XII

Volume XII, Number 2, November 2009

Journal of Applied Economics

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UCEMA

Edited by the Universidad del CEMA

Print ISSN 1514-0326
Online ISSN 1667-6726

Journal of Applied Economics. Vol XII, No. 2 (November 2009), 331-363

REPUTATION ACQUISITION OF UNDERWRITER ANALYSTS – THEORY AND EVIDENCE

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Submitted November 2007; accepted April 2009

I examine the role of reputation in a multi-stage strategic information transmission game between an analyst and an investor. While reputation mitigates the conflict of interest in a repeated game, it may induce the biased analyst to elevate potential underperformers to the highest rating category, thus undermining the information quality of the highest message. Uncertainty about firm value helps the unbiased analyst to communicate better information in a single stage game. However, in a multi-stage game, uncertainty increases misrepresentation by the biased analyst. Empirical implications are tested. I document that 1) affiliated and unaffiliated analysts recommendations differ only in the "Strong Buy" category; 2) the underperformance of underwriter analysts' recommendations increases with the underlying uncertainty.

JEL classification codes: G83, D24
Key words: strategic information transmission, reputational cheap talk, analyst recommendations, market uncertainty

I. Introduction

Sell-side analysts employed by brokerage firms make frequent stock recommendations to the investment community based on the companies' future growth and profitability. They are an important source of information in today's markets, as many in the financial press call it the "age of the analysts" (Nocera 1997). They have, however,

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This paper is a modified version of a chapter of my doctoral dissertation completed at Stanford Graduate School of Business. I am grateful to my advisors Peter DeMarzo, and Jeffrey Zwiebel for generous advice and encouragements. I am indebted to Anat Admati for her meticulous readings and indepth discussions of the paper. I thank Navin Kartik, Jon Levin and Stefan Reichelstein, and two anonymous referees for helpful comments. This paper has benefited from seminar participants at Stanford University, UCLA, University of Washington, the University of Hong Kong and University of Illinois at Chicago.

come under increased scrutiny for alleged bias in their public announcements in recent years. The working environment and the compensation structure may lead to upward distortions in their recommendations. Investment banks rely on analysts to help them land investment-banking deals. Analysts are also influential among institutional investors, which can generate trade commissions for their brokerage firms (Hong and Kubik 2003, Jackson 2005). Indeed, researchers demonstrate empirically that analysts tend to give too strong a recommendation, especially to firms they are underwriting (Michaely and Womack 1999, Dunbar, Hwang, and Shastri 1999, and Iskoz 2003).

While various guidelines and "best practices" have been proposed to regulate the security analyst industry in response to these allegations, many regulatory agents, as well as researchers, believe that reputation may be more important in preventing future scandals (Solomon 2003, Karpoff and Lott 1999). While it is not a surprise that the reputation mechanism can help mitigate conflict of interest, it is unclear how reputational considerations affect strategic communication, especially in the context of analysts' reports. Moreover, as market uncertainty fluctuates from time to time, it is interesting to study how conflicts of interest and reputational incentives vary with the level of uncertainty, and how the interaction of the two drives the subsequent performance of analysts' reports. This latter point generates novel empirical predictions but has not been analyzed in the literature.

This paper formally models repeated strategic information transmission between an analyst and an investor and examines the role of reputation. In the presence of reputational considerations, the biased analyst loses future credibility by misrepresenting the firm today. I show that the equilibrium in the dynamic game involves the biased analyst giving biased recommendations only on stocks whose values are sufficiently low. Moreover, these low quality stocks will be given the highest recommendations, probabilistically. For all other stocks, a biased analyst will give the same recommendation as the unbiased analyst. In this context, recommendations from the biased analyst are as valuable as those from the unbiased analyst, with the exception of the most positive recommendations. If a biased analyst decides to cheat and suffer reputational damage, she might as well go for the *highest* recommendation, thereby maximizing her current profit. This "leap-frogging" behavior of the biased analyst implies that the stock recommendations made by each type of analyst will only differ in the strongest category.[1]

[1] Such "leap-frogging" behavior does not arise in a repeated game with a continuum of senders with different degrees of biases (see Wang 2009).

Moreover, I study how the reputational incentive changes with the underlying uncertainty of the firm value. While uncertainty helps the unbiased analyst to credibly communicate her information in the single stage game, it has a confounding effect when analysts have reputation concerns in a repeated game. I show that greater underlying uncertainty in firm value increases the "leap-frogging" behavior thus resulting in greater underperformance of the highest recommendations from a biased analyst.

Discretizing the model with finite message space preserves the main properties of the equilibrium. Indeed, interpreting the biased analyst as the lead underwriter analyst, I provide evidence for the model's empirical implication.[2] I show that recommendations from the lead underwriter analysts underperform those issued by other analysts only in the "Strong Buy" category. No significant difference arises between the lead underwriter analysts and the other analysts in the remaining rating categories. Most prior research with the exception of Iskoz (2003) has typically investigated the performance of all positive recommendations, that is, "Strong Buy" and "Buy" recommendations as a pool and finds differences in the performance between lead and non-lead analysts (Michaely and Womack 1999, Dunbar, Hwang, and Shastri 1999). My model predicts and the test confirms the underperformance in the "Strong Buy" category. While Iskoz (2003) also finds similar evidence, he claims that this observation is driven by analyst's behavior biases.[3] I argue that the "leap-frogging" effect of analyst's reputation acquisition plays a role in explaining this phenomenon. The evidence presented here shows that "Strong Buy" and "Buy" may be structurally different and warrant more careful treatment for future studies.

Moreover, using analyst's forecast dispersion as a proxy for firm specific uncertainty, I confirm my model's prediction that the underperformance of lead analysts' "Strong Buys" increases with underlying uncertainty. Both the model's prediction and the empirical evidence are new in the literature. The event-period abnormal returns confirm that as the underlying uncertainty increases, investors also react stronger positively (negatively) to "Strong Buy" ("Hold/Sell") recommendations. This evidence is consistent with analysts having stronger incentives to elevate a potential underperforming stock when faced with increased uncertainty.

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[2] As argued in the previous literature, for example, Michaely and Womack (1999), the lead underwriters are mainly responsible for the due diligence process and ultimately for the after-market price support, and hence, are more likely to have stronger incentives to issue a positive report. These associations are less operable for other syndicate members.

[3] There is, however, no direct test of this explanation in his paper.

This paper is organized as follows. Section II reviews the literature and discusses the contribution of this work. I study equilibria of the single-stage game in Section III. Section IV studies equilibria of the multi-stage game. In Section V, I empirically test the model's implications. Concluding remarks are offered in Section VI.

II. Theoretical literature

This paper relates to two branches of the literature in economics, namely, the literature based on the "cheap talk" model of Crawford and Sobel (1982), and that on reputation models. Since the seminal work of Crawford and Sobel (1982), cheap talk models have been studied extensively, with wide applications in economics and finance. Subsequent work includes cheap talk in bargaining games (Farrell and Gibbons 1986, Matthews 1987), broadcasting opinions when the sender might be overconfident (Admati and Pfleiderer 2004), noisy signals (Benabou and Laroque 1992), naive receivers (Kartik, Ottaviani and Sorensen 2007) and multiple referrals (Battaglini 2002).

The paper that is closest in spirit to this paper is that of Morgan and Stocken (2003), who model uncertainty regarding the sender's incentives. While Morgan and Stocken (2003) focus on the static game, the most important contribution of this paper is the reputation acquisition of the senders in a dynamic setting with general uncertainty. Compared to the bounded state space in the previous literature, unbounded state space allows us to better study the role of uncertainty in strategic information transmission and generates new testable implications. I demonstrate the existence of a "Continuum Equilibrium" in the single stage game for unbounded support, analogous to the size-one semi-responsive equilibrium in Morgan and Stocken (2003) for bounded support. Without having to characterize all possible equilibria, I show that the "Continuum Equilibrium" is the Pareto-optimal equilibrium of the single stage game for an arbitrary distribution function.

The modeling of the biased sender's intertemporal preference is also different from that in Morgan and Stocken (2003). I capture the idea that she is subject to conflicts of interest in the short term to give upward biased reports. Accuracy only comes into consideration in a dynamic setting. Specifically, the sender increases her reputation by telling the truth, especially when the information is sufficiently bad. This dynamic change in reputation is not captured in a static game by collapsing the tradeoff between conflicts of interest and accuracy into a single bias parameter as that in Morgan and Stocken (2003). As a result, my model generates different empirical predictions from their paper. My model predicts that the difference between the two types of analysts' messages is significant only in the highest rating category, while Morgan and Stocken (2003) predicts significant differences in all rating categories. Empirical evidence lends support to the former.

