Analyst Forecast and Firm Reporting Bias

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Abstract

This thesis investigates how the presence of an analyst affects the corporate information environment when both the analyst forecast and the manager’s report are endogenously determined. I build two stylized models in which the manager has hidden price incentives in issuing his report to investors, and the analyst has two signals, one about the firm’s fundamental value and the other about the manager’s hidden price incentives. In the first setting, the analyst’s objective is to forecast both reported earnings and firm fundamentals. I find that the analyst’s forecasting strategy depends on the manager’s incentives, even when the analyst does not care about the manager’s report, calling into question Beyer’s (2008) suggestion that the dependence is due to the interaction between the analyst and the manager. Further, I find that the investor’s total information at hand after both the forecast and the report are released is non-monotonic in the quality of the analyst’s information, increases with the manager’s weight on being close to firm fundamentals in his incentives, and decreases with his weight on being close to the analyst forecast. The second setting differs from the first in that the analyst’s objective is to care about the client’s trading profits and forecast accuracy. I find that the properties of the analyst forecast and the manager’s report depend on the analyst’s incentives to boost the client’s trading profits, complementing Beyer’s (2008) finding that the analyst’s forecasting strategy depends on the manager’s incentives due to the interaction between the two. Further, I find that both the forecast distortion and the forecast accuracy are non-monotonic in the quality of the analyst’s value information.
Declaration

This is to certify that

i) The thesis comprises of only my original work towards the PhD;

ii) Due acknowledgement has been made in the text to all other materials used;

iii) The thesis is fewer than 100,000 words in length, exclusive of tables, figures, bibliographies and appendices.

Signature…………………………………………………………..
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Table of Contents

CHAPTER 1: INTRODUCTION .................................................................................................................. 9
  1.1 OVERVIEW OF FIRST SETTING (CHAPTER 3) ........................................................................ 11
  1.2 OVERVIEW OF SECOND SETTING (CHAPTER 4) ....................................................................... 13

CHAPTER 2: ANALYTICAL ANALYSTS’ FORECAST STUDIES: A REVIEW OF THE LITERATURE ........... 15
  2.1 INTRODUCTION ........................................................................................................................ .. 15
  2.2 ANALYST FORECASTS AS AN INDEPENDENT INFORMATION SOURCE .................................. 16
    2.2.1 Strategic Information Acquisition ....................................................................................... 17
    2.2.2 Strategic Forecasting ........................................................................................................... 21
    2.2.3 Non-Strategic Information Acquisition and Forecasting .................................................... 29
  2.3 ANALYST FORECASTS INTERACTING WITH ANOTHER INFORMATION SOURCE .................. 31
  2.4 CONCLUSION .................................................................................................................................. 33

CHAPTER 3: REPORTED AND UNMANAGED TRUE EARNINGS: TWO ANALYST FORECAST INCENTIVES .... 35
  3.1 INTRODUCTION .......................................................................................................................... 35
  3.2 MODEL .......................................................................................................................................... 41
  3.3 EQUILIBRIUM .............................................................................................................................. 46
    3.3.1 The Manager’s Problem ....................................................................................................... 47
    3.3.2 The Analyst’s Problem ......................................................................................................... 48
    3.3.3 The Market Pricing Function ................................................................................................ 48
  3.4 COMPARATIVE STATICS ............................................................................................................. 52
    3.4.1 The Quality of the Analyst’s Two Signals (σ²_s, σ²_M) ............................................................. 53
    3.4.2 The Quality of the Manager’s Signal (σ²_M) ......................................................................... 60
    3.4.3 The Biasing Cost, c_f ............................................................................................................. 64
    3.4.4 The Marginal Cost of the Manager’s Signals to Be Close to the Analyst Forecast, c_f .......... 66
  3.5 COMPARING THE TWO EXTREME CASES ................................................................................ 69
  3.6 CONCLUSIONS ............................................................................................................................. 72

APPENDIX ............................................................................................................................................... 78

CHAPTER 4: ANALYST-INVESTOR INTEREST ALIGNMENT AND FINANCIAL REPORTING .................. 89
  4.1 INTRODUCTION .......................................................................................................................... 89
  4.2 MODEL .......................................................................................................................................... 92
  4.3 EQUILIBRIUM .............................................................................................................................. 96
    4.3.1 The Manager’s Problem ....................................................................................................... 96
    4.3.2 The Market Maker’s Problem at time t = 3 ......................................................................... 98
    4.3.3 The Market Maker’s Problem at time t = 2 ......................................................................... 100
    4.3.4 The Informed Trader’s Problem ............................................................................................ 101
    4.3.5 The Market Maker’s Problem at time t = 1 ........................................................................ 102
    4.3.6 The Analyst’s Problem ......................................................................................................... 102
  4.4 COMPARATIVE STATICS ............................................................................................................. 107
    4.4.1 Informational Content of f and r − f .................................................................................. 108
    4.4.2 The “Cosmetic Effect” in the Analyst Forecast ..................................................................... 110
    4.4.3 The “Cosmetic” Effect in the Financial Report ................................................................. 113
List of Figures

Figure 1 presents the timeline of the game ................................................................. 41
Figure 2 presents the timeline of the game ................................................................. 92
Chapter 1: Introduction

This thesis investigates how the presence of an analyst affects the corporate information environment when both the analyst forecast and the financial report are endogenously determined. Specifically, it examines how analyst incentives interact with manager incentives to affect the corporate information environment in a setting where (1) the manager has hidden reporting incentives and (2) the analyst receives two signals: one about the firm’s fundamental value and the other about the manager’s hidden reporting incentives. Within this general framework, I investigate two specific settings that differ only in the analyst’s forecasting incentives:

1. In the first setting (Chapter 3), the analyst has incentives to accurately report relative to actual reported earnings as well as the firm’s unmanaged “true” earnings;
2. In the second setting (Chapter 4), the analyst’s incentives are to accurately forecast relative to actual reported earnings, as well as to choose a forecast that increases a client’s trading profits.

The extant analyst forecast research has long recognized the importance of analysts’ incentives for the models’ predictions. For example, Beyer, Cohen, Lys, and Walther (2010) have indicated that they expect models’ predictions to vary depending on what analysts’ incentives are assumed to be. However, little is known about how different analyst incentives affect model predictions. My objective is to investigate, via two stylized models, how differing analyst incentives influence a firm’s information environment in a setting in which both analyst forecasts and firm financial reports are endogenously determined.
In both settings, I follow the framework of Fischer and Verrecchia (2000) when specifying the incentives of managers. Fischer and Verrecchia (2000) have modelled a manager with private information to report to investors, as well as a hidden reporting incentive related to stock price. The key innovation of Fischer and Verrecchia (2000) is that investors cannot completely infer the manager’s reporting bias due to his hidden reporting incentive. However, Fischer and Verrecchia (2000) paint an incomplete picture of the corporate information environment by focusing on only the manager’s financial report. Beyer et al. (2010) have shown that earnings announcements make up only about 8% of the total corporate information that affects stock returns. They report that most research to date focuses on only one information source, namely earnings announcements, and they call for more research on the interdependencies of information sources. As a response to this call, in this thesis, I add an analyst to Fischer and Verrecchia’s (2000) model. Beyer et al. (2010) have documented that analyst forecasts make up about 22% of the firm’s total information explained in returns. This thesis thus captures a more complete picture of the corporate information environment by studying the interaction between analyst forecasts and management financial reports.

Beyer (2008) has also examined the interaction between analyst forecasts and management financial reports but focused on forecast revisions and asymmetric manager incentives to ‘meet or beat’ the analyst forecast. In Beyer’s (2008) model, there is no hidden reporting incentive for managers, so investors can perfectly infer the manager’s reporting bias, which is not always true in the real world. This thesis differs from Beyer (2008) by incorporating a hidden reporting incentive for the manager and focusing on the metrics that the manager’s hidden reporting incentive makes meaningful, such as market reactions to the forecast and report, and the investors’ net information at hand after both the forecast and the report are released. This allows me to answer research questions that are not possible within Beyer’s (2008) framework but are important for investors, analysts, managers, and regulators alike.
An additional minor difference between Beyer (2008) and this thesis is that this thesis allows the analyst to have a signal of the manager’s hidden reporting incentive in addition to her signal of the firm’s fundamental value. This thesis is among the first essays to study analysts’ use of non-fundamental value information.

Lastly, but importantly, I extend Beyer’s (2008) work by investigating the effects of different analyst incentives on the corporate information environment via the two settings described above. The first setting puts constraints on a major finding in Beyer (2008), and the second setting complements the finding.

1.1 Overview of the First Setting (Chapter 3)

Beyer (2008) has studied the interaction between analyst forecasts and firm financial reports using a model in which analysts have incentives to disclose earnings forecasts that accurately predict reported earnings, and managers have incentives to report earnings that meet or exceed analysts’ earnings forecasts. To capture the two-way interaction between analysts and managers, Beyer (2008) specifies the analyst’s objective as forecasting reported earnings.

In my first setting, I extend Beyer’s (2008) analysis by allowing the analyst to care about both reported earnings and unmanaged true earnings. There is recent empirical evidence to support this modelling decision. Louis, Sun, and Urcan (2013) have shown that analysts sacrifice forecast accuracy for informativeness. They provide the most direct empirical evidence that analysts fulfil their fiduciary duty to long-term investors by forecasting unmanaged true earnings.

The key takeaways from the first setting are as follows. First, I focus on contrasting the two extreme cases in which the analyst cares only about reported earnings and in which the analyst cares only about unmanaged true earnings. I show that the comparative statics results
are qualitatively the same. In particular, the forecasting strategy of the analyst depends on the incentives of the manager, even if the analyst does not care about the manager’s report. This contrasts with Beyer’s (2008) suggestion that the relationship is due to the interaction between the analyst and the manager. My results instead show that the relationship remains when the manager cares about the analyst forecast unilaterally and the analyst does not care about the manager’s financial report. Further, I show that both the earnings response coefficient and the reporting bias are higher when the analyst cares about reported earnings than when she cares about unmanaged true earnings.

Second, I show that investors’ net information at hand can decrease in the quality of the analyst’s signal about either the firm’s fundamental value or the manager’s reporting incentives. The intuition is that there are two sources of information available to investors: the forecast and the incremental information in the financial report, and one piece of information improves with the quality of the analyst’s information, but the other piece of information deteriorates. My results indicate that either effect could dominate, and for some parameter values, it is possible for the latter effect to dominate. That is, for some (but not all) parameter values, investors’ total information at hand decreases in the quality of the analyst’s information.

Third, I show that investors’ net information at hand is lower when the cost to bias his report from firm fundamentals is higher but is higher when the weight on the manager’s incentives to be close to the analyst forecast is higher. This is because both the forecast and the report are better signals of the firm’s final payoff with higher biasing costs, but both become worse signals with more weight on the manager’s incentives to be close to the analyst forecast.

I also show that the analyst’s information about the manager’s reporting incentives is useful only when the analyst’s incentives are tied to forecasting reported earnings. It is not useful
when the analyst’s incentives are tied only to unmanaged true earnings. When the analyst forecasts reported earnings, the analyst’s information about the manager’s reporting incentives allows the analyst to anticipate some of the bias in the firm financial report and factor that into her forecast. In contrast, if the analyst cares only about forecasting unmanaged true earnings, bias in the financial report is irrelevant.

1.2 Overview of the Second Setting (Chapter 4)

The model in Chapter 3 allows the analyst to care about both reported earnings and unmanaged true earnings. In Chapter 4, I modify the analyst’s incentives. In both chapters, the analyst cares (partially) about accurately forecasting the financial report. In Chapter 4, the analyst also cares about the expected trading profits earned by a subscribed client investor. This incentive of the analyst is intended to capture the real-world phenomenon that analysts first release their forecasts to institutional investors and subsequently to the general public.

I find that the analyst’s forecast distortion due to her incentive to maximize subscribed investor’s trading profits affects both the properties of the manager’s financial report as well as the properties of the analyst’s forecast. This means that both the properties of the manager’s financial report and the properties of the analyst’s forecast depend on the analyst’s incentives due to the interaction between the manager and the analyst. This complements Beyer’s (2008) finding that the analyst’s forecasting strategy depends on the manager’s incentives due to the interaction between the analyst’s forecast and the manager’s financial report.

I also show that the analyst’s forecast distortion due to her incentive to maximize the subscribed investor’s trading profits is non-monotonic in the quality of the analyst’s value information. The intuition is that better analyst’s value information increases the analyst’s
opportunity cost to not minimize forecast error, but it also increases the attractiveness of the distortion due to her incentive to maximize the subscribed investor’s trading profits because she is better able to move prices.

Further, I confirm the finding in Chapter 3 that a higher earnings response coefficient does not necessarily mean a better reporting quality. It is possible for the price response coefficient to increase even as the quality of the information signal that can be extracted from the report worsens. This sounds a note of caution for empirical work that uses the ERC as an indicator of earnings quality; in this version of the model, a higher ERC need not mean a higher quality report.
Chapter 2: Analytical Analysts’ Forecast Studies: A Review of the Literature

2.1 Introduction

This chapter offers a focused, comprehensive, and in-depth review of analytical analyst forecast studies.¹ It aims to contextualize the two analytical analyst forecast articles in the following two chapters. For that purpose, this literature review is limited in two important ways. Firstly, I focus exclusively on analytical studies, and secondly, I review only those studies on analyst forecasts and ignore other forms of the analysts’ output, such as analyst recommendations and target prices.

There have been a number of reviews on the analytical analyst forecast literature. Ramnath, Rock, and Shane (2008) have provided a comprehensive review of analyst empirical studies but do not include an in-depth review of the analytical papers. Although Beyer et al. (2010) do provide a review of some analytical analyst research, they cover only a select group of studies. Further, they organize their analysis around the key decisions faced by an analyst, such as coverage, timing, and biasing, and they are not as up-to-date as the current review.

I organize the papers first around whether analyst forecasts are treated as an independent information source or as interacting with another information source, then around whether the studies feature strategic information acquisition, and finally around incentives. This decision is motivated by the intention to contextualize the following two chapters of this thesis. The analyst’s incentives include trade commission generation, reputation, forecast accuracy, an upward bias, and clients’ utility or profits. Moreover, I examine the assumptions of the models and their consequences, as well as the mechanism that links the assumptions and

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¹ The first analytical analyst forecast study dates to Trueman (1990), and my review starts there.
consequences. Specifically, I summarize how each paper asks and answers the following two questions: (1) What are the analyst’s actions, and what is her behavior?\textsuperscript{2} What other, possibly unintended consequences do her actions have? (2) What are the factors, besides the analysts’ incentives, that cause such behavior and consequences? Beyer et al. (2010) have identified the incentives of analysts as key to their behavior and have studied how the incentives and other factors affect the analysts’ behavior in their analysis, which is also the focus of this review.

The papers included in this review stem from the following seven journals:\textsuperscript{3} the *Journal of Accounting Research*, the *Journal of Accounting and Economics*, the *Accounting Review*, *Review of Accounting Studies*, the *Journal of Financial Economics*, the *Journal of Finance*, and the *Review of Financial Studies*. I also draw on the reviews by Ramnath et al. (2008) and Beyer et al. (2010).

The review is organized as follows. Section 2.2 discusses papers that treat analyst forecasts as an independent information source. Section 2.3 examines papers that feature the interaction of analyst forecasts with another information source. I try to answer the two questions I raised in each of these sections, and section 2.4 provides a conclusion.

### 2.2 Analyst Forecasts as an Independent Information Source

Analyst forecasts have traditionally been treated as an independent information source and studied for their interaction with investors. Some studies feature strategic information acquisition, and some take information as exogenously given. Further, some studies take

\textsuperscript{2} I see the analyst’s behavior as a consequence of her actions.

\textsuperscript{3} The seven journals are representative of top journals in accounting and finance. I supplement them by drawing on Ramnath et al. (2008) and Beyer et al. (2010) to have an as complete review as possible.
analyst forecasts as a mechanical device and features non-strategic forecasting as well. Below I review the three streams of studies separately.

2.2.1 Strategic Information Acquisition

Information acquisition activities by analysts are a prerequisite for their subsequent forecasting activities. However, few analytical models feature strategic information acquisition by analysts, and most studies assume that analysts’ information is exogenously given to focus on their subsequent forecasting activities (see section 2.2.2 of this review and chapters 3 and 4 of my thesis). The aim of this section is to review, summarize, compare, and contrast the few analytical models that feature strategic information acquisition activities by analysts.

The extant empirical literature documents a variety of information acquisition activities by analysts. These include access to management (Chen & Matsumoto, 2006; Ke & Yu, 2006), organizing and participating in conference calls (Bowen, Davis, & Matsumoto, 2002; Kimbrough, 2005; Matsumoto, Pronk, & Roelofsen, 2011; Mayew, 2008), and corporate site visits (Cheng, Du, Wang, & Wang, 2016). Prior studies have documented that such activities help improve analysts’ forecast accuracy.

Similar to papers that examine investor information acquisition (e.g., Feltham & Wu, 2000), analytical studies that feature endogenous information acquisition by analysts usually consider the activity as a trade-off between the precision of the information and the cost of exerting efforts. Both Meng (2015) and Fischer and Stocken (2010) have assumed that the cost of exerting effort to acquire information is an increasing function of the precision of the information and at an increasing rate. Hayes (1998), similarly, has assumed that the variance of the analyst’s information is a decreasing function of the analyst’s information acquisition
effort. However, the three papers differ in terms of their conclusions about the amount of effort analysts spend to gather information due to different economic foci.

Hayes (1998) has argued that truthful reporting by the analyst focuses on information gathering. The investor in Hayes (1998) buys shares with favorable information, takes no action with medium information, and sells shares with unfavorable information. If the investor does not currently hold the shares, the analyst’s expected revenue increases with the precision of her signal, and therefore she expends the amount of effort that sets its marginal benefit as equal to marginal cost. It is a different story when the investor already holds shares. For firms with initial positive performance signals, the analyst’s expected revenue increases with the precision of her signal and she expends as much effort as possible. For firms with poor initial performance signals, the analyst’s expected revenue might decrease with the precision of her signal, and it might be optimal for her to expend low effort. This is because the investor’s optimal holdings increase with the precision of his information, and the analyst’s expected revenue is conditional on the investor selling up to his holdings, which increase with the variance of her second signal. If the analyst’s preliminary information (first signal) suggests that a sale of up to the investor’s holdings is likely, then this effect can outweigh the fact that the analyst’s expected revenue decreases in variance and implies that the analyst’s overall expected revenue increases in variance, which leads her to exert less effort. This counterintuitive result is the key innovation in Hayes (1998).

Fischer and Stocken (2010) have focused on how the precision of the public information and the observability of the analyst’s information precision affect his or her information gathering. Fischer and Stocken (2010) have expanded Hayes’s (1998) findings by studying the misaligned analyst. They find that, when investors know the precision of the analyst’s information, changes in the quality of the public information affect the analyst’s behavior as
follows. On one hand, when the analyst can credibly communicate her information, public information substitutes the analyst’s information and crowds it out. However, the crowding out is insufficient to offset the increased precision of the public information and leaves the investor in a better position. On the other hand, when the analyst cannot credibly communicate her information, her behavior depends on the cost of obtaining information that is sufficiently precise for it to be credibly communicated. When the cost is moderate, more precise public information causes the analyst to gather more precise information to increase the investor’s responsiveness to her report and thereby facilitates credible communication. The heightened precision of the analyst’s information, coupled with more precise public information, combine to improve the investor’s position. Alternatively, when information-gathering costs are high, an increase in the public information’s precision crowds out the analyst’s information. Further, this crowding out could be so serious that the investor is left in a worse position, even with more precise public information. One core assumption the authors make is that the precision of the analyst’s information facilitates her credible communication, which is not always the case in the real world.

When the investor cannot observe the precision of the analyst’s information, the analyst’s information-gathering behavior depends on the realization of the public signal. Specifically, after observing favorable public information, the analyst gathers and credibly communicates more precise information when the precision choice is not publicly observable than when it is. Alternatively, after observing unfavorable public information, the analyst gathers and credibly communicates less precise information.

Unlike Hayes (1998) and Fischer and Stocken (2010), Meng (2015) has assumed two types of analysts, the aligned and the misaligned, and finds that the aligned analyst spends more effort in information acquisition than the misaligned analyst. The author shows that the aligned
analyst has incentives to acquire more information and be more precise in the information acquisition period. Precision has two effects. First, it allows better reputation building, but the misaligned analyst benefits more from reputation and therefore has more incentives to be accurate through this channel. Second, holding reputation constant, precision enables the analyst to increase investors’ payoff. The misaligned analyst does not care about the investors’ payoff, but the aligned analyst internalizes their payoff. Therefore, this channel does not affect the misaligned analyst but is meaningful for the aligned analyst. The author shows that the second channel always dominates, and the aligned analyst has more incentives to be accurate.

The author also shows that the analyst’s future concerns have a non-monotonic effect on the precision of information acquired and on investors’ welfare. The results follow directly from the analyst’s compensation, i.e., the aligned analyst cares about both periods’ forecast accuracy, and the misaligned analyst aims to upwardly influence investors’ actions in both periods and the way investors update their beliefs about the analyst’s type according to her forecast and the state realized. An interesting question for Meng (2015) is then, when there are infinitely many periods, whether the behaviors of the aligned analyst and the misaligned analyst are the same because of both types of analysts’ concern for reputation.

Although Hayes (1998), Fischer and Stocken (2010), and Meng (2015) all feature strategic information acquisition for the analysts, the three papers differ in terms of their research questions. Hayes (1998) studies how investors’ ex ante holding of shares and the analyst’s preliminary information affect the analyst’s information-acquisition effort. Fischer and Stocken (2010) have focused on how the precision of the public information and the observability of the analyst’s information precision affect the analyst’s information gathering.
Meng (2015) investigates how the aligned and the misaligned analysts differ in their information acquisition efforts.

Both Fischer and Stocken (2010) and Meng (2015) have studied the interaction of strategic information acquisition and strategic forecasting by analysts. However, there are still gaps in this literature. Analysts have multiple incentives in their strategic forecasting behavior, but Fischer and Stocken (2010) and Meng (2015) have only examined the reputational concern or overoptimism for the analysts’ strategic forecasting behavior when investigating the interaction. Later studies can examine the interaction with other notable incentives, such as trading volume generation.

2.2.2 Strategic Forecasting

Forecasting is an important part of analysts’ jobs (Beyer et al., 2010). Because of this, and with readily available data, there is vast empirical literature on analysts’ forecasting activities. It is beyond the scope of this literature review to discuss all the empirical literature, but I cite it whenever necessary to illustrate my points and motivate the analytical studies that follow. Analytical studies on strategic forecasting by analysts have flourished, as well, and they reach different conclusions depending on their assumptions about analysts’ incentives. Specifically, these incentives are trade commission generation and reputation, forecast accuracy, an upward bias, and clients’ utility or profits. This section is organized around the different incentives that analysts have and how they affect the studies’ conclusions.

2.2.2.1 Trade Commission Generation

Analysts are employed by brokerage houses, which earn their revenues from trading commissions. Cowen, Groysberg, and Healy (2006) have shown that the brokerage houses usually tie analysts’ compensation to trading volume in the stocks they cover. The importance
of analysts’ trading incentives has been magnified after regulators prohibited linking their compensation to investment banking activities (Beyer & Guttman, 2011). However, analysts’ trading incentives are usually balanced by other considerations, such as reputation in Jackson (2005) and forecast accuracy in Beyer and Guttman (2011). Both papers discuss the effect of analysts’ trading incentives on their optimism, but Jackson (2005) is more concerned with the effect of reputation in analysts’ objective function and the cross-sectional analysis of analysts’ trading incentives on optimism, while Beyer and Guttman (2011) focus on the effect of the trade-off between analysts’ trading incentives and forecast accuracy incentives on their optimism and how they weigh their private information.

Jackson (2005) has built a simple model and empirically tested its predictions. He assumes asymmetric information with regard to the analyst’s weight on reputation in her objective function and short-sale constraints. He finds that analysts with a higher reputation generate a higher future trading volume, accurate analysts are rewarded with increases in their reputation, and optimistic analysts generate more trade for their firms. He has also predicted and empirically tested whether consensus optimism is higher for stocks that have higher probabilities of short-sale constraints when the informativeness of the analyst’s private signal decreases, the equilibrium level of optimism rises, and the equilibrium level of optimism is higher when the proportion of naïve investors is higher.

Beyer and Guttman (2011) have advanced Jackson’s (2005) research by modelling analyst’s incentives for trade commission generation and forecast accuracy directly, instead of through a concern for reputation. They model both analysts’ incentives to maximize forecast accuracy and trade commission and have shown that, if the analyst’s signal is sufficiently unfavorable, she biases the forecast downward; otherwise, she biases the forecast upward. The analyst is shown to bias the forecast upward more often than downward, which means that the analyst’s
forecast is optimistic on average. In addition, an increase in the analyst’s per-share benefit from trading volume increases both the magnitude of the bias for any realization of the analyst’s private signal and the expected forecast bias. The model also predicts that analysts with higher precision of private information do not necessarily issue forecasts that result in smaller expected squared forecast errors. Finally, if the analyst’s private signal conveys either positive or sufficiently negative news, the analyst acts as if she overweighs her private information; if the analyst’s private signal conveys moderately negative news, then the analyst issues a forecast as if he underweights her private information.

Analysts are supposed to have a conflict of interest due to their incentives for trade commission generation and forecast accuracy/reputation. However, neither Jackson (2005) nor Beyer and Guttman (2011) have modelled the conflicts of interest. In Jackson (2005), for the analyst, both trade commission generation incentives and reputation or forecast accuracy generate more trades for the brokerage house, although there is a time difference. In Beyer and Guttman (2011), the trade commission generation incentives completely dominate the analyst’s concern for forecast accuracy.

