effects). \qquad (14)\end{aligned}$$

In the above, *Coverage Dropped*$_{i,j,[t,t+\Delta]}$ is an indicator variable that takes the value one if and only if analyst i drops coverage on firm j in period $[t,t+\Delta]$ and continues to work at the brokerage house and the total coverage on the stocks in her portfolio declines. *Prior Relative Performance*$_{i,j,t}$ and *Prior Boldness*$_{i,j,t}$ are various measures of the analyst's prior relative performance and boldness, respectively, on forecasts of firm *j*'s earnings.

The results of estimating the probability of termination are reported in Panel A of Table 4. In Specification 1, we estimate the probability of termination without controlling for prior boldness. We find a strong negative relation between the probability of termination and prior relative forecasting performance, that is, the likelihood that an analyst is fired increases as her relative performance deteriorates. In Specification 2, we control for the analyst's prior boldness by including a *prior boldness indicator* variable that takes the value one if and only if the analyst's boldness score over the previous quarter exceeds fifty. We continue to find a negative and significant coefficient on *prior relative forecast error score.* In Specifications 3 and 4, we estimate the relationship between the probability of termination and the *prior two quarters' average relative forecast error score* to incorporate the possibility that the analyst could be evaluated over periods longer than one quarter. The coefficient on *prior two quarters' average relative forecast error score* is negative and significant in both specifications. In Specification 4, the coefficient on the *prior two quarters' boldness indicator* is positive and significant, indicating that analysts who are bold in the past are more likely to be fired.

The median probability of termination in Specification 4 is 6.63% with a standard deviation of 5.52%. The 90th percentile is 13.79%, the 95th percentile is 16.92%, the 99th percentile is 28.21%, the 10th percentile is 2.26%, the 5th percentile is 1.59%, and the 1st percentile is 0.98%.

Next, we examine the relation between an analyst's future forecast boldness and the probability of termination obtained above. Specifically, we run OLS regressions of an analyst's *future boldness* (measured in hundredths of a cent) with the *probability of termination* and the *probability of termination*^{2} as explanatory variables. In these regressions, we express the *probability of termination* in percentage terms. We include indicator variables for brokerage effects, quarter effects, and firm effects. For reasons similar to those described earlier, we also estimate the relation between future boldness and the probability of termination controlling for *future relative forecast error score* and *future relative forecast error score*^{2}. More precisely, we estimate the following relation using

[17]As in Hong and Kubik (2003), the *Number of Firms Covered Effects* include a dummy for every five firms covered.

Table 4

The relation between future boldness, the probability of termination, and prior performance

Panel A reports the results of estimating, at the beginning of any quarter, the probability of termination over the quarter using logit analysis. Panels B and C report the results of examining the relation between the boldness of an analyst's forecast in each quarter and the probability of termination using ordinary least squares regressions with and without future relative accuracy controls. To obtain statistical confidence levels for the parameter estimates, we use bootstrap inference by using the original sample to generate 250 random samples. The probability of termination in Panels B and C is expressed in percentage terms, that is, a probability of termination of 10% would be expressed as 10 in the regressions. Future boldness is a measure of the deviation of an analyst's forecast from the consensus forecast over the subsequent quarter as described in the text, and is measured in hundredths of a cent. Prior (two quarters' average) relative forecast error score is the forecasting accuracy score measured over the previous quarter (two quarters), and ranges from zero to one hundred. Future relative forecast error score is the forecasting accuracy score measured over the following quarter and ranges from zero to one hundred. Prior (two quarters' average) boldness score measures the deviation of an analyst's forecast from the consensus over the previous quarter (two quarters) and ranges from zero to one hundred. In each specification in Panel A, we include dummies for the quarter, brokerage house, and number of firms covered as described in the text. In each specification in Panels B and C, we include dummies for quarter, brokerage house, and the firm being covered. Experience effects include indicator variables for each year of the analyst's experience. The numbers in parentheses are the probabilities that the true coefficient has a sign opposite to that of the estimate.

	(1)	(2)	(3)	(4)
Panel A. Estimation of the probability of termination				
Prior relative forecast error score	−0.001	−0.001		
	(0.002)	(0.002)		
Prior two quarters' average relative forecast error score			−0.001	−0.001
			(0.002)	(0.027)
Prior boldness indicator		−0.009		
		(0.636)		
Prior two quarters' boldness indicator				0.001
				(0.047)
Quarter effects	Yes	Yes	Yes	Yes
Experience effects	Yes	Yes	Yes	Yes
Brokerage house effects	Yes	Yes	Yes	Yes
Number of firms covered effects	Yes	Yes	Yes	Yes
Log likelihood	−43,984	−43,984	−42,131	−42,130
Number of observations	182,188	182,188	161,817	161,817
Panel B. Relation between future boldness and probability of termination				
Probability of termination	−1.532	−1.622	−2.13	−1.842
	(0.032)	(0.024)	(0.000)	(0.012)
Probability of termination^2	0.064	0.066	0.088	0.082
	(0.016)	(0.012)	(0.000)	(0.000)
Quarter effects	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes
Brokerage house effects	Yes	Yes	Yes	Yes
R^2	0.379	0.379	0.380	0.378
Number of observations	156,984	156,984	136,613	136,613
Panel C. Relation between future boldness and probability of termination with future relative accuracy controls				
Probability of termination	−1.468	−1.504	−1.83	−1.48
	(0.028)	(0.028)	(0.004)	(0.008)
Probability of termination^2	0.062	0.064	0.083	0.076
	(0.012)	(0.012)	(0.000)	(0.000)

Table 4 (*continued*)

