

TWO ESSAYS ON INVESTORS' PERCEPTIONS ABOUT MANAGEMENT
DISCLOSURES

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TWO ESSAYS ON INVESTORS' PERCEPTIONS ABOUT
MANAGEMENT DISCLOSURES

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In this dissertation, I describe two studies related to investors' perceptions about management disclosures.

In the first study, I use a variant of Dye and Sridhar (2004) to show analytically that investor uncertainty about managers' reporting incentives to manipulate information reduces the degree to which accounting reports should weight manipulable information. I also predict and show experimentally that greater weight on manipulable information in the face of incentive uncertainty harms investor welfare more than predicted by equilibrium analyses, by hindering managers' and investors' ability to predict one another's strategies. The resulting deviations from equilibrium cause the perceived and actual value-relevance of financial reports to vary over time in predictable (and testable) ways.

In the second study, I report an experiment that examines how investor affect might influence investors' perceptions of management disclosure credibility. Based on accounting and psychology literature, I predict that investors in a positive affective state will assess a higher level of management disclosure credibility due to positive interpretation and heuristic processing of information, and this tendency will be mitigated by their awareness of management reporting incentives. The results show that, inconsistent with prior evidence, positive affect does not lead to higher assessments of management disclosure credibility. Instead, positive affect is associated with a more systematic information-processing strategy. The results suggest that the

psychology literature on affect need to be refined to be applied in a management disclosure setting.

BIOGRAPHICAL SKETCH

Hailan Zhou was born in a loving and caring family in China on June 6, 1976. She received her Bachelor of Science in economics from Fudan University in Shanghai, China in 1998. As one of the top students in her class, she was selected to pursue an advanced degree in economics at Hong Kong University of Science and Technology (HKUST). During her time at HKUST, she visited the University of Mannheim in the summer of 2000, where she met her then future advisor Robert Bloomfield in a three-day workshop. She was intrigued by the workshop topic on experimental research in accounting. Inspired by Rob's research, she decided to pursue an accounting PhD in the U.S. She entered Cornell University to pursue a PhD in accounting at the Johnson Graduate School of Management in 2001 and worked with Rob Bloomfield since then. After she completed her studies at Cornell University, she joined the faculty at University of Illinois at Urbana-Champaign in 2006.

This work is dedicated to my parents, for all their love and support through the ups
and downs of my life.

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CHAPTER 1

Incentive Uncertainty, Relevance, and Reliability

I. INTRODUCTION

Accounting regulators seek to make financial statement information both relevant and reliable, but recognize that these two goals often conflict (SFAC No. 2, FASB 1980). Recent moves toward fair value accounting in both domestic and international reporting suggest that regulators believe the relevance of fair value measures outweighs the unreliability that arises from the noise and bias inherent in many value estimates.

Dye and Sridhar (2004, hereafter “DS”) provide a game-theoretic framework that is useful for identifying the extent to which accounting reports should include information that (like a fair value estimate) is not only known privately by managers, but is also manipulable by them. In this paper, I modify their model to show that investors’ uncertainty about managers’ reporting incentives reduces the extent to which estimates should be included in financial reports in equilibrium, if regulators seek to maximize investor welfare. I also use a disequilibrium analysis to show that incorporating manipulable estimates into financial reports in the presence of high incentive uncertainty is likely to impair investors’ ability to assess the usefulness of the reports. I confirm these predictions in a laboratory experiment.

In both my model and DS, a firm reports a weighted average of a non-manipulable signal and a manipulable signal (which, in the absence of manipulation, would provide incremental information to investors). I extend DS by assuming that investors have imperfect information about the benefits of manipulation to the manager. This “incentive uncertainty” implies that investors cannot perfectly undo the manager’s manipulation, as they can in DS. In equilibrium, greater incentive uncertainty lowers

the value-relevance of reports, and also lowers the weight on the manipulable signal that maximizes the value-relevance of the report in equilibrium (and consequently maximizes investor welfare). Incentive uncertainty induces a trade-off between relevance and reliability that is similar to that discussed by accounting regulators: too much weight on the manipulable information reduces the reliability of the aggregated report, and consequently compromises the value-relevance of the aggregated report.

I also conduct a disequilibrium analysis by assuming that players use iterated deletion of dominated strategies (IDD), also called “rationalization,” to narrow the set of feasible strategies, and then choose arbitrarily from those remaining sets. This analysis shows that greater incentive uncertainty and greater weights on manipulable information increase the size of the rationalizable sets, suggesting that players’ expectations of one another’s strategies are likely to be less accurate (as in Bloomfield 1995, 1997). These expectation errors result in disequilibrium outcomes that harm the welfare of investors by reducing their ability to value the firm accurately.

The predictions of the disequilibrium analysis depend crucially on its assumptions about how players select strategies, which may well be inaccurate. I test these predictions by conducting an experiment in which pairs of students play the reporting game in four settings. I manipulate two variables: investor uncertainty in managerial reporting incentives, and the weight of managerial estimates in the aggregated report. The experimental results show that the managers’ and the investors’ welfare losses due to inaccurate expectations of their opponent’s strategy increase with weight on the manipulable information and with the uncertainty in management reporting incentives. High weight on manipulable information also impedes investors’ ability to predict managers’ reporting strategies, although, high incentive uncertainty does not. This mixed result arises because players do not choose strategies arbitrarily from within the rationalizable sets, as assumed by the disequilibrium analysis. Instead, they tend to

avoid high-risk strategies. When incentive uncertainty is high, investors avoid risk by reducing their reliance on reports, and managers avoid risk by responding less strongly to their incentives for manipulation. These patterns of behavior improve expectation accuracy, although investors' welfare is still substantially below equilibrium levels on average.