2.2.2.2 Reputation

Empirically, analysts’ reputation has been equated with their forecast accuracy or STAR analyst status ranked as by institutional investors (Lee & Lo, 2016). Theoretical studies on analyst reputation usually have two periods, and the analysts maximize their second period compensation, which depends on their reputation or forecasting ability gathered from the first period’s forecasting and the realization of the state of the world.

Trueman (1990) was the first to analyze reputation itself. This study builds a model of two periods in which the analyst cares about both her forecast accuracy and her reputation with
the investors. The conclusion is that such reputational concern might cause the analyst to withdraw her information. As a result, analysts’ measured forecast accuracy might underestimate the precision of her information.

Trueman (1994) continues the line of argument of Trueman (1990) in that the analyst incorporates her information in her forecast in a biased manner. What differs is that there are two analysts in Trueman (1994), which are either of the strong or the weak type. When the two analysts simultaneously release their forecasts, the strong analyst always releases a truthful forecast, but the weak analyst either mimics the strong analyst or tries to convince the investor she has observed a less extreme signal. In the case of sequential forecast release, if the second analyst is weak and observes a high signal, she then mimics the first analyst; if the second analyst is weak and observes a low signal, or if the second analyst is strong, her forecast is not affected by that of the first analyst.

Graham (1999) has expanded on Trueman’s (1994) work by deriving conditions for the follower to herd within a richer context. The model is similar, except that Graham (1999) allows the smart analyst’s information to be correlated, and there are only two signals, low or high, instead of four signals, as in Trueman (1994). Graham (1999) has shown that the leader sometimes, but not always, announces his private information, and the follower sometimes, but not always, herds. The leader’s incentives to truthfully announce private information increases in ability, in informative signal correlation, in initial reputation, and in the strength of prior information when it is consistent with his private information; it decreases in the strength of prior information when it is inconsistent with his private information. When the leader truthfully announces in equilibrium, the follower’s incentive to truthfully announce private information increases in ability, decreases in informative signal correlation, decreases in initial reputation, increases in the strength of prior information when it is consistent with
her private information, and decreases in the strength of prior information when it is inconsistent with her private information. When the leader does not announce his private information, the follower’s incentives are identical to those discussed for the leader because the leader’s announcement is effectively ignored, and the follower becomes a leader.

Given that the analyst should maximize her end-of-period reputation, Clarke and Subramanian (2006) have derived conditions for the analyst to issue a bold or conservative forecast, which is a key novelty from earlier reputation models that study analysts’ herding behavior. They find that the analyst issues a bold forecast when she outperforms or underperforms her peers and a conservative forecast when she is an intermediate player. This is because her payoff structure is convex in relation to her performance. It has also been found that, ceteris paribus, the boldness of the analyst’s forecast increases with time or experience. The reason for this is that the growth in the analyst’s forecasting ability with experience causes the ex ante employment risk to decline over time.

On the other hand, Meng (2015) has provided a reputation paper of a kind because it features strategic information acquisition instead of taking it as exogenously given. After Morris (2001) argued that experts’ reputational concerns might discourage truthful communication when they try to avoid being perceived as being misaligned with investors, Meng (2015) has restored prior studies’ findings that reputational concerns tend to reduce agents’ opportunistic behavior by allowing analysts to endogenously choose their forecast precision. She argues that, because both misaligned and aligned analysts want investors to trust their reports in the future, both aim to build a reputation for being aligned. In equilibrium, aligned analysts acquire more information than misaligned analysts. As a result, investors may favorably update their beliefs about the analysts’ type when the report is proven to be accurate. Therefore, both types of analysts have reputational incentives to communicate truthfully. The
paper also derives conditions under which the analysts’ reputational concerns have a non-monotonic effect on aligned analysts’ equilibrium precision choices and investors’ welfare.

Prior literature has shown that analysts’ reputation incentives have many consequences, such as increasing future trades (Jackson, 2005), withholding information (Trueman, 1990), herding (Trueman, 1994, 1999), issuing a conservative forecast (Clarke & Subramanian, 2006), and acquiring more information and communicating truthfully (Meng, 2015). More papers are needed to study other consequences of the analysts’ reputation concern. Another suggestion for further study is to have infinitely many periods and see whether the conclusions change from the current, two-period model specification. Within a two-period model, reputational concerns can cause the misaligned analyst to communicate truthfully in the first period. Therefore, it is expected that, in infinitely many periods, reputational concerns might cause the misaligned analyst to communicate truthfully in all periods, as well.

2.2.2.3 Forecast Accuracy

Empirical support for analysts caring about forecast accuracy is abundant. For example, Mikhail, Walther, and Willis (1999) have found that, controlling for firm- and time-period effects, forecast horizon, and industry forecasting experience, an analyst is more likely to turn over if his forecast accuracy is lower than that of his peers. Hong and Kubik (2003) have shown that forecast accuracy is rewarded with favorable job separations and internal labor market incentives. The analytical analyst literature has addressed the puzzle of why analysts’ forecasts are optimistically biased although their objective is to maximize forecast accuracy.

Lim (2001) has provided a rationale for the analyst to rationally, optimistically, and predictably bias her forecast, although her objective is to be accurate. In the model, analysts’ related behavior crucially hinges on the assumption that, by biasing the forecast upward, the
analyst is can obtain a more precise information signal. Without such an assumption, or when the precision of the analyst’s private signal does not depend on her upward bias, the analyst does not bias her forecast upward. The author justifies this assumption by appealing to the management access literature, i.e., he assumes that management favors upwardly biased analyst forecasts and that the analyst would be more accurate with better access to management. Comparative statics show that the analyst’s forecast is more biased for firms with less predictable earnings and for analysts for whom cultivating management relations is more important for obtaining information. Lim (2001) has examined the analyst in isolation in a one-person decision setting. The paper’s conclusions follow mechanically from the author’s assumption that management access is important for analysts.

2.2.2.4 Forecast Accuracy and an Upward Bias

One observation that Bradshaw (2011) has made about analyst forecasts is that they are optimistically biased. While analytical papers in the previous section tried to explain this fact when allowing analysts to maximize forecast accuracy only, the theoretical studies in this section explicitly model the analysts’ preference for an upward bias in their objective functions and explore how that preference affects the credibility of the analysts’ communication. Fischer and Stocken (2010) have proposed that the upward bias is in line with the phenomenon that the analyst’s incentives are misaligned with investors’, and that she tries to induce an action that is higher than what the investors prefer but is constrained from inducing an action that is too high because of reputation or litigation concerns. Therefore, analytical papers that feature an upward bias in the analyst’s objective usually function balance the upward bias with forecast accuracy.

Fischer and Stocken (2001) have studied how the upward bias creates a credibility issue within the setting of the interaction of an analyst and risk-neutral investors. The authors
assume the analyst’s incentives are misaligned with those of investors by favoring an upward bias. They have found that the relationship between analysts’ information quality and investors’ information quality is non-monotonic. That is, investor information quality is maximized when the analyst has coarse or imperfect information. This results from the assumption that, in addition to accuracy, the analyst’s utility increases with the investors’ action, which means that the analyst has incentives to upwardly bias her information communication. The upward bias incentives create credibility issues. An increase in the analyst’s information quality has two effects on investors’ information quality. The direct effect is that the analyst has better quality information to communicate. The indirect effect is that improved sender information adversely affects the credibility of the sender’s communication because of the upward bias incentives. The key takeaway from Fischer and Stocken (2001) is that, sometimes, the indirect effect dominates. This contrasts with Fischer and Stocken (2010), who assume that better quality analyst information facilitates credible communication.

2.2.2.5 Clients’ Utility/Profits

Analysts supply their forecasts to institutional investors and are ranked by them. Therefore, there are reasons to believe that analysts care about these institutional investors’ utility or profits. Guttman (2010) has modelled this objective function of the analyst in a strategic timing structure and found that, when there is only one analyst, if the precision of the analyst’s initial independent private signal is sufficiently high, or if the initial precision of the public information is sufficiently high, then the analyst issues his forecast immediately, at the beginning of the forecasting period. Otherwise, a higher precision of the analyst's initial independent private signal reduces an earlier forecast, and a higher learning ability of the analyst induces a later forecast. When there are two analysts, the equilibrium takes one of two
possible patterns. When the two analysts are sufficiently different from each other, each issues a forecast at his unconstrained, optimal time. In this case, a positive amount of time passes between the first and the second forecasts. The alternative pattern is when the two analysts cluster in their timing of the forecasts.

2.2.3 Non-Strategic Information Acquisition and Forecasting

In addition to studies with strategic information acquisition or strategic forecasting, early studies employed analysts as mechanical devices for other purposes, or they respond to early empirical studies that test whether analysts’ forecasts are a better surrogate for market expectations than time series forecasts.

In Abarbanell, Lanen, and Verrecchia (1995), analysts play diminished roles. The authors first show that there is an inverse relationship between dispersion and forecast precision, which they take to mean that dispersion is a proxy for investor uncertainty about returns. However, the authors argue that dispersion alone is not sufficient to capture investor uncertainty because other factors, such as the precision of information common to all analysts, the number of analysts contributing to the consensus, and the precision of the earnings announcements also affect forecast precision. Without controlling for these other properties of analyst forecasts, dispersion is insufficient to capture investor uncertainty. The authors then show that there is a measurement error in using the mean analyst forecast as a proxy for investor beliefs.

By studying the relationship between forecast precision and market reactions to earnings announcements, the authors allow analysts to endogenize information acquisition and contrast it with the case of exogenous information acquisition. When information acquisition is exogenous, the earnings response coefficient is unrelated to forecast precision, but when
information acquisition is endogenous, it increases with forecast precision, while the variance of price change decreases in forecast precision.

Similarly, Barron, Kim, Lim, and Stevens (1998) have deprived analysts of both strategic information acquisition and strategic reporting to arrive at simple conclusions about the relationship between the properties of analyst forecasts and the properties of their information environment. They have shown that dispersion is an increasing function of uncertainty and a decreasing function of consensus, while error in the mean forecast is an increasing function of both uncertainty and consensus. They have also shown that uncertainty and consensus can be expressed in terms of dispersion and error in the mean forecast. However, they admit that analysts’ incentives to strategically acquire and report information might complicate their conclusions.

Kim, Lim, and Shaw (2001) have also dispensed with strategic information acquisition and strategic forecasting for their purposes to show that the mean forecast is not a useful summary measure for analysts’ forecast because it overweighs common information and underweighs analysts’ private information. They suggest using the prior mean forecast to reduce this inefficiency.

The above three studies share the common goal of responding to concurrent empirical studies that show that analyst forecasts are a better surrogate for market expectations than time series forecasts. All three studies show that there are problems with the extant summary measures of the firms’ information environment using analysts’ forecast properties.

Cheynel and Levine (2012) do not consider analysts’ information acquisition, and their analysts have no incentives to strategically report because the analysts’ revenues increase with the number of subscribers, which in turn increases in the precision of the analysts’
reports. Cheynel and Levine have shown that analysts always choose to sell their non-fundamental information, such as uninformed demand, rather than retaining monopoly rights over it; further, as information becomes more precise or the variance of liquidity shocks in the market becomes larger, the number of clients to whom the analyst sells increases. They provide an alternative rationale for the inconsistency between analysts’ recommendations and their reports rather than conflict of interests. That is, their explanation is based on different types of information. Although it is uncorrelated with fundamental information, analysts’ recommendations based on uninformed demand can be profitable. Cheynel and Levine have also shown that, although price efficiency is unchanged and demand-based trading is profitable, demand-based traders are not parasitic but reduce transaction costs by supplying the offsetting liquidity.

2.3 Analyst Forecasts Interacting with Another Information Source

Several papers have studied the interaction of analyst forecasts with another information source. Mittendorf and Zhang (2005) have examined the interaction of analyst forecasts with managers’ earnings guidance and implicitly investigated analysts’ strategic information acquisition. In this paper, the analyst has disutility over her research effort and cares about forecast accuracy. The paper employs a principal-agent model to show that biased earnings guidance on the manager’s part is necessary to motivate the analyst to conduct research. In addition to biased earnings guidance, other conditions to having a solution to the problem include a sufficiently low cost of effort and a sufficiently high forecast accuracy.

Dutta and Trueman (2002) and Arya and Mittendorf (2007) have also investigated the interaction of analyst forecasts and managers’ voluntary disclosure. Dutta and Trueman (2002) focus on manager’s voluntary disclosure strategies; in their study, the analyst releases a forecast as the market’s prior valuation of the firm and, at the same time, interprets the
manager’s disclosure. How the analyst interprets the manager’s disclosure determines the manager’s disclosure strategy; unlike in prior analytical studies, in this case, it could have disjoint intervals in disclosure and non-disclosure regions.

Arya and Mittendorf (2007) do not consider information acquisition or reporting by the analyst but focus on her following a firm to motivate that firm’s disclosure. They have found that, without an analyst following or with a guaranteed analyst following, the firms’ dominant strategy is not to disclose; however, when disclosure can encourage analyst following, as long as the market is not too competitive, there is an equilibrium where both firms disclose their signals, and Pareto dominates the no-disclosure equilibrium.

Both Dutta and Trueman (2002) and Arya and Mittendorf (2007) have used analyst forecasts as a mechanical device to study firms’ disclosure decisions, and they do not use either strategic information acquisition or strategic forecasting for their purposes.

Beyer's (2008) study is the closest to my thesis and studies the interaction of analyst forecast and manager reporting. A key feature of her model is that the manager’s objective function is asymmetric. She studies how the analyst forecast responds to this asymmetry in the manager’s objective function. She finds that, due to the asymmetry, the analyst is optimistically biased, although her objective is to maximize forecast accuracy. Her model predicts that the analyst is more likely to revise her forecast downward than upward, providing an alternative explanation to the “walk-down” phenomenon. She has also shown that the manager’s reporting incentives affect this likelihood to revise downward rather than upward. She predicts that investors, by anticipating the manager’s reporting behavior due to asymmetric incentives, react more strongly to negative earnings surprises than positive earnings surprises, especially when the cost of manipulating earnings is low. Her comparative statics show that the analyst’s forecast bias, measured by either mean or median forecast error,
is greater for firms for which the analyst’s information is less precise. However, investors play an insignificant role in Beyer (2008) due to the exogenous nature of the capital market mechanism. Therefore, Beyer’s (2008) examination of the market reactions to forecast and report, or the investors’ total information at hand after both the forecast and the report are issued, may be incomplete.

2.4 Conclusion

The main themes of the analytical analyst forecast literature are as follows. First, there are far fewer studies that treat analyst forecasts as interacting with another information source than there are those that treat them as an independent information source on their own. Notably, few studies have examined the interaction of analyst forecasts with another information source, and they feature no strategic information acquisition or strategic forecasting. Notable exceptions are Beyer (2008) and the following two chapters of my thesis.

Second, a review of the extant literature on analysts’ behavior reveals that a broad range of incentives for the analyst in a variety of contexts has already been discussed. However, none of the previous studies have examined the analyst’s incentives to be close to firm fundamental value, although Louis et al. (2013) have shown that analysts sacrifice forecast accuracy for being close to firm fundamentals. My next chapter addresses this question. Similarly, previous studies have not examined the analyst’s concern for the client’s trading profits balanced out by her forecast accuracy incentives within the strategic forecasting context. My fourth chapter focuses on this issue. More papers are called for to examine the analyst’s other incentives.

Third, there are also gaps in the literature on strategic information acquisition and the consequences of the analyst’s reputational incentives. Hayes (1998) concentrates on the
analyst’s strategic information acquisition alone. Fischer and Stocken (2010) have studied the interaction of the analyst’s strategic information acquisition with her strategic forecasting for the misaligned analyst. Meng (2015) has also studied the interaction when both the aligned and the misaligned analyst have reputational concerns. These are all the papers that feature endogenous information acquisition. Future studies could focus on how strategic information acquisition interacts with the analysts’ strategic forecasting within the context of incentives other than reputational concerns or an upward bias.

Fourth, more papers are also called for to study other consequences of the analyst’s reputational concerns. Analysts’ reputation incentives have been shown to have many consequences in prior literature. These consequences include increasing future trade volume (Jackson, 2005), withholding private information (Trueman, 1990), herding (Graham, 1999; Trueman, 1994), issuing a conservative forecast (Clarke and Subramanian 2006), and acquiring more information and communicating truthfully (Meng, 2015). However, this list does not exhaust the consequences of the analyst’s reputational concerns, and later studies should explore these other consequences. It is also of interest to future researchers to extend current reputational models to infinitely many periods and beyond two periods, and to investigate whether the conclusions change.
Chapter 3: Reported and Unmanaged True Earnings: Two Analyst Forecast Incentives

3.1 Introduction

This chapter investigates how the presence of an analyst affects a firm’s information environment in a setting in which analyst forecasts and firm financial reports are both endogenously chosen. Specifically, I examine how analyst forecasts and managers’ reports interact to affect the corporate information environment when the manager has hidden reporting incentives so that neither the analyst nor investors can back out his reporting bias. Prior literature has not been able to examine the net effect of analyst forecasts and managers’ reports on the corporate information environment.

I build on two related studies by Fisher and Verrecchia (2000) and Beyer (2008). Fisher and Verrecchia (2000) have modelled a setting in which a manager has access to private information regarding the firm’s value but has incentives to potentially distort this information in his public financial report. Investors are unable to perfectly infer the manager’s distortion due to uncertainty regarding the manager’s reporting incentives. I extend the work of Fischer and Verrecchia (2000) by including an analyst as an additional endogenous agent in the model. The analyst issues a forecast based on private information regarding both the firm’s value and the manager’s reporting incentives, but she is also influenced by her own forecasting incentives. Thus, a feature of my model is that the analyst and manager interact in their forecasting and reporting decisions, respectively. That is, each takes the other party’s choices into account when making his or her own optimizing decisions. My objective is to investigate how analyst and firm characteristics affect the firm’s information environment in such a setting. Thus, my research responds to Beyer et al.’s (2010)
call for research in settings where analyst forecasts and managers’ financial reports interact in this way.

Beyer (2008) has also investigated the interaction between analyst forecasts and firm financial reports but focuses on forecast revisions in a setting in which the manager faces asymmetric, “meet or beat” reporting incentives. Her model setting allows investors to fully identify any reporting distortion by the manager and thus perfectly infer the manager’s private information. My focus is different. I emphasize capital market reactions to the forecasts and financial reports in my analysis, as well as the amount of information that investors are able to access through forecasts and financial reports. As a consequence, a key aspect of my model is that investors are unable to perfectly infer the manager’s private information. This enables me to investigate how the availability of analyst forecasts affects investors’ ability to infer firm value in the presence of potentially distorted firm financial reports, and how this in turn affects investor uncertainty – the net effect of forecast and report on a firm’s information environment. Beyer’s (2008) model is not designed to, and does not permit, such an analysis.

My model features an analyst, a firm manager, and investors. The firm manager releases a report after privately observing his own pricing incentives, a signal about the firm’s fundamentals, and the analyst’s public forecast. Following Fischer and Verrecchia (2000), I assume that the manager has pricing incentives to distort his report away from his perceived firm fundamental value, but at a cost. In addition, the manager incurs a cost if his report deviates from the analyst’s forecast. Prior to the corporate reporting stage, the analyst issues a forecast after observing two signals about the firm’s fundamental value and the manager’s incentives, respectively. The analyst’s objective is to issue a forecast that is close to both reported earnings and the firm’s fundamental value. After both the forecast and the report are
released, investors price the firm at expected value, and the firm’s fundamentals are realized at the end. Within this model setting, I solve for the equilibrium forecast and reporting choices by the analyst and manager, respectively, as well as the equilibrium price. I then investigate how the firm’s information environment is affected by characteristics of both the analyst and the firm/manager.

My model presents four major findings. First, I focus on contrasting the case in which the analyst aims to forecast reported earnings with the case in which the analyst aims to forecast unmanaged true earnings; I find that the comparative static results are qualitatively the same. This shows that the analyst’s forecasting strategies depend on the manager’s incentives even when the analyst does not care about the manager’s report, and the manager cares about the analyst’s forecast unilaterally. This calls into question Beyer’s (2008) suggestion that the relationship is due to the interaction of the analyst forecast and the manager’s report. Further, I show that both the earnings response coefficient and the reporting bias are higher when the analyst aims to forecast reported earnings than when she forecasts the unmanaged firm true value. It is natural that the reported bias is higher, as the analyst is expected to succumb to the manager’s pressure to bias his report in the former case. The higher reporting bias is also a result of a higher earnings response coefficient. However, the fact that the earnings response coefficient is higher (i.e., the report is more informative) when the analyst maximizes forecast accuracy than when she minimizes the forecast’s deviation from firm true value is counterintuitive. This results from the interaction between the analyst forecast and the manager’s report. When the analyst minimizes the forecast’s deviation from firm true value, her forecast response coefficient remains maximum, and her forecast pre-empts the information content of the manager’s report. On the other hand, when the analyst maximizes forecast accuracy, her forecast is less informative but incorporates the manager’s reporting
bias and thus enables investors to back out more of the reporting bias in the manager report, which results in the report being more informative.

Second, the quality of the analyst’s information has non-monotonic net effects on the corporate information environment. Specifically, investors’ residual uncertainty regarding the firm’s final payoff, a measure of the net effect of the analyst forecast and firm financial report on the firm’s information environment, increases in the quality of the analyst’s information for some parameter values. This occurs because better information about the manager’s reporting incentives has two opposing effects on investor residual uncertainty: one signal, $f$, the forecast, declines in quality, while the other incremental signal, $(r - f)$, the report net of the forecast, improves. The former causes residual uncertainty to increase, while the latter reduces residual uncertainty. The result in proposition 2 indicates that it is possible for either effect to dominate. In particular, it is possible that the improvement in the incremental signal available from the financial report is outweighed by the decrease in quality (as a signal of $u$, the firm’s final payoff) of the analyst forecast. Thus, for some (but not all) parameter values, it is possible for higher-quality analyst information about reporting incentives to result in less overall information available to investors. The rationale for the effect of better information about the firm’s fundamental value on investors’ residual uncertainty is similar, although the directions of the effects are opposite.

Third, firm reporting bias is non-monotonic in the cost of the manager’s incentive to issue a report that is close to the analyst’s forecast. This means that a stronger incentive for the manager to avoid deviating from the analyst’s forecast decreases firm reporting bias for some parameter values, which is partially contrary to what has been documented in the empirical literature (Matsumoto, 2002). There are two effects at play. The direct effect is that a stronger incentive for the manager to be close to the analyst’s forecast provides more incentives to
distort the report, and it introduces more reporting bias. The indirect effect causes the manager to place a relatively low weight (compared to the manager's incentive to be close to analyst forecast) on his bias due to market incentives, thus reducing firm reporting bias. My results indicate that, for some parameter values, the indirect effect dominates, and the stronger incentive for the manager to be close to analyst forecast decreases firm reporting bias. Specifically, the manager’s incentive increases firm reporting bias when the analyst is certain of the manager’s market incentives. A sufficient condition for the incentive to decrease firm reporting bias is when the analyst has poor information about the manager’s market incentives, the manager places little weight on his incentive to be close to analyst forecast, and he is as likely to deflate prices as he is to inflate prices.

Fourth, my model finds that having better-informed managers is not necessarily a benefit for the corporate information environment, although numerical analysis shows that the net effect is positive. Although better manager information quality (or ability) about the firm’s fundamentals leads to higher earnings association, it also increases the forecast error, the reporting bias, and the forecast’s deviation from firm fundamentals. It is intuitive that better manager information quality makes his report more informative and thus results in a higher earnings association. However, a higher earnings association leads to higher forecast error, higher reporting bias, and larger forecast deviation from firm fundamentals. This is also because a relatively large variance of the manager’s signal means a relatively low improvement of the manager’s signal over the analyst’s and a relatively better analyst’s signal; however, a better analyst’s signal increases forecast accuracy and decreases both reporting bias and forecast’s deviation from firm fundamentals. In a word, my model predicts that worse manager’s information results in higher forecast accuracy and lower reporting bias and forecast deviation from firm fundamentals, although numerical analysis shows that it also results in lower investors’ residual uncertainty.
My study contributes to the literature in two important ways. First, I derive the net effect of analyst characteristics and firm/manager characteristics on the corporate information environment in a setting in which both the analyst forecast and the manager’s report are endogenously determined. The result was not previously possible within the frameworks of either Beyer (2008) or Fischer and Verrecchia (2000), the two most closely related analytical studies, but it is important for our understanding of firms’ information environment. Analyst and firm/manager characteristics affect different aspects of the corporate information environment in different ways, but ultimately, what matters to investors is the net effect, especially for long-term investors. Specifically, I predict that the quality of both of the analyst’s types of information has a non-monotonic net effect on the corporate information environment, the manager’s weight on being close to the analyst forecast has a negative net effect on the corporate information environment, and the manager’s biasing cost has a positive net effect on the corporate information environment.

Second, I characterize the effect of the analyst’s use of information about the manager’s hidden reporting incentives with respect to price on the corporate information environment. Although prior empirical studies have shown that analysts use such information, its effect on the corporate information environment remains largely unknown. My study shows that, when the analyst’s goal is to forecast firm fundamentals, the non-fundamental information has no effect on the corporate information environment, thus justifying earlier studies’ relative neglect of this type of information. However, Proposition 2 shows that, when the analyst’s objective function is to minimize forecast error, the analyst’s signal about the manager’s incentives plays key roles in the firm’s information environment. It increases forecast accuracy, the forecast’s deviation from firm fundamentals, the manager’s reporting bias, and the earnings response coefficient; it decreases the forecast response coefficient and has a non-monotonic net effect on the firm’s information environment.
The remainder of the paper is organized as follows. In section 3.2, I develop the full model and derive the equilibrium in section 3.3. In section 3.4, I perform comparative static analysis to answer some empirical questions. Section 3.5 contrasts the case in which the analyst forecasts reported earnings with the case in which she forecasts unmanaged true earnings. Section 3.6 concludes.