Another closely related paper is that of Morris (2001), who studies repeated cheap talk in which a sender acquires reputation by staying "politically correct." Similar to Morris (2001) and unlike Sobel (1985), the unbiased sender in my model is not restricted to tell the truth. Morris (2001) focuses on the adverse effect of reputation in communication in the sense that the good sender may lie in the first period by "downgrading" the signal in order to stay "politically correct". In my model, the good sender never lies from the good state to the bad. However, when the signal is sufficiently good, she is not able to *credibly* communicate her information. As a result, she will pool all the good information and send one message.[4] One key driving factor for Morris' (2001) "politically correctness" effect is the assumption of noise. While the base version of my model assumes perfect observability of information, layering on noise will not change the main characteristic of the equilibrium. When noise around the observed state is introduced, the bad sender will fudge around locally, however, when the incentives get sufficiently large, the "leap-frogging" behavior will emerge and the biased sender will cash in on her reputation by pooling the bad with the good.

More recent papers that study reputational cheap talk models include Ottaviani and Sorensen (2006a, 2006b). While they focus on the senders with different *ability* to acquire accurate information, my model focuses on the incentives to truthfully communicate information.[5]

III. The single-stage game

A. Model setup

There are two players in the game, an analyst (A) and an investor (I). The analyst, A, has private information about the state variable $\theta \in \Re$, which represents the value of the firm, and has density function $f(\theta)$, with zero mean and standard deviation

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[4] Alternatively, the unbiased sender can send all the good information, however, the receiver will form only one belief for sufficiently good messages.

[5] Indeed, prior research (Michaely and Womack 1999 and Iskoz 2003) suggests that affiliated analysts have no information advantage relative to independent analysts when making stock recommendations.

σ and is independently and identically distributed across periods. The analyst then sends a message $m \in M$ to I, where $M = \Re$ is the message space.[6]

There are two types of analysts in the population. With probability λ, the analyst's incentives are perfectly aligned with those of the investor. This analyst, who I refer to as the "unbiased" analyst (U), hopes that the investor's belief with respect to θ, $\hat{\theta}$, is as close to the true value as possible. The unbiased analyst's payoff function is given by

$$u^U\left(\theta,\hat{\theta}\right) = -\left(\theta - \hat{\theta}\right)^2.$$

With probability $1 - \lambda$, the analyst is "biased" in the sense that she prefers that the investor's belief $\hat{\theta}$ be as high as possible, independent of θ. The biased analyst's payoff function is defined by

$$u^B\left(\hat{\theta}\right) = \hat{\theta}.$$

Linearity of the utility function is assumed here for simplicity. The nature of the equilibrium remains the same if we assume $u^B\left(\hat{\theta}\right) = g\left(\hat{\theta}\right)$ for some increasing function $g(\cdot)$. The assumed utility function is to capture the biased sender's current incentive to mislead the investor and not the accuracy of the report in a *one-shot game*. Accuracy comes into consideration only in a repeated game setting when the analyst cares about being believed and being able to influence the price in the future.

The investor has a prior belief about θ, which she updates on the basis of the analyst's report. That is, aware of the uncertainty in the analyst's incentives, the investor forms belief $\hat{\theta}$ with respect to θ conditioning on the message she receives. The investor's preference is given by the following quadratic loss utility function, which captures her attempt to make the correct inference:

$$u^I\left(\theta,\hat{\theta}\right) = -\left(\theta - \hat{\theta}\right)^2.$$

Note that for quadratic loss utility functions, the optimal belief is given by the conditional expectation of θ given the message $m : \hat{\theta} = \arg\max_{\hat{\theta}} - E\{(\theta - \hat{\theta})^2 \mid m\}$ $= \mathrm{E}\left\{\theta \mid m\right\}$.

[6] This assumption is without loss of generality. One can potentially allow for a more general message space, say a Borel set M. However, as long as the message space is no smaller than the state space Θ, all results hold.

The game proceeds as follows. The analyst learns her type, which stays the same throughout the entire game and is the analyst's private information. She then observes the realized state variable θ and sends a message m to the investor. The investor processes the information in the message m and forms a belief $\hat{\theta}$, which determines the players' payoffs.

B. Bayesian Nash Equilibria

I wish to study the Perfect Bayesian Equilibrium of the above game. Formally, an equilibrium consists of a family of signaling rules for the analyst, denoted by $q^A(m \mid \theta): \Theta \to \Delta(M)$, where $A \in \{U, B\}$, and a belief rule for the investor, denoted by $\hat{\theta}(m): M \to \Theta$, such that

(1) For every message m, the investor forms a rational belief $\hat{\theta}$ conditioning on the message she receives, that is,

$$\hat{\theta}(m) = \mathrm{E}\{\theta \mid m\} = p(U \mid m) E\{\theta \mid U, m\} + (1 - p(U \mid m)) E\{\theta \mid B, m\},$$

where $p(U \mid m) = \dfrac{\lambda \int_{-\infty}^{\infty} q^U(m \mid \theta) f(\theta) d\theta}{\lambda \int_{-\infty}^{\infty} q^U(m \mid \theta) f(\theta) d\theta + (1-\lambda) \int_{-\infty}^{\infty} q^B(m \mid \theta) f(\theta) d\theta}$ is the probability that the analyst is unbiased given the message m.[7]

(2) In any state θ, the analyst sends a message m^* that maximizes her payoff: $\forall \theta \in \Re, \int_M q^A(m \mid \theta) dm = 1$. If m^* is in the support of $q^A(\cdot \mid \theta)$, then m^* solves

$$\max_{m \in M} u^A\left(\theta, \hat{\theta}(m)\right)$$

For cheap talk games, it is sufficient to characterize the beliefs that are induced by the analyst in each state, instead of focusing on the messages sent in equilibrium. I assume that off-equilibrium messages are sent by the biased analyst.

[7] The notation of "a family of signaling rules" and their definitions follow from Crawford and Sobel (1982). The signaling rule is a density function over the message space. The model, following the convention in the literature, focuses on the beliefs that are induced in equilibrium.

C. The Pareto-optimal equilibrium

In this section, I characterize the set of beliefs that are induced in an equilibrium of the single-stage game. Moreover, I show the existence of a Pareto-optimal equilibrium.

The following lemma demonstrates the existence of a maximum equilibrium belief. This result is particularly interesting for a distribution with infinite support.

Let $\hat{\Theta}$ be the set of all beliefs induced in an equilibrium with positive probability. Formally,

$$\hat{\Theta} = \left\{ \hat{\theta}(m) \mid m : q^A(m \mid \theta) > 0 \text{ for some } \theta \right\}$$

Lemma 1 *In any equilibrium of the single-stage game, the set of equilibrium beliefs, $\hat{\Theta}$, has a maximum, that is,* $\sup \hat{\Theta} \in \hat{\Theta}$.

Let $\theta^* \equiv \sup \hat{\Theta}$ denote the highest possible belief that can be induced in equilibrium. Given the biased sender's preference, she will induce the maximum belief, θ^*, regardless of the state θ. Clearly, if the analyst is believed to be unbiased for sure, then her information is communicated fully and perfectly to the investor. If, however, there is a positive probability that the analyst is biased, then sufficiently high beliefs cannot be induced in equilibrium, as the rational investor will "discount" the message that attempts to induce the highest belief.

This leads us to the Continuum Equilibrium. In this equilibrium, the unbiased analyst credibly reveals all information up to a cutoff point θ^* by sending a continuum of messages that create a one-to-one mapping from θ to belief $\hat{\theta}$.[8] For all states above θ^*, this analyst is not able to credibly reveal her information, and thus, for these states, she will induce the highest belief θ^* and pool with the biased analyst, whose message is independent of θ and induces the highest belief.