Overall, the results suggest that incentive uncertainty dramatically reduces the extent to which regulators should incorporate fair value and other manipulable information into financial reports, because of both their equilibrium effects and their tendency to cause disequilibrium outcomes. The results also provide testable hypotheses: the actual and perceived reliability of financial reports are likely to vary more over time, and be more misaligned with each other, when more manipulable information is incorporated in financial reports.

The rest of the paper is organized as follows. Section II presents the model of the manager and investors and derives predictions of behavior based on the notion of strategic dependence. Section III describes the experiment. Section IV analyzes the experimental results. Finally, section V provides the conclusion.

II. MODEL AND HYPOTHESES

In this section I first describe the specification of the model (players, information, actions and incentives). I next describe the equilibrium, in which the manager and investor each behave optimally given the behavior of the other. I then describe the disequilibrium analysis, which assumes that players apply a process of rationalization to select strategies. Finally, I present hypotheses derived from the disequilibrium analysis.

Specifications of Model

As in the DS model, information about the firm's net assets comes from a non-

manipulable signal and the manager's claim about a manipulable signal. The manager privately observes the manipulable signal of the net assets and needs to determine the amount to report on the balance sheet.

Value and Information. The economic value of the firm's net assets, $\tilde{\omega}$, follows a normal distribution with a publicly known mean $\bar{\omega}$ and variance σ_{ω}^2 . The non-manipulable signal of the firm's net assets provides a noisy measure of the economic value of the firm's net assets, $\tilde{\omega}_h = \tilde{\omega} + \tilde{\delta}$, where $\tilde{\delta}$ follows a normal distribution with mean zero and variance σ_{δ}^2 .

The manager also makes a claim ω_m after observing another measure of the firm's net assets, $\omega_f = \tilde{\omega} + \tilde{\epsilon}_{\omega}$, where $\tilde{\epsilon}_{\omega}$ is a normal random variable independent of the non-manipulable signal, with mean zero and variance σ_{ϵ}^2 .

The firm's reported net assets are determined by a weighted average of the manager's reported manipulable signal and the non-manipulable signal of the firm's net assets according to the equation $r = \lambda\omega_m + (1-\lambda)\omega_h$, where λ can be viewed as the portion of the manipulable measure in the firm's balance sheet. Investors are assumed not to be able to disaggregate the manipulable and non-manipulable signals.

The model setup can be mapped into the framework in Maines and Wahlen (2005). The non-manipulable signal captures the measurement attribute of a historical cost measure and the manipulable (and therefore potentially less-reliable) signal captures the measurement attribute of a fair value measure. The optimal choice of λ represents the optimal extent to which regulators should choose to incorporate fair value. The optimal λ also reflects the optimal trade-off between relevance and reliability.

Note that my model assumes that, since accounting policies are public knowledge, the aggregator λ is assumed to be known to investors. Despite investors' knowledge about λ , I assume that investors are unable to differentiate between the non-manipulable and manipulable components of accounting reports. As Sunder (1997)

points out, in the process of aggregation, accountants add their knowledge and judgments about similarities and dissimilarities of various accounts. Each line in the accounting report is an aggregation of various inputs and accounting experts' knowledge. Investors often lack the expertise to disaggregate financial reports to more or less reliable items.¹

Actions and Incentives. The manager incurs an expected cost of $\frac{c}{2} E[(\omega_m - \omega_f)^2]$

for stating an estimate that is higher or lower than the objective information suggests, where c is a fixed positive constant. The cost to manipulate can reflect regulatory costs, reputation cost, the degree of slack in the firm's financial position that can be used to manipulate the balance sheet, and personal effort of manipulation.

I extend DS by relaxing the assumption that the manager's incentives are fixed and known by investors. Instead, in my model, the manager's incentives to manipulate the firm's financial reports are uncertain and cannot be communicated to investors credibly. This change allows my model to reflect investors' uncertainty over whether a given report reflects optimism or pessimism (perhaps because managers are setting up 'cookie-jar' reserves that provide slack to report optimistically at a later date).²

Specifically, I assume that the manager receives a payoff proportional to the

¹ Even at the individual account level, investors often face difficulty in disaggregating an accounting item to components with different degrees of manipulability. For example, FASB Statement No. 123, Share-Based Payment, requires companies to measure the cost of employee services received in exchange for an award of equity instruments based on the grant-date fair value of the award. It specifies that if an observable market price is not available for a share option with the same or similar terms and conditions, the fair value of that instrument must be estimated. In estimating the fair value, a company must choose a valuation model, and must develop reasonable and supportable estimates for each assumption used in the model. Given the complexity, investors are unlikely to disentangle the contributions of different inputs in determining the estimated fair value.