	(1)	(2)	(3)	(4)
Future relative forecast error score	−20.07 (0.000)	−20.07 (0.000)	−20.03 (0.000)	−20.03 (0.000)
Future relative forecast error score^2	0.176 (0.000)	0.176 (0.000)	0.175 (0.000)	0.175 (0.000)
Quarter effects	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes
Brokerage house effects	Yes	Yes	Yes	Yes
R^2	0.463	0.463	0.464	0.464
Number of observations	156,984	156,984	136,613	136,613

OLS regressions:

$$\begin{aligned} &\textit{future boldness}_{i,j,t} \\ &\quad = \mu + \upsilon_1 * \textit{probability of termination}_{i,j,t} + \upsilon_2 * \textit{probability of termination}^2_{i,j,t} \\ &\qquad + \omega_1 * \textit{future relative forecast error}_{i,j,t} + \omega_2 * \textit{future relative forecast error}^2_{i,j,t} \\ &\qquad + \kappa * \textit{quarter effects} + \lambda * \textit{firm effects} + \pi * \textit{brokerage effects} + \textit{error term} \quad (15) \end{aligned}$$

Because an analyst's probability of termination at any date decreases with her perceived ability, our theory predicts that the coefficient υ_2 in Eq. (15) is positive. The results of estimating Eq. (15) are reported in Panel B (without future relative accuracy controls) and Panel C (with future relative accuracy controls) of Table 4. In each specification in Panels B and C, we examine the relation between future forecast boldness and the probability of termination obtained in the corresponding specification in Panel A. As predicted by our theory, the coefficient on the *probability of termination*^{2} is positive and highly significant in all specifications in Panel B and Panel C; that is, there is a U-shaped relation between future forecast boldness and the probability of termination. The coefficients on *probability of termination* are negative and significant. Combined with the results of Panel A, these findings, therefore, imply that outperforming (underperforming) analysts are less (more) likely to be fired, and these are also the ones more likely to issue bolder forecasts.

From the coefficients in Specification 4 of Panel B, the future boldness attains a minimum at a probability of termination of approximately 11%, ceteris paribus. It increases by approximately 0.10 cents when the probability of termination declines from 11% to 0%, and increases by 0.29 cents when the probability of termination increases from 11% to 30%. These represent increases of 3.3% (9%), and 10% (25%), respectively, as proportions of the mean (median) forecast boldness as reported in Table 1.[18]

4.4.5. *Relation between future forecast boldness and the probability of future termination*

We now examine the relation between forecast boldness in any quarter and the conditional probability that a surviving analyst, who issues a forecast for the quarter, is

[18] For robustness, we also examine the relation between future boldness and the probability of termination in the next two quarters, that is, the dependent variable in Eq. (14) is *Coverage Dropped*$_{i,j,[t,t+2\Delta]}$. Because our results are qualitatively unchanged, they are not reported for brevity.

terminated in the following quarter. We refer to this probability as the analyst's *probability of future termination* to clearly distinguish it from the *probability of termination* in Table 4. Specifically, we estimate

$$\begin{aligned}\Pr\big(\textit{Coverage Dropped}_{i,j,[t+\Delta,t+2\Delta]}\big) &= F(\alpha + \beta * \textit{Prior Relative Performance}_{i,j,t} + \gamma * \textit{Prior Boldness}_{i,j,t} \\ &\quad + \delta * \textit{Experience Effects} + \chi * \textit{Quarter Effects} + \sigma * \textit{Brokerage House Effects} \\ &\quad + \phi * \textit{Number of Firms Covered Effects}) \qquad (16)\end{aligned}$$

In the above, $\textit{Coverage Dropped}_{i,j,[t+\Delta,t+2\Delta]}$ is an indicator variable that takes the value one if and only if analyst i covers firm j in quarter $[t,t+\Delta]$ and does not cover firm j in quarter $[t+\Delta,t+2\Delta]$ (but continues to work at the brokerage house and the total coverage of her portfolio declines). From the above, we obtain the conditional probability (based on information available at date t) that an analyst who covers the firm for the quarter $[t,t+\Delta]$ is terminated in the following quarter.

Panel A of Table 5 displays the results of estimating the probability of future termination using specifications similar to those used in Panel A of Table 4. In Specifications 1 and 2, we obtain a significantly negative relationship between the *probability of future termination* and the *prior relative forecast error score*. In Specifications 3 and 4, however, we obtain a positive, but insignificant, coefficient on the *prior two quarters' average relative forecast error score,* implying that more recent prior performance has a more significant impact on the probability of future termination. In Panels B and C, we report the results of examining the relation between *future forecast boldness* and the *probability of future termination.* Consistent with our theory, in all cases, the coefficient on *probability of future termination*^{2} is positive and highly significant.

In summary, the results reported in Tables 4 and 5 establish a direct link between an analyst's forecasting behavior and her implicit incentives arising from employment risk. Consistent with the theory, analysts with inferior (superior) past forecasting performance face higher (lower) employment risk in that they are more (less) likely to be forced to drop coverage on the stock. Further, analysts with high or low employment risk are more likely to deviate from the consensus by issuing bolder forecasts compared with those with intermediate employment risk.

5. Conclusions

We propose a positive theory to examine the dynamic forecasting behavior of security analysts. In our unified framework, we simultaneously analyze the relationships between the investment bank, its customers, and its analysts. If the demand for investment banking services is perfectly competitive, and the bank's operating costs are increasing and convex in business volume, we show that the bank's surplus is increasing and convex in its reputation that, in turn, increases with the analyst's reputation. We then show that, if the bank and the analyst bargain over the surplus that the analyst generates in each period because of her reputation, the analyst's compensation at each date is convex in her reputation. We also demonstrate the presence of employment risk for the analyst, that is, the possibility of being fired if her average perceived ability is below a threshold.