The investor's highest possible belief, θ^*, is determined endogenously in equilibrium. When the investor receives the message that induces θ^*, say, m^*, she understands that if the message comes from the unbiased analyst, then $\theta \in [\theta^*, \infty)$, whereas if the message comes from the biased analyst, then it carries no information. Given the message m^*, the posterior probability that the analyst is unbiased is given by

[8] Potentially, I can allow the cutoff point, call it $\tilde{\theta}$, up to which the unbiased analyst credibly reveals all information to be different from the highest belief θ^*. I show in Lemma 2 that $\tilde{\theta} = \theta^*$ in equilibrium.

$$p\left(U \mid m^*\right)=\frac{\lambda \int_{-\infty}^{\infty} q^U\left(m^* \mid \theta\right) f(\theta) d\theta}{\lambda \int_{-\infty}^{\infty} q^U\left(m^* \mid \theta\right) f(\theta) d\theta+(1-\lambda)}=\frac{\lambda\left(1-\Phi\left(\theta^*\right)\right)}{\lambda\left(1-\Phi\left(\theta^*\right)\right)+1-\lambda},$$

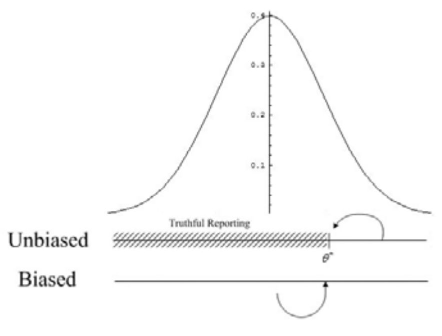
where $\Phi(\cdot)$ is the cumulative distribution function of θ.

Proposition 1 (The Continuum Equilibrium) *There is an equilibrium in which U induces belief* $\hat{\theta}=\theta$ *for* $\theta \in\left(-\infty, \theta^*\right)$ *and* $\hat{\theta}=\theta^*$ *for* $\theta \in\left[\theta^*, \infty\right)$, *and B induces* $\hat{\theta}=\theta^*$ *for all* θ, *where* θ^* *satisfies*

$$\theta^*=\frac{\lambda \int_{\theta^*}^{\infty} \theta f(\theta) d\theta}{\lambda\left(1-\Phi\left(\theta^*\right)\right)+1-\lambda}. \tag{1}$$

The equilibrium strategies for both the biased and the unbiased analysts are depicted in Figure 1.

Figure 1. Analysts' strategies in the Continuum Equilibrium of the single-stage game



Corollary 1 (Properties of the Continuum Equilibrium) *In a Continuum Equilibrium:*

1. θ^* *is positive.*
2. $\theta^* \propto \sigma$, *that is, the unbiased analyst can credibly reveal more information when the underlying state variable is more volatile.*
3. θ^* *increases with* λ, *that is, the unbiased analyst can credibly reveal more information when her prior reputation is high.*

The highest belief θ^* increases with the analyst's prior reputation λ. This provides incentives for the analyst to acquire a reputation for being unbiased in early stages of the game. More interestingly, θ^* increases with and is proportional to the standard deviation σ. When θ is drawn from a distribution with greater volatility, it is more likely that θ comes from the right tail, and thus, a message that induces a higher θ becomes credible. This implies that when there is more uncertainty in the state variable, the unbiased analyst can credibly communicate more information. Notice that the nature of the uncertainty modeled here is to linearly scale up or down the distribution of θ. This linear transformation is only one of many possible ways to change the variance of θ.

I first show that the highest belief that can possibly be induced in any equilibrium is θ^*, the highest belief in the Continuum Equilibrium. An immediate corollary of this result is that both types of analysts prefer the Continuum Equilibrium to any other equilibria.

Proposition 2 *Belief θ^* that is the solution to equation (1) is the highest belief that can possibly be induced in any equilibrium.*

The informational efficiency of an equilibrium is measured by the residual uncertainty of the unbiased analyst's message, $\sigma_U = \int_{-\infty}^{\infty} \left(\theta - \hat{\theta}(\theta)\right)^2 f(\theta)d\theta$, where $\hat{\theta}(\theta)$ is the equilibrium belief induced by the unbiased analyst in state θ. This is a reasonable measure since the biased analyst's message contains no information in any single-stage equilibrium.

Corollary 2 (Informational efficiency of the Continuum Equilibrium) *The residual uncertainty of the unbiased analyst's message, σ_U, is smallest in the Continuum Equilibrium, relative to any other equilibrium.*

Since there is no information loss when $\theta \in (-\infty, \theta^*]$, the above result follows immediately from Proposition 2.

It is easy to verify that the unbiased analyst's ex-ante expected utility is given by $\upsilon_U = -\sigma_U$ where σ_U is the residual uncertainty of the unbiased analyst's message. It follows immediately that both the unbiased analyst and the investor prefer the Continuum Equilibrium to any other equilibrium.

Proposition 3 (Pareto-optimality of the Continuum Equilibrium) *The Continuum Equilibrium is ex-ante Pareto-superior to all other equilibria.*

For the reasons above, I claim that the Continuum Equilibrium is the most efficient equilibrium, and is the one the players should coordinate on in the second stage of the two-period game. In a model with finite message space, it is reasonable to assume that the same number of messages will be used across periods, in which case the partition equilibrium of the corresponding size will be played in the continuation play. However, the analysis of the multi-stage game that follows does not depend on a particular equilibrium being played, except for the babbling equilibrium. We only need to assume that the continuation payoff is increasing in the analyst's reputation.

The singe-stage game has features similar to Morgan and Stocken (2003). However, a distribution with infinite support offers new insights on how uncertainty affects the efficiency of communication. Moreover, I show that the Continuum Equilibrium Pareto dominates all possible equilibria. The analysis can be easily extended to distributions with finite support.

IV. The multi-stage game

In this section, I extend the game to two periods. At the end of the first period, the state of the world θ is made public, and the investor updates her belief about the analyst's type based on the message he receives and the realized state of the world. The game is then repeated a second time. In the second period, the analyst has no reputation concerns. The second period, therefore, is played as the single-stage game. In particular, I assume that the Continuum Equilibrium will be played as it is the Pareto-optimal equilibrium. The analysis that follows, however, does not depend on any particular equilibrium being played. We only need the assumption that the continuation payoff for the sender increases with her reputation.

Assume that the analyst's payoff is a weighted average of her payoffs in the first and second periods.

The unbiased analyst's payoff is given by

$$-\left(\hat{\theta}-\theta\right)^2+\gamma\upsilon_U\left[\Lambda\left(\lambda,\theta,m\right)\right]. \tag{2}$$

The biased analyst's payoff is given by

$$\hat{\theta}+\gamma\upsilon_B\left[\Lambda\left(\lambda,\theta,m\right)\right], \tag{3}$$

where $\upsilon_A\,[\Lambda]$ is analyst A's continuation payoff, for $A\in\{U,B\}$, given the investor's belief, $\Lambda\,(\lambda,\theta,m)$about the analyst's type.

The parameter γ can be interpreted as the discount factor. Alternatively in a model with a positive measure of memoryless investors, γ is the probability that the investor updates her belief about the analyst's type.

The continuation payoff, $\upsilon_A[\Lambda]$, is the discounted sum of all future payoffs in a finitely repeated game. For simplicity, I assume that the game is only repeated once, and in particular, the Continuum Equilibrium is played in the future period. Thus, the biased sender's continuation payoffs in period 2 is given by

$$\upsilon_B\left[\Lambda\right]=\theta^*\left(\Lambda\right), \tag{4}$$

where θ^* is the highest belief induced in the Continuum Equilibrium.

The analyst's strategy in the first period of the two-period game, denoted by $q^A\left(m\,|\,\theta\right):\Theta\rightarrow\Delta\left(M\right)$, maximizes the analyst's payoff given in equations (2) and (3). I assume that the investor maximizes her single-period payoff, that is, she is myopic in her decision making, or she cannot commit to a long-term strategy.

In equilibrium, the analyst and the investor maximize their payoffs given each other's strategies. The investor's belief about the analyst's type at the end of each period, $\Lambda\left(\lambda,\theta,m\right)$, is formed by Bayes' rule:

$$\Lambda\left(\lambda,\theta,m\right)=\frac{\lambda q^U\left(m\,|\,\theta\right)}{\lambda q^U\left(m\,|\,\theta\right)+\left(1-\lambda\right)q^B\left(m\,|\,\theta\right)}.$$

A. Full revelation

In this section, I study whether all the information can be credibly communicated in the first stage game.

Assume that the off-equilibrium belief is that the analyst who lies in the first period is taken to be the biased analyst. Any message from this analyst will not be believed in the second period, because in the single-stage game, a biased analyst's message contains no information.