² To focus on the interaction between the manager and investors, I also assume that the investment level is determined exogenously, rather than chosen by the manager as in DS. This simplification does not affect the nature of the interaction between the manager's reporting decision and investors' use of the firm's financial reports. When investment is assumed to be endogenous, it is determined purely by investors' reliance on the aggregated report. Thus, the results in this paper can be readily extended to an investment setting.

investors' estimate of the firm's net assets, $m\omega_e$, where m is an incentive multiplier that captures the sensitivity of the manager's payoff to the investors' estimate of the firm's performance, ω_e . \tilde{m} is assumed to follow a normal distribution with mean zero³ and variance σ_m^2 . The realization of \tilde{m} is only observed by the manager and cannot be credibly communicated to other people. Allowing for variation in this incentive (including both positive and negative values) reflects the fact that firms sometimes have incentives to inflate reported assets, and sometimes have incentives to deflate them, and that firms may have incentives to inflate or deflate reported assets to different extent. The magnitude of the multiplier can be affected by multiple factors, such as the proportion of stock-based compensation in the manager's incentive scheme and the sensitivity of market valuation of firm performance to the firm's financial reports.

The investors estimate the firm's performance based on the aggregated report of the firm's net assets. As in DS, I assume that the investors use a linear function of the form $\omega_e(r) = a + br$ to arrive at their evaluation of the firm's performance. (I prove in Appendix I.F. that a pricing function that is linear in r is an optimal response to a reporting function that is linear in b).

Best Response Functions and Equilibrium

The manager's strategy can be characterized as choosing an "adjustment factor," denoted θ ($\theta > 0$), which is multiplied by m to determine the difference between ω_m and ω_f . A high adjustment factor implies that the manager's report is highly sensitive to the realization of the manager's (random) incentive. To identify the optimal choice of θ given the investors' level of reliance b , note that the manager's payoff is $m(a + br) - \frac{c}{2}(m\theta)^2$, and (solving for the first-order condition) the

³ The assumption that \tilde{m} has a mean of zero is not crucial to the qualitative aspects of the results.

manager's best reporting strategy is $\omega_m(\omega, \varepsilon_\omega) = \frac{mb\lambda}{c} + \omega + \varepsilon_\omega = m\theta + \omega + \varepsilon_\omega$.

Therefore, the manager's best response function θ^* can be written as:

$$\theta^*(b) = \frac{b\lambda}{c} \quad (1)$$

The manager's best response function $\theta^*(b)$ increases linearly in his expectation of investors' reliance on the report. As expected reliance increases, the manager benefits more by manipulating more of his information, *ceteris paribus*. An increase in the weight on the manipulable signal, as measured by λ , increases the optimal level of manipulation for each expected level of reliance. Similarly, a decrease in the reporting cost increases the optimal level of manipulation for each expected level of reliance.

The investors' strategy can be characterized as choosing an intercept term, a , and a slope term, b , which when multiplied by the reported value r determines a valuation of the firm's net assets. The optimal intercept term is always 0, given the assumption that $\bar{\omega}$ and \bar{m} are drawn from a distribution with a mean of 0. Therefore, my analysis focuses on the slope term, b , which represents the investors' reliance on the report.

For any adjustment factor, θ , the investors' best response can be represented as

$$b^*(\theta) = \frac{\sigma_\omega^2}{\sigma_\omega^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2 + \lambda^2 \sigma_m^2 \theta^2} \quad (2)$$

where a and b are as in the investors' linear evaluation model $\omega_e(r) = a + br$. The last term in the denominator of $b^*(\theta)$, $\lambda^2 \sigma_m^2 \theta^2$, indicates the effect of the expected level of manipulation on the investors' reliance. An increase in the adjustment factor decreases the investors' optimal level of reliance because the reported net assets contain more of management manipulation. The optimal level of reliance is always non-negative and bounded from above by the informational value of the report in the absence of any manipulation. An increase in λ or an increase in the manager's

reporting uncertainty σ_m^2 decreases the optimal level of reliance for every level of manipulation the investors expect.

Incentive uncertainty qualitatively alters investors' best response function, relative to DS. In DS, the manager's certain incentive allows investors to know exactly how much the manager has altered the report, and therefore allows investors to undo the manipulation by adjusting the intercept to the valuation model. In the presence of incentive uncertainty, however, investors cannot know exactly how much the manager has altered the report, or in which direction. As a result, investors reduce the slope of the model, effectively viewing the report as less value-relevant, with perceived value-relevance decreasing with increasing expectations of adjustment.

Figure 1.1 depicts an example of the manager and investors' best responses. The level of adjustment factor θ is shown on the X-axis, and the level of reliance b is shown on the Y-axis. The level of reliance ranges from 0% to 100%, and the level of adjustment factor ranges from 0 to infinity. For ease of presentation, I report the level of adjustment factor as a percentage of 5 throughout the paper (e.g., an adjustment factor of 3 is reported as 60%), because 5 is significantly higher than any reasonable level of adjustment factor in the numerical examples used in the paper and experiment. The downward sloping line depicts the investors' optimal reliance $b^*(\theta)$ on the aggregated report for every level of adjustment factor θ . The investors' optimal reliance on the report increases as the investors' belief of the adjustment factor decreases. The upward sloping line depicts the manager's optimal magnitude of adjustment factor $\theta^*(b)$ for every level of the investors' reliance b on the aggregated report. The optimal adjustment factor increases as the manager's belief of the investors' reliance increases. When both the manager and investors have correct