3.2 Model

In my model, there is a single firm in the economy with true underlying value (or firm fundamentals) \( u \). \( u \) has a prior normal distribution with mean \( \mu_u \) and variance \( \sigma_u^2 \). All assumptions about distributions are common knowledge. There are three dates in the model, which are portrayed in figure 1. At time \( t = 3 \), the firm’s final payoff, \( u \), is realised.

\[
\begin{array}{c|c|c}
\hline
\text{t=1} & \text{t=2} & \text{t=3} \\
\hline
\text{Analyst sees a signal } y_A = u + e_M + e_A \text{ about the firm’s final payoff and another } z = x + \delta \text{ about the manager’s hidden reporting incentive and makes a forecast to minimize her objective function.} & \text{Manager sees a signal } y_M = u + e_M \text{ about the firm’s final payoff and releases a report to maximize his objective function.} & \text{Firm’s final payoff } u \sim N(\mu_u, \sigma_u^2) \text{ is realized.} \\
\hline
\end{array}
\]

*Figure 1 presents the timeline of the game.*

At time \( t=2 \), the firm’s manager privately observes a signal \( y_M = u + e_M \), where \( e_M \) is distributed normally and independently of other variables with mean zero and variance \( \sigma_{e_M}^2 \).
At $t=2$, the manager also issues a public report to investors, $r$. He chooses $r$ to maximise

$$xP_2 - \frac{c_x}{2} E[(u - r)^2 | y_M, f] - \frac{c_f}{2} (r - f)^2,$$

where $x$ is the manager’s hidden reporting incentive relating to price, which is normally and independently distributed with mean $\mu_x$ and variance $\sigma_x^2$. $P_2$ is the firm’s share price at time $t=2$, $f$ is the analyst’s forecast, and $c_x, c_f$ are non-negative constants that represent the cost to the manager if his report deviates from the firm’s fundamental value and the analyst’s forecast, respectively. This objective function follows Fischer and Verrecchia (2000) and extends it via the final term, $-\frac{c_f}{2} (r - f)^2$, which provides the manager with an additional incentive to report close to the analyst’s forecast.

This is consistent with prior empirical research that has shown that managers have incentives to meet or beat analysts’ forecasts (Bartov, Givoly, & Hayn, 2002; Matsumoto, 2002).

The first part of the manager’s objective function is his hidden incentive to manipulate price. Because $x$ is normally distributed and can be either positive or negative, the manager can have incentives to inflate or deflate the firm’s share price. This feature of the model reflects the observation that, although managers generally have an incentive to inflate firm share price to maximise shareholder wealth and/or personal gain, they are also known to have occasional incentives to deflate share prices, such as when they want to repurchase shares (Brockman, Khurana, & Martin, 2008; Louis & White, 2007) or push down the exercise price of their options at option grant dates (Aboody & Kasznik, 2000; McAnally, Srivastava, & Weaver, 2008; Yermack, 1997). This is why the manager’s price incentives are hidden but his

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4 This structure does not capture the asymmetric nature of the manager’s “meet or beat” incentives. I adopt the symmetric structure because the manager faces pressure for meeting or beating past earnings in the next period if he surpasses the forecast by a large margin in this period, which becomes an implicit cost for him. Therefore, I assume that the manager wants to stay close to the analyst’s forecast and does not want to deviate from it for too far on either side. As a practical matter, employing an asymmetric structure (as in Beyer, 2008) but retaining the feature that investors are unable to fully back out the manager’s distortion of the report would result in an intractable model.
incentives to be close to the analyst forecast, which are well known in the literature, are explicit.

There is a single analyst who, at time $t=1$, observes a noisy signal $y_A = u + e_M + e_A$ regarding the firm’s fundamental value. I further assume that the analyst observes an additional noisy signal $z = x + \delta$ regarding the manager’s hidden reporting incentive. I assume that $e_M, e_A, \delta$ are normally and independently (of each other and of other variables) distributed, with means of zero and variances of $\sigma_{e_M}^2, \sigma_{e_A}^2, \sigma_{\delta}^2$, respectively.

Note that the signal available to the analyst regarding the firm’s final payoff, $y_A = u + e_M + e_A$, is redundant information given the manager’s signal, $y_M = u + e_M$. That is, the manager has superior information to the analyst. This is consistent with prior research, such as that of Hutton, Lee, and Shu (2012), which shows that management forecasts are more accurate than analysts’ forecasts when firms’ earnings are more affected by managers’ actions.

Based on the signals $y_A$ and $z$, the analyst issues a forecast $f$ to minimise the weighted sum of the expected squared forecast error, or the deviation from the manager’s report $r$, and the expected squared forecast bias, or the deviation from the firm’s true underlying value $u$, i.e.

$$\frac{k_r}{2} E[(r - f)^2 \mid y_A, z] + \frac{k_u}{2} E[(u - f)^2 \mid y_A, z],$$

where $k_r, k_u$ are positive constants representing the analyst’s cost for issuing a forecast that deviates from the manager’s report and the firm’s fundamentals, respectively. This objective function captures important aspects of the analyst’s incentives. Numerous empirical studies have shown that analysts care about forecast accuracy due to reputation or career concerns. For example, Mikhail et al. (1999) have found that, controlling for firm- and time-period effects, forecast horizon, and industry forecasting
experience, an analyst is more likely to turn over if his forecast accuracy is lower than that of his peers. Hong and Kubik (2003) have shown that forecast accuracy is rewarded with favorable job separations and internal labor market incentives. Analytical research has traditionally specified analysts’ objectives as minimizing forecast error (the deviation from reported earnings) (Beyer, 2008).

More recent studies have shown that analysts also care about (unmanaged) true earnings. Louis et al. (2013) have supplied preliminary evidence that analysts sacrifice forecast accuracy for informativeness that is consistent with analysts’ concern for the informativeness of their forecasts, or their forecasts’ closeness to the firm’s true value. Louis et al. (2013) have argued that long-term investors such as institutions are primarily concerned with firms’ true underlying value and have a demand for analysts to forecast unmanaged true earnings, which might deviate from reported earnings. They have argued, “analysts’ primary function should be to provide useful valuation information to their clients and to help them uncover mispricing. Failing in this function can have severe valuation consequences, considering that investors often use earnings models, including some crude ones (e.g., forward price-to-earnings multiples), to value firms” (Louis et al., 2013, p. 1688). They have shown that analysts indeed deviate from management guidance, although reiterating it would increase forecast accuracy. They have found that such deviations are informative and concluded that they convey analysts’ best estimates of the firms’ true, underlying performance.

Finally, I assume that investors are risk-neutral and price the firm’s shares according to the expected value of the firm’s true, underlying value given available information. That is,

\[ P_0 = \mu_e, P_1 = E[u | \Phi_i = f], P_2 = E[u | \Phi_i = r, f], \]

where \(\Phi_i\) represents investors’ available information.
There are three main distinguishing features of my model. First, the model features interaction between the analyst’s forecast and the manager’s financial report. I argue that earnings reports and analyst forecasts do not impact the firm’s information environment independently of one another. Rather, they impact the information environment through their interplay. Beyer (2008), for example, has argued that analyst forecasts and managers’ earnings reports interact because analysts have incentives to release earnings forecasts that accurately predict the manager’s earnings reports, while managers have incentives to report earnings that do not greatly deviate from analysts’ expectations. Thus, each of the manager’s and the analyst’s objective functions depends on choices made by the other, which injects interdependence into the model. There is much empirical support for Beyer’s (2008) argument. Mikhail et al. (1999) have presented evidence that analysts have incentives to forecast accurately; Basu and Markov (2004) have shown that analysts strive to minimize their absolute forecast errors, arguing that it is costly for them to make forecast errors; Bartov et al. (2002) and Lopez and Rees (2002) have shown that it is costly for managers to report earnings that fall short of analysts’ expectations.

Second, in my model, the analyst has access to information about the firm’s true value and the manager’s (uncertain) reporting incentives. Information about firms’ fundamentals is an important input for analysts’ forecasts. However, significant information is available to analysts that is not related to firms’ fundamentals. An alternative, potentially useful source of information for analysts concerns managers’ reporting incentives. Kim and Schroeder (1990) have empirically shown that analysts use managerial bonus incentives in forecasting earnings. This provides the most direct empirical support for my modelling decision. Givoly, Hayn, and Yoder (2011) have also shown that analysts can anticipate managers’ earnings management and account for it in their forecasts, thus providing indirect support that, when
making forecasts, analysts use information about managers’ incentives to bias their financial reports.

I also model the analyst’s objective as a weighted sum of the expected squared forecast error (deviations from reported earnings) and expected deviation from the firm’s fundamentals. This feature of the model is motivated by an ongoing debate about whether analysts’ objective is to forecast reported earnings or unmanaged true earnings in the empirical literature.

3.3 Equilibrium

The equilibrium in my model consists of three components: the analyst’s forecast, $f$; the firm’s financial report, $r$; and the price at time $t = 2$, $P_2$. Consistent with prior research, I consider only linear equilibria to retain tractability. To determine the equilibrium, I consider the manager, analyst, and market in turn and solve by backward induction. I employ the following definitions to simplify notation:

**Definitions**: Define:

$$c = c_u + c_{f}; \lambda_m = \frac{c_u}{c};$$

$$\mu_{u_m} = E(u \mid y_m) = (1 - \alpha_{y_m}) \mu_u + \alpha_{y_m} y_M, \text{ where } \alpha_{y_m} = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_{y_m}^2};$$

$$\mu_{u_a} = E(u \mid y_A) = (1 - \alpha_{y_A}) \mu_u + \alpha_{y_A} y_A, \text{ where } \alpha_{y_A} = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_{y_A}^2 + \sigma_{e_A}^2};$$

$$\mu_{x} = E(x \mid z) = (1 - \alpha_{z}) \mu_x + \alpha_{z} z, \text{ where } \alpha_{z} = \frac{\sigma_z^2}{\sigma_z^2 + \sigma_{\delta}^2}.$$
Among these, $\mu_{m}, \mu_{a}$ are the expected values of the firm’s fundamentals given the manager’s and the analyst’s information, respectively, and $\mu_{s_{a}}$ is the expected value of the manager’s incentive parameter given the analyst’s information. $\alpha_{m}, \alpha_{a}, \alpha_{s}$ are the coefficients in the three expected values on the respective information signals. Finally, 

$$\lambda_{M} = \frac{c_{u}}{c_{a} + c_{f}}$$

represents the importance to the manager of issuing a report that does not deviate substantially from the firm’s fundamental value (relative to deviating from the analyst’s forecast).

### 3.3.1 The Manager’s Problem

At time $t=2$, the manager (who knows his own hidden incentive parameter $x$) privately observes signal $y_{M} = u + e_{M}$, as well as the analyst’s public forecast, $f$, and chooses his report, $r$, to maximize the objective function, $xP_{2} - \frac{c_{u}}{2}E[(u-r)^{2} | \Phi_{u}] - \frac{c_{f}}{2}(r-f)^{2}$. In doing so, he conjectures that the market sets firm value equal to a linear function of his report and the analyst’s forecast, $P_{2} = \beta_{02} + \beta_{r}(r-f) + \beta_{f}f$. Solving this maximisation problem via the first order condition yields

$$r = f + \lambda_{M}(\mu_{m} - f) + \frac{\beta_{r}}{c}x.$$ 

---

$^{5}$ I specify price as a linear function of $r - f$ rather than $r$ for algebraic convenience. This means that $\beta_{r}$ represents price responsiveness to “unexpected earnings” using the analyst’s forecast as the earnings expectations benchmark, which is consistent with a large body of empirical research (Atiase, Supattarakul, & Tse, 2006; Brown & Pinello, 2007; Keung, Lin, & Shih, 2010; Kinney, Burgstahler, & Martin, 2002).
The above equation indicates that the manager’s report is composed of three components: the analyst forecast, part of the incremental information about the firm’s fundamentals by the manager \( \lambda_M (\mu_u - f) \), and distortion due to the manager’s hidden price incentives \( \frac{\beta_i}{c} \).

### 3.3.2 The Analyst’s Problem

At time \( t=1 \), the analyst anticipates the form of the manager’s report at time \( t=2 \) given in equation (1) and chooses \( f \) to minimise

\[
\frac{k_u}{2} E[(u - f)^2 | \Phi_A] + \frac{k_r}{2} E[(r - f)^2 | \Phi_A].
\]

Solving this minimisation problem via the first order condition yields

\[
f = \mu_u + q \frac{\beta_r}{c} \mu_s,
\]

where \( q = \frac{k_r}{k_u + k_r \lambda_M} \). The above equation indicates that the analyst’s forecast is her expected value of the firm’s fundamentals given her information, plus distortion due to the analyst’s expectation of the manager’s hidden price incentives.

### 3.3.3 The Market Pricing Function

Investors are risk-neutral and price the firm’s shares as the expectation of the firm’s final payoff given available information, i.e., the analyst forecast and manager’s report. Thus, they set price as \( P_2 = E(u | r, f) = E(u | r - f, f) \).

To facilitate the derivation of \( P_2 \), I define

\[
\hat{f} = E(r | f) = \gamma_0 + \gamma_1 f
\]
Where $\gamma_1 = \frac{\text{cov}(r, f)}{\text{var}(f)} = 1 + \frac{q(\beta_c)}{\alpha_u \sigma^2} (1 - \lambda_m q)$, $\gamma_0 = E(r) - \gamma_1 E(f)$. According to the definition, $\hat{f}$ is the expected $r$ given the analyst’s forecast, $f$. It adjusts for any bias or distortion in the analyst’s forecast. However, it contains the same information as $f$ because it is simply a linear transformation of $f$.

Note that when either $k_u = 0$ or $k_r = 0$, then $\text{cov}(r, f) = \text{var}(f)$, and $\hat{f} = f$. In these two cases, $f$ is an unbiased forecast of $r$. Otherwise, $f$ is biased/distorted by the analyst due to her competing incentives.

Since $\hat{f}$ has the same information as $f$, $P_2$ can be expressed as a linear function of $\hat{f}$ and $r - \hat{f}$:

$$P_2 = E(u \mid r - f, f) = E(u \mid r - \hat{f}, \hat{f}) = \beta_0 + \beta_{\hat{f}} \hat{f} + \beta_r (r - \hat{f}).$$

In addition, since $\hat{f} = E(r \mid f)$, $\text{cov}(\hat{f}, r - \hat{f}) = 0$ and so

$$\beta_{\hat{f}} = \frac{\text{cov}(u, \hat{f})}{\text{var}(f)} \quad \text{and} \quad \beta_r = \frac{\text{cov}(u, r - \hat{f})}{\text{var}(r - f)}.$$

That is, we have

$$\beta_r = \frac{(1 - \lambda_m - \gamma_1) \alpha_u \sigma^2 + \lambda_M \alpha_{\hat{f}} \sigma^2}{\lambda_m [(\alpha_{\hat{f}} - \alpha_u) \sigma^2 + (q \beta_c)^2 \alpha \sigma^2] + (q \beta_c)^2 \sigma^2 - 2 \lambda_m (q \beta_c)^2 q \alpha \sigma^2 - (1 - \gamma_1)^2 [\alpha_u \sigma^2 + (q \beta_c)^2 \alpha \sigma^2]}.$$ (3.1)
\[
\beta_j = \frac{\alpha_{\gamma_u} \sigma_u^2}{\gamma_1(\alpha_{\gamma_u} \sigma_u^2 + (q \frac{\beta_f}{c})^2 \alpha_{\gamma_u} \sigma_u^2)} = \frac{\alpha_{\gamma_u} \sigma_u^2}{\alpha_{\gamma_u} \sigma_u^2 + q(\frac{\beta_f}{c})^2 \alpha_{\gamma_u} \sigma_u^2 (1-\lambda_M q + q)}
\]

The appendix that the right-hand side (RHS) of equation (3.1) decreases in \( \beta_f \). Together with the conditions that RHS>0 when \( (\frac{\beta_f}{c})^2 = 0 \) and RHS goes to zero as \( (\frac{\beta_f}{c})^2 \rightarrow \infty \), this implies that \( \beta_j \) is uniquely determined. Because \( \beta_j \) is uniquely determined by \( \beta_f \), there is a unique equilibrium. The following proposition summarizes these results.

Proposition 1: There is a unique equilibrium where \( r = f + \lambda_M (\mu_{bu} - f) + \frac{\beta_f}{c} x \),

\[
f = \mu_{ua} + q \frac{\beta_f}{c} \mu_{sa} \text{ with } q = \frac{k_r}{k_u + k_r \lambda_M} , \quad \hat{f} = E(r \mid f) = \gamma_0 + \gamma_1 f \text{ with } \gamma_0 = E(r) - \gamma_1 E(f),
\]

\[
\gamma_1 = 1 + \frac{q(\frac{\beta_f}{c})^2 \alpha_{\gamma_u} \sigma_x^2 (1 - \lambda_M q)}{\alpha_{\gamma_u} \sigma_u^2 + (q \frac{\beta_f}{c})^2 \alpha_{\gamma_u} \sigma_x^2}, \quad \text{and } P_2 = \beta_0 + \beta_1 \hat{f} + \beta_f (r - \hat{f}) \text{ where}
\]

\[
\beta_f = \frac{(1 - \lambda_M - \gamma_1) \alpha_{\gamma_u} \sigma_u^2 + \lambda_M \alpha_{\gamma_u} \sigma_x^2}{\lambda_M \{(\alpha_{\gamma_u} - \alpha_{\gamma_x}) \sigma_u^2 + (q \frac{\beta_f}{c})^2 \alpha_{\gamma_u} \sigma_x^2\} + (\frac{\beta_f}{c})^2 \sigma_u^2 - 2 \lambda_M (\frac{\beta_f}{c})^2 q \alpha_{\gamma_u} \sigma_x^2 - (1-\gamma_1)^2 [\alpha_{\gamma_u} \sigma_u^2 + (q \frac{\beta_f}{c})^2 \alpha_{\gamma_u} \sigma_x^2]}
\]

\[
\beta_j = \frac{\alpha_{\gamma_u} \sigma_u^2}{\gamma_1(\alpha_{\gamma_u} \sigma_u^2 + (q \frac{\beta_f}{c})^2 \alpha_{\gamma_u} \sigma_x^2)} = \frac{\alpha_{\gamma_u} \sigma_u^2}{\alpha_{\gamma_u} \sigma_u^2 + q(\frac{\beta_f}{c})^2 \alpha_{\gamma_u} \sigma_x^2 (1-\lambda_M q + q)}
\]

Because the equilibrium in Proposition 1 is too complex for the purposes of tractable comparative statics, I investigate two special (extreme) cases: where \( k_u = 0 \) or \( k_r = 0 \). \( k_u = 0 \) corresponds to the situation in which the analyst is concerned only with issuing a
forecast that does not significantly deviate from the manager’s eventual report (i.e., forecast accuracy). In contrast, \( k_r = 0 \) corresponds to the situation in which the analyst is concerned only with forecasting close to the firm’s underlying fundamental value (i.e., forecast informativeness). The following two corollaries provide the equilibria for these two cases.

**Corollary 1:** When the analyst’s objective is to minimize forecast error or deviation from the manager’s report (i.e., \( k_u = 0 \Rightarrow q = \frac{1}{\lambda_M} \)), there is a unique equilibrium where

\[
r = f + \lambda_M (\mu_{u} - f) + \frac{\beta_r}{c} x, \quad f = \mu_u + \frac{1}{\lambda_M} \frac{\beta_r}{c} \mu_u \quad \text{and} \quad P_z = \beta_0 + \beta_f f + \beta_r (r - f) \quad \text{with}
\]

\[
\beta_r = \frac{\lambda_M (\alpha_{y,u} - \alpha_{y,s}) \sigma_u^2}{\lambda_M^2 (\alpha_{y,u} - \alpha_{y,s}) \sigma_u^2 + (\frac{\beta_r}{c})^2 \sigma_x^2 (1 - \alpha_z)}
\]

\[
\beta_f = \frac{\alpha_{y,s} \sigma_u^2}{\gamma_1 (\alpha_{y,s} \sigma_u^2 + (q \frac{\beta_r}{c})^2 \alpha_z \sigma_x^2)} = \frac{\alpha_{y,s} \sigma_u^2}{\lambda_M^2 \frac{\beta_r}{c} \alpha_z \sigma_x^2}.
\]

**Corollary 2:** When the analyst’s objective is to minimize deviation from the firm’s true value (i.e., \( k_r = 0 \Rightarrow q = 0 \)), there is a unique equilibrium where

\[
r = f + \lambda_M (\mu_{u} - f) + \frac{\beta_r}{c} x,
\]

\[
f = \mu_u, \quad \text{and} \quad P_z = \beta_0 + \beta_f f + \beta_r (r - f) \quad \text{with}
\]

\[
\beta_r = \frac{\lambda_M (\alpha_{y,u} - \alpha_{y,s}) \sigma_u^2}{\lambda_M^2 (\alpha_{y,u} - \alpha_{y,s}) \sigma_u^2 + (\frac{\beta_r}{c})^2 \sigma_x^2}
\]

\[
\beta_f = 1.
\]

For the remainder of the chapter, I focus on the case in which the analyst is assumed to minimize the expected forecast error (i.e., \( k_u = 0 \)). I omit discussion of the other case, in which the analyst is motivated solely by forecast informativeness (i.e., \( k_r = 0 \)), because the
two are qualitatively similar. The only difference is the fact that the managerial incentives signal of the analyst does not work when the analyst is motivated solely by forecast informativeness.

**Lemma 1:** The analyst’s information about the manager’s incentives has no effect when the analyst is motivated solely by forecast informativeness.

**Lemma 2:** The case in which the analyst is assumed to minimize the expected forecast error and the case in which the analyst is motivated solely by forecast informativeness have qualitatively similar results.

Lemma 2 shows that, even when the analyst does not care about the manager’s report and cares only about the firm’s fundamental value, her forecasting strategy still depends on the incentives of the manager. This contrasts with Beyer’s (2008) claim that the analyst’s forecasting strategy depends on the incentives of the manager because of the interdependence between the analyst forecast and manager’s report. My results show instead that the relationship obtains even when the analyst does not care about the manager’s report and the manager cares about the analyst forecast unilaterally.

### 3.4 Comparative Statics

In this section, I investigate the effect of several analyst and firm/manager characteristics on the firm’s information environment. Specifically, I derive comparative statics for information environment-related metrics with respect to the following exogenous parameters: the variances of noise in the analyst’s two signals, \((\sigma_a^2, \sigma_f^2)\); the variance of noise in the manager’s signal, \(\sigma_m^2\); the biasing cost, \(c_u\); and the marginal cost of the manager’s incentive to be close to the analyst forecast, \(c_f\). The noise variance parameters represent the quality of
the signals available to the analyst ( \( y_A \) regarding the firm’s payoff \( u \), and \( z \) regarding the manager’s reporting incentive parameter \( x \)) and the firm manager ( \( y_M \) regarding \( u \)). The cost parameters reflect the importance to the manager of issuing a financial report that does not significantly deviate from the firm’s final payoff (or true fundamental value) and the analyst’s forecast. The information environment metrics I investigate are as follows: the analyst’s forecast accuracy and deviation from the firm’s underlying value, the manager’s reporting distortion (i.e., the deviation from the manager’s expectation of the firm’s underlying value), price responsiveness to the analyst’s forecast (\( \beta_f \)) and the manager’s report (\( \beta_r \)), and investors’ residual uncertainty (the variance of the firm’s fundamental value given information available from the forecast and the report). The first three metrics speak to the measurement properties of the forecast and report, and the next two relate to how prices reflect the forecast and report. The final metric relates to how much information (in total) is jointly communicated to investors by the forecast and report.

### 3.4.1 The Quality of the Analyst’s Two Signals (\( \sigma_{\epsilon A}^2, \sigma_{\epsilon \delta}^2 \))

A straightforward approach is to use the results in Corollary 1 to derive the relevant comparative statics (see the appendix), which result in the following proposition:

**Proposition 2:** When the analyst’s objective is to maximize forecast accuracy (\( k_u = 0 \)):

i) Forecast accuracy increases in the quality of both analyst signals;

ii) The forecast’s deviation from the firm’s underlying fundamental value decreases (increases) in the quality of the analyst’s signal about firm value (the manager’s reporting incentives);
iii) The manager’s reporting bias decreases (increases) in the quality of the analyst’s signal about firm value (the manager’s reporting incentives);

iv) The firm’s price is less (more) responsive to the firm’s financial report for a higher-quality analyst’s signal about firm value (the manager’s reporting incentives);

v) The firm’s price is more (less) responsive to the analyst’s forecast for higher quality analyst signals about firm value (the manager’s reporting incentives);

vi) Investors’ residual uncertainty is non-monotonic in the quality of the analyst’s signal about firm value (the manager’s reporting incentives).