The interplay between the convexity in an analyst's compensation and the presence of employment risk leads to a U-shaped relation between her forecast boldness and prior

Table 5

The relation between future boldness, the probability of future termination, and prior performance

Panel A reports the results of estimating, at the beginning of any quarter, the probability that an analyst, who issues a forecast for the quarter, is terminated in the following quarter. We use logit analysis in this estimation. This is referred to as the probability of future termination. Panels B and C report the results of examining the relationship between the boldness of an analyst's forecast in each quarter and the probability of future termination using ordinary least squares regressions with and without future relative accuracy controls. To obtain statistical confidence levels for the parameter estimates, we use bootstrap inference by using the original sample to generate 250 random samples. The probability of future termination in Panels B and C is expressed in percentage terms, that is, a probability of termination of 10% would be expressed as 10 in the regressions in Panels B and C. Prior (two quarters' average) relative forecast error score is the forecasting accuracy score measured over the previous quarter (two quarters), and ranges from zero to one hundred. Future relative forecast error score is the forecasting accuracy score measured over the following quarter and ranges from zero to one hundred. Future boldness is a measure of the deviation of an analyst's forecast from the consensus forecast over the subsequent quarter, and is measured in hundredths of a cent. Prior (two quarters' average) boldness indicator is an indicator variable that takes the value of one if the analyst's prior (two quarters' average) boldness score exceeds 50. In each specification in Panel A, we include dummies for the quarter, brokerage house, and number of firms covered as described in the text. In each specification in Panels B and C, we include dummies for quarter, brokerage house, and the firm being covered. Experience effects include indicator variables for each year of the analyst's experience. The numbers in parentheses are the probabilities that the true coefficient has a sign opposite to that of the estimate.

	(1)	(2)	(3)	(4)
Panel A. Estimation of the probability of future termination				
Prior relative forecast error score	−0.001	−0.001		
	(0.043)	(0.089)		
Prior two quarters' average relative forecast error score			0.0003	0.0006
			(0.500)	(0.269)
Prior boldness indicator		0.024		
		(0.225)		
Prior two quarters' boldness indicator				0.057
				(0.007)
Quarter effects	Yes	Yes	Yes	Yes
Experience effects	Yes	Yes	Yes	Yes
Brokerage house effects	Yes	Yes	Yes	Yes
Number of firms covered effects	Yes	Yes	Yes	Yes
Log likelihood	−42,132	−42,132	−35,466	−35,462
Number of observations	161,817	161,817	139,623	139,623
Panel B. Relation between future boldness and probability of future termination				
Probability of future termination	−1.088	−0.863	−2.358	−2.057
	(0.160)	(0.158)	(0.000)	(0.008)
Probability of future termination^2	0.053	0.051	0.090	0.085
	(0.000)	(0.004)	(0.000)	(0.000)
Quarter effects	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes
Brokerage house effects	Yes	Yes	Yes	Yes
R^2	0.384	0.384	0.385	0.385
Number of observations	161,817	161,817	139,623	139,623
Panel C. Relationship between future boldness and probability of future termination with future relative accuracy controls				
Probability of future termination	−0.546	−0.470	−1.233	−1.087
	(0.380)	(0.174)	(0.060)	(0.064)

Table 5 (*continued*)

	(1)	(2)	(3)	(4)
Probability of future termination^2	0.043	0.042	0.066	0.063
	(0.001)	(0.001)	(0.000)	(0.000)
Future relative forecast error score	−20.69	−20.69	−20.66	−20.66
	(0.000)	(0.000)	(0.000)	(0.000)
Future relative forecast error score^2	0.182	0.182	0.181	0.181
	(0.000)	(0.000)	(0.000)	(0.000)
Quarter effects	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes
Brokerage house effects	Yes	Yes	Yes	Yes
R^2	0.468	0.468	0.469	0.469
Number of observations	161,817	161,817	139,623	139,623

relative forecasting performance and a positive relation between her forecast boldness and experience. An important insight offered by our analysis is that the presence of significant employment risk is the crucial factor that induces an analyst to alter her forecasting behavior over time and in response to her prior performance.

Finally, consistent with our theory, we empirically show, for the first time, a statistically and economically significant U-shaped relation between the boldness of analysts' forecasts and their prior relative performance. We also directly test the implications of our theory that emphasizes the importance of implicit incentives arising from employment risk in driving variations in forecasting behavior. We show that analysts with either very high or very low employment risk are more likely to issue bolder forecasts.

Appendix A. The analyst's payoff structure and employment risk

In this appendix, we derive the analyst's payoff structure by analyzing the interactions between customers, the investment bank, and the analyst. An investment bank has operations in several areas that are not affected by the analyst. We focus on those services that are directly or indirectly affected by the analyst's perceived ability or reputation such as brokerage and underwriting activities. Because the explicit modeling of the various ways in which an analyst could affect the bank's business is rather complex and would lead to a significant digression from the focus of our study, we adopt a reduced form approach in which we directly model the expected payoff to customers as a function of the bank's and, therefore, the analyst's reputation.