It is easy to show that there always exist a pair θ_H and $\theta_L\in\Re$ such that for any γ and λ,

$$\theta_H-\theta_L>\gamma\left(\upsilon_B\left(\lambda\right)-\upsilon_B\left(0\right)\right), \tag{5}$$

If the biased analyst mimics the unbiased analyst by telling the truth, he gets reputation λ in the second period. Otherwise, if she deviates, she will lose her reputation completely and receive continuation payoff υ_B (0) For distributions with infinite support, there is always a pair of states such that if she deviates from the low state θ_L to the high state θ_H, her current gain will be larger than her reputation loss.

B. Equilibrium with misrepresentation

We see that the biased analyst will not tell the truth in the states near the left tail of the distribution. Consequently, the unbiased analyst cannot credibly reveal sufficiently high states in equilibrium. Consider an equilibrium in which $\hat{\theta}_H$ is the highest belief induced, for some $\hat{\theta}_H \in \Re$.[9] Then there exists a belief $\hat{\theta}_L$ such that the following equation holds

$$\hat{\theta}_H - \hat{\theta}_L = \gamma\left(\upsilon_B(\lambda) - \upsilon_B(0)\right). \tag{6}$$

Note that $\hat{\theta}_L$ is the lowest state in which the biased analyst (weakly) prefers to tell the truth. For an equilibrium to exist, we must reward those senders who tell the truth near the left tail of the distribution with a higher reputation. This happens when the biased analyst randomizes between misrepresenting the true state and telling the truth with some probability $\rho(\theta)$.[10]

When the biased analyst plays mixed strategies, the resulting equilibrium has similar features with those of the single-stage game. The unbiased analyst can credibly induce all beliefs below some cutoff point, θ_H, above which she will pool with the biased analyst and induce the maximal belief, $\hat{\theta}_H$.[11] For states below θ_L, the biased analyst will randomize between telling the truth and pooling with the unbiased analyst, and inducing the highest belief, $\hat{\theta}_H$.

Let $\rho(\theta)$ denote the probability that the biased analyst tells the truth in state θ. This implies that she induces the highest belief $\hat{\theta}_H$ with probability $1 - \rho(\theta)$.

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[9] By an argument similar to that in Lemma 1, I can show that in the repeated game, the set of all equilibrium beliefs induced with positive probability must contain a maximum point.

[10] Because of the nature of continuous state variable, reputation changes must also be continuous.

[11] To be precise, the cutoff point θ_H could be different from the highest belief induced, $\hat{\theta}_H$, in the multi-stage game. However, letting $\theta_H = \hat{\theta}_H$ is without loss of generality. We must have $\hat{\theta}_H \geq \theta_H$. As we move θ_H upwards, that is, we enlarge the region in which the unbiased analyst tells the truth, $\hat{\theta}_H$ will also move upwards. However, $\hat{\theta}_H$ will move upwards at a slower rate, as the decision maker takes a weighted average of $(\theta_H, 1]$ and the region in which the biased analyst induces the highest belief. Eventually, $\hat{\theta}_H$ will coincide with θ_H. Therefore, without loss of generality, we can restrict our attention to the equilibrium in which $\theta_H = \hat{\theta}_H$.

In states $\left(-\infty,\theta_L\right]$, the biased analyst randomizes between truthfully reporting the state θ, and inducing the highest belief $\hat{\theta}_H$ and losing reputation completely once the state variable is made public. Since the unbiased analyst also tells the truth in states $\left(-\infty,\theta_L\right]$, the belief $\hat{\theta}(\theta) = \theta$ is induced in these states. The existence of a mixed strategy equilibrium dictates that the biased analyst be indifferent between these two strategies. This implies, in turn, that $\rho(\theta)$ is defined by

$$\theta + \gamma \upsilon_B\left(\Lambda\left(\lambda,\theta,\theta\right)\right) = \theta_H + \gamma \upsilon_B\left(0\right), \tag{7}$$

where $\Lambda\left(\lambda,\theta,\theta\right) = \dfrac{\lambda}{\lambda + \left(1-\lambda\right)\rho\left(\theta\right)}$, for $\theta \in \left(-\infty,\theta_L\right]$.

If the Continuum Equilibrium is played in the second period of the two-period game, the continuation payoff is given by $\upsilon_B\left(\Lambda\right) = \theta^*\left(\Lambda\right)$.

Corollary 3 *The probability that the biased analyst tells the truth, $\rho(\theta)$, increases with λ, θ and γ, for $\theta < \theta_L$, ceteris paribus.*

As the realized state gets lower, the biased analyst lies with higher probability. On the other hand, ρ increases with the analyst's prior reputation, λ. If her prior reputation is high, the biased analyst has more incentive to tell the truth as it is more costly for her to lose her reputation. Moreover, interpreting γ as the probability of the state being revealed at the end of the first period, the biased analyst lies more frequently when there is less probability of detection.

Proposition 4 *In the first period of the multi-stage game, there exist cut-off points θ_H and θ_L such that the unbiased analyst truthfully reports all states $\theta \in (-\infty,\theta_H]$ and induces belief θ_H for $\theta \in (\theta_H,+\infty)$. The biased analyst mimics the unbiased analyst's reports, in all states except for $\theta \in (-\infty,\theta_L]$, for which she randomizes between truthfully reporting θ with probability $\rho(\theta)$ and inducing the highest belief θ_H.*

The biased and the unbiased analysts' equilibrium strategies in the multi-stage game are depicted in Figure 2.

Note that θ_H is the belief the investor forms when he receives the highest message, m_H, taking into consideration the analyst's equilibrium strategy. θ_H is the weighted-average of the conditional expectation of the states from which each type of analyst induces the highest belief.

$$\theta_H = \mathrm{E}\{\theta \mid m_H\} = \psi\bar{\theta}_U + (1-\psi)\bar{\theta}_B, \tag{8}$$

where $\bar{\theta}_A$ is the expected value of the state variable θ given that the highest message is sent by analyst type $A \in \{U, B\}$ (see Equations (8) and (9) in the Appendix).

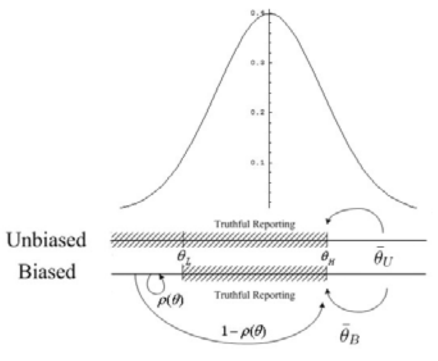
It is possible to solve θ_H, θ_L, and $\rho(\theta)$ jointly from equations (6), (7) and (8). While the system of equations does not have a closed-form algebraic solution, comparative static results can be derived from these equations.

Corollary 4 *In a misrepresentation equilibrium of the multi-stage game,*

1. *The cutoff points θ_H and θ_L are proportional to σ, thus the distance between the highest message and the lowest message increases with uncertainty.*[12]
2. *Conditioning on the highest message, the difference in the expected θ between the two types of analyst is proportional to σ, that is, $\bar{\theta}_U - \bar{\theta}_B \propto \sigma$.*
3 *The range in which the unbiased analyst can credibly reveal all information, $(-\infty, \theta_H]$ is larger when the analyst has a higher reputation, that is, θ_H increases with λ.*

The effect of uncertainty on communication is rather interesting here. We see in the single stage game, when there is more underlying uncertainty, the unbiased

Figure 2. Analysts' strategies in the first period of the multi-stage game



[12] The distance refers to the distance between the expected states from which the highest and the lowest message are being sent. I use the term the "lowest" message loosely here to refer to the messages sent from the states below θ_L. Discretizing the model to 3 equilibrium messages, the lowest message is being sent from those states.

analyst can credibly reveal higher states. This effect, however, becomes a double-edge sword when analysts have reputation concerns. When the unbiased analyst can credibly reveal higher states, it gives the biased analyst more incentive to elevate a potential underperformer to the highest rating category, thus undermining the informational efficiency of the highest message. This phenomenon generates a novel testable implication examined in the next section.

Notice that the probability of honest reporting, ρ, diminishes from one at $\theta = \theta_L$ to zero, as θ decreases. From equation (7), we see that since θ_H and θ_L become further apart as uncertainty increases, this probability of truthful reporting decreases at a faster rate. This implies that the biased analyst reports less honestly when there is more uncertainty.

V. Empirical implications and evidence

A considerable amount of empirical work assesses the performance of analyst recommendations, especially in regard to the conflicts of interest of sell-side analysts (Michaely and Womack 1999, Lin and McNichols 1998), the reputation of security analysts (Stickel 1992, Fang and Yasuda 2005), and the investment value and economical significance of analyst recommendations (Barber et. al. 2003). Theoretical work in this area, however, is inadequate. The multi-stage game model specification and equilibrium characterization above offer a number of novel empirical implications. In this section, I provide some empirical tests.