Proposition 2 directly answers the research question of how the presence of an analyst affects the corporate information environment by investigating the effects of the quality of the analyst’s information on the properties of the analyst forecast and the manager’s report, their market reactions, and the net effect on the corporate information environment. To understand the intuition underlying part i) of proposition 2, recall that from corollary 1:

\[ f = \mu_{u_a} + \frac{1}{\lambda_M} \frac{\beta}{c} \mu_s; \]  
(3.2)

\[ r - f = (\mu_{u_a} - \mu_s) + \frac{1}{\lambda_M} \frac{\beta}{c} (x - \mu_s). \]  
(3.3)

The LHS of equilibrium equation (3.3) represents the (deflated) forecast error, and the RHS indicates that this is comprised of two components. The first component is the difference between the analyst’s and the manager’s perception of the firm’s fundamental value, while the second component reflects the deviation of the manager’s reporting incentive parameter from the analyst’s perception of that parameter. If the analyst receives higher-quality information about the firm’s fundamental value \( u \), then this decreases the magnitude of the
first part of (3.3), the difference between the analyst’s and the manager’s perception of the firm’s fundamental value, and thus the magnitude of the forecast error. This direct effect holds that, if the analyst receives higher-quality information about the firm’s fundamental value, the difference between the analyst’s and the manager’s perception of the firm’s fundamental value is reduced, thus reducing forecast error. However, it also has an indirect effect on the second part of (3.3), the deviation of the manager’s reporting incentive parameter from the analyst’s perception of that parameter, through its effect on equilibrium \( \beta_r \), the earnings association; it causes the forecast in the equilibrium equation (3.2) to be a better signal of the firm’s fundamental value \( u \) for investors, and since the forecast in (3.2) and the report net of the forecast in (3.3) are conditionally independent signals for the firm’s fundamental value \( u \), investors will place less weight on \( r - f \), the report net of the forecast, in the setting price; i.e., the earnings association \( \beta_r \) will be lower. This means that the magnitude of the second part of (3.3), the deviation of the manager’s reporting incentive parameter from the analyst’s perception of that parameter (and thus the forecast error) will also be lower, thus reinforcing the initial direct effect.

In contrast to the situation in which the analyst receives higher-quality information about \( x \) (the manager’s reporting incentive parameter), the ‘direct’ effect of this is to make the \( (x - \mu_{x_a}) \) component of (3.3) smaller in magnitude (i.e., the analyst’s expectation of \( x \), the manager’s hidden reporting incentives parameter, is closer to its actual value). However, there is again an “indirect” effect through the earnings association \( \beta_r \). This is because the signal in (3.2) (the forecast) is now a worse signal about the firm’s fundamental value \( u \) (because \( \mu_{x_a} \), the analyst’s expectation of the manager’s hidden reporting incentives parameter, is more variable due to the analyst’s better information). This means that the
equilibrium earnings association $\beta_r$ will be higher because the forecast and the report net of the forecast are independent in setting prices, as was discussed in the above paragraph. This effect counters the direct effect. The result in proposition 2 i) indicates that the direct effect dominates.

Regarding part ii) of proposition 2, the forecast’s deviation from the firm’s underlying fundamental value is the following:

$$u - f = (u - \mu_u) - \frac{\beta_r}{\lambda_{M^c}} \mu_{s_k}.$$  (3.4)

The forecast’s deviation from the firm’s underlying fundamental value consists of two parts: the deviation of the analyst’s perception of the firm’s fundamental value from its true value, and the analyst’s distortion of the forecast due to her information about the manager’s reporting incentive parameter. If the analyst receives higher-quality information about the firm’s fundamental value $u$, then this decreases the magnitude of the first part of (3.4), the variance of the analyst’s expectation of the firm’s fundamental value from the firm’s true fundamental value, but again, there is an indirect effect on the second part through the effect on the equilibrium earnings association $\beta_r$, which decreases (as in part i) of proposition 2).

Again, the indirect effect reinforces the direct effect. If the analyst receives higher-quality information about the manager’s reporting incentive parameter $x$, then the direct effect is that the analyst’s perception of that parameter $\mu_{s_k}$ will be more variable due to the analyst’s better information, so the magnitude of the deviation of the forecast from the fundamental value increases. The indirect effect is through the effect on earnings association $\beta_r$, which also increases (for the reasons discussed in i)). Again, the two effects are in the same direction, but they are in the opposite direction of the higher-quality information about firm
value \((u)\). Essentially, better information about the manager’s price incentive parameter causes the analyst to move her forecast towards the part of the manager’s report driven by the manager’s reporting incentives and away from the underlying fundamental value of the firm.

The intuition for part iii) is similar; there is a direct effect and an indirect effect (through the effect on earnings association \(\beta_r\)). The reporting bias can be expressed as:

\[
(r-u) = -(1-\lambda_M)\mu_{uw} - \lambda_M \mu_{uw} + (1-\lambda_M) \frac{\beta_r}{\lambda_M c} \mu_{xw} + \frac{\beta_r}{c} x. \tag{3.5}
\]

Equation (3.5) shows that the reporting bias consists of two parts, like the forecast error: the difference between the analyst’s and the manager’s perception of the firm’s fundamental value and the difference between the manager’s reporting incentive parameter and the analyst’s perception of that parameter. The direct effect is straightforward: when the analyst receives better information about the firm’s fundamental value \(u\), it decreases the magnitude of the difference between the analyst’s and the manager’s perception of the firm’s fundamental value on the RHS of (3.5). Since the earnings response coefficient \(\beta_r\) also decreases, the indirect effect is that the coefficient on the difference between the manager’s reporting incentive parameter and the analyst’s perception of that parameter on the RHS of (3.5) decreases in magnitude. Therefore, both effects decrease the magnitude of reporting bias.

When the analyst receives better information about the manager’s reporting incentives, the direct effect is that the difference between the analyst’s perception of the manager’s reporting incentive parameter and the true value of that parameter decreases, thus decreasing the reporting bias. The indirect effect is that the earnings response coefficient \(\beta_r\) increases, which increases the coefficient on the difference between the manager’s reporting incentive parameter and the analyst’s perception of that parameter on the RHS of (3.5).
parameter and the analyst’s perception of that parameter. Part iii) of my Proposition 2 shows that the indirect effect dominates, and the overall effect of the analyst having higher-quality information about the manager’s reporting incentives is that it increases the manager’s reporting bias.

Part iv) is intuitive because, as discussed above, when the quality of the analyst’s information about firm value is higher, the analyst’s forecast in equation (3.2) is a better signal of the firm’s fundamental value \( u \), which results in a higher forecast response coefficient \( \beta_f \).

However, when the quality of the analyst’s signal about the manager’s reporting incentive parameter is higher, the analyst’s forecast in (3.2) is a worse signal of the firm’s fundamental value \( u \), which results in a lower forecast response coefficient \( \beta_f \). Part v) follows naturally from part iv) because the forecast and the report net of the forecast are independent in setting prices, as was discussed in part i) of Proposition 2.

Finally, regarding part vi) of proposition 2, better information about the manager’s reporting incentives has two opposing effects on investor residual uncertainty: one signal, \( f \), the forecast, declines in quality, while the other incremental signal, \( r - f \), the report net of the forecast, improves. The first causes residual uncertainty to increase, while the second reduces residual uncertainty. The result in proposition 2 indicates that it is possible for either effect to dominate. In particular, it is possible that the improvement in the incremental signal available from the financial report is outweighed by the decrease in quality of the analyst forecast. The rationale for the effect of better information about the firm’s fundamental value on investors’ residual uncertainty is similar, although the directions of the effects are opposite. Thus, for some (but not all) parameter values, it is possible for higher-quality analyst information (about either firm fundamental value or manager reporting incentives) to result in less overall information available to investors.
These results are consistent with Beyer’s (2008) result that forecast error decreases with the quality of the analyst’s information about firm performance, and they add the finding that it also decreases with the quality of the analyst’s information about the manager’s incentives. Beyer (2008) does not provide results regarding other parts of Proposition 2 because her investors can completely back out the manager’s reporting bias, and the analyst’s forecast becomes redundant after the report is released.

Proposition 2 shows that, when the analyst’s objective function is to minimize forecast error, the analyst’s signal about the manager’s incentives plays key roles in the firm’s information environment. It increases forecast accuracy, the forecast’s deviation from firm fundamentals, the manager’s reporting bias, and the earnings response coefficient; it decreases the forecast response coefficient and has a non-monotonic net effect on the firm’s information environment.

As was shown in Chapter 2, there are analytical analyst forecast studies that endogenize the analyst’s decision to acquire information and thus the quality of her information. For simplicity and tractability, I assume that the quality of the analyst’s information is exogenously given in both settings. Empirically, because the quality of the analyst’s information is not observable, there has been no direct study of the effect of the quality of the analyst’s information on the corporate information environment. However, if higher-quality information is an indicator of higher ability, Clement (1999), using experience as a proxy for ability, has shown that analysts of higher ability are more accurate, which in line with the prediction of part i) of this proposition. Some recent studies have used analysts’ corporate site visits as a proxy for their information acquisition activities to show that they bring information advantage and increase analysts’ forecast accuracy (Cheng et al., 2016; Han, Kong, & Liu, 2018). These empirical studies confirm part i) of Proposition 2. My model
predicts not only that the properties of the analyst forecast and the forecast response coefficient depend on the quality of the analyst’s information, but also that the properties of the manager’s report such as reporting bias, the earnings response coefficient, and the investor’s total information at hand after both the forecast and the report are released also depend on the quality of the analyst’s information due to the interaction of the analyst forecast and the manager’s report. These relationships have not been empirically tested.

3.4.2 The Quality of the Manager’s Signal ($\sigma_{ru}^2$)

This subsection examines how changing the quality of the manager’s signal, $\sigma_{ru}^2$, changes the analyst’s forecast accuracy, the forecast’s deviation from firm fundamental value, the manager’s reporting bias, the price response to the manager’s report ($\beta_r$) and the analyst’s forecast ($\beta_f$), and the investor’s residual uncertainty. The next proposition summarizes the key results:

**Proposition 3**: When the analyst’s objective is to maximize forecast accuracy ($k_u = 0$):

(i) Forecast error, the forecast’s deviation from the firm’s fundamental value, and the reporting bias all increase with the quality of the manager’s signal about firm value;

(ii) Firm price is more responsive to the financial report with a higher-quality manager’s signal about firm value;

(iii) The effect of the manager’s signal quality on the forecast response coefficient is ambiguous;

---

6 I have been unable to derive a result relating to residual uncertainty, although numerical analysis suggests that it decreases with the quality of the manager’s signal.
Proof: See the appendix.

Proposition 3 provides a comparison with the baseline results in Fischer and Verrecchia (2000) and finds that adding an analyst to the model does not change the effect of the manager’s information quality on the corporate information environment, although it does add something. Regarding the forecast error, and again referring to the components of the forecast error in equation (3.3),

\[
\frac{r - f}{\lambda_M} = (\mu_{u_M} - \mu_{u_x}) + \frac{1}{\lambda_M} \frac{\beta_c}{c} (x - \mu_{x_c}),
\]

(3.3)

a higher-quality manager’s value signal increases the magnitude of both the first part, the difference between the analyst’s and the manager’s perception of the firm’s fundamental value (the direct effect) because the manager’s signal is much better than the analyst’s signal, and of the second part, the earnings response coefficient (the indirect effect), as in Fischer and Verrecchia (2000). Therefore, a higher-quality manager’s value signal increases the magnitude of the forecast error. This result is an addition to Fischer and Verrecchia’s (2000) findings.

Regarding the deviation of the forecast from the firm’s fundamental value, if the manager receives a better signal about firm value, the first part of equation (3.4), the deviation of the analyst’s perception of the firm’s fundamental value from its true value, stays the same.

\[
u - f = (u - \mu_{u_a}) - \frac{\beta_c}{\lambda_M c} \mu_{x_a}.
\]

(3.4)

However, there is an indirect effect through the increased equilibrium earnings response coefficient \( \beta_c \). Since the forecast’s deviation from firm fundamentals increases in
equilibrium earnings association $\beta_r$ (see the expression for the forecast’s deviation from the firm fundamentals in the appendix, which is the squared expected difference between the forecast and the firm fundamental value that is conditional on the analyst’s value information), this means that a higher-quality manager’s signal increases the forecast’s deviation from firm fundamentals.

Regarding firm reporting bias, a higher-quality manager signal has two effects. There is a direct effect through an increase in the difference between the analyst’s and the manager’s perception of the firm’s fundamentals on the RHS of equation (3.5).

$$r - u = -(1 - \lambda_M) \mu_u - \lambda_M \mu_{u_a} + (1 - \lambda_M) \frac{\beta_r}{\lambda_M} \mu_{x_a} + \frac{\beta_r}{c} x.$$ (3.5)

There is also an indirect effect because the equilibrium earnings association $\beta_r$ increases. Therefore, both the direct effect and the indirect effect indicate that the manager having better value information increases reporting bias. This confirms the result in Fischer and Verrecchia (2000).

Part ii) of Proposition 3 is quite intuitive. It indicates that, the better the quality of the manager’s signal, the more precise the manager’s report is about firm fundamentals, and thus the greater the price response to the firm report. This is consistent with a similar result in Fischer and Verrecchia (2000).

Regarding the forecast response coefficient (part iii) of Proposition 3), the quality of the manager’s signal again has two effects. The direct effect is a result of the model assumption that the analyst’s value signal is a noisy version of the manager’s information. Thus, when the quality of the manager’s signal is better, the analyst has a better value signal and therefore a higher forecast response coefficient. The indirect effect is via the second term in equation
(3.2), the analyst’s distortion of the forecast due to her knowledge of the manager’s hidden reporting incentives.

\[ f = \mu_{x_a} + \frac{1}{\lambda_M} \beta_{c} \mu_{x_a} ; \]

(3.2)

Because the earnings response coefficient \( \beta_{c} \) is higher, there is more noise in the error component of the forecast. This offsets the increased variation in the first part of equation (3.2), the analyst’s perception of the firm’s fundamental value. Thus, the net effect of the forecast signal is unclear. My result indicates that it is can go either way, and neither always dominates.

Part iii) is an interesting result when considered together with the result that the forecast’s deviation from the firm fundamental value increases in the quality of the manager’s value signal in part i). This means that the forecast response coefficient could be higher when the forecast’s deviation from the firm fundamental value is also higher. This is a direct result of the model set-up that the analyst’s signal is a noisy version of the manager’s signal.\(^7\)

The quality of a manager’s value information could be seen as a proxy for his ability.\(^8\)

Empirically, Demerjian, Lev, Lewis, and McVay (2012) have shown that there is a positive relation between a manager’s ability and earnings quality. They proxy earnings quality by the likelihood to restate earnings. Their finding is only partially in line with my model’s predictions. If the earnings response coefficient can be taken as an indicator of earnings quality, as many empirical studies have argued, then my model also predicts that there is a positive relation between managerial ability and earnings quality. However, my model also

\(^7\) My results are tractable because of this model set-up. Completely independent signals of the analyst and the manager are too complicated to yield any results.

\(^8\) I see this as the manager’s ability to acquire information. As management is a key source of the analyst’s information, this justifies the earlier model set-up that the manager and the analyst have dependent signals.
predicts that higher managerial ability leads to higher reporting bias, which indicates lower earnings quality. My model further predicts that the properties of the analyst forecast and the forecast response coefficient also depend on the manager’s ability due to the fact that the manager cares about the analyst’s forecast, but this relationship has largely been dismissed in the empirical literature as far-fetched.

3.4.3 The Biasing Cost, \( c_u \)

This subsection examines how changing the biasing cost \( c_u \) changes the analyst’s forecast accuracy, the forecast’s deviation from firm fundamental value, firm reporting bias, the price responsiveness of the manager’s report \( (\beta_r) \) and the analyst’s forecast \( (\beta_f) \), and investors’ residual uncertainty. I summarize the results in the following proposition:

**Proposition 4:** When the analyst’s objective is to maximize forecast accuracy \( (k_u = 0) \):

i) Forecast accuracy is non-monotonic in biasing cost;

ii) The forecast’s deviation from firm fundamental value is lower for a higher biasing cost;

iii) Reporting bias is lower for higher biasing cost;

iv) Firm price is more responsive to the financial report for a higher biasing cost;

v) Firm price is more responsive to the analyst forecast for a higher biasing cost;

vi) Investors’ residual uncertainty is lower for a higher biasing cost.

Proof: See the appendix.

Proposition 4 can also be compared with Fischer and Verrecchia (2000) to produce consistent, additive results. Regarding forecast accuracy (part i) of Proposition 4), a higher biasing cost
(c_\alpha) only affects the second component of the forecast error in equation (3.3), the difference between the manager’s reporting incentives parameter and the analyst’s perception of that parameter.

\[
\frac{r-f}{\lambda_M} = (\mu_{\alpha \alpha} - \mu_{\alpha \alpha}) + \frac{1}{\lambda_M} \frac{\beta_r}{c} (x - \mu_{\alpha \alpha}).
\] (3.3)

It increases the earnings response coefficient \( \beta_r \) and the numerator in the second part of (3.3), but it also increases the denominator of the second part of (3.3), which is the biasing cost. Whether the biasing cost increases or decreases, the forecast accuracy depends on the relative magnitudes of these two effects.

Part ii) and part iii) are straightforward. The same denominator and numerator issue occurs for these in equations (3.4) and (3.5).

\[
u - f = (u - \mu_{\alpha \alpha}) - \frac{\beta_r}{\lambda_M} \mu_{\alpha \alpha}.
\] (3.4)

\[
r - u = -(1 - \lambda_M) \mu_{\alpha \alpha} - \lambda_M \mu_{\alpha \alpha} + (1 - \lambda_M) \frac{\beta_r}{\lambda_M} \mu_{\alpha \alpha} + \frac{\beta_r}{c} x.
\] (3.5)

However, when the biasing cost is higher, the manager weights his report more towards the true value. This causes both the forecast and the report to be closer to the true firm value. The ambiguous result in i) is because the forecast error depends on how much both the report and the forecast move toward the true firm value u.

Part iv) is intuitive. With a higher biasing cost, the financial report is closer to firm fundamentals and thus more informative. Therefore, a firm price is more responsive to the
financial report for a higher biasing cost. This confirms the result in Fischer and Verrecchia (2000).

Part v) is also straightforward. Since the financial report is closer to firm fundamentals with a higher biasing cost, the analyst forecast in turn will be closer to firm fundamentals to maximize forecast accuracy. Therefore, the analyst forecast is more informative, and firm price is more responsive to the analyst forecast for a higher biasing cost.

Finally, because a higher biasing cost results in both signals available to investors (\( f \) and \( r - f \)) being of higher quality, it also results in lower residual uncertainty for investors.

3.4.4 The Marginal Cost of the Manager’s Incentives to Be Close to the Analyst Forecast, \( c_f \)

This subsection examines how changing the marginal cost of the manager’s incentive to be close to analyst forecast \( c_f \) changes the analyst’s forecast accuracy, the forecast’s deviation from firm fundamental value, firm reporting bias, the responsiveness of the manager’s report \( (\beta_r) \) and the analyst’s forecast \( (\beta_f) \), and investors’ residual uncertainty. I summarize the results in the following proposition:

**Proposition 5:** When the analyst’s objective is to maximize forecast accuracy \( (k_u = 0) \):

i) Forecast accuracy increases in the marginal cost for the manager to be close to analyst forecast;

ii) The forecast’s deviation from firm fundamental value increases in the marginal cost for the manager to be close to analyst forecast;
iii) The manager’s reporting bias is non-monotonic in the marginal cost for the manager to be close to the analyst forecast;

iv) The firm’s price is more responsive to the financial report with a higher marginal cost for the manager to be close to the analyst forecast;

v) The firm’s price is less responsive to the analyst’s forecast with a higher marginal cost for the manager to be close to the analyst forecast;

vi) Investors’ residual uncertainty increases with the marginal cost for the manager to be close to the analyst forecast.

Proof: See the appendix.

Part i) is very intuitive as it implies that forecast accuracy increases in the marginal cost of the manager’s incentives to be close to analyst forecast. Holding everything else constant, the higher the cost of being away from analyst forecast, the closer the report is to the forecast, which means a smaller forecast error.

Part ii) means that, holding everything else constant, the forecast’s deviation from firm fundamentals increases with the importance the manager assigns to being close to the analyst forecast. Equation (3.4) shows there is only an indirect effect for \( c_f \) through its effect on equilibrium \( \beta_r \). Further, part iv) indicates that \( \beta_r \) increases with \( c_f \). Thus, from equation (3.4) the magnitude of the deviation is larger, which is due to the indirect effect on \( \beta_r \).

\[
 u - f = (u - \mu_{u_{\mu}}) - \frac{\beta_r}{\lambda_c} \mu_{x_{\mu}}. 
\]  
\( (3.4) \)
Together with part i), this predicts that the analyst is more accurate but deviates more from firm fundamentals when the manager attaches a higher weight to his incentive to be close to forecast.

Part iii) indicates that firm reporting bias is non-monotonic in the cost of the manager’s incentive to issue a report that is close to the analyst’s forecast. This means that a stronger incentive for the manager to avoid deviating from the analyst’s forecast decreases firm reporting bias for some parameter values, which is partially contrary to what has been documented in the empirical literature (Matsumoto, 2002). There are two effects at play. The direct effect is that a stronger incentive for the manager to be close to the analyst’s forecast provides more incentives to distort the report, and it introduces more reporting bias. The indirect effect causes the manager to place a relatively lower weight (compared to the manager’s incentive to be close to analyst forecast) on his bias due to market incentives, thus reducing firm reporting bias. The result in iii) indicates that, for some parameter values, the indirect effect dominates, and a stronger incentive for the manager to be close to the analyst forecast decreases firm reporting bias.

\[
\frac{r - f}{\lambda_M} = (\mu_{ae} - \mu_{e}) + \frac{1}{\lambda_M} \beta_r (x - \mu_{s}).
\]  

Equation (3.3) shows that the incremental signal provided by \( r-f \) is worse because \( \beta_r \) is higher, which seems to be a contradiction. However, it is because the investors have to divide \( r-f \) through by \( \lambda \) to obtain the incremental signal, and a higher \( c_f \) means a lower \( \lambda \). Two effects are active: the signal that can be extracted from \( r-f \) worsens, but the divisor used to back out that signal from \( r-f \) changes in a way that works in the opposite direction on \( \beta_r \). Here, the divisor (or “backing out” effect) dominates. The interesting result here, however, is
that the incremental signal available from the report (i.e., r-f) worsens, but the equilibrium $\beta_r$ is higher. That sounds a note of caution for using $\beta_r$ (or the earnings response coefficient) as a proxy for signal quality (or earnings quality) in empirical work.

Part v) shows that the analyst forecast has a lower price coefficient when the manager suffers a greater cost for his incentive to be close to analyst forecast.

$$f = \mu_u + \frac{1}{\lambda_M} \frac{\beta_r}{r} \mu_u;$$

Equation (3.2) indicates that the forecast is a poorer quality signal of the firm fundamental value $u$ (due to the indirect effect through $\beta_r$). Thus, the forecast response coefficient $\beta_f$ is lower.

Because both the forecast $f$ and the incremental report $r-f$ become worse signals with a higher marginal cost for the manager to be close to the analyst forecast, investors’ residual uncertainty increases in the marginal cost for the manager to be close to the analyst forecast.

The empirical literature generally agrees that firms manage their earnings to meet or beat analyst forecasts, but the relationship between earnings management and different strengths of the manager’s incentives to be close to analyst forecast has not yet been tested because the strengths of the manager’s incentives are unobservable. For similar reasons, the other relationships the model predicts in this section are not empirically tested.

3.5 Comparing the Two Extreme Cases

In this section, I compare the two extreme cases when the analyst cares only about the firm’s final payoff ($q=0$) or when the analyst cares only about forecast accuracy or closeness to the
manager’s report \( q = \frac{1}{\lambda_m} \). I examine the same six metrics investigated in section 3.4: the analyst’s forecast accuracy, the forecast’s deviation from the firm fundamental value, the manager’s reporting bias, price responsiveness to the manager’s report and the analyst’s forecast, and investors’ residual uncertainty. The following proposition summarizes the results:

**Proposition 6:** Holding all other parameters constant, compared with the case in which the analyst cares only about the firm’s final payoff \( q = 0 \), the case in which the analyst forecasts reported earnings \( q = \frac{1}{\lambda_m} \):

i) Has higher analyst forecast accuracy;

ii) Has higher forecast deviation from the firm fundamental value;

iii) Has greater reporting bias;

iv) Has a higher firm financial report response coefficient, but lower forecast response coefficient;

v) May have either higher or lower investors’ residual uncertainty.

As might be expected, part i) shows that when the analyst cares only about forecast accuracy, forecasts are more accurate than when the analyst cares only about being close to the firm’s fundamental value. While parts ii) and iii) indicate that both the forecast and the firm financial report deviate further from the firm’s fundamental value, the price responsiveness of the manager’s report is larger when the analyst’s objective is to minimize forecast error (deviation from the manager’s report) than when the analyst’s objective is to minimize the forecast’s deviation from the firm’s true value. This result is intuitive, coupled with the fact that the price responsiveness of the analyst’s forecast is smaller when the analyst’s objective
is to minimize forecast error than when it is to minimize forecast’s deviation from firm fundamentals. The reason behind my results is that the analyst’s forecast involves the manager’s reporting bias when the analyst’s objective is to minimize forecast error and is thus less price-responsive than when the objective is to minimize the forecast’s deviation from firm fundamentals. Because the information content of the analyst’s forecast pre-empts that of the manager’s report, the earnings association is higher when the analyst’s objective is to minimize forecast error than when her objective is to minimize the forecast’s deviation from firm fundamentals.