The customers' expectation of their payoff from utilizing the bank's services (before fees) increases with its reputation that is, in turn, affected by the analyst's ability. For simplicity, we assume that customers' expectation of their payoff $P(t)$ per dollar of services purchases (before investment banking fees) is an increasing linear function of the analyst's average perceived ability $\widehat{l}(t)$:

$$P(t) = A + B\,\widehat{l}(t);\; A>0, B>0. \tag{17}$$

Denote the bank's operating costs as a function of business volume by $C(\cdot)$ and the fee it charges per unit of services rendered by $f(t)$. We assume that $C(\cdot)$ is strictly increasing and convex and $C'(\cdot)$ is a surjective mapping from R_+ to R_+. We assume a competitive market for the demand for investment banking services so that risk-neutral customers receive zero expected payoff in equilibrium net of investment banking fees. If $q(t)\geqslant 1$ is the business volume that is directly or indirectly affected by the analyst's reputation, then

$$q(t)P(t) - q(t)f(t) = 0. \tag{18}$$

Hence, from Eq. (17) and Eq. (18), we must have

$$P(t) = f(t) = A + B\,\widehat{l}(t). \tag{19}$$

As we show in Proposition A.2 below, the investment bank receives a constant proportion of the total surplus (net of operating costs) after bargaining with the analyst. Hence, for a given fee, the risk-neutral bank chooses the volume of services it supplies to maximize the total surplus

$$q(t) = \arg\max_{\phi} f(t)\phi - C(\phi) = C'^{-1}(f(t)). \tag{20}$$

From Eq. (19) and Eq. (20), the business volume $q(t)$ as a function of the analyst's perceived ability is:

$$q(t) = C'^{-1}\left(A + B\,\widehat{l}(t)\right). \tag{21}$$

From Eq. (20) and Eq. (21), the total surplus $S(t)$ is given by

$$S(t) = \left(A + B\,\widehat{l}(t)\right)C'^{-1}\left(A + B\,\widehat{l}(t)\right) - C\left(C'^{-1}\left(A + B\,\widehat{l}(t)\right)\right). \tag{22}$$

Proposition A.1. *The surplus $S(t)$ over the period $[t,t+\Delta]$ is increasing and convex in the analyst's average perceived ability $\widehat{l}(t)$.*

Proof. From Eq. (19), it suffices to show that $S(t)$ is strictly increasing and convex in the expected payoff $P(t)$. From Eq. (19)

$$S(t) = P(t)C'^{-1}(P(t)) - C\left(C'^{-1}(P(t))\right). \tag{23}$$

From Eq. (23), we have

$$\frac{\mathrm{d}S(t)}{\mathrm{d}P(t)} = C'^{-1}(P(t)\geqslant 0, \tag{24}$$

because $C(\cdot)$ is an increasing, convex function. From Eq. (24), we see that

$$\frac{\mathrm{d}^2S(t)}{\mathrm{d}P(t)^2} = \frac{1}{C''\left(C'^{-1}(P(t)\right)} > 0. \tag{25}$$

because $C(\cdot)$ is strictly convex. □

The result of Proposition A.1 is consistent with the empirical evidence shown in Jackson (2005) that brokerage revenue increases with analyst reputation that, in turn, increases with forecasting performance.

The investment bank and the analyst bargain over the surplus $S(t)$ in each period. Upon disagreement, the bank and the analyst incur personal costs that are proportional to $S(t)$ in the current period, but neither bears personal costs in future periods due to the current bargaining process ending in disagreement. We adopt generalized Nash bargaining as the solution concept. In Proposition A.2, we show that the analyst's share of the surplus and, therefore, her compensation is also convex in her average perceived ability.

Proposition A.2. *The analyst's and the bank's equilibrium payoffs are given by*

$$Q(t) = \theta S(t); Q_B(t) = (1-\theta)S(t), \theta > 0 \text{ is a constant} \tag{26}$$

Proof. Upon disagreement, the bank and the analyst receive proportions $(1-\delta_B)$ and $(1-\delta_A)$of the surplus, respectively, where $\delta_B + \delta_A > 1$, that is, there is some loss in the total surplus if no agreement is reached between the bank and the analyst. By the theory of generalized Nash bargaining (Myerson, 1992), the analyst's share of the surplus solves

$$\begin{aligned} Q(t) = &\ \arg\max_{x \leqslant S(t)} (x - (1-\delta_A)S(t))^{\alpha} (\delta_B S(t) - x)^{1-\alpha} \\ = &\ \arg\max_{x \leqslant S(t)} \alpha \log(x - (1-\delta_A)S(t)) + (1-\alpha)\log(\delta_B S(t) - x) \\ = &\ [\alpha\delta_B + (1-\alpha)(1-\delta_A)]S(t), \end{aligned}$$

where $\alpha \in (0,1)$ is the analyst's bargaining power with the investment bank. □

To simplify the subsequent exposition, and for concreteness, we henceforth assume the following (increasing and convex) functional form for the investment bank's operating costs:

$$C(x) = Mx + Nx\log(x); M, N > 0, x \geqslant 1. \tag{27}$$

The following result describes the analyst's compensation at any date t provided she is employed by the bank for the period $[t, t+\Delta]$.

Proposition A.3. *The analyst's compensation at date t if she is employed by the investment bank for the period* $[t, t+\Delta]$ *is given by*

$$ge^{c\hat{l}(t)} \text{ at date } t \text{ where } 0 < c < \infty, g > 0, \tag{28}$$

where c is a constant.

Proof. By Eq. (27), we see that

$$C'^{-1}(y) = \exp\left(\frac{y - M - N}{N}\right). \tag{29}$$

By Eqs. (23) and (29), it follows that the surplus is given by

$$\begin{aligned} S(t) &= P(t)\exp\left(\frac{P(t)-M-N}{N}\right) - M\exp\left(\frac{P(t)-M-N}{N}\right) \\ &\quad - (P(t)-M-N)\exp\left(\frac{P(t)-M-N}{N}\right) \\ &= N\exp\left(\frac{P(t)-M-N}{N}\right). \end{aligned} \tag{30}$$

The analyst's payoff structure then follows from Eqs. (17), (26) and (30).