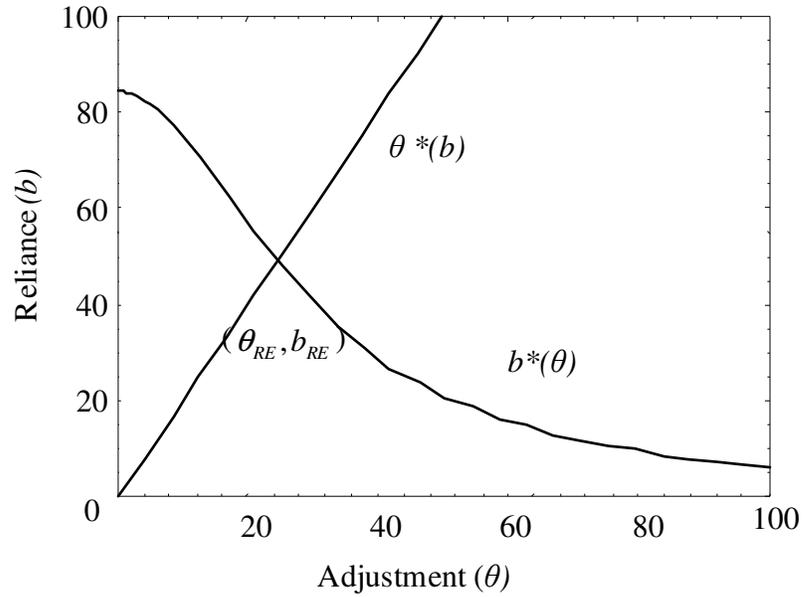


FIGURE 1.1

Example of Best Responses

This figure shows an example of the manager and investor's best responses. The X-axis depicts the level of the investor's reliance, and the Y-axis depicts the level of the manager's adjustment factor. The downward sloping line depicts the investor's optimal reliance $b^*(\theta)$ on the aggregated report for every level of adjustment factor θ^* . The upward sloping line depicts the manager's optimal adjustment factor $\theta^*(b)$ for every level of the investor's reliance on the aggregated report. The intersection of the two best response functions indicates the rational expectations equilibrium (θ_{RE}, b_{RE}) .

beliefs about their opponents' strategies and play the best responses to their beliefs, they are at the rational expectations equilibrium indicated by the intersection of the two best response curves.

Formally, the rational expectations equilibrium is defined as follows:

Definition 1. An equilibrium relative to the aggregation rule λ consists of a valuation equation $\omega_e(\cdot)$ and a reporting function $\omega_m(\cdot)$ such that:

(i) The reporting rule $\omega_m(\omega, \mathcal{E}_\omega)$ maximizes

$$m\omega_e[\lambda\omega_m + (1-\lambda)\omega_h] - \frac{c}{2}(\omega_m - \omega_f)^2;$$

(ii) The valuation rule $\omega_e(\cdot)$ satisfies $\omega_e[r] = E[\tilde{\omega} | r]$ for each report r .

This definition of equilibrium requires that the manager chooses the adjustment factor that maximizes his payoff given investors' valuation model, and that the investors choose the valuation model that minimizes their estimation error given the manager's adjustment factor. Given this definition, the unique linear equilibrium is given in the following proposition.

Proposition 1. For any aggregation rule $\lambda \in [0, 1]$, there is a unique linear equilibrium given by

(i) $\omega_e[r] = (a + br)$, where $b = \frac{\sigma_\omega^2}{\sigma_\omega^2 + \lambda^2(\theta)^2\sigma_m^2 + \lambda^2\sigma_\varepsilon^2 + (1-\lambda)^2\sigma_\delta^2}$ and $a = 0$;

(ii) The manager's equilibrium report is given by $\omega_m(\omega, \mathcal{E}_\omega) = m\theta + \omega + \varepsilon_\omega$, where $\theta(b) = \frac{b\lambda}{c}$.

(See Appendix I.A. for a Proof of Proposition 1.)

A hypothetical regulator seeking to maximize investor welfare in equilibrium will choose a value of λ , denoted λ^* , that maximizes the equilibrium level of b , which

measures the value-relevance of the report (Appendix I.E. proves the optimal λ that maximizes the equilibrium b also maximizes the investor welfare). Appendix I.B. shows that an increase in incentive uncertainty causes a decrease in λ^* . An increase in incentive uncertainty decreases the reliability of the report for each level of management manipulation and effectively reduces the value-relevance of the report. Thus, the regulator seeking to maximize the value-relevance of the report will reduce the weight on the manipulable information to suppress the manager's incentive to misreport. The discussion above highlights the key difference between my model and DS. In my model, with incentive uncertainty, the optimal incorporation of estimates in the report reflects a trade-off between relevance and reliability, as opposed to DS, where λ^* is unaffected by reliability due to a fixed reporting incentive.

Disequilibrium Behavior and Strategic Dependence

Having characterized equilibrium outcomes, I now examine forces that might make equilibrium more or less difficult to achieve. The rational expectations equilibrium requires both the manager and investors to accurately predict one another's strategies. However, many game theorists have argued that players will develop accurate expectations only if there is some process that leads them to do so (Binmore 1987). For my analysis, I assume that players use the process of "rationalization", which is equivalent to the process of "iterated deletion of dominated strategies" (IDD) in my setting (Bernheim 1984; Pearce 1984), to eliminate all but a set of feasible strategies.