The following two equations, which correspond to equations (3.2) and (3.3), also illustrate this:

\[ f = \mu_{u}; \]  \hspace{1cm} (3.6)

\[ \frac{r - f}{\lambda_{M}} = (\mu_{u} - \mu_{u}) + \frac{\beta_{r} - \lambda}{\lambda_{M}}x. \]  \hspace{1cm} (3.7)

These two equations come from corollary (2) and show the forecast and forecast error divided by \( \lambda_{M} \) when the analyst’s objective is to minimize the forecast’s deviation from firm fundamentals. Compared with equation (3.2), equation (3.6) shows that the forecast is a better signal when the analyst’s objective is to minimize the forecast’s deviation from firm fundamentals than when her objective is to minimize the forecast’s deviation from the report. Therefore, the forecast response coefficient is higher when the analyst’s objective is to minimize the forecast’s deviation from firm fundamentals than it is to minimize the forecast’s deviation from the report. Because (3.2) and (3.3) are independent and (3.6) and (3.7) are also independent, a higher forecast response coefficient means that relatively less weight is put on the earnings in the market pricing equation, resulting in a lower forecast response coefficient.
The result in part ii) is intuitive, as the forecast’s deviation from the firm fundamentals is lower when the analyst’s objective is to minimize her forecast’s deviation from firm fundamentals than when it is to minimize the deviation from the firm report.

The result in part iii) is also expected because the analyst’s forecast acts as a constraining mechanism to curb the manager’s reporting bias when the analyst’s objective is to minimize the forecast’s deviation from the true value; however, it is likely to succumb to the manager’s reporting bias when the analyst’s objective is to minimize forecast error (deviation from the manager’s report).

Because the forecast is a better signal, but the incremental report signal is worse in the former case, I cannot determine the relative magnitudes of the investors’ residual uncertainty in the two cases.

3.6 Conclusions

In my model, the analyst’s forecast and the manager’s report interact to affect the corporate information environment. Three important features of my model are that the manager has hidden incentives in his reporting objective; the analyst’s information is classified into two components, one based on the firm’s final payoff, and the other is based on the manager’s hidden incentives; and the analyst’s objective is to minimize a weighted average of forecast error and the forecast’s deviation from the firm fundamentals. With these three important features of my model, I derive a number of interesting findings.

The incremental contribution of this chapter over that of Fischer and Verrecchia (2000) is that it finds consistent results about the manager and adds new insights about the effect of the presence of an analyst on the corporate information environment. I find that the presence of an analyst does not necessarily improve the corporate information environment. Both the
quality of the analyst’s value information and the quality of her information about the manager’s hidden reporting incentives have non-monotonic net effects on the corporate information environment. Specifically, when the quality of the analyst’s value information is high, the quality of the analyst’s value information has negative net effects on the corporate information environment, and the quality of the analyst’s incentives information has positive net effects on the corporate information environment. When the quality of the analyst’s value information is low, it has positive net effects on the corporate information environment, and the quality of the analyst’s incentives information has negative net effects on the corporate information environment. The economic intuition for the results is that better information about the manager’s reporting incentives has two opposing effects on investors’ residual uncertainty: one signal, $f$, the forecast, declines in quality, while the other incremental signal, $(r - f)$, the report net of the forecast, improves. The first causes residual uncertainty to increase, while the second reduces it. The above result indicates that it is possible for either effect to dominate. In particular, it is possible that the improvement in the incremental signal available from the financial report is outweighed by the decrease in the quality of the analyst forecast. The rationale for the effect of better information about the firm’s fundamental value on investors’ residual uncertainty is similar, although the directions of the effects are opposite. Thus, for some (but not all) parameter values, it is possible for higher-quality analyst information (about either firm fundamental value or manager reporting incentives) to result in less overall information available to investors.

My Chapter 3 is also related to Beyer (2008) because I largely examine the interaction between the analyst’s forecast and the manager’s report. As Beyer (2008) has argued, the analyst tries to forecast the manager’s report, and the manager tries to issue a report that is as

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9 This is equivalent to the investor’s residual uncertainty after both the analyst forecast and the manager’s report are released.

10 No presence of the analyst could be seen as an extreme case of the analyst having very bad information.
close to the analyst forecast as possible. In this sense, the analyst forecast and the manager’s report are interdependent and interact with each other. The incremental contribution of my Chapter 3 over Beyer (2008) is fourfold.

Firstly, I can derive investors’ residual uncertainty after both the analyst forecast and the manager’s report are released, which is the opposite of investors’ total information after receiving the two information signals and the same as the two information signals’ net effects on the corporate information environment. This metric is not possible under the frameworks of either Fischer and Verrecchia (2000) or Beyer (2008). Fischer and Verrecchia (2000) do not include an analyst, and Beyer’s (2008) investors can completely back out the analyst’s and the manager’s bias and therefore have information equivalent to that of the analyst and the manager. In my model, however, because of the manager’s hidden reporting incentives with respect to prices, investors cannot completely back out the manager’s bias, and it is thus meaningful to talk about investors’ total information available after the analyst forecast and the manager’s report are both released as an independent and different metric.

In addition to the non-monotonic net effects on the corporate information environment by the quality of the analyst’s information discussed previously, I derive two monotonic relationships between investors’ residual uncertainty and the manager’s incentives. Specifically, I show that the manager’s incentives to be close to the analyst forecast have negative effects on the total information investors have after both the analyst forecast and the manager’s report are issued. Second, I show that the manager’s incentives to be close to firm fundamentals have positive net effects on the corporate information environment. The economic intuition for the former finding is that the manager’s incentives to be close to the analyst forecast are incentives for distortion, and they make the report a worse signal of the firm’s fundamental value. By anticipating the manager’s incentives for distortion to be close
to the analyst forecast, the analyst can afford to distort her forecast away from firm fundamentals, and thus the analyst’s forecast also becomes a worse signal of the firm’s fundamental value due to the manager’s incentives to be close to the analyst forecast. Since both the analyst’s forecast and the manager’s report are worse signals of the firm’s fundamental value, the net effects of the manager’s incentives to be close to the analyst forecast on the corporate information environment are negative. The economic intuition for the latter finding is similar: the managers’ incentives to be close to firm fundamentals make the manager’s report contain less distortion from the firm’s fundamentals, and thus a better signal. Anticipating this, the analyst’s forecast is closer to the firm fundamentals, and it becomes a more informative signal. Since both the analyst’s forecast and the manager’s report are better signals due to the manager’s incentives to be close to the firm fundamentals, the net effects of these incentives on the corporate information environment are positive.

Second, this chapter is one of the first papers to investigate the analyst’s use of non-fundamental information. Information about firms’ fundamentals is an important input for analysts’ forecasts. However, a large amount of information available to analysts is not related to firms’ fundamentals. An alternative, potentially useful source of information for analysts concerns managers’ reporting incentives. Kim and Schroeder (1990) have empirically shown that analysts use managerial bonus incentives in forecasting earnings. This provides the most direct empirical support for my modelling decision. Givoly et al. (2011) have also shown that analysts can anticipate managers’ earnings management and account for it in their forecasts, thus providing indirect support that, when making forecasts, analysts use information about managers’ incentives to bias their financial reports.

I predict that, when the analyst’s objective is to forecast firm fundamentals, her information about the manager’s hidden reporting incentives has no effect; however, when the analyst’s
objective is to forecast the manager’s report, her information about the manager’s hidden reporting incentives plays a key role. It increases forecast accuracy, the forecast’s deviation from firm fundamentals, the manager’s reporting bias, and the earnings response coefficient, and it decreases the forecast response coefficient and has a non-monotonic net effect on the firm’s information environment.

A third incremental contribution of this chapter over Beyer (2008) is that I modify her suggestion that the analyst’s forecasting strategy depends on the manager’s incentives due to the interaction between the analyst’s forecast and the manager’s report. I find that the analyst’s forecasting strategy depends on the manager’s incentives even when the analyst does not care about the manager’s report, and the manager cares about the analyst forecast unilaterally. This can be seen from the fact that all comparative static results are qualitatively the same when the analyst forecasts firm fundamentals as when the analyst forecasts the manager’s report. The economic intuition is that there might still be implicit interdependence between the analyst’s forecast and the manager’s report when the analyst forecasts firm fundamentals because the manager also has incentives to be close to them.

Fourth, I compared the predictions of the model when the analyst has different incentives. The extant analyst forecast research has long recognized the importance of analysts’ incentives for the models’ predictions. For example, Beyer et al. (2010) have indicated that they expect models’ predictions to vary depending on what analysts’ incentives are assumed to be. However, little is known about how different analyst incentives affect model predictions. Here, I compare the model predictions of the analyst’s two different incentives: (1) the analyst forecasts the firm fundamentals; (2) the analyst forecasts the manager’s report. I find that all comparative static results are qualitatively the same in the two cases. In particular, although the firm financial report deviates further from the firm’s fundamental
value, the price responsiveness of the manager’s report is larger when the analyst’s objective is to minimize forecast error (deviation from the manager’s report) than when the goal is to minimize the forecast’s deviation from the firm’s true value. This result is highly intuitive coupled with the fact that the price responsiveness of the analyst’s forecast is lower when the analyst’s objective is to minimize forecast error than her objective is to minimize the forecast’s deviation from firm fundamentals. The reason behind our results is that the analyst’s forecast involves the manager’s reporting bias when the analyst’s objective is to minimize forecast error; thus, it is less price-responsive than when the analyst’s objective is to minimize the forecast’s deviation from the firm fundamentals. Because the information content of the analyst’s forecast pre-empts that of the manager’s report, the earnings association is higher when the analyst’s objective is to minimize the forecast error than when her objective is to minimize the forecast’s deviation from the firm fundamentals.

The reporting bias is higher when the analyst’s objective is to minimize forecast error than when it is to minimize deviation from the firm fundamentals because the analyst’s forecast acts as a constraining mechanism to curb the manager’s reporting bias when the analyst’s objective is to minimize forecast’s deviation from the true value; however, it is likely to succumb to the manager’s reporting bias when the analyst’s objective is to minimize the forecast error (deviation from manager’s report).

Because the forecast is a better signal, but the incremental report signal is worse in the former case than in the latter, I cannot determine the relative magnitudes of the investors’ residual uncertainty in the two cases.
Appendix

Proof of Proposition 1:

The numerator of the RHS is

\[ \lambda_M (\alpha_{y_u} - \alpha_{y_h})\sigma_u^2 + (1 - \gamma_1)\alpha_{y_h}\sigma_u^2 \]

The denominator of the RHS is

\[ \lambda_M^2 [(\alpha_{y_u} - \alpha_{y_h})\sigma_u^2 + (q\frac{\beta_c}{c})^2 \alpha_z\sigma_x^2] + (\frac{\beta_c}{c})^2 2(1 - \gamma_1)^2 [\alpha_{y_h}\sigma_u^2 + (q\frac{\beta_c}{c})^2 \alpha_z\sigma_x^2] \]

Meanwhile,

\[ 1 - \gamma_1 = \frac{q(\frac{\beta_c}{c})^2 \alpha_z\sigma_x^2 (1 - \lambda_M q)}{\alpha_{y_h}\sigma_u^2 + (q\frac{\beta_c}{c})^2 \alpha_z\sigma_x^2} = -\frac{k_x}{k_r} \frac{(\frac{\beta_c}{c})^2 \alpha_z\sigma_x^2}{\alpha_{y_h}\sigma_u^2 + (q\frac{\beta_c}{c})^2 \alpha_z\sigma_x^2} \]

First, note that \( 1 - \gamma_1 \) decreases in \( (\frac{\beta_c}{c})^2 \) (i.e., becomes more negative), which means that the numerator of the RHS decreases in \( (\frac{\beta_c}{c})^2 \) (and in \( \beta_c \)).

Thus, to prove a unique equilibrium, all that is needed is to show that the denominator of the RHS increases. (This is because it is easy to show that RHS > 0 when \( (\frac{\beta_c}{c})^2 = 0 \) and RHS goes to zero as \( (\frac{\beta_c}{c})^2 \to \infty. \))
Take the derivative of the denominator of RHS with respect to \( \left( \frac{\beta}{c} \right)^2 \):

\[
\frac{\partial \text{denominator}}{\partial \left( \frac{\beta}{c} \right)^2} = \lambda_M^2 q^2 \alpha_c \sigma_x^2 + \sigma_x^2 - 2\lambda_M q \alpha_c \sigma_x^2 - 2(1-\gamma_1) \frac{\partial}{\partial \left( \frac{\beta}{c} \right)^2} \left[ \alpha_y \sigma_u^2 + (q \frac{\beta}{c})^2 \alpha_c \sigma_x^2 \right] - (1-\gamma_1)^2 q^2 \alpha_c \sigma_x^2
\]

\[
= \lambda_M^2 q^2 \alpha_c \sigma_x^2 + \sigma_x^2 - 2\lambda_M q \alpha_c \sigma_x^2 + 2(1-\gamma_1) \frac{k_u}{k_r} q^2 \alpha_c \sigma_x^2 (1 + \frac{k_u}{k_r} (1-\gamma_1)) - (1-\gamma_1)^2 q^2 \alpha_c \sigma_x^2
\]

\[
= \lambda_M^2 q^2 \alpha_c \sigma_x^2 + \sigma_x^2 - 2\lambda_M q \alpha_c \sigma_x^2 + 2(1-\gamma_1) \frac{k_u}{k_r} q^2 \alpha_c \sigma_x^2 + (1-\gamma_1)^2 q^2 \alpha_c \sigma_x^2
\]

\[
= \sigma_x^2 + (\lambda_M q - 1)^2 \alpha_c \sigma_x^2 - \alpha_c \sigma_x^2 + (1-\gamma_1)^2 q^2 \alpha_c \sigma_x^2 (2 \frac{k_u}{k_r} + (1-\gamma_1))
\]

\[
= (1-\alpha_c^2) \sigma_x^2 + \alpha_c \sigma_x^2 [(\lambda_M q - 1)^2 + (1-\gamma_1)^2 q^2 (2 \frac{k_u}{k_r} + (1-\gamma_1))]
\]

\[
\geq 0
\]

because \( (\lambda_M q - 1)^2 = \left( \frac{k_u}{k_u + k_r \lambda_M} \right)^2 ; (1-\gamma_1)^2 q^2 (2 \frac{k_u}{k_r} + (1-\gamma_1)) \geq -q^2 \left( \frac{k_u}{k_r} \right)^2 = -\left( \frac{k_u}{k_u + k_r \lambda_M} \right)^2 \)

This proves that the denominator increases in \( \square \), and the RHS decreases in \( \square \).

Therefore, we have one unique equilibrium.

Proof of Proposition 2:

From Corollary 1 (minimizing forecast error), we have

(a)

\[
E[(r - f)^2] \quad q^{-1} \frac{1}{\theta_u} = \lambda_M^2 (\alpha_y \sigma_u^2 - \alpha_y \sigma_x^2) + (1-\alpha_c) (\frac{\beta}{c})^2 \sigma_x^2
\]

\[
\frac{\partial E[(r - f)^2]}{\partial \sigma_x^2} \quad q^{-1} \frac{1}{\theta_u} = \lambda_M^2 \alpha_y \sigma_x^2 + 2 \frac{\beta}{c} \frac{\partial \beta}{\partial \sigma_x^2} (1-\alpha_c) \sigma_x^2 > 0
\]

(1)
\[
\frac{\partial E[(r-f)^2]}{\partial \sigma^2_{\delta}}_{y_A}^{-1} = 2 \frac{\beta_{\delta}}{c^2} \frac{\partial \beta_{\delta}}{\partial \sigma^2_{\delta}} (1-\alpha_{\delta}) \sigma^2_{\delta} + \left( \frac{\beta_{\delta}}{c} \right)^2 \alpha_{\delta}^2 > 0 \]  \hspace{1cm} (2)

(b)

\[
E[(f-u)^2 \mid y_A]^{-1} = \left( \frac{1}{\lambda_M} \frac{\beta_c}{c} \right)^2 (\alpha_{\delta} \sigma^2_{\delta} + \mu_{\delta}^2).
\]

\[
\frac{\partial E[(f-u)^2 \mid y_A]}{\partial \sigma^2_{\alpha}}_{y_A}^{-1} = \left( \frac{1}{\lambda_M} \frac{1}{c} \right)^2 2 \beta_{\alpha} \frac{\partial \beta_{\alpha}}{\partial \sigma^2_{\alpha}} (\alpha_{\alpha} \sigma^2_{\alpha} + \mu_{\alpha}^2) > 0 \]  \hspace{1cm} (3)

\[
\frac{\partial E[(f-u)^2 \mid y_A]}{\partial \sigma^2_{\delta}}_{y_A}^{-1} = \left( \frac{1}{\lambda_M} \frac{1}{c} \right)^2 2 \beta_{\delta} \frac{\partial \beta_{\delta}}{\partial \sigma^2_{\delta}} (\alpha_{\delta} \sigma^2_{\delta} + \mu_{\delta}^2) - \left( \frac{1}{\lambda_M} \frac{\beta_{\delta}}{c} \right)^2 \alpha_{\delta}^2 < 0 \]  \hspace{1cm} (4)

(c)

\[
E[(r-u)^2 \mid y_M]_{y_M}^{-1} = (1-\lambda_M)^2 (\alpha_{y_M} - \alpha_{y_M}) \sigma^2_{y_M} + \left( \frac{\beta_{y_M}}{c} \right)^2 \left[ \frac{1}{\lambda_M^2} \alpha_{y_M} \sigma^2_{y_M} + (1-\alpha_{y_M}) \sigma^2_{y_M} + \frac{1}{\lambda_M} \mu_{y_M}^2 \right].
\]

\[
\frac{\partial E[(r-u)^2 \mid y_M]}{\partial \sigma^2_{\alpha}}_{y_M}^{-1} = (1-\lambda_M)^2 \alpha_{\alpha}^2 + \frac{2 \beta_{\alpha}}{c^2} \frac{\partial \beta_{\alpha}}{\partial \sigma^2_{\alpha}} \left[ \frac{1}{\lambda_M^2} \alpha_{\alpha} \sigma^2_{\alpha} + (1-\alpha_{\alpha}) \sigma^2_{\alpha} + \frac{1}{\lambda_M} \mu_{\alpha}^2 \right] > 0 \]  \hspace{1cm} (5)

\[
\frac{\partial E[(r-u)^2 \mid y_M]}{\partial \sigma^2_{\delta}}_{y_M}^{-1} = \frac{2 \beta_{\delta}}{c^2} \frac{\partial \beta_{\delta}}{\partial \sigma^2_{\delta}} \left[ \frac{1}{\lambda_M^2} \alpha_{\delta} \sigma^2_{\delta} + (1-\alpha_{\delta}) \sigma^2_{\delta} + \frac{1}{\lambda_M} \mu_{\delta}^2 \right] + \left( \frac{\beta_{\delta}}{c} \right)^2 (1-\lambda_M)^2 \alpha_{\delta}^2 < 0 \]  \hspace{1cm} (6)

(d)
\[
\frac{\partial \beta_i}{\partial \sigma_{e_i}^2} = \frac{\lambda_M \alpha^2 \lambda_M (1 - \lambda_M \beta_i)}{3(\beta_i \kappa_i)^2 (1 - \alpha_i) \sigma^2_i + \lambda^2_M (\alpha_{y_i} - \alpha_{y_i}) \sigma^2_i} > 0
\]  
(7)

\[
\frac{\partial \beta_i}{\partial \sigma^2_S} = \frac{-\beta_i^3}{3(\beta_i \kappa_i)^2 (1 - \alpha_i) \sigma^2_i + \lambda^2_M (\alpha_{y_i} - \alpha_{y_i}) \sigma^2_i} < 0
\]  
(8)

\[
\frac{\partial \beta_i}{\partial \sigma_{e_i}^2} = \frac{(\beta_i - 1) \alpha^2 \lambda_M - \frac{2}{\alpha_i} \frac{\beta_i}{\sigma_i} \frac{\partial \beta_i}{\partial \sigma^2_{e_i}} \alpha_i \sigma^2_i}{\alpha_{y_i} \sigma^2_u + \frac{1}{\lambda_M} \frac{\beta_i}{\sigma_i} \frac{\partial \beta_i}{\partial \sigma^2_S} \alpha_i \sigma^2_i} < 0
\]  
(9)

\[
\frac{\partial \beta_i}{\partial \sigma^2_S} = \frac{\beta_i \alpha^2 \lambda_M - \frac{2}{\alpha_i} \frac{\beta_i}{\sigma_i} \frac{\partial \beta_i}{\partial \sigma^2_{e_i}} \alpha_i \sigma^2_i}{\alpha_{y_i} \sigma^2_u + \frac{1}{\lambda_M} \frac{\beta_i}{\sigma_i} \frac{\partial \beta_i}{\partial \sigma^2_S} \alpha_i \sigma^2_i} > 0
\]  
(10)

(f)

\[q = \frac{1}{\lambda_M}
\]

When \(q = \frac{1}{\lambda_M}\),

\[
\text{var}(u | r, f) = \sigma^2_u - \beta_i \lambda_M (\alpha_{y_i} - \alpha_{y_i}) \sigma^2_u - \beta_i \alpha_{y_i} \sigma^2_u.
\]

Therefore, we have
\[ \frac{\partial \text{var}(y | r, f)}{\partial \sigma_{\epsilon_a}^2} = -\lambda_M (\alpha_{\epsilon_a} - \alpha_{\gamma_a}) \frac{\partial \beta_f}{\partial \sigma_{\epsilon_a}^2} + \beta_f \lambda_M \alpha_{\gamma_a}^2 \]
\[ \frac{\partial \text{var}(y | r, f)}{\partial \sigma_{\epsilon_a}^2} = -\lambda_M (\alpha_{\epsilon_a} - \alpha_{\gamma_a}) \frac{\partial \beta_f}{\partial \sigma_{\epsilon_a}^2} + \beta_f \lambda_M \alpha_{\gamma_a}^2. \]

It can be shown that, when \( \sigma_{\epsilon_a}^2 = 0, \alpha_{\gamma_a} = \alpha_{\gamma_a} \), we have

\[ \frac{\partial \text{var}(y | r, f)}{\partial \sigma_{\epsilon_a}^2} = -\lambda_M (\alpha_{\epsilon_a} - \alpha_{\gamma_a}) \frac{\partial \beta_f}{\partial \sigma_{\epsilon_a}^2} + \beta_f \lambda_M \alpha_{\gamma_a}^2 > 0 \]
\[ \frac{\partial \text{var}(y | r, f)}{\partial \sigma_{\epsilon_a}^2} = -\lambda_M (\alpha_{\epsilon_a} - \alpha_{\gamma_a}) \frac{\partial \beta_f}{\partial \sigma_{\epsilon_a}^2} + \beta_f \lambda_M \alpha_{\gamma_a}^2 < 0 \]

When \( \sigma_{\epsilon_a}^2 = +\infty, \alpha_{\gamma_a} = 0 \), we have

\[ \frac{\partial \text{var}(y | r, f)}{\partial \sigma_{\epsilon_a}^2} = -\lambda_M \alpha_{\gamma_a} \sigma_u^2 \frac{\partial \beta_f}{\partial \sigma_{\epsilon_a}^2} < 0 \]
\[ \frac{\partial \text{var}(y | r, f)}{\partial \sigma_{\epsilon_a}^2} = -\lambda_M \alpha_{\gamma_a} \sigma_u^2 \frac{\partial \beta_f}{\partial \sigma_{\epsilon_a}^2} > 0 \]

This completes the proof that \( \frac{\partial \text{var}(y | r, f)}{\partial \sigma_{\epsilon_a}^2} \), \( \frac{\partial \text{var}(y | r, f)}{\partial \sigma_{\epsilon_a}^2} \) are non-monotonic or ambiguous in signs.