So far, we have described the analyst's compensation provided she continues to be employed by the investment bank. However, at any date t, the bank could choose to replace the analyst with another analyst. The bank makes its replacement decision to maximize its income for the period $[t, t+\Delta]$. Because it is possible that the replacement perhaps has been a lead analyst before or has not covered the particular firm before, there is uncertainty regarding the market's perception of her ability. Suppose that $n(l')\,dl'$ is the probability that the new analyst's average perceived ability is l'. Suppose also that the bank incurs fixed costs $F>0$ in searching for a replacement, and the probability of finding a replacement is $\alpha \in (0,1)$. Proposition A.4 then describes the nature of the employment risk faced by the analyst.

Proposition A.4. *At any date, there exists a threshold l_b such that the incumbent analyst can be replaced with nonzero probability if and only if her average perceived ability $\widehat{l}(t) \leqslant l_b$. Moreover, she is not replaced with certainty even if her average perceived ability is below this threshold.*

Proof. By the results of Propositions A.2 and A.3, the risk-neutral bank's payoff at date t (that is, its income for the period $[t, t+\Delta)$) is

$$Q_{\widehat{l},B}(t) = he^{c\,\widehat{l}(t)}, \tag{31}$$

where h is a constant and the subscripts indicate the dependence of the payoff on the incumbent analyst's perceived ability. The bank decides whether or not to replace the incumbent analyst to maximize its income for the period $[t, t+\Delta)$. Suppose that the bank incurs fixed costs $F>0$ in finding a new analyst. It is worthwhile for the bank to replace the incumbent if and only if

$$\int_{-\infty}^{\infty}\left(Q_{l',B}(t) - Q_{\widehat{l},B}(t)\right)n(l')\,\mathrm{d}l' \geqslant F. \tag{32}$$

By Eqs. (31) and (32), it follows that it is profitable for the bank to replace the incumbent if and only if

$$h\int_{-\infty}^{\infty}\left[e^{cl'(t)} - e^{c\,\widehat{l}(t)}\right]n(l')\,\mathrm{d}l' \geqslant F. \tag{33}$$

It follows from Eq. (33) that there exists a threshold l_b such that the incumbent analyst faces a nonzero probability $\alpha \in (0,1)$ of being replaced if and only if her perceived ability $\widehat{l}(t)$ is less than l_b. $\square$

Appendix B

Proof of Proposition 2. (a) For notational convenience, throughout the rest of this Appendix, we write $c(t) = c\sigma^2_{\text{initial}}/\left(\sigma^2_{\text{initial}}(t+\Delta)+\sigma_0^2\right)$. From Eqs. (6) and (10), we see that it is optimal for the analyst to issue the bold forecast if and only if

$$
\begin{aligned}
&e^{-c(t)r_l(t)}e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\sigma_{\max}(t)^2c(t)^2\Delta+\frac{1}{2}\sigma_a(t)^2c(t)^2\Delta^2}\\
&-(\alpha\delta)e^{-c(t)r_l(t)}e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\sigma_{\max}(t)^2c(t)^2\Delta+\frac{1}{2}\sigma_a(t)^2c(t)^2\Delta^2}N\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\sqrt{\sigma_{\max}(t)^2\Delta+\sigma_a(t)^2\Delta^2}}-c(t)\sqrt{\sigma_{\max}(t)^2\Delta+\sigma_a(t)^2\Delta^2}\right)\\
&\geqslant e^{-c(t)r_l(t)}e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\sigma_{\min}(t)^2c(t)^2\Delta+\frac{1}{2}\sigma_a(t)^2c(t)^2\Delta^2}\\
&-(\alpha\delta)e^{-c(t)r_l(t)}e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\sigma_{\min}(t)^2c(t)^2\Delta+\frac{1}{2}\sigma_a(t)^2c(t)^2\Delta^2}N\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\sqrt{\sigma_{\min}(t)^2\Delta+\sigma_a(t)^2\Delta^2}}-c(t)\sqrt{\sigma_{\min}(t)^2\Delta+\sigma_a(t)^2\Delta^2}]\right).
\end{aligned}
$$

To simplify the subsequent notation, we define $\overline{\sigma_i}(t) = \sqrt{\sigma_i(t)^2\Delta+\sigma_a(t)^2\Delta^2}; i \in \{\max, \min\}$. It follows that it is optimal to issue the bold (conservative) forecast whenever

$$
\begin{aligned}
&e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\max}}(t)^2c(t)^2} - e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\min}}(t)^2c(t)^2}\\
&>(<)(\alpha\delta)e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\max}}(t)^2c(t)^2}N\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\overline{\sigma_{\max}}(t)}-c(t)\overline{\sigma_{\max}}(t)\right)\\
&-(\alpha\delta)e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\min}}(t)^2c(t)^2}N\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\overline{\sigma_{\min}}(t)}-c(t)\overline{\sigma_{\min}}(t)\right).
\end{aligned}
\tag{34}
$$