In rationalization, players iteratively restrict their choices by eliminating actions that are not the best response to at least one possible strategy not yet eliminated by the other player. To formalize this, let B denote all possible choices of b , and let H represent all possible choices of θ . Then define the operator $R(\cdot)$ to indicate the set of all best responses to a set of strategies. Let $B_0 = R(H)$ denote the set of values of b

that are not eliminated by the first application of this rule, and let $H_0 = R(B)$ denote the set of values of θ that are not eliminated by the first application of this rule. In successive iterations of this thought process, each player eliminates strategies that are not the best response to any choice of the other player that has not been eliminated in a previous iteration. Thus, H_1 is the set of strategies that are best responses to some element of B_0 , and B_1 is the set of strategies that are best responses to some element of H_0 . Generalizing this process, H_K is the set of strategies that are best responses to some element of B_{K-1} , and B_K is the set of strategies that are best responses to some element of H_{K-1} . The index K can be viewed as the “degree” of rationality of the players. An infinite value of K represents common knowledge of rationality. Following Bloomfield (1995, 1997), I refer to the size of the set that remains after a given number of rounds as a measure of the “strategic dependence” of the game.

To establish formally that increases in incentive uncertainty and weight on manipulable information increase strategic dependence, I calculate the product of the slopes of the best response functions at the equilibrium. If the best response functions were both straight lines, rationalization would eliminate all but the equilibrium outcome if the product of the slopes of the best response functions was smaller than 1. Even though the best response functions are not straight lines, the product of the slopes at equilibrium still serves as a good indicator of the degree of strategic dependence, especially near the equilibrium. I find that an increase in incentive uncertainty and weight (when the manipulable information is sufficiently informative) increases this measure of strategic dependence, and therefore should make equilibrium more difficult to achieve. This result is summarized in the following proposition.

Proposition 2. The product of the slopes of the best response functions increases with incentive uncertainty, σ_m^2 . The product of the slopes of the best response functions increases with weight, λ , when the manager’s information is sufficiently

informative. (See Appendices I.C. and I.D. for proofs).

To illustrate how the power of rationalization to eliminate strategies can vary with characteristics of the reporting game, Figure 1.2 shows four scenarios of the best response functions where σ_ω^2 is set to 100 and c is set to 0.2. The same four scenarios are used in the experiment. The weight on management report (λ) is 40% in Scenarios A and B, and 80% in Scenarios C and D. The incentive multiplier (m) has a standard deviation of 5 in Scenarios A and C, and 15 in Scenarios B and D. For the ease of illustration, σ_ε^2 and σ_δ^2 are set to 0, implying that both the manipulable and non-manipulable signals are perfect representations of the economic value of the firm's net assets. This dramatically simplifies the explanation of the task given to participants (who play the games depicted in Figure 1.2), and does not substantially alter the qualitative aspects of the analysis⁴. Because the manipulable estimate adds no information to the non-manipulable information, the lack of noise implies that the optimal weight on the management report is zero in all games; this assumption therefore eliminates a potential source of variation across settings, which is not the focus of this study.

Figure 1.2 depicts how the process of rationalization determines the accuracy of expectations in four parameterizations of the model. In scenario A, both the weight on the manager's report and the incentive uncertainty are low, resulting in low strategic dependence. The investors prefer relatively high reliance even if their expectation of the manager's adjustment level is high, while the manager prefers a relatively low adjustment level even if his expectation of the investors' reliance is high. As a result,

⁴ Setting σ_ε^2 and σ_δ^2 to zero does not change the manager's best response function. It does reduce the slope of the investors' best response, and therefore slightly reduces strategic dependence. However, the qualitative predictions of the model are not changed. In particular, all the proofs provided in the Appendices are based on the general model with non-zero σ_ε^2 and σ_δ^2 .