Proof of Proposition 3:

From Corollary 1 (minimizing forecast error), we have
\[
\frac{\partial \beta_f}{\partial \sigma_{u}^2} = \frac{-\lambda_M^2 (\alpha_{y_m}^2 - \alpha_{y_u}^2)(1 - \beta, \lambda_M)}{3(\frac{\beta_f}{c})^2 (1 - \alpha_z)\sigma_i^2 + \lambda_M^2 (\alpha_{y_m} - \alpha_{y_u})}\sigma_u^2 < 0
\]  

(11)

\[
\frac{\partial \beta_f}{\partial \sigma_{e_m}^2} = \frac{(\beta_f - 1)\alpha_{y_u}^2 - 2 \beta_f \frac{\partial \beta_f}{\partial \sigma_{e_m}^2} \alpha_{z} \sigma_i^2}{\alpha_{y_u}^2 + 1 \left(\frac{\beta_f}{c}\right)^2 \alpha_{z} \sigma_i^2} < 0
\]  

(12)

\[
\frac{\partial E[(r - f)^2]}{\partial \sigma_{e_m}^2} = \frac{1}{\lambda_M} \left(\lambda_M^2 (\alpha_{y_m}^2 - \alpha_{y_u}^2) + 2 \frac{\beta_f}{c^2} \frac{\partial \beta_f}{\partial \sigma_{e_m}^2} (1 - \alpha_z)\sigma_i^2\right) < 0
\]  

(13)

\[
\frac{\partial E[(f - u)^2 \mid y_A]}{\partial \sigma_{e_m}^2} = \left(\frac{1}{\lambda_M c^2}\right)^2 2 \beta_f \frac{\partial \beta_f}{\partial \sigma_{e_m}^2} (\alpha_{y_u} \sigma_i^2 + \mu_z^2) < 0
\]  

(14)

\[
\frac{\partial E[(r - \mu_u)^2]}{\partial \sigma_{e_m}^2} = (1 - \lambda_M)^2 (\alpha_{y_m}^2 - \alpha_{y_u}^2) + 2 \frac{\beta_f}{c^2} \frac{\partial \beta_f}{\partial \sigma_{e_m}^2} \left[\frac{1}{\lambda_M} \alpha_{y_u} \sigma_i^2 + (1 - \alpha_z)\sigma_i^2 + \frac{1}{\lambda_M} \mu_z^2\right] < 0
\]  

(15)

\[
\frac{\partial \text{var}(u \mid r, f)}{\partial \sigma_{e_m}^2} = \lambda_M (\alpha_{y_m} - \alpha_{y_u})[-\sigma_u^2 \frac{\partial \beta_f}{\partial \sigma_{e_m}^2} \beta, \lambda_M (\alpha_{y_m} + \alpha_{y_u})] + \alpha_{y_u} (\beta_f \alpha_{y_u} - \sigma_u^2 \frac{\partial \beta_f}{\partial \sigma_{e_m}^2})
\]

(16)

Proof of Proposition 4:

From Corollary 1 (minimizing forecast error), we have

\[
\frac{\partial \beta_f}{\partial c_u} = \frac{c(\lambda + 1 - 2 \beta_f \lambda)(\alpha_{y_m} - \alpha_{y_u})\sigma_u^2}{3\beta_f^2 (1 - \alpha_z)\sigma_i^2 + c_u^2 (\alpha_{y_m} - \alpha_{y_u})\sigma_u^2} > 0
\]  

(17)
\[ \frac{\partial \beta}{\partial c_u} = - \frac{2\beta f}{\lambda M c^2} \left( \frac{\partial \beta}{\partial c_u} - \frac{\beta f}{c} \right) \alpha_z \sigma^2_x > 0 \]  
(18)

\[ \frac{\partial E[(r-f)^2]}{\partial c_u} = 2\lambda \left( \frac{c_f}{c_u + c_f} \right)^2 (\alpha_y - \alpha_{y, u}) \sigma^2_u + 2 \frac{\beta f}{c^2} \left( \frac{\partial \beta}{\partial c_u} - \frac{\beta f}{c} \right) (1 - \alpha_z) \sigma^2_x > 0 \]  
(19)

\[ \frac{\partial E[(f-u)^2 | y_A]}{\partial c_u} = \left( \frac{1}{\lambda_M} \right)^2 \left( \frac{2\beta f}{\lambda_M} \left( \frac{\partial \beta}{\partial c_u} - \frac{\beta f}{c} \right) (\alpha_z \sigma^2_x + \mu^2_z) < 0 \right) \]  
(20)

\[ \frac{\partial E[(r-\mu_{y,u})^2]}{\partial c_u} = -2(1 - \lambda_M) \left( \frac{1}{c} \frac{c_u (\alpha_y - \alpha_{y, u}) \sigma^2_u + 2 \frac{\beta f}{\lambda_M} \left( \frac{\partial \beta}{\partial c_u} - \frac{\beta f}{c} \right) (\alpha_z \sigma^2_x + \lambda^3_M (1 - \alpha_z) \sigma^2_x + \mu^2_z) < 0 \right) \]  
(21)

\[ \frac{\partial \text{var}(u | r, f)}{\partial c_u} = -\lambda_M (\alpha_{y, u} - \alpha_y) \sigma^2_u \frac{\partial \beta}{\partial c_u} - \alpha_{y, u} \sigma^2_u \frac{\partial \beta}{\partial c_u} < 0 \]  
(22)

Proof of Proposition 5:

From Corollary 1 (minimizing forecast error), we have

\[ \frac{\partial \beta}{\partial c_f} = \frac{c_u (\alpha_{y, u} - \alpha_y) \sigma^2_u}{3\beta f (1 - \alpha_z) \sigma^2_x + c^2 f (\alpha_{y, u} - \alpha_y) \sigma^2_u} > 0 \]  
(23)

\[ \frac{\partial \beta}{\partial c_f} = -\frac{2\beta f}{\lambda^2 M c^2} \left( \frac{\partial \beta}{\partial c_f} - \frac{\beta f}{c} \right) \frac{\alpha_z \sigma^2_x}{\alpha_{y, u} \sigma^2_u + \left( \frac{\beta f}{c} \right)^2} < 0 \]  
(24)

\[ \frac{\partial E[(r-f)^2]}{\partial c_f} = -2\lambda \left( \frac{c_u}{c_u + c_f} \right)^2 (\alpha_{y, u} - \alpha_y) \sigma^2_u + 2 \frac{\beta f}{c^2} \left( \frac{\partial \beta}{\partial c_f} - \frac{\beta f}{c} \right) (1 - \alpha_z) \sigma^2_x < 0 \]  
(25)
\[
\frac{\partial E[(f - u)^2]}{\partial c_f} \big|_{y_A} = \frac{1}{c_u}^2 \beta \frac{\partial \beta_u}{\partial c_f} (\alpha \sigma_u^2 + \mu_u) > 0
\]
(26)

\[
\frac{\partial E[(r - \mu_u)^2]}{\partial c_f} \big|_{y_A} = 2(1 - \lambda_u) \frac{\lambda_u}{c_u} \frac{1}{c_u} (\alpha \sigma_u^2 + \mu_u) + 2 \lambda_u \frac{\partial \beta_u}{\partial c_f} (\alpha \sigma_u^2 + \mu_u) - 2 \beta_u^2 (1 - \alpha \sigma_u^2)
\]
(27)

\[
\frac{\partial \var{u}{r,f}}{\partial c_f} \big|_{y_A} = - (\alpha \sigma_u^2 + \mu_u) \frac{\partial \lambda u \beta_u}{\partial c_f} - \alpha \sigma_u^2 \frac{\partial \beta_u}{\partial c_f} > 0
\]
(28)

**Proof of Proposition 6:**

(a) Market reaction to report

When \( q = 0 \),

\[
\text{Numerator} = \lambda_u (\alpha \sigma_u^2 + \mu_u)
\]

\[
\text{Deno} = \min{\alpha \sigma_u^2 + \mu_u}
\]

When \( q = \frac{1}{\lambda_M} \),

\[
\text{Numerator} = \lambda_M (\alpha \sigma_u^2 + \mu_u)
\]

\[
\text{Deno} = \min{\alpha \sigma_u^2 + \mu_u}
\]

Because \( \text{numerator}_{q=0} = \text{numerator}_{q=\frac{1}{\lambda_M}} \), \( \text{deno}_{q=0} > \text{deno}_{q=\frac{1}{\lambda_M}} \), we have

\[
\text{RHS}_{q=0} < \text{RHS}_{q=\frac{1}{\lambda_M}}, \beta_{r-q=0} < \beta_{r-q=\frac{1}{\lambda_M}}.
\]

85
We also have that, when $q=0$, $\beta_j = 1$. However, when

$$q = \frac{1}{\lambda_M}, \beta_j = \frac{\alpha_{\gamma_s} \sigma_{\gamma_s}^2}{\alpha_{\gamma_s} \sigma_{\gamma_s}^2 + \left(\frac{\beta_c}{c \lambda_M}\right)^2 \alpha_{\gamma_c} \sigma_{\gamma_c}^2} < 1.$$ 

We thus prove that $\beta_{j-q=0} > \beta_{j-q=\frac{1}{\lambda_M}}$.

(b) Manager’s bias

When $q = 0$, we have

$$E[(r - \mu_{uv})^2] = (1 - \lambda_M)^2 (\alpha_{\gamma_u} - \alpha_{\gamma_x}) \sigma_{\gamma_u}^2 + \left(\frac{\beta_c}{c}\right)^2 (\sigma_{\gamma_c}^2 + \mu_{\gamma_c}^2).$$

When $q = \frac{1}{\lambda_M}$, we have

$$E[(r - \mu_{uv})^2] = (1 - \lambda_M)^2 (\alpha_{\gamma_u} - \alpha_{\gamma_x}) \sigma_{\gamma_u}^2 + \left(\frac{\beta_c}{c}\right)^2 \left[\frac{1}{\lambda_M^2} \alpha_{\gamma_c} \sigma_{\gamma_c}^2 + (1 - \alpha_{\gamma_x}) \sigma_{\gamma_x}^2 + \frac{1}{\lambda_M^2} \mu_{\gamma_x}^2\right].$$

Clearly, the reporting bias for $q=0$ is lower than the reporting bias when $q = \frac{1}{\lambda_M}$.

(c) Analyst’s Forecast Accuracy

When $q = 0$, we have

$$E[(r - f)^2] = \lambda_M^2 (\alpha_{\gamma_x} - \alpha_{\gamma_s}) \sigma_{\gamma_u}^2 + \left(\frac{\beta_c}{c}\right)^2 (\sigma_{\gamma_c}^2 + \mu_{\gamma_c}^2)$$
When \( q = \frac{1}{\lambda_M} \), we have

\[
E[(r - f)^2] = \lambda_M^2 (\alpha_{\gamma_M} - \alpha_{\gamma_A}) \sigma_u^2 + (1 - \alpha_z) (\frac{\beta}{c})^2 \sigma_z^2
\]

It can be shown that we have

\[
\frac{\partial E[(r - f)^2]}{\partial \alpha_z} \bigg|_{q=0} = 0,
\]

\[
\frac{\partial E[(r - f)^2]}{\partial \alpha_z} \bigg|_{q=0} = \frac{1}{\lambda_M} \left( -\frac{\beta}{c} \right)^2 \sigma_x^2 + 2(1 - \alpha_z) \frac{\beta}{c^2} \sigma_x^2 \left( -\frac{\beta}{c} \right)^2 (1 - \alpha_z) \sigma_z^2 + \lambda_M^2 (\alpha_{\gamma_M} - \alpha_{\gamma_A}) \sigma_u^2
\]

\[
= \left( \frac{\beta}{c} \right)^2 \sigma_x^2 \left[ \frac{2(1 - \alpha_z) \sigma_z^2}{3\left( \frac{\beta}{c} \right)^2 (1 - \alpha_z) \sigma_z^2 + \lambda_M^2 (\alpha_{\gamma_M} - \alpha_{\gamma_A}) \sigma_u^2} - 1 \right]
\]

\[
< 0
\]

It can also be shown that, when \( \alpha_z = 0 \), we have

\[
E[(r - f)^2] \bigg|_{q=0} > E[(r - f)^2] \bigg|_{q=\frac{1}{\lambda_M}}
\]

Since \( E[(r - f)^2] \bigg|_{q=\frac{1}{\lambda_M}} \) decreases in \( \alpha_z \) and \( E[(r - f)^2] \bigg|_{q=0} \) is constant with regard to \( \alpha_z \), we therefore have the above relationship for all values of \( \alpha_z \).

(d) Forecast’s Deviation from Firm Fundamentals

We have

\[
E[(f - u)^2 \mid y_A]_{q=0} < E[(f - u)^2 \mid y_A]_{q=\frac{1}{\lambda_M}}.
\]
vi) Investor’s Residual Uncertainty

When \( q = 0 \),

\[
\text{var}(u \mid r, f) = \sigma_u^2 - \beta_f \lambda_M (\alpha_{y_u} - \alpha_{y_x}) \sigma_u^2 - \alpha_{y_x} \sigma_u^2.
\]

When \( q = \frac{1}{\lambda_M} \),

\[
\text{var}(u \mid r, f) = \sigma_u^2 - \beta_f \lambda_M (\alpha_{y_u} - \alpha_{y_x}) \sigma_u^2 - \beta_f \alpha_{y_x} \sigma_u^2.
\]

Because \( \beta_{r-u \mid q = 0} < \beta_{r-u \mid q = \frac{1}{\lambda_M}} \), I cannot determine the relative magnitudes of the investors’ residual uncertainty in the two cases.
Chapter 4: Analyst-Investor Interest Alignment and Financial Reporting

4.1 Introduction

This chapter studies a similar question to that of Chapter 3: How does the presence of an analyst affect the corporate information environment when both the analyst forecast and the manager’s financial report are endogenously chosen? This chapter differs from Chapter 3, however, with regard to the analyst’s incentives. In Chapter 3, the analyst is motivated about forecast informativeness as well as forecast accuracy. In this chapter, I allow the analyst to first release her forecast to a subscribed investor, who exits the market in the next time period, for a subscription fee, and then she releases it to all investors. The analyst is thus featured to care about the subscribed investor’s trading profits as well as the forecast accuracy.

Beyer et al. (2010) have listed two analytical analyst papers that have the client’s utility or profits as objectives: Irvine, Lipson, and Puckett (2006) and Guttman (2010). The objective of caring about the client’s utility or profits is to capture the real-world phenomenon that analysts first release their forecasts to institutional investors for a subscription fee and then to the general public. However, Irvine et al. (2006) have focused on analyst recommendations instead of forecasts, and Guttman (2010) has studied a different research question, i.e., the timing of analysts’ earnings forecasts.

I choose this objective for my analyst with a view to studying whether an additional incentive to distort the analyst’s forecast, such as a subscribed investor’s profits, impacts the analyst’s forecasting strategy as well as the manager’s reporting strategy when the analyst forecast and the manager’s report interact. An important finding of Beyer (2008) is that the analyst’s reporting strategy depends on the manager’s incentives due to the interdependency between
the analyst’s forecast and the manager’s report. In Chapter 3, I showed that the relationship remains when the analyst does not care about the manager’s report, but the manager’s report is unilaterally close to the analyst forecast. This chapter complements Beyer (2008) by showing how the properties of the manager’s report depend on the incentives of the analyst when the analyst and the manager interact.

Specifically, my model has four periods and five players: the analyst, the manager, the subscribed investor, all other investors, and the market maker. At time $t=1$, the analyst observes two signals, one about firm value and the other about the manager’s hidden price incentives, and issues a private forecast exclusively to the subscribed investor. At time $t=2$, the analyst releases the forecast to all investors, and the subscribed investor exits the market. At time $t=3$, the manager observes the firm value and issues a report to the public. At time $t=4$, the firm value is realized. I derive the equilibrium for this game and conduct comparative statics analysis to derive testable, empirical relationships.

There are four major findings from this study. First, the manager is found to distort his report in the same direction as the forecast distortion due to the analyst’s incentives to increase the subscribed investor’s expected trading profits. Further analysis shows that the distortion in the report due to the manager’s incentives to care about being close to the analyst forecast, the “cosmetic” effect in the forecast error; the forecast error; and the reporting bias all depend on the forecast distortion due to the analyst’s incentives to increase the subscribed investor’s profits. The dependence on the analyst’s incentives results from the interaction of the incentives of the analyst and the manager. This finding complements Beyer’s (2008) suggestion that the analyst’s forecasting strategy depends on the manager’s incentives due to the interaction between the analyst’s forecast and the manager’s report.
Second, both the forecast distortion due to the analyst’s incentives to increase her client’s expected trading profits and the forecast error are non-monotonic in the quality of the analyst’s value information. The intuition is similar: better analyst’s value information increases the analyst’s opportunity cost to not minimize the forecast error, but it also increases the attractiveness of the distortion due to her incentive to maximize the subscribed investor’s trading profits because she is better able to move prices. Either of the two countervailing effects could dominate, and this leads to non-monotonicity.

Third, I confirm the finding in Chapter 3 that a higher earnings response coefficient does not necessarily mean higher reporting quality. It is possible for the price response coefficient to increase even as the quality of the information signal that can be extracted from the report worsens. This sounds a note of caution to empirical work that uses the ERC as an indicator of earnings quality; in this version of the model, a higher ERC need not mean a higher-quality report.

Fourth, the distortion coefficient on the analyst forecast is non-monotonic in the quality of the analyst’s value information. The analyst’s distortion coefficient of her expected forecast increases (decreases) with the quality of the analyst’s value information when the earnings response coefficient is high (low). Because the earnings response coefficient always decreases in the quality of the analyst’s value information, this also means that the analyst’s distortion coefficient of her expected forecast increases (decreases) with the quality of the analyst’s value information when the information is coarse (fine). This happens because of the dual role of the analyst’s objective function to care about the subscribing investor’s trading profits and forecast accuracy, as well as the interaction between the analyst forecast and the manager’s report.
This chapter is organized as follows. Section 4.2 establishes the model, section 4.3 solves the equilibrium, section 4.4 derives comparative static results, and section 4.5 concludes.

4.2 Model

In our model, there is a single firm in the economy with a final payoff \( u = u_1 + u_2 \), where \( u \) has a prior normal and independent distribution with mean zero and variance \( \sigma_u^2 \). We also assume that \( u_1 \) and \( u_2 \) are normally and independently distributed with means of zero and variances of \( \alpha_u \sigma_u^2 \) and \( (1 - \alpha_u) \sigma_u^2 \), respectively, with \( \alpha_u \in [0,1] \). The distributions of the firm’s final payoff \( u \) and its components are common knowledge. There are five players and four dates in the model. Figure 1 presents the timeline.

\[
\begin{array}{c|c|c|c|c}
 t=1 & t=2 & t=3 & t=4 \\
\hline
\text{Analyst sees } u_1 \text{ and } x_1 \text{ and releases a private forecast } f \text{ public, and the informed trader exits the market.} & \text{Manager sees } u \text{ and releases public report } r. \text{ and the firm’s final payoff is realized.} & \\
\end{array}
\]

Figure 2 presents the timeline of the game.

At time \( t = 3 \), the manager observes the firm’s final payoff \( u \) and releases a public report \( r \) to maximize \( \lambda P_3 - \frac{c_M}{2} [\lambda (r - f)^2 + (1 - \lambda)(r - u)^2] \), where \( x \) is the manager’s hidden reporting incentives with respect to current price \( P_3 \), \( c_M \) is a non-negative constant, \( f \) is the analyst’s forecast, and \( \lambda \in [0,1] \). We follow Fischer and Verrecchia (2000) in the
specification of $x$ and extend it by adding the second term $\frac{c_w}{2} \lambda (r - f)^2$, i.e., the manager’s incentives to not be far from the analyst’s forecast. We assume that $x = \mu_i + x_i + x_2$ is normally and independently distributed with mean $\mu_i$ and variance $\sigma_i^2$, which is common knowledge, and that $x_i$ and $x_2$ are also normally and independently distributed with means of zero and variances of $\alpha_i \sigma_i^2$ and $(1 - \alpha_i) \sigma_i^2$, respectively, where $\alpha_i \in [0, 1]$. This objective function is consistent with prior literature that suggests that managers seek to meet analyst forecasts (Bartov et al., 2002; Matsumoto, 2002). Notice that $x$ is normally distributed and can be both positive and negative, which means that the manager sometimes has incentives to inflate or deflate the firm’s share price. This feature of the model originates from the observation that, although managers generally have incentives to inflate firm share prices to maximise shareholder wealth and/or personal gain, they are also known to have occasional incentives to deflate share prices, such as when they want to repurchase shares (Brockman et al., 2008; Louis & White, 2007) or reduce exercise prices of their options at options grant dates (Aboody & Kasznik, 2000; McAnally et al., 2008; Yermack, 1997).

There is a single analyst who, at time $t = 1$, observes $u_i$, a component of the firm’s final payoff\(^{11}\), and $x_i$, a component of the manager’s hidden reporting incentives with respect to price. Based on her information ($u_i$ and $x_i$), the analyst makes a private forecast $f$ to a single subscribed investor, who trades at time $t = 1$ on the basis of this information. The forecast is private in the sense that only the subscribed investor (and not the other investors) sees it. The analyst’s objective is to maximize the weighted sum of the informed trader’s (subscribed investor’s) profit and a loss from being away from the manager’s report, i.e.,

\[^{11}\text{Because the manager observes the firm’s final payoff, this set-up is similar to Chapter 3 where the analyst’s signal is a noisy version of the manager’s signal.}\]
\[ kE(\Pi_f | u_t, x_t, f) - \frac{c_A}{2}E[(r - f)^2 | u_t, x_t, f], \] where \( \Pi_f \) is the informed trader’s profit, \( r \) is the manager’s report as previously defined, and \( k \) and \( c_A \) are nonnegative constants less than or equal to one.

This objective function captures important aspects of the analyst’s incentives. Specifically, it allows the analyst to be concerned about both the client’s profit and the forecast error. This is a fairly general specification of the analyst’s objective function, and it is consistent with the view held in prior studies. Recent studies have shown that the value of access to analyst recommendations lies in clients’ trading profits (Green, 2006; Kadan, Michaely, & Moulton, 2013). Similarly, as an important input for analyst recommendations, analyst forecasts have their value in clients’ trading profits. Therefore, it is possible to say that the analyst cares about her client’s trading profits.

Numerous empirical and analytical studies have also shown that analysts care about forecast accuracy due to reputation or career concerns. For example, Mikhail et al. (1999) have found that, after controlling for firm- and time-period effects, forecast horizon, and industry forecasting experience, an analyst is more likely to turn over if his forecast accuracy is lower than his peers. Similarly, Basu and Markov (2004) have argued that analysts bear a cost for forecast inaccuracy and strive to minimise their absolute forecast errors.

In addition, at time \( t = 1 \), the single subscribed investor privately sees the analyst’s forecast \( f \) and trades to maximize trading profit \( E(\Pi_f | f, z_f) \), where \( z_f \) is the demand of the subscribed investor. At time \( t = 2 \), the analyst makes her previous forecast \( f \) public, and the informed trader exits the market.
Note that we allow the analyst to have some idea of the firm’s final payoff \((u)\), but make the manager have accurate knowledge of the firm’s final payoff. Given that, in our model, the manager’s report comes after the analyst’s forecast, one could argue that the manager’s report might be more informative about the final payoff, particularly if the final payoff is more significantly affected by firm-specific factors (Hutton et al., 2012).\(^{12}\) It is a simplification in our model that we allow the manager to accurately know the firm’s final payoff, which helps with the exposition but does not change the tenor of our conclusions. However, to the extent that the firm’s report depends on the manager’s private reporting incentives as well as being close to the analyst's forecast, the analyst’s forecast might still retain relevance after the manager learns the accurate number of the firm’s final payoff before it is realized (Hutton et al., 2012).

In sum, therefore, our model assumes that the analyst and investors are uncertain about managers’ incentives with regard to the market price of their firms’ shares. We assume that the distribution of the hidden incentives parameter \(x\) is common knowledge, and the analyst knows part of it. The third term in the manager’s objective function, \(-\frac{\text{C}_M}{2} (1 - \lambda)(r - u)^2\), represents the expected loss from misreporting. Notice that, because manager has a perfect signal about the firm’s final payoff at this stage, misreporting, which is modelled as the report’s deviation from the firm’s final payoff, includes only intentional bias.

We also assume that there is a market maker who sets prices equal to \(E(u \mid \Phi_{pub})\), where \(\Phi_{pub}\) is the publicly available information. At time \(t = 1\), this public information refers to market demand \(z = z_t + z_U\), where \(z_U\) is the demand of noise traders and is assumed to be

\(^{12}\) We assume for ease of exposition the manager gets to see the firm's final payoff, which does not affect the results of our analysis.
normally distributed with a mean of zero and variance of $\sigma_z^2$. At time $t = 2$, the public information is equivalent to the analyst’s forecast $f$. At time $t = 3$, the public information means both the manager’s report $r$ and the analyst’s forecast $f$. Notice that, at time $t = 2$ and time $t = 3$, information about the market demand $z$ becomes redundant with the releases of the analyst’s forecast $f$ and the manager’s report $r$. At time $t = 4$, the firm’s final payoff, $u^*$, is realized.

4.3 Equilibrium

The equilibrium in our model consists of four components: the analyst’s forecast, $f$; the firm’s report, $r$; the prices, $P_1, P_2, P_3$; and the informed trader’s demand, $z_I$. Consistent with prior research, we consider only linear equilibria to retain tractability. To determine the equilibrium, we consider the manager, analyst, the market maker, and the informed trader in turn.

4.3.1 The Manager’s Problem

At time $t = 3$, the manager knows his own hidden incentive parameter $\lambda$, the firm’s final payoff $u^*$, as well as the analyst’s forecast, $\hat{f}$, and chooses his report, $r$, to maximize the objective function, $x P_3 - \frac{c}{2} (\lambda (r - f)^2 + (1 - \lambda) (r - u)^2)$. In doing so, he conjectures that the market maker sets the firm value equal to a linear function of his report and the analyst’s
forecast, \( P_t = \beta_0 + \beta_r (r - f) + \beta_f f \).\(^{13}\) Solving this maximisation problem via the first order condition yields

\[
r = \lambda f + (1 - \lambda)u + \frac{\beta_r}{c_M} x.
\]

As the above equation shows, the manager’s equilibrium report is a function of the analyst’s forecast, the firm’s final payoff and the manager’s hidden incentive. Specifically, the report is a weighted sum of the analyst’s forecast and the firm’s final payoff plus a bias due to the manager’s private incentive \( x \). The report is positively related to the analyst’s forecast, but the correspondence is less than or equal to one and is equal to the weight the manager includes in his objective function of being close to the analyst’s forecast. This is consistent with prior empirical evidence that shows that managers strive to report earnings that meet or beat analysts’ expectations. The report is also positively related to the firm’s final payoff, where the correspondence is also less than or equal to one and equal to the weight the managers includes in his objective function of being close to the firm’s final payoff. Finally, the report is influenced by the manager’s private incentive \( x \), and its sign depends on the sign of the manager’s private incentive \( x \) as well as the sign of the report’s price responsiveness \( \beta_r \).