The proof proceeds by showing that the expression on the right hand side above goes to zero as $r_l(t) \to \infty$, to

$$
(\alpha\delta)\left(e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\max}}(t)^2c(t)^2} - e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\min}}(t)^2c(t)^2}\right) \leqslant \left(e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\max}}(t)^2c(t)^2} - e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\min}}(t)^2c(t)^2}\right)
$$

as $r_l(t) \to \infty$, and has at most one local maximum. Therefore, it can intersect the straight line $\left(e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\max}}(t)^2c(t)^2} - e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\min}}(t)^2c(t)^2}\right)$ at most twice and these are the triggers $r_{\text{low}}(t)$,$r_{\text{high}}(t)$ in the statement of the proposition. The first two statements follow from the fact that for $x \in \{\max,\min\}$

$$
\begin{aligned}
&\lim_{r_l(t)\to-\infty}N\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\overline{\sigma_x}(t)}-c(t)\overline{\sigma_x}(t)\right)=1,\\
&\lim_{r_l(t)\to\infty}N\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\overline{\sigma_x}(t)}-c(t)\overline{\sigma_x}(t)\right)=0.
\end{aligned}
\tag{35}
$$

The third statement will follow if we show that the derivative of the expression on the right hand side of Eq. (34) with respect to $r_l(t)$ has at most two zeroes (we could check that one of these corresponds to a local maximum and the other to a local minimum). It can be shown that this derivative has zeroes at values of $r_l(t)$ that solve the equation

$$\exp\left[\frac{1}{2}\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\overline{\sigma_{\max}}(t)}-c(t)\overline{\sigma_{\max}}(t)\right)^2 -\frac{1}{2}\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\overline{\sigma_{\min}}(t)}-c(t)\overline{\sigma_{\min}}(t)\right)^2\right] =\frac{\overline{\sigma_{\min}}(t)}{\overline{\sigma_{\max}}(t)}e^{\left[\frac{1}{2}c(t)^2\left(\sigma_{\max}(t)^2-\sigma_{\min}(t)^2\right)\right]\Delta} \tag{36}$$

or taking the logarithms of both sides of Eq. (36) above,

$$\frac{1}{2}\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\overline{\sigma_{\max}}(t)}-c(t)\overline{\sigma_{\max}}(t)\right)^2 -\frac{1}{2}\left(\frac{-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta}{\overline{\sigma_{\min}}(t)}-c(t)\overline{\sigma_{\min}}(t)\right)^2 =\log\left(\frac{\overline{\sigma_{\min}}(t)}{\overline{\sigma_{\max}}(t)}\right)+\left[\frac{1}{2}c(t)^2\left(\sigma_{\max}(t)^2-\sigma_{\min}(t)^2\right)\right]\Delta. \tag{37}$$

Setting $u=-r_b(t+\Delta)+r_l(t)-\mu_a(t)\Delta$ above, the left hand side as a function of u is a parabola that goes to $-\infty$ as $u\to\pm\infty$ given that $\overline{\sigma_{\max}}(t)>\overline{\sigma_{\min}}(t)$. Therefore, Eq. (36) has at most two zeroes $u_{\min}(t)$,$u_{\max}(t)$.

(b) From the proof of part (a), there exists an intermediate region where issuing the conservative forecast is optimal if and only if there are values of $r_l(t)$ for which the right-hand side of Eq. (34) exceeds the left-hand side. The maximum possible value of the expression on the right hand side of Eq. (34) is lower than $(\alpha\delta)e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\max}}(t)^2c(t)^2}$. If $\left[\frac{1}{2}\left(\sigma_{\max}(t)^2-\sigma_{\min}(t)^2\right)c(t)^2\right]\Delta>\log\left(\frac{1}{1-\alpha\delta}\right)$, then

$$(\alpha\delta)e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\max}}(t)^2c(t)^2}<e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\max}}(t)^2c(t)^2}-e^{\mu_a(t)c(t)\Delta+\frac{1}{2}\overline{\sigma_{\min}}(t)^2c(t)^2}. \tag{38}$$

Therefore, from Eq. (34), the condition $\left[\frac{1}{2}\left(\sigma_{\max}(t)^2-\sigma_{\min}(t)^2\right)c(t)^2\right]\Delta<\log(1/(1-\alpha\delta))$ is necessary for the existence of an intermediate interval where issuing the conservative forecast is optimal. □

Proof of Proposition 3. From Eq. (6), it follows that, because the expectation of $\mu_a(t)$ increases linearly with t and $\sigma_a(t)$ is uniformly bounded,

$$\lim_{t\to\infty}\mu_a(t)=\infty \text{ in probability.} \tag{39}$$

From Eq. (9), we see that

$$\lim_{t\to\infty}r_b(t)=\infty. \tag{40}$$

From Eq. (5), and the definitions of $\overline{\sigma_x}(t); x\in\{\max,\min\}$, we can see that $\overline{\sigma_x}(t); x\in\{\max,\min\}$ are uniformly bounded above and below away from zero. Further, $c(t)$ (defined at the beginning of the proof of Proposition 2) is uniformly bounded. Hence, for any relative performance level $r\in R$, we can use Eqs. (39) and (40) to show that

$$\lim_{t\to\infty}N\left(\frac{r'-r_b(t+\Delta)-\mu_a(t)\Delta}{\overline{\sigma_x}(t)}-c(t)\overline{\sigma_x}(t)\right)=0; x\in\{\max,\min\},$$

uniformly in probability for all $r' \leqslant r$. It follows that the right-hand side of Eq. (34) with $r(t) = r'$ tends to zero uniformly in probability for all $r' \leqslant r$ as $t \to \infty$. Hence, Eq. (39) and the uniform boundedness of $\overline{\sigma_x}(t); x \in \{\max, \min\}$ imply that the right hand side of Eq. (34) is strictly less than the left-hand side uniformly in probability for $r(t) = r' \leqslant r$ as $t \to \infty$. Therefore, $r < \lim_{t\to\infty} r_{\text{low}}(t)$ in probability.