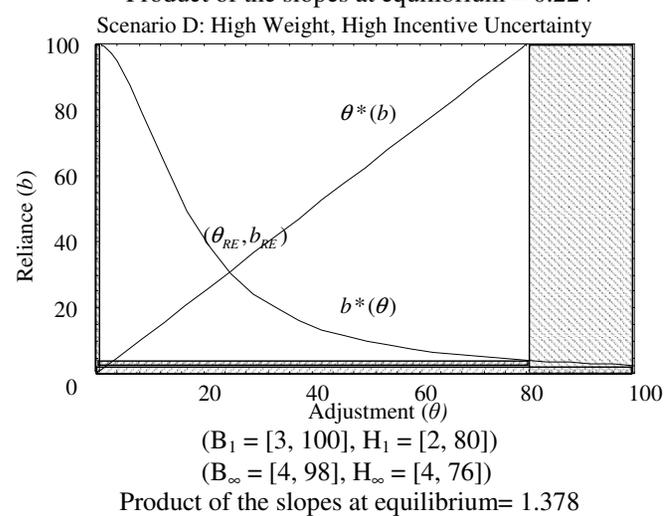
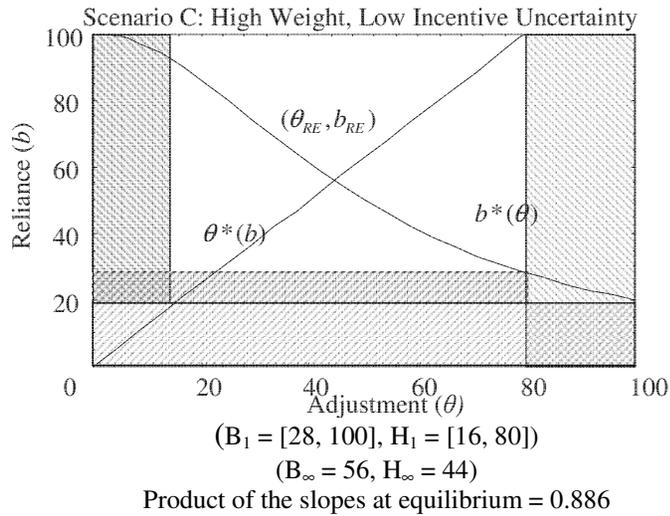
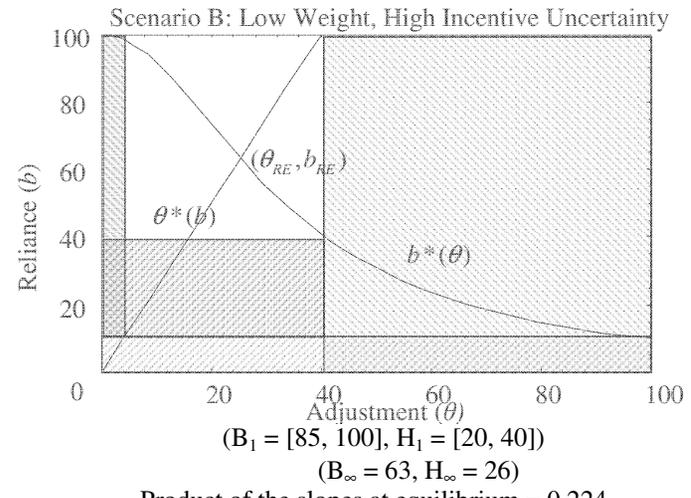
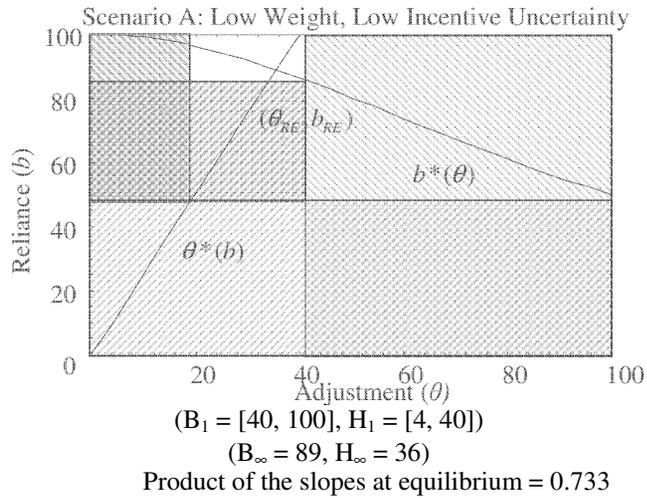
FIGURE 1.2

Four Scenarios of Strategic Dependence

This figure shows four scenarios of strategic dependence that are used in the experiment. For each scenario, the X-axis depicts the level of the investor's reliance, b , and the Y-axis depicts the level of the manager's adjustment factor, θ . The downward sloping line depicts the investor's optimal reliance $b^*(\theta)$ on the aggregated report for every level of the manager's adjustment factor θ^* . The upward sloping line depicts the manager's optimal level of adjustment factor $\theta^*(b)$ for every level of the investor's reliance on the aggregated report. The intersection of the two best response functions indicates the rational expectations equilibrium (θ_{RE}, b_{RE}) . The value of the firm's net asset is normally distributed with mean zero and standard deviation 10. Both σ_ε^2 and σ_δ^2 are zero. The incentive multiplier, m , has a standard deviation of 5 in scenario A and scenario C and 15 in scenario B and scenario D. The weight on the manager's adjustment is 40% in scenario A and scenario B and 80% in scenario C and scenario D.

The shaded areas show zero- and first-order rationalization for both the manager and investor. The areas shaded with  and  indicate the manager's strategies that are eliminated in the zero- and first-order rationalization. The areas shaded with  and  contain the investor's strategies that are eliminated in the zero- and first-order rationalization. Infinite iterations of the rationalization process reduce the rationalizable sets to zero in scenarios A, B and C with a much slower speed for scenario C. Infinite iterations of the rationalization process leaves the rationalizable set to a range for scenario D. Strategic dependence is the lowest in scenario A and the highest in scenario D.

B_i denotes the set of reliance that remains after i th-order rationalization. H_i denotes the set of adjustment factor that remains after i th-order rationalization. Product of the best response curves at equilibrium is a measure of the degree of strategic dependence. Strategic dependence is high when the product is greater than 1.



$B_0 = [50, 100]$ and $H_0 = [0, 40]$. The flatness of the best response curves implies that the next iteration of rationalization eliminates even more strategies, with $B_1 = [85, 100]$ and $H_1 = [20, 40]$. One more iteration of the rationalization process eliminates some dominated strategies and limits the final rationalizable set of strategies to the RE equilibrium.