It is possible to express the manager’s report as follows:

\[
r = (1 - \lambda)^{\hat{r}} + \lambda^r f,
\]

---

\(^{13}\) We specify price as a linear function of \( r - f \) rather than \( r \) for algebraic convenience. This means that \( \hat{\beta}_r \) represents price responsiveness to ‘unexpected earnings’ using the analyst’s forecast as the earnings expectations benchmark, which is consistent with a large body of empirical research.
where $\lambda$ is the weight in the manager’s objective function for deviations from the analyst’s forecast; $\hat{r} = u + \frac{\beta}{(1-\lambda)c_M}x$ is the report the manager would issue if he did not care about deviating from the analyst’s forecast,\(^{14}\), i.e., if $\lambda = 0$; and $f$ is the analyst’s forecast. Thus, the manager’s report is a weighted average of what he would report if he did not care about deviating from the analyst’s forecast, where the weights reflect the costs the manager experiences from deviating from underlying economic earnings ($u$) and the analyst’s forecast ($f$).

Rearranging yields

$$r = \hat{r} - \lambda(\hat{r} - f).$$

Thus, the manager “smoothes” what he would report without an analyst towards the analyst’s forecast, as might be expected given the nature of the incentives in his assumed objective function. Note that this does not (necessarily) mean that the report will be less distorted relative to underlying economic earnings. This depends on what is in $f$.

### 4.3.2 The Market Maker’s Problem at time $t = 3$

For ease of exposition, we define $\hat{f} = E(r \mid u_i, x_i) = u_i + \frac{1}{1-\lambda} \frac{\beta}{c_M} (\mu_i + x_i)$ as the expected value of the manager’s report given the analyst’s information and

$$\hat{r} = \frac{r - f}{1-\lambda} + f = u_2 + \frac{1}{1-\lambda} \frac{\beta}{c_M} x_2 + \hat{f} \quad \text{or} \quad \hat{r} - f = u_2 + \frac{1}{1-\lambda} \frac{\beta}{c_M} x_2$$

as the unexpected component

\(^{14}\) Another interpretation of this is that the reporting bias is solely determined by the manager’s incentives to deviation from the firm’s fundamental value.
of the manager’s report, given the analyst’s information. It is clear that \( r - \hat{f} \) and \( \hat{f} \) are independent.

At time \( t = 3 \), the market maker sets the price equal to the expected value of the firm’s final payoff given his information on the manager’s report and the analyst’s forecast. In doing so, the market maker correctly anticipates \( r = \lambda f + (1 - \lambda)u + \frac{\beta}{c_M}x \) and conjectures

\[ f = \theta_0 + \theta_{f, \hat{f}}. \]

That is, the market maker conjectures that the analyst’s forecast will be a linear function of the expected value of the manager’s report given her information \( \hat{f} \). To retain tractability, we consider only the linear equilibrium here. To achieve equilibrium, the market maker’s conjecture about the analyst’s forecast must be confirmed later. In addition, the pricing function set by the market maker must confirm the manager’s earlier conjecture of being linear in the manager’s report and the analyst’s forecast. That is,

\[ P_3 = E(u \mid r, f) = E(u \mid r - f, f) = \beta_0 + \beta_r (r - f) + \beta_{f, \hat{f}}. \]

Because the information in \( r - f \) and \( f \) is equivalent to that in \( r - \hat{f} \) and \( \hat{f}, \) we also have

\[ P_3 = E(u \mid r - \hat{f}, \hat{f}) = \beta_0 + \beta_r (r - \hat{f}) + \beta_{\hat{f}, \hat{f}}. \]

Because \( u, r - \hat{f}, \) and \( \hat{f} \) are all normally and independently distributed, using the properties of conditional multivariate normal distributions, we have

\[ \beta_{\hat{f}, \hat{f}} = \beta_{f, f}. \]

\[ \beta_{r, \hat{f}} = \beta_{r, f}. \]

\[ \beta_{\hat{f}, \hat{f}} = \beta_{\hat{f}, f}. \]

15 This is because the latter are merely linear transformations of the former.
\begin{align*}
\beta_r &= \frac{\text{cov}(\hat{u}, \hat{r} - \hat{f})}{\text{var}(\hat{r} - \hat{f})} = \frac{(1 - \alpha_u)\sigma_u^2}{(1 - \alpha_u)\sigma_u^2 + \frac{1}{(1 - \lambda)}(\frac{\beta_r}{c_M})^2(1 - \alpha_x)\sigma_x^2}; \\
\beta_f &= \frac{\text{cov}(\hat{u}, \hat{f})}{\text{var}(\hat{f})} = \frac{\alpha_u\sigma_u^2}{\alpha_u\sigma_u^2 + \frac{1}{(1 - \lambda)}(\frac{\beta_f}{c_M})^2\alpha_x\sigma_x^2}; \\
\beta_0 &= -\beta_r \hat{E}(\hat{r} - \hat{f}) - \beta_f \hat{E}(\hat{f}) = -\beta_r \frac{1}{1 - \lambda} \frac{\beta_f}{c_M} \mu_x.
\end{align*}

Simple linear algebra shows

\begin{align*}
\beta_r &= \frac{1}{1 - \lambda_M} \beta_r; \\
\beta_f &= \frac{1}{\theta_f} [\beta_f + (\theta_f - 1)\beta_r]; \\
\beta_0 &= \beta_0 - \frac{\theta_f}{\theta_f} (\beta_f - \beta_r).
\end{align*}

Thus, \( \beta_r \) is uniquely determined by the equation

\begin{equation*}
\beta_r = \frac{1}{1 - \lambda} \frac{(1 - \alpha_u)\sigma_u^2}{(1 - \alpha_u)\sigma_u^2 + \frac{1}{(1 - \lambda)}(\frac{\beta_r}{c_M})^2(1 - \alpha_x)\sigma_x^2},
\end{equation*}

which increases in \( \beta_r \) on the LHS and decreases in \( \beta_r \) on the RHS, since \( \beta_r \) is positive. The \( \beta_f \) then uniquely determines \( \beta_f \) and \( \beta_0 \). However, \( \beta_f \) and \( \beta_0 \) also depend on \( \theta_f \), which is later shown to be uniquely determined by an equation at equilibrium.

**4.3.3 The Market Maker’s Problem at time \( t = 2 \)**

Similarly, at time \( t = 2 \), the market maker sets the price equal to the expected value of the firm’s final payoff given his information on the analyst’s forecast. Again, the market maker conjectures that the analyst’s forecast is a linear function of the expected value of the
manager’s report given her information, i.e., \( f = \theta_0 + \theta_f \hat{f} \). It can be easily shown that

\[
P_2 = E(u \mid f) = E(u \mid \hat{f}) = \beta_0 + \beta_f \hat{f},
\]
where \( \beta_0 \) and \( \beta_f \) are the same coefficients as those for \( P_1 \). This makes sense, as the only new information at time \( t = 3 \) is \( r - f \), which has a mean of zero and is independent of \( f \). Simple algebraic manipulation shows that

\[
P_2 = \beta_0 + \beta_f \frac{f - \theta_0}{\theta_f} = \beta_0 - \beta_f \frac{\theta_0}{\theta_f} + \beta_f \frac{f}{\theta_f}.
\]
Notice that the coefficient is different from that for \( P_1 \). Specifically, it is smaller.

### 4.3.4 The Informed Trader’s Problem

At time \( t = 1 \), the informed trader conjectures that the analyst’s forecast is a linear function of the expected value of the manager’s report given her information, i.e., \( f = \theta_0 + \theta_f \hat{f} \), and that price is a linear function of market demand \( z \), i.e., \( P_1 = \gamma_0 + \gamma_z z \), where \( z = z_I + z_u \) is the total market demand and the sum of the informed trader’s demand \( z_I \) and the uninformed traders’ demand \( z_u \). We assume that the uninformed traders’ demand \( z_u \) is normally and independently distributed with a mean of zero and variance of \( \sigma^2_z \). Again, we consider only linear equilibrium to retain tractability. The informed trader’s objective is to choose his demand \( z_I \) to maximize his expected trading profit, which is the product of the informed trader’s demand and the price difference between time \( t = 2 \) and time \( t = 1 \), i.e.,

\[
\Pi_I = z_I (P_2 - P_1).
\]
The form of the informed trader’s profit function means that the informed trader’s informational advantage lasts only until \( t = 2 \), when the analyst forecast becomes public. Thus, we have
\[ E(\Pi_t \mid f, z_t) = z_t(P_2 - \gamma_0 - \gamma_z z_t). \]

Solving for the first-order condition, we have

\[ z_t = \frac{P_2 - \gamma_0}{2\gamma_z}. \]

Note that the informed trader knows what \( P_2 \) will be because he knows \( \hat{f} \) and \( P_2 = E(u \mid \hat{f}) \).

### 4.3.5 The Market Maker’s Problem at Time \( t = 1 \)

At time \( t = 1 \), the market maker makes a conjecture about the informed trader’s demand and chooses a price \( P_1 = E(u \mid z) \) to clear the market. Because, at equilibrium, all conjectures must be fulfilled, we assume that the market maker correctly conjectures the form of the informed trader’s demand, that is, \( z_t = \frac{P_2 - \gamma_0}{2\gamma_z} \). Using the properties of multivariate normal distribution, we can obtain \( P_1 = \gamma_0 + \gamma_z z \), where \( \gamma_0 = 0, \gamma_z = \frac{1}{2} \sqrt{\frac{\beta \cdot \alpha \cdot \sigma_u^2}{\sigma_z^2}} \).

### 4.3.6 The Analyst’s Problem

At time \( t = 1 \), the analyst must make a conjecture about the form of the manager’s report and the informed trader’s demand, which are in the analyst’s objective function in order to maximize it. To qualify for an equilibrium, the manager’s conjecture of market price at time \( t = 3 \), the analyst’s conjecture of the manager’s report, and the informed trader’s demand must be satisfied. Therefore, we assume here that the analyst correctly conjectures the form of the manager’s report at time \( t = 3 \) and the informed trader’s demand at time \( t = 1 \). Thus,
the analyst conjectures that $r = \lambda f + (1 - \lambda)u + \frac{\beta_r}{c_M}$ and chooses $f$ to maximise

$$kE(\Pi_i | u_i, x_i, f) - \frac{c_A}{2} E[(r - f)^2 | u_i, x_i, f].$$

Solving this minimization problem via the first-order condition yields

$$f = \frac{c_A (1 - \lambda)}{c_A (1 - \lambda) - \frac{k}{2\gamma_z^2} \left( \frac{\beta_r}{\theta_f} \right)^2} \left[ f + \frac{1}{k} \left( \frac{\beta_r}{\theta_f} (\beta_r - \frac{\beta_r}{\theta_f}) \right) \right].$$

This confirms that $f$ is a linear function of $\hat{f}$ as previously conjectured, i.e., $f = \theta_f + \theta_f \hat{f}$

where $\theta_0 = \frac{1}{k} \cdot \frac{\beta_r}{2\gamma_z} \cdot \frac{\beta_r}{\theta_f}$, $\theta_f = \frac{1 + \frac{2}{c_A (1 - \lambda) \gamma_z \theta_f}}{2 \cdot \frac{\beta_r^2}{\theta_f}}$.

Some rearranging yields:

$$f = \hat{f} + (\theta_f - 1) (f - \frac{\beta_r}{(1 - \lambda) c_M} \mu_r).$$

Since $E(r) = \frac{\beta_r}{(1 - \lambda) c_M} \mu_r$, the above equation indicates that the analyst distorts her forecast by “exaggerating” deviations of her expectation of $r$ from its unconditional expected values.

We can combine the above equation with $r = \hat{r} - \lambda(\hat{r} - f)$ to obtain:

$$r = \hat{r} - \lambda(\hat{r} - f) + \lambda (\theta_f - 1) (f - E(r)).$$
This helps provide some structure to the distortion that occurs in the manager’s report. First, there is the price-driven distortion (as in Fischer and Verrecchia, 2000) that is in $r$, the first term on the RHS of the above equation. The next two terms only exist if $\lambda > 0$, that is, if the manager cares about deviating from the analyst’s forecast. The second term on the RHS of the above equation indicates that the manager moves towards the analyst’s expectation of the manager’s report. Thus, if the combination of the manager’s unique signal about underlying economic earnings ($u_t$) and his unique information about his price-driven incentive parameter ($x_z$) is positive (negative), he smooths “downwards” (“upwards”) towards the analyst’s expectation. The third term in the above equation indicates that, if the analyst cares about her client’s expected trading profits, then the resulting forecast distortion causes the manager to distort his report in the same direction as the analyst’s distortion (relative to the unconditional expected value of the manager’s report). Thus, these are the sources of distortion in the manager’s report.

**Lemma 1:** The analyst’s forecast distortion resulting from her goal of caring about her client’s expected trading profits causes the manager to distort his report in the same direction as the analyst’s distortion.

The above equation can be rearranged in the following way:

$$r - u = \frac{\beta_f}{(1 - \lambda)c_M} x - \lambda(u_t + \frac{1}{1 - \lambda} \frac{\beta_f}{c_M} x_z) + \lambda(\theta_f - 1)(u_t + \frac{1}{1 - \lambda} \frac{\beta_f}{c_M} x_z).$$

This isolates the different components of distortion in the manager’s report relative to underlying economic earnings. The first term on the RHS is the same distortion as in Fischer and Verrecchia (2000). The other two terms are distortion introduced by our model structure,
the manager’s concern over not deviating too far from the analyst’s forecast and the analyst’s concern for her client’s expected trading profits.

Since \( \theta_0 \) and \( \theta_j \) are uniquely determined, \( \beta_r \) and \( \beta_o \) are uniquely determined. We thus have an equilibrium, as in the following proposition.

**Proposition 1**

Define:

\[
\hat{r} = u + \frac{\beta_r}{(1-\lambda)c_M} x;
\]
\[
\hat{f} = E(\hat{r} | u, x) = u + \frac{\beta_r}{(1-\lambda)c_M} (\mu + x);
\]
\[
\beta_r = \frac{\text{cov}(u, \hat{r} - \hat{f})}{\text{var}(\hat{r} - \hat{f})} = \frac{(1-\alpha_u)\sigma_u^2}{(1-\alpha_u)\sigma_u^2 + \left(\frac{\beta_r}{(1-\lambda)c_M}\right)^2 (1-\alpha_s)\sigma_s^2};
\]
\[
\beta_j = \frac{\text{cov}(u, \hat{f})}{\text{var}(\hat{f})} = \frac{\alpha_u \sigma_u^2 + \left(\beta_r\right)^2}{\alpha_u \sigma_u^2 + \left(\beta_r/(1-\lambda)c_M\right)^2 \alpha_s \sigma_s^2};
\]
\[
\beta_0 = -\beta_r E(\hat{r} - \hat{f}) - \beta_j E(\hat{f}) = -\frac{\beta_j \beta_r}{(1-\lambda)c_M} \mu_s,
\]

where \( \beta_r \) is the response coefficient on \( (r - f) \) in \( E(u | r - f, f) = \beta_0 + \beta_r (r - f) + \beta_j f \).

**A. Equilibrium at t = 3**

In equilibrium at \( t = 3 \), the manager reports \( r = \lambda f + (1-\lambda)\hat{r} \) and, given \( f = \theta_0 + \theta_j \hat{f} \) (see part C of the proposition below), the price is \( P_3 = \beta_0 + \beta_r (r - f) + \beta_j f \), where \( \beta_r \) is the unique solution to the following equation:
\[(1 - \lambda)\beta_r = \frac{(1 - \alpha_s)\sigma_i^2}{(1 - \alpha_v)\sigma_i^2 + \left(\frac{\beta_r}{(1 - \lambda)c_M}\right)(1 - \alpha_x)\sigma_x^2},\]

\[\beta_f = \frac{1}{\phi_j}[\beta_f + (\theta_f - 1)\beta_f], \quad \beta_0 = \beta_0 - \frac{\theta_0}{\phi_j}(\beta_f - \beta), \quad \text{and} \quad \beta_0 = \beta_0 - \frac{\theta_0}{\phi_j}(\beta_f - \beta),\]

B. Equilibrium at t = 2

\[P_z = \beta_0 - \frac{\beta_f}{\phi_j} + \frac{\beta_i}{\phi_j} f\]

Equilibrium price at t = 2 is given by

C. Equilibrium at t = 1

In equilibrium at t = 1, the analyst issues the forecast \(f = \theta_0 + \theta_f \hat{f}\), the informed trader chooses to trade \(z_i = \frac{\beta_0 + \beta_f \hat{f}}{2\gamma}\) shares, and the price is \(P_i = \gamma z\), where:

\[\gamma = \frac{1}{2} \sqrt{\frac{\alpha_s\sigma_i^2\beta_f}{\sigma_x^2}};\]

\[\theta_f = \frac{1}{2} \left(1 + \sqrt{1 + \frac{2k\beta_f}{(1 - \lambda)c_M\gamma}}\right);\]

\[\theta_0 = \frac{k\beta_f \phi_0}{2(1 - \lambda)c_M\gamma \phi_j};\]

and \(z = z_i + z_u\), the sum of trades by the informed and noise traders.
4.4 Comparative Statics

Proposition 1 indicates that both the firm’s financial report, \( r \), and the analyst’s forecast, \( f \), comprise an underlying informational signal (\( \hat{r} \) and \( \hat{f} \), respectively) that is subject to a known linear transformation:

\[
r = \lambda f + (1 - \lambda)\hat{r}
\]

\[
f = \theta_0 + \theta_f \hat{f}.
\]

That is, both the financial report and the forecast differ cosmetically from the underlying informational signals that the market maker and investors can extract. Thus, these cosmetic biases are driven by the same explanation as reporting biases, without the uncertainty of the reporting objective: in equilibrium, the sender induces a bias because he can, and the receiver knows that the sender can bias the report. Therefore, in equilibrium, the report is biased, and the receiver can perfectly back out this bias. The sender would be better off by committing not to biasing the report, but such commitment is not possible. Therefore, we should care about these cosmetic effects because they affect the cost of biasing the forecast by the analyst and the report by the manager. In this section, I investigate comparative statics related to both the informational content of \( r - f \) and \( f \), as well as the cosmetic content of \( r - f \) and \( f \). The parameters I focus on are \( \alpha_u \) and \( \alpha_s \) (the quality of information available to the analyst), \( \lambda \) (the importance to the manager of not deviating too far from the analyst’s forecast), \( k \) (the importance of the informed trader’s profit to the analyst), and \( \sigma_z^2 \) (the noisy trade that affects the market maker’s ability to extract the informed investor’s private information).
4.4.1 Informational Content of $f$ and $r - f$

The information signals available from $f$ and $r - f$ are $\hat{f}$ and $\hat{r} - \hat{f}$, respectively.

$\hat{r} = u + \frac{\beta_r}{(1-\lambda)c_M} x$ represents what the manager would choose to report absent any incentive to report close to the analyst’s forecast, and it corresponds to the report solution in Fischer and Verrecchia (2002). $\hat{f} = u_1 + \frac{\beta_r}{(1-\lambda)c_M} (\mu_x + x_1)$ is the expected $\hat{r}$ given the analyst’s information. Because $\hat{r} - \hat{f} = u_2 + \frac{\beta_r}{(1-\lambda)c_M} x_2$ and $\hat{f}$ are uncorrelated, $\hat{r} - \hat{f}$ represents the incremental information in $\hat{r}$ over $\hat{f}$. It is then straightforward to derive the informational content of $\hat{r} - \hat{f}$ and $\hat{f}$ via the following conditional variances:

$$\text{var}(u \mid \hat{f}) = \sigma_u^2 - \beta_f \alpha_u \sigma_u^2;$$

$$\text{var}(u \mid \hat{r} - \hat{f}) = \sigma_u^2 - \beta_f (1 - \alpha_u) \sigma_u^2.$$

These represent the residual uncertainty of the market maker and investor regarding the firm’s fundamental value after seeing the analyst’s forecast and the manager’s financial report, respectively. It is also clear that $\frac{\partial \beta_f}{\partial \alpha_u} > 0, \frac{\partial \beta_f}{\partial \alpha_x} < 0, \text{ and } \frac{\partial \beta_f}{\partial \lambda} < 0$, which implies that

$$\frac{\partial \text{var}(u \mid \hat{f})}{\partial \alpha_u} < 0, \frac{\partial \text{var}(u \mid \hat{f})}{\partial \alpha_x} > 0, \text{ and } \frac{\partial \text{var}(u \mid \hat{f})}{\partial \lambda} > 0.$$ It is also plain that

$$\frac{\partial \beta_f}{\partial \alpha_u} < 0, \frac{\partial \beta_f}{\partial \alpha_x} > 0, \text{ and } \frac{\partial \beta_f}{\partial \lambda} < 0,$$ which implies
This yields the following proposition:

**Proposition 2:** The market maker’s residual uncertainty after seeing the forecast decreases with the quality of the analyst’s value information, increases with the quality of the analyst’s incentive information, and increases with the manager’s relative weight on being close to the forecast, i.e.,

\[
\frac{\partial \text{var}(u | \hat{r} - \hat{f})}{\partial \alpha_u} > 0, \frac{\partial \text{var}(u | \hat{r} - \hat{f})}{\partial \alpha_x} < 0, \frac{\partial \text{var}(u | \hat{r} - \hat{f})}{\partial \lambda} > 0.
\]

The market maker’s residual uncertainty after seeing the financial report increases with the quality of the analyst’s value information, decreases with the quality of the analyst’s incentive information, and increases with the manager’s relative weight on being close to the forecast, i.e.,

\[
\frac{\partial \text{var}(u | \hat{f})}{\partial \alpha_u} < 0, \frac{\partial \text{var}(u | \hat{f})}{\partial \alpha_x} > 0, \frac{\partial \text{var}(u | \hat{f})}{\partial \lambda} > 0.
\]

It is very intuitive that the market maker’s residual uncertainty after seeing the forecast decreases with the quality of the analyst’s value information. After all, the more information the analyst has about the firm’s fundamental value, the more information is contained in the forecast, and the less noise the market maker and investors have about the firm’s fundamental value after seeing the forecast.

Similarly, it is clear that the market maker’s residual uncertainty after seeing the forecast increases with the quality of the analyst’s information about the manager’s market incentives. The more accurate the information the analyst has about the manager’s market incentives, the more distortion due to the manager’s market incentives is contained in the forecast, and the more noise the market maker and investors have about the firm’s fundamental value after seeing the forecast.
When the manager cares more about the analyst forecast, the analyst has more power to distort the forecast away from the firm’s fundamental value. Therefore, the residual uncertainty of the market maker after seeing the forecast increases with the weight the manager attaches to the analyst’s forecast.

When the analyst has better value information, the forecast is more informative, and the incremental information contained in the forecast error is lower. Therefore, there is relatively more noise after seeing the manager’s report, and the market maker’s residual uncertainty after seeing the financial report increases with the quality of the analyst’s value information.

When the analyst has better information about the manager’s market incentives, the forecast contains more distortion due to the manager’s market incentives. This has two reinforcing effects on the informational content of the manager’s report. The direct effect is that there is relatively more incremental information about the firm’s fundamental value contained in the forecast error; the indirect effect is that the market maker and investors are better able to back out the distortion contained in the forecast error due to the manager’s market incentives. Both effects lead to higher information content in the forecast error. Therefore, the residual uncertainty of the market maker after seeing the financial report increases with the quality of the analyst’s incentives information.

When the manager attaches more weight to the analyst’s forecast, he has more reasons to distort the financial report; thus, more weight on the analyst’s forecast leads to more distortion in the financial report. Therefore, the market maker’s residual uncertainty after seeing the financial report increases with the weight given to the analyst’s forecast.

### 4.4.2 “Cosmetic Effect” in Analyst Forecast

From Proposition 1, we have
\[ f - \hat{f} = (\theta_j - 1) \left( \hat{f} - \text{E}[\hat{f}] \right). \]

This immediately indicates that \( f - \hat{f} \) is mean zero, and so

\[ \text{E}\left[ (f - \hat{f})^2 \right] = (\theta_j - 1)^2 \text{Var}(\hat{f}). \] (4.1)

Note that \( f - \hat{f} \) represents the “cosmetic” effect of the analyst’s incentives on the forecast she issues, or the effect of the analyst’s incentive to care about the subscribed investor’s profits on the forecast. Equation (4.1) shows that the expected squared “cosmetic” effect is a product of two components: a function of the distortion coefficient \( \theta_j \) and the variance of the informational content of \( f \), \( \text{var}(\hat{f}) \). This means that the “cosmetic” effect of the analyst’s incentives on the forecast is proportional to the variance of the informational content of the forecast, and the proportion is determined by a quadratic function of the distortion coefficient. The “cosmetic” effect is possible only because there is uncertainty about the informational content of the forecast, and the extent to which this uncertainty is passed on as the “cosmetic” effect is determined by the magnitude of the distortion coefficient.

Because \( \theta_j \) and \( \text{var}(\hat{f}) \) are both non-monotonic in \( \alpha_u \), we cannot algebraically determine the monotonicity or non-monotonicity of the “cosmetic” effect in \( \alpha_u \), but numerical analysis (untabulated) shows that the “cosmetic” effect is non-monotonic in \( \alpha_u \). Because \( \theta_j \) decreases in \( \alpha_x \) and \( \text{var}(\hat{f}) \) increases in \( \alpha_x \), we cannot algebraically determine whether the “cosmetic” effect is monotonic or non-monotonic in \( \alpha_u \). Because \( \theta_j \) and \( \text{var}(\hat{f}) \) both increase in \( \lambda \), the expected squared “cosmetic” effect increases in \( \lambda \). Because \( \theta_j \) increases
in k and decreases in $\sigma^2$, and $\text{var}(\hat{f})$ is independent of the two parameters, the expected squared “cosmetic” effect increases in k and decreases in $\sigma^2$. We collect the above results in the following proposition.

**Proposition 3:** The expected squared “cosmetic” effect in the analyst forecast is non-monotonic in the quality of the analyst’s value information, increases with the relative weight of the manager’s incentive to be close to analyst’s forecast, increases with the importance of the subscribed investor’s profit in the analyst’s incentives, and decreases with the amount of noise trade.