To examine the empirical implications of the model, I compare the recommendations issued by lead underwriter analysts and all other analysts (including co-underwriter analysts) for IPO stocks, as the lead underwriters are mainly responsible for providing price support after IPO (Lewellen 2006).[13]

In order for the model to be applicable to the data, we need to first examine the model's assumptions.[14] The model relies on the assumption that investors remain uncertain about analysts' incentives. It is costly for the investors, especially small investors, to find out whether the analyst belongs to the brokerage firm who was the lead underwriter of an IPO. Moreover, in much of the sample period (1993 - 2002), the public was not as aware of the conflict of interest of sell-side analysts as it is

[13] This classification is also consistent with the convention in the literature (see Dunbar et al. 1999, Iskoz 2003 and Michael and Womack 1999).

[14] A similar argument is made in Morgan and Stocken (2003).

now.[15] Indeed, using data from the same sample period, Malmendier and Shanthikumar (2007) document that small investors do not account for the differences in analyst affiliations.

A. Sample data

The data used in this study comes from three sources. Data on IPOs is from the Securities Data Corporation (SDC) New Issues Database. Data includes the company name, the date of IPO, the lead underwriter as well as the underwriter syndicate. The source of analyst recommendations used in this study is from I/B/E/S Summary recommendations database, starting from October 1993 up to December 2002. The recommendations file contains analysts' ratings for a particular company. Each data record also contains the company name, the date of recommendation, and the brokerage house issuing the report. Daily and monthly stock returns and market capitalization data is taken from the Center for Research in Security Prices (CRSP) database. Finally, Fama-French daily and monthly factors were downloaded from Professor Ken French's website. The dataset includes recommendations on IPO stocks. We study analyst recommendations made within one year of IPO issuance. This is done by comparing the date of IPO issuance, as recorded in the SDC database, and the recommendation date, obtained from the I/B/E/S database. Each recommendation is assigned to one of the following two categories: those made by analysts who acted as the lead underwriters in the IPO issue (Lead), and those made by the non-lead underwriter analysts (Non-lead), i.e., brokers who were not the lead underwriters of the IPO processes.[16] Since the I/B/E/S and the SDC databases use different codes for analysts, the link between the underwriter data is obtained by matching the names of the investment banks in the two databases.[17]

The sample includes 5163 IPO firms with issuance date between 1/1/1993 and 12/31/2002. Among these firms, 3178 receive recommendations from any analyst within one year of issuance and 3038 receive at least one recommendation from

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[15] In the empirical analysis that follows, we observe some structural change after the year 2000.

[16] This follows the convention in the literature. See Dunbar et al. (1999), Iskoz (2003) and Michael and Womack (1999).

[17] The authors are grateful to Devin Shantikumar for making this mapping available for NYSE stocks. This mapping is refined by using Hoover's Online, the Directory of corporate Affiliations, Lexus-Nexus archive, and corporate websites.

the brokerage house who was the lead underwriter in the IPO process. The SDC IPO/ IBES merged data set contains 21,619 recommendations, extending from 10/30/1993 to 12/31/2002, 4531 of which are from the lead underwriter analysts. Out of 16339 recommendations from the non-lead underwriter analysts, 529 are made by independent research firms who never participated in IPO underwriting business.

B. The underperformance of the underwriter's "Strong Buy" recommendations

An important implication of the multi-stage game is that the biased analyst lies only when the value of the firm is sufficiently low. Moreover, when she lies, she induces the highest belief by sending the highest message. In other words, when the biased analyst sends the highest message, it is possible that the firm's value is actually very low. On the other hand, the unbiased analyst sends the highest message only when the firm is indeed good. This generates Prediction 1: stocks that receive "Strong Buy" recommendations from their lead underwriter analysts underperform those from non-lead analysts; the differences in other rating categories are relatively insignificant. This prediction does not rely on the perfect observability of information currently assumed in the model. In a model with noise, it is easy to see that the biased analyst will hide behind the noise and fudge around locally with small upward lies. However, once the incentive gets large enough, we will still see occurrences of big lies, which generate the above prediction. The differences in other categories will be small.

We first observe from Table 1 that lead analysts issue more positive recommendations than non-lead analysts, as documented in the literature. A detailed break-down of different rating categories reveals that lead analysts issue "Strong Buy" more frequently and "Hold/Sell" less frequently than non-lead analysts. However, there is not much difference between the proportion of "Buy" recommendations issued by lead and non-lead analysts.[18] One possible explanation for this empirical regularity is that the lead analysts give more favorable recommendations to stocks in general. This implies that the entire distribution of the recommendations is shifted upward. This is the view traditionally held in the literature. Alternatively, it is possible that lead analysts give "Strong Buy" recommendations to some of the potential underperforming stocks that actually belong to the "Hold/Sell" category. To distinguish between these two competing hypotheses, I examine the post-recommendation abnormal returns.

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[18] Most of the papers in the literature examine analysts recommendations by combining "Strong Buy" and "Buy" recommendations.

Specifically, I regress each stock's monthly return within one year of the recommendation date against monthly Fama-French factors. The risk-adjusted abnormal return is measured by the intercept (alpha) of the regression. The mean abnormal return and t-statistics for stocks in each recommendation category is reported in Table 2.

The most discernible pattern is that there are no significant differences between Lead and Non-lead recommendations, except for the "Strong Buy" category. Stocks that receive a "Strong Buy" recommendation from their lead underwriters under perform those in other categories. This difference is, however, statistically significant only at the 10% level.

Table 1. Distribution of recommendations

	Panel A: lead analysts		Panel B: non-lead analysts	
Rating	Frequency	Percentage	Frequency	Percentage
Strong Buy	2052	45.29	6463	39.56
Buy	1944	42.90	6981	42.73
Hold/Sell/Strong Sell	535	11.81	2895	17.72
Total	4531	100.00	16339	100.00

Note: the table shows the distribution of recommendations for IPOs during the first year of issuance, made by analysts who were the lead underwriter in the IPO issue (Lead), and analysts who were not the lead-underwriter in the IPO (Non-lead).

Table 2. Fama-French monthly abnormal returns, in percentage

Recommendations	By lead	By non-lead	Differences
Strong Buy	-0.40	-0.03	-0.37
(t-stat)	(-1.86)	(-0.25)	(-1.50)
Buy	-0.11	-0.17	0.06
(t-stat)	(-0.54)	(-1.41)	-0.25
Hold/Sell/Strong Sell	-0.19	-0.30	0.11
(t-stat)	(-0.30)	(-1.08)	(0.16)

Note: the table shows the intercepts in percentage from monthly return regressions on monthly Fama-French factors. The sample contains recommendations made within one year after IPO issuance. The number in each cell is the average of α from the Fama-French regression on stocks in each category. t-statistics are reported in the brackets.

Corollary 3 shows that the probability that a biased analyst tells the truth $\rho(\theta)$ increases with γ, the likelihood that the investor updates his belief accordingly after a lie is revealed. In other words, a biased analyst lies more frequently when it is less likely to be found out ex-post. This implies Prediction 2: The underperformance of Lead "Strong Buy" is stronger when the likelihood of the "booster shot" being found out is low.

To test this prediction, I filter out the stocks that are followed by the lead underwriter only (Lead Only), and those that are followed by the non-lead analysts only. I argue that when nobody else is following the stock, it is easier to justify a biased recommendation.

Table 3 provides a distribution of different recommendation categories. Similar to previously, lead analysts issue more "Strong Buy" recommendations, and less negative recommendations. In contrast, there is no significant difference in the proportion of "Buy" recommendations. I then examine the Fama-French abnormal returns. The results are reported in Table 4. The inferior performance in the "Strong Buy" category becomes even more significant. The difference is significant at 5% level. There are no significant differences between the two groups for other recommendation categories. Figure 3 shows the histogram of these abnormal returns for each recommendation group. It can be seen from the histogram that there is a much fatter tail in the left end for the Lead Only "Strong Buy" category, which is not observed in the other recommendation groups. This pattern suggests that the lead underwriters deliberately provide "Strong Buy" recommendations to some underperforming stocks, especially when there are no other analysts following these stocks.