It now follows that the interval $[r_{\text{low}}(t), r_{\text{high}}(t)]$ lies to the right of r with probability arbitrarily close to one for sufficiently large t. In other words, for any $\varepsilon > 0$, there exists t_* such that $\text{Prob}[r < r_{\text{low}}(t)] > 1 - \varepsilon$; for $t > t_*$. □

Appendix C. Effort choices by the analyst

As discussed in Section 2, the improvement of analysts' forecasting abilities over time can be more rigorously justified by also explicitly modeling their effort choices in each period. It turns out that the analysis of this more complex model does not qualitatively alter any of our results regarding a representative analyst's forecasting behavior that is the primary focus of this study. Hence, we present only a brief description of this generalization and state our results without providing their proofs (detailed proofs are available upon request)

The representative analyst exerts unobservable effort $e_a(t)$ in each period to gather information about the firm. Similar to Gibbons and Murphy (1992) and Holmstrom (1999), the change in her relative forecasting error over the period depends on her ability and effort. Specifically,

$$dr_{l,e_a}(t) = (-l(t) - e_a(t))\Delta + \sigma(t)\sqrt{\Delta}N(t); \sigma(t) \in [\sigma_{\min}(t), \sigma_{\max}(t)], \tag{41}$$

where the subscripts on the analyst's relative forecasting error indicate its dependence on the analyst's forecasting ability and effort. To simplify the notation, we drop these subscripts in the following discussion. From Eq. (41), greater effort improves the analyst's forecasting performance. The analyst's forecasting ability grows over time as she acquires human capital through the effort that she exerts in each period. Specifically,

$$l(n\Delta) = l(0) + \sum_{i=0}^{n-1} e_a(i\Delta)\Delta. \tag{42}$$

As in Gibbons and Murphy (1992), the analyst's effort in each period proportionately reduces her utility payoff at the end of the period, that is, higher effort has the effect of increasing her discount rate for future cash flows. At any date t, the analyst's objective is

$$\sup_{ea(t)\in R_+, \sigma(t)\in[\sigma_{\min}(t), \sigma_{\max}(t)]} = \mathrm{E}\left[e^{-\beta\Delta ea(t)^n}\left[P_{ea(t),\sigma(t)}(t+\Delta) - \delta 1_{\widehat{l}(t+\Delta)\leqslant l_b} 1_{fired=1} P_{ea(t),\sigma(t)}(t+\Delta)\right]|F_t\right], \tag{43}$$

where $e^{-\beta\Delta ea(t)^n}; n \geqslant 1$ is the analyst's proportional disutility of effort and $P_{ea(t),\sigma(t)}(t+\Delta)$ is the analyst's payoff at date $t+\Delta$ that can be derived using the arguments in Appendix B. The mean $\mu_a(t)$ of the analyst's posterior assessment of her own ability is now given by

$$\mathrm{d}\mu_a(t) = e_a(t)\mathrm{d}t + \left(\sigma_a(t)^2/\sigma^*(t)^2\right)\mathrm{d}W(t), \tag{44}$$

with the variance being the same as in the simpler model. Therefore, the expected growth in the analyst's assessment of her own ability is equal to her effort. However, the mean and variance of the market's posterior assessment of the analyst's ability at any date t are given by

$$\widehat{l}(t) = \frac{\sigma_0^2 \mu_{\text{initial}} + \sigma_{\text{initial}}^2 \left(r(t) + \int_0^t s e_m(s)\,\mathrm{d}s \right) + \sigma^2 \int_0^t e_m(s)\,\mathrm{d}s}{\sigma_{\text{initial}}^2 t + \sigma_0^2}; \widehat{\sigma}(t)^2 = \frac{\sigma_{\text{initial}}^2 \sigma_0^2}{\sigma_{\text{initial}}^2 t + \sigma_0^2}. \quad (45)$$

In the above, $e_m(\cdot)$ is the market's inference of the analyst's effort in each period. In general, this differs from the analyst's actual effort because the market's assessment of the analyst's ability differs from the analyst's own assessment over time. The analysis of this model requires the characterization of the equilibrium of the dynamic game in which the analyst's effort and forecast choices and the market's assessment of her effort choices are endogenously determined. We have analyzed this model and derived the following main results.

Proposition C.1. *In the hypothetical absence of employment risk, the analyst exerts deterministic effort* $\xi(t) > 0$ *in period* $[t, t+\Delta]$ *regardless of her prior performance. In the presence of employment risk, Ceteris paribus, there exist triggers* $r_1(t) \leqslant r_2(t) \leqslant r_3(t)$ *such that the analyst's equilibrium effort* $e_a^*(t)$ *in period* $[t, t+\Delta]$ *is monotonically increasing for* $r(t) < r_1(t); r(t) \in (r_2(t), r_3(t))$ *and monotonically decreasing for* $r(t) > r_3(t); r(t) \in (r_1(t), r_2(t))$. *Further,* $\lim_{r(t) \to \pm\infty} e_a^*(t) = \xi(t)$.

The result of the above proposition implies that, on average, the analyst exerts lower effort when she significantly outperforms or underperforms her peers than when she is an intermediate performer. The intuition is that when she significantly outperforms her peers, her employment risk is very low so that she approaches her no employment risk effort level. When she underperforms, she is almost certain to be fired in the future so that it is not worthwhile for her to incur the disutility of exerting effort significantly above her no employment risk level. In the intermediate region, the presence of employment risk causes her to exert greater effort on average. The interaction between her effort and forecast choices leads to the following result describing the analyst's forecasting behavior.