The intuition that the “cosmetic” effect in the analyst’s forecast is non-monotonic in the quality of the analyst’s value information is that more accurate analyst’s value information increases the analyst’s opportunity cost to not minimize forecast error; however, it also increases the attractiveness of the distortion due to her incentive to maximize the subscribed investor’s trading profits because she is better able to move prices. Either of the two countervailing effects could dominate, and this leads to non-monotonicity.

The relative weight on the manager’s incentives to be close to the analyst’s forecast $\lambda$ has two effects on the analyst’s forecast distortion due to her incentives to care about the subscribed investor’s profits. The direct effect is that more weight leads to a higher distortion coefficient because the analyst has higher power to manipulate earnings. The indirect effect is that higher weight means lower weight on the biasing cost and higher uncertainty in the expected report if the manager does not care about the analyst’s forecast, and higher uncertainty in the expected forecast $\hat{f}$ and thus higher forecast distortion.
The effects of the weight on the analyst’s incentives to care about the subscribed investor’s profits $k$ and the amount of noise trade $\sigma_i^2$ on the “cosmetic” effect in the analyst’s forecast work solely through the distortion coefficient and are straightforward. The higher the weight, the more incentives there are to distort the forecast, and the higher the “cosmetic” effect is. With a larger amount of noise trade, there is less ability to move prices via the analyst’s forecast, and thus there is a lower distortion and “cosmetic” effect.

4.4.3 The “Cosmetic” Effect in the Financial Report

It is easy to show that

$$r - \hat{r} = -\lambda(\hat{r} - f) = -\frac{\lambda}{1 - \lambda}(r - f).$$

Thus, we have

$$\mathbb{E}[(r - \hat{r})^2] = \lambda^2 \left(\operatorname{Var}(\hat{r} - \hat{f}) + (\theta_{ij} - 1)^2 \operatorname{Var}(\hat{f})\right).$$ (4.2)

Note that $r - \hat{r}$ represents the “cosmetic” effect in the financial report due to the manager’s incentive to be close to the analyst’s forecast. Equation (4.2) shows that the expected squared “cosmetic” effect in the financial report is a product of two components: a function of $\lambda$ and the sum of the variance of the informational content in $r-f$ and the expected squared “cosmetic” effect in the analyst forecast. This means that there are two sources for the “cosmetic” effect in the financial report: the uncertainty over the informational content of the forecast error and the “cosmetic” effect in the forecast. These are the two reasons for the manager to distort the report to move toward the analyst’s forecast. The extent to which these two sources of distortion are passed on to the “cosmetic” effect in the financial report is determined by the weight on the manager’s incentive to be close to the analyst forecast.
Because $\lambda^2$ is not dependent on $\alpha_u$, $\text{Var}(\hat{r} - \hat{f})$ decreases in $\alpha_u$, and $E[(f - \hat{f})^2]$ is undetermined for it, we cannot determine whether the expected squared “cosmetic” effect in the financial report is monotonic or non-monotonic in $\alpha_u$. Because $\lambda^2$ is not dependent on $\alpha_x$, and both $\text{Var}(\hat{r} - \hat{f})$ and $E[(f - \hat{f})^2]$ are undetermined in $\alpha_x$, the expected squared “cosmetic” effect in the financial report is undetermined in $\alpha_x$. Because all three components increase in $\lambda$, the expected squared “cosmetic” effect in the financial report increases in $\lambda$. Because the first two components are independent of $k$ and $\sigma_z^2$, and $E[(f - \hat{f})^2]$ increases in $k$ and decreases in $\sigma_z^2$, the expected squared “cosmetic” effect in the financial report increases in $k$ and decreases in $\sigma_z^2$. We collect the above results in the following proposition.

**Proposition 4:** The expected squared “cosmetic” effect in the financial report increases in the relative weight on the manager’s incentive to be close to analyst’s forecast, increases in the importance of the subscribed investor’s profit in the analyst’s incentives, and decreases in the amount of noise trade.

It is clear that the “cosmetic” effect in the financial report due to the manager’s incentives to be close to the analyst’s forecast increases in the relative weight on the manager’s incentives to do so. The effects of the weight on the analyst’s incentives to care about the subscribed investor’s profits and the amount of noise trade on the “cosmetic” effects in the financial report work solely through the “cosmetic” effect in the analyst’s forecast.

**4.4.4 The “Cosmetic” Effect in Forecast Error**

It can clearly be shown that

$$(r - f) - (\hat{r} - \hat{f}) = -\left[\lambda(\hat{r} - \hat{f}) + (1 - \lambda)(f - \hat{f})\right].$$
Thus, the magnitude of the cosmetic effect in the forecast error is

\[
E \left[ \left( (r - f) - (\hat{r} - \hat{f}) \right)^2 \right] = \lambda^2 \text{Var}(\hat{r} - \hat{f}) + (1 - \lambda)^2 (\theta_j - 1)^2 \text{Var}(\hat{f}).
\] (4.3)

Equation (4.3) shows that the expected squared “cosmetic” effect in the forecast error consists of the sum of two components. The first is the product of a quadratic function of \( \lambda \) and the variance of the informational content in \( r - f \). The second component is the product of a quadratic function of \( 1 - \lambda \) and the expected squared “cosmetic” effect in the analyst’s forecast. Like the “cosmetic” effect in the financial report, the “cosmetic” effect in the forecast error has two sources: the uncertainty over the informational content of the forecast error and the “cosmetic” effect in the forecast. The extent to which the uncertainty over the informational content of the forecast error is passed onto the “cosmetic” effect in the forecast error is determined by the weight on the manager’s incentive to be close to the analyst’s forecast; however, the extent to which the “cosmetic” effect in the forecast is passed on is determined by the weight on the manager’s incentive to be close to firm fundamental value.

It is clear that the expected squared “cosmetic” effect in the forecast error is undetermined in \( \alpha_u, \theta, \) and \( \lambda \), and it increases in \( k \) and decreases in \( \sigma_z^2 \). We collect the above results in the following proposition.

**Proposition 5:** The expected squared “cosmetic” effect in the forecast error increases with the importance of the subscribed investor’s profit in the analyst’s incentives and decreases with the amount of noise trade.

The effects of the importance of the subscribed investor’s profits in the analyst’s incentives and the amount of noise trade on the “cosmetic” effect in the forecast error work solely through the “cosmetic” effect in the analyst’s forecast.
4.4.5 Forecast Error

From Proposition 1, we have

\[ r - f = (1 - \lambda) \left( (\hat{r} - \hat{f}) - (f - \hat{f}) \right). \]

Note that \( \hat{r} - \hat{f} \) and \( f - \hat{f} \) are both mean zero and are uncorrelated, so, using equation (4.2),

\[ \mathbb{E}[(r - f)^2] = (1 - \lambda)^2 \left( \text{Var}(\hat{r} - \hat{f}) + (\theta_j - 1)^2 \text{Var}(\hat{f}) \right). \] (4.4)

Equation (4.4) shows that the forecast error, like the expected squared “cosmetic” effect in the financial report, is a product of two components: a function of \( \lambda \) and the sum of the variance of the informational content in \( r-f \) and the expected squared “cosmetic” effect in the analyst’s forecast. The forecast error has two sources: the uncertainty over the informational content of the forecast error and the “cosmetic” effect in the forecast. The extent to which these two sources of distortion is passed onto the forecast error is determined by the weight on the manager’s incentive to be close to the firm fundamentals.

It is clear that the forecast error is undetermined in \( \alpha_u, \alpha_s \), and \( \lambda \), and it increases in \( k \) and decreases in \( \sigma_i^2 \). However, numerical analysis (untabulated) shows that the forecast error is non-monotonic in \( \alpha_u \). We collect the above results in the following proposition.

**Proposition 6:** The forecast error is non-monotonic in the quality of the analyst’s value information, increases with the importance of the subscribed investor’s profit in the analyst’s incentives, and decreases with the amount of noise trade.

The intuition for the forecast error to be non-monotonic in the quality of the analyst’s value information is the same as for the “cosmetic” effect in the analyst forecast: better analyst’s
value information increases the analyst’s opportunity cost to not minimize forecast error, but it also increases the attractiveness of the distortion due to her incentive to maximize the subscribed investor’s trading profits because she is better able to move prices. Either of the two countervailing effects could dominate, and this leads to non-monotonicity.

The effects of the importance of the subscribed investor’s profits in the analyst’s incentives and the amount of noise trade on the forecast error work solely through the “cosmetic” effect in the analyst’s forecast.

4.4.6 Reporting Bias

The reporting bias can be decomposed as follows:

\[ r - u = (r - \hat{r}) + (\hat{r} - u). \]

The first part is the cosmetic effect in \( r \), while the second is the distortion in the information signal that can be extracted from \( r \) (which is the same as the distortion in the Fischer-Verrecchia basic model). What makes this more difficult is the fact that the two parts are correlated. However, the magnitude of the distortion might still be broken down into distinct parts that can be discussed separately.

\[
E[(r - u)^2] = \text{Var}(r - \hat{r}) + 2\text{Cov}(r - \hat{r}, \hat{r} - u) + E[(\hat{r} - u)^2].
\tag{4.5}
\]

The third part is the same as the Fischer-Verrecchia distortion, the first part is the cosmetic effect in the firm’s financial report, and the middle part is the covariance between the two.

**Lemma 2:** The distortion in the report due to the manager’s incentives to be close to the analyst’s forecast, the “cosmetic” effect in the forecast error, the forecast error, and the
reporting bias all depend on the forecast distortion due to the analyst’s incentives to care about the subscribed investor’s profits.

This indicates that the distortion in the report due to the manager’s incentives to be close to the analyst forecast, the “cosmetic” effect in the forecast error, the forecast error, and the reporting bias all depend on the analyst’s incentives to increase the subscribed investor’s profits. This result is due to the interaction between the analyst’s forecast and the manager’s financial report, and it complements Beyer’s (2008) finding that the analyst’s forecasting strategy depends on the manager’s incentives.

**4.4.7 Earnings Response Coefficient**

\[
\frac{\partial \beta_r}{\partial \alpha_u} = \frac{(1-\lambda)c_M^2\sigma_u^2[(1-\lambda)\beta_r-1]}{3\beta_r^2(1-\alpha_v)\sigma_s^2 + (1-\lambda)^2c_M^2(1-\alpha_u)\sigma_u^2} < 0
\]  

\[\text{(4.6)}\]

\[
\frac{\partial \beta_r}{\partial \alpha_i} = \frac{\beta_i^3\sigma_s^2}{3\beta_r^2(1-\alpha_v)\sigma_s^2 + (1-\lambda)^2c_M^2(1-\alpha_u)\sigma_u^2} > 0
\]  

\[\text{(4.7)}\]

To see the intuition in the above result, I rewrite the report as follows:

\[r = (1-\lambda)(\hat{r} - \hat{f}) + \lambda f + (1-\lambda)\hat{f}\]

This separates the manager’s report into the incremental information signal that investors (or the market maker) can obtain from the report, \((\hat{r} - \hat{f})\), and how the incremental information signal is distorted because of the manager’s desire to not deviate too far from the analyst’s forecast. The incremental information signal part distorts the manager’s knowledge about the true, underlying firm value due to his price-driven incentives, which the market maker is unable to fully undo because there is uncertainty about the reporting incentives. However, the manager also distorts the report from the incremental information signal due to the desire to
be close to the forecast. However, this distortion can be fully backed out by the market maker. Changing a parameter value can thus have two kinds of effects: the effect on the incremental information signal part, where the market maker tries to undo the distortion based on the underlying distributions as much as possible, and the effect on the forecast’s incentives-driven distortion, which the market maker can fully undo. Both have an impact on the equilibrium response coefficient, but for different reasons. The underlying incremental informational value changes $\beta_r$. The known distortion (due to the manager’s desire to be close to the forecast) changes the adjustment from $\beta_r$ to $\beta_r$. The total impact on $\beta_r$ contains both of these effects.

Increasing $\alpha_u$ causes the incremental signal in $(\hat{r} - \hat{f})$ to become noisier because it increases the informational content of $\hat{f}$. This would cause $\beta_r$ to become smaller. Meanwhile, a more informative $\hat{f}$ would mean that it is more costly to deviate from $u$ due to the manager’s incentive to be close to the analyst’s forecast. This means that the manager will lower his known distortion, which the market maker is able to back out. As a result, the earnings response coefficient is smaller. These two reinforcing effects mean that the earnings response coefficient decreases with the quality of the analyst’s value information.

Similarly, better analyst’s information about the manager’s incentives would result in a lower informational content of the forecast and higher incremental information value in $(\hat{r} - \hat{f})$, which causes $\beta_r$ to increase. Meanwhile, a less informative $\hat{f}$ reduces the manager’s cost to deviate from $u$ due to his incentive to be close to the analyst’s forecast, and he reacts by increasing the known distortion, which causes the earnings response coefficient to be larger because the market maker can back out this distortion. These two reinforcing effects mean
that the earnings response coefficient increases with the quality of the analyst’s incentives information.

\[
\frac{\partial \beta_r}{\partial \lambda} = \frac{(2(1-\lambda)\beta_r - 1)c_M^2(1-\alpha_u)\sigma_u^2}{3\beta_r^2(1-\alpha_x)\sigma_x^2 + (1-\lambda)^2 c_M^2(1-\alpha_u)\sigma_u^2} \tag{4.8}
\]

Increasing \(\lambda\) (holding everything else constant) causes the incremental signal in \((\hat{r} - \hat{f})\) to become noisier. That is, it is a worse signal in the sense that \(\text{var}(u | \hat{r} - \hat{f})\) is larger. This is because it reduces the cost to the manager of deviating from \(u\), and he reacts by increasing the price incentives-driven distortion in \(\hat{r}\). This should unambiguously cause \(\beta_{\hat{r}}\) to decrease.

However, increasing \(\lambda\) also means that the actual report \(r\) is more driven by \(f\) (this is reflected in the expression, which shows that \(r = \lambda f + (1-\lambda)\hat{r}\)). The market maker undoes this by dividing the report \(r\) by \((1-\lambda)\) to arrive at the signal in \(\hat{r}\). This causes the response coefficient on \(r\) to be higher. (This is reflected in the equation that links \(\beta_{\hat{r}}\) to \(\beta_{\hat{r}.}\)) Thus, there are two offsetting effects: \(\beta_{\hat{r}}\) decreases, while the adjustment from \(\beta_{\hat{r}}\) to \(\beta_{\hat{r}.}\) increases.

The comparative static result indicates that, when \(\beta_{\hat{r}}\) is small, the first effect dominates, and vice versa when \(\beta_{\hat{r}}\) is large.

Equation (4.8) is positive when \(\beta_{\hat{r}} > \frac{1}{2}\) and negative when \(\beta_{\hat{r}} < \frac{1}{2}\). This means that the earnings response coefficient \(\beta_{\hat{r}}\) increases with the weight the manager attaches to his incentive to be close to analyst’s forecast, relative to his biasing cost when the report’s information signal part \(\beta_{\hat{r}}\) is larger than one-half; it decreases with it when the report’s information signal part is less than one-half. It can be shown that \(\beta_{\hat{r}}\) decreases in \(\lambda\), and
approaches 0 as \( \lambda \) approaches 1. This means that, if \( \beta_\ell < 0.5 \) when \( \lambda = 0 \), \( \beta_r \)
monotonically decreases in \( \lambda \). However, if \( \beta_\ell > 0.5 \) when \( \lambda = 0 \), then \( \beta_r \) first increases
with \( \lambda \) and then eventually decreases with it. This is an interesting result, and it suggests that
it is possible for the price response coefficient \( \beta_r \) to increase even as the quality of the
information signal that can be extracted from \( r \) worsens. That sounds a note of caution to
empirical work that uses the ERC as an indicator of earnings quality; in this model, a higher
“ERC” (\( \beta_r \)) need not mean a higher quality report, \( r \).

We collect the above results in the following proposition.

**Proposition 7:** The earnings response coefficient

(i) Decreases with the quality of the analyst’s value information;

(ii) Increases with the quality of the analyst’s incentives information;

(iii) Increases with the weight on the manager’s incentive to be close to the analyst’s
forecast when \( \beta_\ell > \frac{1}{2} \) and decreases with it when \( \beta_\ell < \frac{1}{2} \).

4.4.8 The Analyst’s Distortion Coefficient on her Expected Forecast \( \theta_f \)

The reason we should care about the distortion coefficient on the analyst’s expected forecast
is the same as that for the cosmetic effect. Although investors can back out the analyst’s
distortion, it nonetheless affects the cost of biasing the forecast by the analyst.

**Proposition 8:** The analyst’s adjustment coefficient on her expected forecast \( \theta_f \)

(i) Is U-shaped in the quality of the analyst’s value information;

(ii) Decreases with the quality of the analyst’s incentives information.
Proof: See appendix.

For part (i), a necessary and sufficient condition for $\theta_j$ to increase with the quality of the analyst’s value information $\alpha_a$ is

$$\beta_r > \frac{(1-\lambda)c_a\sqrt{c}}{\sigma_x},$$

where $\tau$ is shown in appendix A.

Otherwise, $\theta_j$ decreases in $\alpha_a$. This means that the analyst’s distortion coefficient of her expected forecast increases (decreases) with the quality of the analyst’s value information when the earnings response coefficient is high (low). Because the earnings response coefficient always decreases with the quality of the analyst’s value information, this also means that the analyst’s distortion coefficient of her expected forecast increases (decreases) with the quality of the analyst’s value information when the information is coarse (fine). This happens because of the dual role of the analyst’s objective function to care about the subscribing investor’s trading profits and forecast accuracy, as well as the interaction between the analyst’s forecast and the manager’s report. There are two offsetting effects. The direct effect is that the higher quality of the analyst’s value information leads to a higher expected forecast response coefficient, which in turn leads to lower distortion of the expected forecast to achieve a high level of the subscribed investor’s trading profits and forecast accuracy. The indirect effect indicates that the marginal expected forecast response coefficient increases with the quality of the analyst’s value information and incentivizes more distortion of the expected forecast because the analyst possesses more power. My result indicates that, when the analyst’s value information is coarse, the indirect effect dominates, but the direct effect dominates when the analyst’s value information is fine.

Part (ii) shows that, holding everything else constant, the forecast’s distortion of the expected forecast decreases with the quality of the analyst’s signal about the manager’s incentives. This is because the expected forecast response coefficient decreases with the quality of the
analyst’s signal about the manager’s incentives, and the analyst is less able to move prices at time t=2 and time t=3.

4.5 Conclusion

In this paper, I established a model in which the manager has private information about firm value and has to issue a report; however, he also has hidden price incentives and an incentive to be close to the analyst’s forecast. Before the manager issues his report, the analyst observes two signals, one about firm value and one about the manager’s hidden price incentives. She then issues a forecast first to the subscribed investor alone, who exits the market at time t=2, and then to other investors. The analyst cares about the subscribed investor’s profits and forecast accuracy. Another player in the model is the market maker, who sets prices equal to the expected value of the firm’s final payoff, given the available information.

I derive the equilibrium of the game and a number of interesting results. For example, I find that the earnings response coefficient increases with the relative weight the manager attaches to his incentive to be close to analyst’s forecast when the report’s information signal is large, but it decreases with it when the report’s information signal is small. It can easily be demonstrated that $\beta_i$ decreases in $\lambda$ and approaches 0 as $\lambda$ becomes large. Thus, if the value of $\beta_i$ when $\lambda = 0$ is less than 0.5, $\beta_i$ monotonically decreases in $\lambda$. However, if the value of $\beta_i$ when $\lambda = 0$ is greater than 0.5, then $\beta_i$ first increases in $\lambda$ and then eventually decreases with it. This is an interesting result. It suggests that it is possible for the price response coefficient $\beta_i$ to increase, even as the quality of the information signal that can be extracted from $r$ worsens. That sounds a note of caution to empirical work that uses the ERC
as an indicator of earnings quality; in this model, a higher ‘ERC’ ($\beta_r$) need not mean a higher quality report, $r$.

Future studies should focus on algebraically deriving the comparative statics of reporting bias, forecast error, forecast distortion, and investors’ residual uncertainty, and they should draw more definitive conclusions.
Appendix

Proof of Proposition 8

Part (i): From the equilibrium equation for $\theta_f$, we have

$$\frac{1}{2}k\frac{\beta_{\sigma f}}{\sigma^2} (3 \frac{\partial \beta_{\sigma f}}{\partial \alpha_u} - \frac{\beta_{\sigma f}}{\alpha_u})$$

$$\frac{\partial \theta_f}{\partial \alpha_u} = \frac{1}{c_{\lambda}(1-\lambda)(2\theta_f -1)}$$

The equation below is quartic in $\beta_f$. In order to find its roots, we need to solve

$$3 \frac{\beta_{f\alpha u}}{\alpha_u} - \frac{\beta_{f\alpha u}}{\alpha_u} = 3(1-\beta_f) \frac{\beta_{f\alpha u}}{\alpha_u} (1-2 \frac{\alpha_u}{\beta_f} \frac{\partial \beta_{f\alpha u}}{\partial \alpha_u}) - \frac{\beta_{f\alpha u}}{\alpha_u} = 0$$

Or

$$3(1-\beta_f) [1-2 \frac{\alpha_u}{\beta_f} \frac{\partial \beta_{f\alpha u}}{\partial \alpha_u}] - 1 = 0$$

Let $c = \frac{\beta_{f\alpha u}^2}{(1-\lambda)^2 c_{\alpha u}^2 \sigma^2}$; this is equivalent to solving

$$3 \frac{c \alpha_u}{\alpha_u \sigma^2 + c \alpha_u} \left[1 + 2 \frac{\alpha_u}{1-\alpha_u} \frac{1}{3c(1-\alpha_u) + (1-\alpha_u)\sigma^2} \right] - 1 = 0$$

Solving for $c$, we have

$$\bar{c} = \frac{(1-\alpha_u)\sigma^2 [\sqrt{4\alpha_u^2 + \alpha_u^2 \alpha^2 + \alpha_u^2 - 2\alpha_u^2 \alpha_u + 28\alpha_u \alpha_u - 28\alpha_u^2 \alpha_u - (2\alpha_u - \alpha_u \alpha_u + \alpha_u)]}{12\alpha_u(1-\alpha_u)}$$
When $c > r$ or $\beta_i > \frac{(1-\lambda)c_m \sqrt{c}}{\sigma_x}$, we have $3 \frac{\partial \beta_i}{\partial \alpha_u} - \frac{\beta_i}{\alpha_u} > 0$. Otherwise, we have

$$3 \frac{\partial \beta_i}{\partial \alpha_u} - \frac{\beta_i}{\alpha_u} < 0.$$ 

Part (ii):

$$\frac{\partial \theta_i}{\partial \alpha_s} = \frac{k \beta_i}{\gamma \alpha_s} \frac{\partial \beta_i}{\partial \alpha_s} < 0$$

because

$$\frac{\partial \beta_i}{\partial \alpha_s} = \frac{\beta_i^3 \sigma_x^2}{3 \beta_i^2 (1-\alpha_u) \sigma_x^2 + (1-\lambda)^2 c_M (1-\alpha_u) \sigma_x^2} > 0$$

$$\frac{\partial \beta_i}{\partial \alpha_s} = -\frac{1}{\alpha_u \sigma_u^2 + (\frac{\beta_i}{(1-\lambda)c_M})^2 \alpha_u \sigma_u^2} \frac{\partial \beta_i}{\partial \alpha_s} + \frac{\beta_i}{(1-\lambda)c_M} \frac{\sigma_x^2}{\alpha_u \sigma_u^2 + (\frac{\beta_i}{(1-\lambda)c_M})^2 \alpha_u \sigma_u^2} < 0$$
Chapter 5: Conclusion

In this thesis, I study how the presence of an analyst affects the corporate information environment when both the analyst’s forecast and the manager’s financial report are endogenously chosen. I extend Beyer’s (2008) work by allowing the manager to have hidden price incentives and the analyst to have a signal about the manager’s hidden reporting incentive. I also study different analyst incentives from Beyer (2008). In Chapter 3, I show the questionable nature of Beyer’s (2008) suggestion that the fact that the analyst’s forecasting strategy depends on the manager’s incentives is due to the interaction between the analyst and the manager. The properties of the analyst’s forecast, such as forecast accuracy and the forecast’s deviation from the firm’s fundamentals, depend on the manager’s incentives, even if the analyst does not care about the manager’s report. The manager, however, tries to be as unilaterally close to the analyst’s forecast as possible. Another key takeaway from the chapter is that investors’ total information at hand after both the forecast and the report are released is non-monotonic in the quality of the analyst’s information, increases with the manager’s weight on being close to firm fundamentals, and decreases with the manager’s weight on being close to the analyst’s forecast. Further, I demonstrate that the analyst’s signal about the manager’s incentives has no effect when the analyst’s objective is to minimize deviation from firm fundamentals.

In Chapter 4, I complement Beyer’s (2008) research by showing that the properties of the analyst’s forecast and the manager’s report depend on the analyst’s incentives due to the interaction between the analyst and the manager. I also show that both the analyst’s forecast
distortion and forecast accuracy are non-monotonic in the quality of the analyst’s value information, which is different from Chapter 3 and Beyer (2008).

My research might be extended in important ways by studying other analyst incentives. In addition to forecast accuracy, this thesis also studies the analyst’s incentive to be close to firm fundamentals in Chapter 3 and to care about client’s trading profits in Chapter 4. I derive different results for different analyst incentives. It might help our understanding of analyst behavior to investigate her other incentives.
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