Table 3. Distribution of recommendations from Lead Only and Non-lead Only

	Panel A:Lead Only stocks		Panel B: Non-lead Only stocks	
Rating	Frequency	Percentage	Frequency	Percentage
Strong Buy	155	43.42	1023	38.91
Buy	152	42.58	1143	43.48
Hold/Sell/Strong Sell	50	14.00	463	17.61
Total	357	100.00	2629	100.00

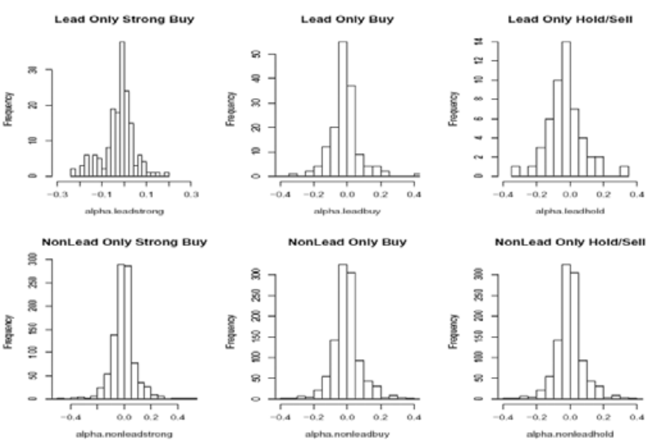
Note: the table shows the distribution of recommendations for stocks that are followed by the lead underwriter analysts only (Lead Only), and stocks that are followed by non-lead analysts only (Non-lead Only).

Table 4. Fama-French monthly abnormal return, in percentage

Recommendations	By Lead Only	By Non-lead Only	Differences
Strong Buy	-1.51	-0.08	-1.43
(t-stat)	(-3.13)	(-0.19)	(-2.26)
Buy	-1.19	-0.85	-0.34
(t-stat)	(-1.20)	(-2.12)	(-0.32)
Hold/Sell/Strong Sell	-2.38	-2.02	-0.36
(t-stat)	(-1.60)	(-4.01)	(-0.23)

Note: the table shows the intercepts in percentage from monthly return regressions on monthly Fama-French factors. The sample contains recommendations made within one year after IPO issuance. The number in each cell is the average of α from the Fama-French regression on stocks in each category. t-statistics are reported in the brackets.

Figure 3. Distribution of Fama-French abnormal returns for stocks in each category



C. Analyst recommendations and market uncertainty

One question that has been overlooked in the literature is how market uncertainty affects the incentives of the analysts and the performance of analyst recommendations. Market uncertainty captures the amount of information available to the investors and the degree of information asymmetry between the firm and the investors. The model developed in the above sections allows us to study the effect of market uncertainty on the performance of analyst recommendations.

Uncertainty is a measure of the array of potential outcomes for a firm, or in our context the volatility σ.

In the previous section, I define $\overline{\theta}_U$ and $\overline{\theta}_B$ to be the expected value of θ over which the analyst sends the highest message. In the empirical analysis, these two variables are proxied by the average alphas from the Fama-French regression on stocks that receive "Strong Buy" from their lead underwriters and the non-lead analysts. I assume that in the long run, the true value of the firm will be revealed. $\overline{\theta}_U - \overline{\theta}_B$, therefore, corresponds to the underperformance of Lead "Strong Buy" relative to the Non-lead "Strong Buy". I show in Corollary 4 that this difference increases with volatility σ, which leads to Prediction 3: The underperformance of Lead "Strong Buy" relative to Non-lead "Strong Buy" increases with market uncertainty.

On the other hand, investor's belief of θ upon a recommendation announcement can be proxied by the event period market reaction to analyst recommendations. Thus, θ_H captures the investor's reaction towards analyst's "Strong Buy", and θ_L "Hold/Sell." I show that the distance between the two beliefs, $\theta_H - \theta_L$, increases with σ. When a "Strong Buy" generates greater abnormal return compared to a "Hold/Sell" recommendation, analysts have greater incentive to elevate a potential underperformer. Thus, we have Prediction 4: When the market is more volatile, investors react stronger towards analyst's extreme messages, thus giving an analyst more incentive to elevate a potential underperformer.

I use analyst forecast dispersion to measure firm specific uncertainty. Athanassakos and Kalimipalli (2003) document strong positive relationship between analyst forecast dispersion and future stock return volatility. This measure of firm specific uncertainty is also used by several prior researchers (Barron and Stuerke 1998, Ang and Ciccone 2002, Qu, Starks and Yan 2007).

I identify the forecast date in the I/B/E/S Summary Annual Earnings per share forecast database that is the closest date prior to the recommendation date for a given IPO.[19] For that forecast date corresponding to the earnings forecast for the forthcoming annual earnings, I use the standard deviation among the reporting analysts as a measure of dispersion or disagreement among analysts (STDEV). Next, I construct quintile portfolios sorted by the STDEV of earnings forecasts immediately preceding the date the recommendation was issued. The number of

[19] I thank Somnath Das for making the forecast dispersion data available.

"Strong Buy" recommendations from lead analysts is held approximately constant in each of the portfolios. Using the cutoff values in STDEV from the quintile portfolios of the lead analysts, I then form the portfolios of the non-lead analysts. This construction allows us to compare the performance of lead analysts versus non-lead analysts holding STDEV constant.

Next, I examine how the underperformance of the lead analyst in the "Strong Buy" category varies over these quintile portfolios. Table 5 reports the average alpha from the Fama-French monthly return regression in each quintile portfolio and the differences between Strong Buy recommendations from lead and non-lead analysts. Given the evidence of a structural shift since 2000, I report results based on the full sample as well as the sample excluding calendar years 2001 and 2002.[20] Panel A presents the results with the entire sample. Panel B reports the results for sample data up to and including 2000. The results in Table 5 provide evidence that as the degree of the underlying firm specific uncertainty increases, the underperformance of Lead "Strong Buy" relative to their Non-lead "Strong Buy" also increases. Moreover,

Table 5. Fama-French abnormal returns on STDEV sorted "Strong Buy" portfolios, in percentage

	Panel A: 1993-2002			Panel B: 1993-2000		
STDEV	Lead "Strong Buy"	Non-lead "Strong Buy"	Differences	Lead "Strong Buy"	Non-lead "Strong Buy"	Differences
U1	-1.18	-1.90	0.72	-2.08	-1.00	-1.08
			(-1.33)			(1.90)
U2	-1.16	-0.15	-1.01	-1.06	-0.08	-0.98
			(2.88)			(3.17)
U3	-0.47	-0.54	0.07	-0.50	-0.07	-0.43
			(-0.21)			(1.94)
U4	0.34	0.49	-0.15	0.12	0.31	-0.19
			(0.55)			(1.62)
U5	1.17	1.53	-0.36	1.39	1.46	-0.06
			(1.07)			(0.10)

Note: the table shows the equal-weighted average alpha from Fama-French monthly regressions of the quintile portfolios sorted by STDEV. U1 represents the portfolio with the greatest STDEV and U5 the least. The sample contains recommendations made within one year after IPO issuance. The differences and its their t-statistics are reported in the last column. Panel A includes the entire sample of IPOs between year 1993 to year 2002. Panel B includes the subsample of IPOs between year 1993 to year 2000.

[20] Barber et al. (2001, 2003) and Das et al. (2006) show that the returns and the distribution of recommendation ratings have undergone significant structural changes since 2000, possibly in response to several regulatory changes.

it can be seen that the monotonic relationship is more distinct for the sub-sample comprising of recommendations in the years prior to and including calendar 2000.

Next, I examine the market's immediate response towards analyst recommendations. This is measured by the three-day event-period size-adjusted buy-hold-abnormal-return (BHAR). The three-day event-period size-adjusted BHAR for the recommendations in each quintile portfolio of STDEV are reported in Table 6. The results show that the difference between the markets immediate reaction to a "Strong Buy" and to a "Hold/Sell" is larger when the underlying uncertainty is high. This adds credence to the story that not only does increased uncertainty provide increased opportunities, but the benefits of a "Strong Buy" (as measured by short term market response) are also most pronounced when the underlying firm specific uncertainty is greatest. Hence, an analyst's incentive to "boost" a stock from a negative recommendation to a "Strong Buy" recommendation also increases as the underlying uncertainty increases.