Comparing across scenarios, Figure 2 shows that two iterations of rationalization leave larger sets of strategies remaining when the report places more weight on the manipulable information (comparing A to C and B to D), and when incentive uncertainty is greater (comparing A to B and C to D). Additional iterations tell a slightly different story: with infinite iterations, the rationalization process eliminates all strategies other than the equilibrium outcome in Scenarios A, B and C, although the process is far slower in scenario C; however, additional iterations eliminate hardly any additional strategies in Scenario D, in which both the weight on the manager's report and the reporting incentive uncertainty are high. In Scenario D, strategic dependence predicts that the RE equilibrium is likely to lose predictive power on subjects' behaviors.

Hypotheses

The preceding analyses suggest that it is harder for the manager and investors to form correct expectations of their opponent's strategy when either higher weight on manipulable estimates or higher incentive uncertainty creates high strategic dependence. I therefore predict that these aspects of the reporting environment lead players' expectations to be less accurate, and lead players to deviate more from equilibrium.

H1: Managers' assessments of investors' reliance and investors' assessments of managers' adjustments are less accurate when reports place more weight on managers' value estimates, and when managers' incentives are more uncertain.

H2: Managers' manipulations and investors' reliance deviate more from equilibrium when reports place more weight on managers' value estimates, and when managers' incentives are more uncertain.

H2 focuses on absolute, rather than signed deviations, because there is no reason that time-averaged strategies must deviate from equilibrium over many rounds, just because no single round is close to equilibrium⁵. Note also that the analyses on the measurements of strategic dependence seem to suggest that the effect of each variable is stronger when the other variable is at a high level. In particular, the rationalizable set of strategies is nonzero, and the product of the two best response curves is greater than 1, only when both weight and incentive uncertainty are high. This result suggests that the weight placed on the manager's estimate and the uncertainty in the manager's reporting incentives may interact. However, because strategic dependence is used only as a heuristic to generate qualitative predictions about unknown equilibrating processes, I do not hypothesize an interaction.

It is possible that inaccurate expectations and deviations from equilibrium arise not from players' inability to settle into a stable pattern of behavior, but from their tendency to settle into a stable pattern in which expectations are incorrect and far from equilibrium. To rule out this possibility, I examine instability in behavior over time.

H3: Managers' manipulations and investors' reliance vary more over time and converge to equilibrium more slowly when reports place more weight on managers' estimates, and when managers' incentives are more uncertain.

Note that the hypotheses above are not susceptible to the criticism (articulated by Kachelmeier (1996)) that they are foregone conclusions as long as the experiment successfully induces the correct payoffs and utility functions assumed by the

⁵ Hofbauer and Sigmund (1988) show that time average of players' strategies converge to equilibrium under certain conditions.

equilibrium model. Instead, the hypotheses are founded on an essentially psychological model of the process (rationalization) by which players choose their strategies. The hypotheses would be rejected if players were somehow able to select equilibrium strategies even when many other strategies are rationalizable. The hypotheses would also be rejected if characteristics of the players' payoff functions might alter how they choose among strategies that survive rationalization. In particular, the analysis ignores the fact that high incentive uncertainty dramatically increases the possible losses that the manager could face by choosing a high adjustment factor, or that investors could face by choosing high reliance, even though these strategies survive rationalization. To the extent that players' choices are determined by the risks involved in choosing strategies, rather than simply whether the strategies are *ever* best responses, the predictions of strategic dependence may not be upheld. Because there is no theory that predicts how players' risk preferences might interact with the prediction of strategic dependence in determining their choices, I do not form hypotheses on the effect of risk preferences.

III. THE EXPERIMENT

Design

To test the hypotheses laid out above, I conducted a laboratory experiment in a 2 (high vs. low weight) x 2 (high vs. low incentive uncertainty) x 10 (repetition) x 2 (order) mixed design as shown in Table 1.1. All variables except order were manipulated within-subjects. The design also includes two additional 10-round blocks for the high weight, high incentive uncertainty scenario to provide the subjects the best chance of learning in the high strategic dependence scenario. The parameter values in the experiment are identical to those used in generating Figure 1.2. Order of treatments was manipulated between-subjects to control for a potential order effect. A within-

subjects design controls for variance due to differences across subjects and enhances the power of the experiment. A within-subjects design can also cause demand effects, but these demand effects are unlikely to change the accuracy of subjects' expectations about other subjects' choices (which is the focus of the experiment).

TABLE 1.1

The Experimental Design

Treatment	Block I	Block II	Block III	Block IV	Block V	Block VI
Order I	LoW, LoU	HiW, HiU	LoW, HiU	HiW, HiU	HiW, HiU	HiW, LoU
Order II	HiW, LoU	HiW, HiU	HiW, HiU	LoW, HiU	HiW, HiU	LoW, LoU

*Note: LoW, LoU = low weight and low incentive uncertainty (Scenario A); LoW, HiU= low weight and high incentive uncertainty (scenario B); HiW, LoU= High weight and low incentive uncertainty (scenario C); and HiW, HiU= High weight and high incentive uncertainty (scenario D).

40 students at a private university participated in the experiment. Half of the subjects were randomly assigned the role of manager throughout the session, and the other half were assigned the role of investor. Subjects' identities were held anonymous throughout the session. To avoid the possibility that subjects' behaviors would be affected by real-world knowledge associated with the roles of manager and investor, all the instructions and experimental materials were worded neutrally. The managers were called 'reporters,' and the investors were called 'appraisers.' For the ease of presentation, I refer to the players as managers and investors in the paper. (See Appendix II for instructions to participants.)