Proposition C.2. *Ceteris paribus, at each date t, there exist triggers* $r_{\text{low}}(t), r_{\text{high}}(t)$ *with* $-\infty < r_{\text{low}}(t) \leqslant r_{\text{high}}(t) < \infty$ *such that analyst issues her boldest forecast* $\sigma_{\max}(t)$ *if* $r(t) \leqslant r_{\text{low}}(t)$ or $r(t) \geqslant r_{\text{high}}(t)$.

The above result implies that, as in the simpler model, there is, on average, a U-shaped relation between the analyst's forecast boldness and her prior relative forecasting performance. The intuition is similar to the intuition for Proposition 2. In the intermediate region of relative performance, the analyst's forecast boldness varies in a complex manner with her prior relative performance because of the interaction between the analyst's effort and forecast choices. The following result describes the variation of the analyst's effort and forecast choices with experience.

Proposition C.3. (a) *Given any* $\varepsilon > 0$ *and* $r \in R$, *there exists* $t^* > 0$ *such that, for all* $t_2 > t_1 > t^{**}$, *if* $r(t_1) = r(t_2) = r$, *then* $\text{Prob}(e_a^*(t_1) > e_a^*(t_2)) > 1 - \varepsilon$.

(b) *Given any* $\varepsilon > 0$ *and* $r \in R$, *there exists* $t_* > 0$ *such that, for all* $t > t_*$, *Probability*$[r > r_{\text{high}}(t)] > 1 - \varepsilon$. *Hence, the probability that the analyst with relative performance* $r(t) = r$ *issues her boldest forecast is greater than* $1 - \varepsilon$ *for* $t > t_*$.

The intuition for the above results is that the improvement of the analyst's ability over time resulting from the effort that she exerts in each period (that is always at least equal to

$\xi(\cdot)$ by the result of Proposition C.1) reduces her employment risk. Hence, her effort declines over time, and she issues bolder forecasts, ceteris paribus.

References

Avery, C., Chevalier, J., 1999. Herding over the career. Economics Letters 63, 327–333.

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

Bensoussan, A., 1992. Stochastic Control of Partially Observable Systems. University of Cambridge Press, Cambridge.

Bernhardt, D., Kutsoati, E., 2000. Can relative performance compensation explain analysts' forecast of earnings? Unpublished working paper. Tufts University, Medford, MA.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy 100, 797–818.

Bikhchandani, S., Sharma, S., 2001. Herd behavior in financial markets. IMF Staff Papers 47 (3), 279–310.

Chen, Q., Jiang, W., 2005. Analysts' weighting of public and private information. Review of Financial Studies, forthcoming.

Chevalier, J., Ellison, G., 1999. Career concerns of mutual fund managers. Quarterly Journal of Economics, May, 389–432.

Clement, M., Tse, S., 2005. Financial analysts characteristics and herding behavior in forecasting. Journal of Finance 60, 307–341.

Gibbons, R., Murphy, K.J., 1992. Optimal incentive contracts in the presence of career concerns: theory and evidence. Journal of Political Economy 100, 468–505.

Graham, J., 1999. Herding among investment newsletters: theory and evidence. Journal of Finance 54, 237–268.

Hilary, G., Menzly, L., 2001. Does past success lead analysts to become overconfident? Unpublished working paper. University of Chicago, Chicago, IL.

Holden, C., Stuerke, S., 2000. The frequency of financial analysts' forecast revisions: theory and Evidence. Unpublished working paper. Indiana University, Bloomington, IN.

Holmstrom, B., 1999. Managerial incentive problems: a dynamic perspective. Review of Economic Studies 66, 169–182.

Hong, H., Kubik, J., 2003. Analyzing the analysts: career concerns and biased earnings forecasts. Journal of Finance 58, 313–350.

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

Hu, P., Kale, J., Subramanian, A., 2005. Learning and risk-taking by fund managers: theory and evidence. Unpublished working paper. Georgia State University, Atlanta, GA.

Jackson, A., 2005. Trade generation, reputation and sell-side analysts. Journal of Finance 60, 673–717.

Lamont, O., 2002. Macroeconomic forecasts and microeconomic forecasters. Journal of Economic Behavior and Organization 48, 265–280.

Leone, A., Wu, J., 2002. What does it take to become a superstar? Evidence from institutional investor rankings of financial analysts. Unpublished working paper. University of Rochester, Rochester, NY.

MacKinnon, J., 2002. Bootstrap inference in econometrics. Canadian Journal of Economics 35, 615–645.

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

Mikhail, M., Walther, B., Willis, R., 2003. The effect of experience on security snalyst underreaction. Journal of Accounting and Economics 35, 101–116.

Myerson, R., 1992. Game Theory: Analysis of Conflict. Harvard University Press, Cambridge, MA.

Oksendal, B., 2001. Stochastic Differential Equations: An Introduction with Applications. Springer, Heidelberg, Germany.

Prendergast, C., Stole, L., 1996. Impetuous youngsters and jaded oldtimers: acquiring a reputation for learning. Journal of Political Economy 104, 1105–1134.

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

Stole, L., Zwiebel, J., 1996. Intra-firm bargaining under non-binding contracts. Review of Economic Studies 63, 375–410.

Trueman, B., 1994. Analyst forecasts and herding behavior. Review of Financial Studies 71, 97–124.

Welch, I., 2000. Herding among security analysts. Journal of Financial Economics 58, 369–396.

Zwiebel, J., 1995. Corporate conservatism and relative compensation. Journal of Political Economy 103, 1–25.