Table 6. Event period size-adjusted BHAR on STDEV sorted portfolios, in percentage

	Panel A: 1993-2002				Panel B: 1993-2000			
STDEV	Strong Buy	Buy	Hold/Sell	Strong Buy	Strong Buy	Buy	Hold/Sell	Strong Buy
U1	2.88	-0.81	-6.74	9.63	3.07	-0.70	-7.14	10.21
				(7.81)				(8.17)
U2	2.40	0.12	-5.90	8.30	2.28	0.12	-5.40	7.68
				(11.58)				(9.65)
U3	2.25	-0.19	-4.48	6.73	2.85	0.20	-5.00	7.85
				(8.43)				(10.37)
U4	2.16	0.26	-4.87	7.03	1.86	0.50	-5.20	7.06
				(9.36)				(8.72)
U5	1.64	0.31	-4.51	6.15	2.20	0.53	-4.14	6.34
				(7.14)				(7.77)

Note: the table shows the equal-weighted average three-day event-period size-adjusted buy-hold-abnormal-returns of the quintile portfolios sorted by STDEV. U1 represents the portfolio with the greatest STDEV and U5 the least. The sample contains recommendations made within one year after IPO issuance. The differences between event period BHARs of Strong Buy and Hold/Sell and their t-statistics are reported in the last column of each panel. Panel A includes the entire sample of IPOs between year 1993 to year 2002. Panel B includes the subsample of IPOs between year 1993 to year 2000.

D. Reputation and the value of analyst recommendations

The role of reputation in the presence of sell-side analyst conflicts of interest has received much attention in the literature (Stickel 1992, Fang and Yasuda 2005). The model above allows us to study the effect of reputation on the performance of analyst recommendations.

Corollary 3 states that a biased analyst lies less frequently to the highest message when she has a higher reputation, and Corollary 4 states that an unbiased analyst is able to communicate better information when she has a higher reputation. These two imply Prediction 5: independent of analyst's affiliation, the value of analyst's "Strong Buy" recommendation increases with her reputation; and the underperformance of a biased analyst's "Strong Buy" recommendation decreases with her reputation, whereas the relative performance of negative recommendations does not change with the analyst's reputation.

Fang and Yasuda (2005) examine the role of reputation by comparing the performance of All-American (AA) analysts with non-AA analysts. They find that AA analysts outperform non-AA analysts in the buy category (combining "Strong Buy" and "Buy" recommendations), and there is no significant difference between the two groups in the sell category. Using top-tier banks (large underwriters) as a proxy for potential conflict of interest, Fang and Yasuda (2005) find that non-AA analysts at top-tier banks underperform most severely in the buy category (combining "Strong Buy" and "Buy" recommendations). This provides evidence that personal reputation indeed plays a disciplinary role in mitigating conflict of interest when it comes to making positive recommendations.

While the evidence is consistent with the model's prediction, the theory presented here indicts that there might be structural differences between "Strong Buy" and "Buy". A more careful study examining "Strong Buy" and "Buy" separately may offer stronger evidence and additional insight.

VI. Conclusion

In this paper, I study how reputation can be acquired by sending messages that do not have a direct cost, and further how information can be conveyed when the analysts have reputation at stake.

In the single-stage game absent reputation concerns, information can be credibly conveyed by the unbiased analyst, except when the information is sufficiently good. The greater the underlying uncertainty, the better the information that can be credibly conveyed. In the case of good information, all information about the firm will be pooled into a single message, that is, a message sent by both types of analysts. The biased analyst's incentive in this context is so distorted that she is not willing to communicate any information to the investor.

In the multi-stage game, analyst's reputation acquisition concern generates a "leap-frogging" behavior. When the biased analyst deviates from truth-telling, she will deviate by elevating only the worst stocks to the strongest recommendation. Reputation concerns keep her honest for all other stocks. In addition, I show that the "leap-frogging" behavior increases with underlying uncertainty, thus decreasing the information efficiency of the highest message.

The existence of the "leap-frogging" behavior does not depend on the assumption of perfect observability of the true state. It is driven by the biased analyst's current incentive to induce a higher belief and her incentive to cash in on her reputation when the current gain gets sufficiently large. Indeed, imposing punishment on big lies would deter this type of behavior. However, it is not the big lies that we should punish, but those analysts who have no incentive to convey accurate information to the investor. However, with noise, a biased analyst will make small lies to hide behind noise, while an unbiased analyst will make honest mistakes. Adding noise to the model, we expect to see this type of behavior.[21]

The empirical evidences in Section V confirm the model's predictions. Recommendations from lead underwriter analysts underperform those from other analysts only in the "Strong Buy" category. Moreover, the underperformance increases with firm specific uncertainty.

While the primary focus of the empirical tests in this paper is to provide evidence for the model's prediction, the empirical evidence adds to the ongoing debate on the potential explanations for why affiliated analysts seem to provide more favorable recommendations. The conflict-of-interest hypothesis (Michaely and Womack 1999) argues that sell side analysts issue upward biased recommendations in order to gain future underwriting business and hence desire to maintain good relations with the firm. In contrast, the genuine optimism hypothesis argues that underwriter analysts are more optimistic about the firms they underwrite because they genuinely believe that the stocks they underwrite are indeed better than the firms underwritten by other investment banks. Such optimism can either arise endogenously as underwriters are selected because they value the firm more, or arise from analysts' cognitive biases as documented in the psychology literature (Kahneman and Lovallo 1993). A third hypothesis, the superior information hypothesis, argues that underwriter analysts may possess more information about the firm they underwrite. Allen and Faulhaber (1989) suggest that investment banks have better information on the firms they underwrite. They gain better insights of the firms

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[21] In light of Morris (2001), adding noise to the model will also induce the "political correctness" effect on the unbiased sender, which will add significant complexity to the model. This observation is, therefore, left intuitive for the readers.

during the IPO process and thus will have an informational advantage over their competitors. If this indeed is a dominant effect, then recommendations from underwriter analysts, although more favorable, are also more accurate.

The empirical evidences do not support the “genuine optimism” and “superior information” hypotheses. If underwriter analysts are genuinely optimistic about the firms they underwrite, their recommendations should be biased upwards for all rating categories. I document that recommendations from lead analysts underperform in the “Strong Buy” category only. In addition, examination of the underlying uncertainty also provides evidence against the superior information hypothesis. When there is greater uncertainty regarding underlying firm value, we would expect lead analysts to outperform other analysts if they possess superior information. My analysis shows that the underperformance of Lead “Strong Buy” is greater when there is more uncertainty. This is because the benefit of lying in a more uncertain market is greater in the sense that it is easier to induce a higher belief of the firm value. Moreover, post-recommendation return data shows that the recommendations from Non-lead are as good as those from the Lead, except for the “Strong Buy” recommendations, thus rejecting the superior information hypothesis. My results are most consistent with the conflict-of-interest hypothesis where an affiliated analyst rather than biasing all recommendations upward, trades off future reputation concerns with short term rewards/incentives by deliberately pooling some underperforming IPOs with the highest recommendation category.

A more direct test of the reputation mechanism that is driving the results here would be interesting. The comparative static results in section IV.B show that the biased analyst lies less frequently when she has a higher reputation. The unbiased analyst, in this case, can credibly communicate more information. The model predicts that controlling for analyst affiliation, reputation serves as a good disciplinary device mitigating conflicts of interest. Fang and Yasuda (2005) find evidence consistent with the model’s prediction. The theory presented calls for a more careful study controlling for analyst affiliation and examining “Strong Buy” and “Buy” recommendations separately.

Appendix

Proof of Lemma 1: The biased analyst always induces the highest belief in $\hat{\Theta}$, call it θ^*. If sup $\hat{\Theta}$ does not belong to the set $\hat{\Theta}$, then it follows from the definition of sup that $\hat{\Theta}$ such that $\theta_0 > \theta^*$, and the biased analyst will deviate to θ_0. QED.

Lemma 2 *In the Continuum Equilibrium, $\theta^* = \tilde{\theta}$, where $\tilde{\theta}$ is the cutoff point up to which the unbiased analyst credibly reveals all information.*

Proof of Lemma 2: In the Continuum Equilibrium, the unbiased analyst induces belief $\hat{\theta} = \theta$, for $\theta \in (-\infty; \tilde{\theta}]$, and induces belief θ^* for $\theta \in \left(\tilde{\theta}, +\infty\right)$. By definition, θ^* is the highest belief induced in equilibrium. Therefore, it must be that $\theta^* \geq \tilde{\theta}$. Moreover, we cannot have $\theta^* > \tilde{\theta}$. Otherwise, $\exists \theta_0 \in \left(\tilde{\theta}, \theta^*\right)$, such that $\theta_0 - \tilde{\theta} > \theta^* - \theta_0$, in which case, in state θ_0, the unbiased analyst would be better off inducing $\tilde{\theta}$ and would deviate from her equilibrium strategy. QED.

Proof of Proposition 1: In equilibrium, θ^* is determined endogenously by the following equation:

$$\left\{\theta \mid \theta > \theta^*\right\} + \left(1 - p\left(U \mid m^*\right)\right) \cdot 0 = \frac{\lambda \int_{\theta^*}^{\infty} \theta f\left(\theta\right) d\theta}{\lambda\left(1 - \Phi\left(\theta^*\right)\right) + 1 - \lambda}. \ QED.$$

Proof of Corollary 1: Let $\xi = \frac{\theta}{\sigma}$. ξ follows distribution $f0(\cdot)$which has standard deviation 1 and satisfies $f\left(\xi\sigma\right) = f_0\left(\xi\right)/\sigma$. Let $\xi^*\sigma = \theta^*$. Therefore,

$$\int_{\theta^*}^{\infty} \theta f\left(\theta\right) d\theta = \int_{\xi^*\sigma}^{\infty} \xi\sigma f_0\left(\xi\right)/\sigma d\xi\sigma = \sigma \int_{\xi^*}^{\infty} \xi f_0\left(\xi\right) d\xi, \tag{A1}$$

$$\Phi_f\left(\theta^*\right) = \Phi_{f_0}\left(\xi^*\right). \tag{A2}$$

Thus, after the change of variable, equation (1) becomes:

$$\theta^* = \frac{\sigma\lambda \int_{\xi^*}^{\infty} \xi f_0\left(\xi\right) d\xi}{\lambda\left(1 - \Phi_{f_0}\left(\xi^*\right)\right) + 1 - \lambda}. \text{ QED.}$$

Proof of Proposition 2: For any equilibrium of the single-stage game, E, Lemma 1 guarantees that the set of equilibrium beliefs contains a maximum point, call it θ_E^*. Let θ_C^* denote the highest belief in the Continuum Equilibrium characterized by equation (1). I wish to show that $\theta_E^* \leq \theta_C^*$, $\forall E$.

Note that θ_E^* can be expressed as follows:

$$\theta_E^* = \frac{\int_{-\infty}^{\infty} \theta q^U\left(m^* \mid \theta\right) f\left(\theta\right) d\theta}{\int_{-\infty}^{\infty} q^U\left(m^* \mid \theta\right) f\left(\theta\right) d\theta + \omega_B}, \text{ where } \omega_B = \frac{1-\lambda}{\lambda}.$$

Similarly, θ_C^* can be written as

$$\theta_C^* = \frac{\int_{\theta_C^*}^{\infty} \theta f\left(\theta\right) d\theta}{\int_{\theta_C^*}^{\infty} f\left(\theta\right) d\theta + \omega_B}.$$

It follows that

$$\int_{\theta_C^*}^{\infty} \left(\theta - \theta_C^*\right) f\left(\theta\right) d\theta - \theta_C^* \omega_B = 0. \tag{A3}$$

Thus

$$\theta_E^* - \theta_C^* \leq 0, \tag{A4}$$

$$\Leftrightarrow \frac{\int_{-\infty}^{\infty} \left(\theta - \theta_C^*\right) q^U\left(m^* \mid \theta\right) f\left(\theta\right) d\theta - \theta_C^* \omega_B}{\int_{-\infty}^{\infty} q^U\left(m^* \mid \theta\right) f\left(\theta\right) d\theta + \omega_B} \leq 0, \tag{A5}$$

$$\Leftrightarrow \int_{-\infty}^{\infty} \left(\theta - \theta_C^*\right) q^U\left(m^* \mid \theta\right) f\left(\theta\right) d\theta - \theta_C^* \omega_B \leq 0, \tag{A6}$$

$$\Leftrightarrow \int_{-\infty}^{\infty} \left(\theta - \theta_C^*\right) q^U\left(m^* \mid \theta\right) f\left(\theta\right) d\theta \leq \int_{\theta_C^*}^{\infty} \left(\theta - \theta_C^*\right) f\left(\theta\right) d\theta, \tag{A7}$$

where equation (A7) follows from equation (A3). It is easy to show that inequality (A7) holds:

$$\int_{-\infty}^{\infty}\left(\theta-\theta_C^*\right)q^U\left(m^*\mid\theta\right)f\left(\theta\right)d\theta=\int_{-\infty}^{\theta_C^*}\left(\theta-\theta_C^*\right)q^U\left(m^*\mid\theta\right)f\left(\theta\right)d\theta$$
$$+\int_{\theta_C^*}^{\infty}\left(\theta-\theta_C^*\right)q^U\left(m^*\mid\theta\right)f\left(\theta\right)d\theta$$
$$\leq\int_{\theta_C^*}^{\infty}\left(\theta-\theta_C^*\right)f\left(\theta\right)d\theta.\text{ QED.}$$

Proof of Corollary 3: Assume that the Continuum Equilibrium is played in the second period. Rearrange equation (7) as

$$\frac{\int_{\theta^*}^{\infty}\theta f\left(\theta\right)d\theta}{1-\Phi\left(\theta^*\right)+\dfrac{1-\lambda}{\lambda}\rho\left(\theta\right)}=\frac{1}{\gamma}\left(\theta_H-\theta\right),$$

Holding all else equal, the left-hand side of the above equation increases with λ, therefore, $\rho(\theta)$ must increases with λ point-wise. Similarly, the right-hand side of the equation decreases with γ and decreases with θ, thus, $\rho(\theta)$ increases with θ and increases with γ. QED.

Given that the highest message is sent by analyst type $A\in\left\{U,B\right\}$, the expected value of θ is given by

$$\bar{\theta}_U=P\left\{\theta\mid U,\theta_H\right\}=\frac{1}{P_U^H}\int_{\theta_H}^{\infty}\theta f\left(\theta\right)d\theta, \tag{A8}$$

$$\bar{\theta}_B=P\left\{\theta\mid B,\theta_H\right\}=\frac{1}{P_B^H}\left(\int_{-\infty}^{\theta_L}\rho\left(\theta\right)\theta f\left(\theta\right)d\theta+\int_{\theta_H}^{\infty}\theta f\left(\theta\right)d\theta\right), \tag{A9}$$

$$\psi=\frac{\lambda P_U^H}{\lambda P_U^H+\left(1-\lambda\right)P_B^H}, \tag{A10}$$

where PAH is the probability that type A analyst sends the highest message, that is,

$$P_U^H=P\left\{m_H\mid U\right\}=1-\Phi\left(\theta_H\right),$$

$$P_B^H = P\left\{m_H \mid B\right\} = \int_{-\infty}^{\theta_L} \rho(\theta) f(\theta) d\theta + 1 - \Phi(\theta_H).$$

Proof of Corollary 4: Apply similar change of measure technics as that in the proof of Corollary 1 to map the variables to a standard distribution with variance of one. Assume the Continuum Equilibrium will be played in the second stage of the game, then

$$\upsilon_B(\Lambda) = \frac{\int_{\theta^*}^{\infty} \theta f(\theta) d\theta}{1 - \Phi(\theta^*) + \frac{1-\lambda}{\lambda}\rho(\theta)} = \sigma \frac{\int_{\xi^*}^{\infty} \xi f_0(\xi) d\xi}{1 - \Phi(\xi^*) + \frac{1-\lambda}{\lambda}\rho_0(\xi)},$$

where $\rho_0(\xi\sigma) = \rho(\theta)$. Thus, equation (7) becomes

$$\theta_H = \theta + \frac{\int_{\theta^*}^{\infty} \theta f(\theta) d\theta}{1 - \Phi(\theta^*) + \frac{1-\lambda}{\lambda}\rho(\theta)} = \xi\sigma + \sigma \frac{\int_{\xi^*}^{\infty} \xi f_0(\xi) d\xi}{1 - \Phi(\xi^*) + \frac{1-\lambda}{\lambda}\rho_0(\xi)} = \sigma\xi_H.$$

Similarly, equation (6) implies that $\theta_L = \sigma\xi_L$.

Applying change of measure to equation (A8) and equation (A9), it is easy to see that $\overline{\theta}_U = \sigma\overline{\xi}_U$, and $\overline{\theta}_B = \sigma\overline{\xi}_B$, where $\overline{\xi}_U$ and $\overline{\xi}_B$ satisfy the equations under a standard distribution with variance one. QED.

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