Each manager was randomly paired with an investor at the beginning of the experiment and played with the same investor for the entire session. Fixed pairing is preferable to random pairing because it requires fewer subjects for the same statistical power, increases the opportunity for subjects to learn their opponents' strategy, and better reflects the interaction between managers and investors in the real world. A

potential cost of this choice is that fixed pairs may allow players to use multi-period strategies, and equilibria of the repeated game may differ from the equilibrium of the stage game if players can identify a cycle of outcomes that provide higher average payoffs for each player than their equilibrium payoffs in the stage game (Aumann, 1976). However, I test for and find no evidence of such behavior in the analysis.

The Task

In each round of play, each manager entered an expectation of the investor's choice of reliance, and also chose a level of adjustment. Their computer screens (see Appendix III for screen shots) showed the payoff they would expect to receive from their strategy given that their expectation was correct. Managers were allowed to alter their expectations and strategy choices as often as they wished before confirming their choices. Similarly, each investor entered an expectation of the manager's choice of adjustment factor, and also chose a level of reliance. The possible choice for the level of reliance ranged from 0% to 100%, and for the level of adjustment from 0 to 5 (where 5 is significantly higher than any reasonable level of adjustment predicted by the model).

Actual payoffs in each round were determined by the average payoff received from 100 representative realizations of the various random variables in the model (the error in manager's private information and manager's incentive). The use of 100 reports instead of one report per round has several benefits. It provides better measures of subjects' actual strategies, rather than strategies associated with individual realizations of base value and incentive multiplier of a report. The payoffs calculated based on the average result of all 100 reports are more comparable across rounds, providing each player with more precise feedback about the other player's strategy, therefore enhancing learning (Bloomfield, 1994).

In addition, I provided the subjects with graphs of the best response curves of their

own role in each scenario. Providing the best response curves reduces the noise in subjects' strategies and is likely to increase the possibility for the subjects to reach the equilibrium. In each round, both players made their decisions simultaneously. After both players had made their choices, they moved on to the feedback screen where they reviewed their opponent's actual strategy and their actual payoff calculated based on the actual strategies played. In addition, both the decision-making and feedback screens showed their decision history up to the last 5 rounds to facilitate their expectation formation.

Administration

Each session began with a short training session during which subjects learned about the experiment and became familiar with the task screen in four practice rounds. At the end of the session, subjects answered debriefing questions regarding their understanding of the experiment and their decision-making process. Subjects were told at the beginning of the experiment that their total laboratory winnings summed over all rounds excluding practice rounds would be used to determine their cash winnings in US dollars. They were also told that each subject's performance would be compared to the average performance of the subjects in the same role in determining their cash winnings. This approach reduces the chance that a player believes that one's payoff depends on the role that he/she plays. On average, each subject received \$20 for the 80 minute session in addition to a minimum show-up fee of \$5.

IV. ANALYSIS

This experimental design generates one block of 10 rounds for each of the four scenarios, along with an additional two blocks of 10 rounds each for the high strategic dependence scenario (High-Weight, High-Incentive Uncertainty). For hypothesis tests, I only use the first blocks of all scenarios in order to have a balanced statistical design.

In my exploratory analysis of dynamic behavior, I include all three blocks of the high strategic dependence scenario and examine its time series properties in detail.

A total of 20 independent pairs played the four scenarios. To control for the dependence in subjects' responses across rounds within each pair, dependent variables in the ANOVA analyses are generated by averaging relevant dependent variables over rounds within each treatment per pair. This provides in total $20 \times 4 = 80$ data points with 4 generated by each pair. All tests of hypotheses use a repeated-measures analysis to account for the fact that each cohort provides four (non-independent) observations.

Hypothesis Tests

H1 predicts that greater weight on the manager's estimate and greater incentive uncertainty reduces the accuracy of participants' expectations. I use two types of measurements to test this hypothesis: the absolute errors in subjects' expectations and the costs to them due to their expectation errors. I first calculate the second measure as the absolute difference between each subject's actual payoff and the best payoff they could have obtained had they been able to predict their opponent's strategy perfectly. This measure captures the true loss function of the players (rather than using the linear loss function assumed by the first measure), and also reveals the welfare consequences of expectation errors. I then calculate the absolute difference between the subject's opponent's choice and the subject's expectation of that choice implied by their own choice (the choice to which their own is a best response).

Figure 1.3 displays the results based on round 3 to round 10. Subjects' responses in round 1 and round 2 are deleted to avoid noise due to inexperience with the game. Including the first two rounds in each scenario does not change the conclusion. Panel A of Figure 3 shows the charts of the average payoff losses due to expectation errors and the average absolute errors in subjects' expectations of their opponents' strategies

FIGURE 1.3

Expectation Errors and Welfare Effects

Panel A presents the average payoff losses due to the errors in expectations and the average absolute errors in subjects' expectations of their opponents' strategies over round 3 to round 10 for each scenario. Panel B presents the main effects of weight and incentive uncertainty and their interaction on the payoff losses and expectation errors. PayLossInv (PayLossMA) is defined as the difference between investors/managers' actual payoffs and the optimal payoffs they would have obtained if their expectations were perfectly accurate. By construction, PayLossInv (PayLossMA) is always non-positive. ExpRel(ExpAdj) is defined as managers (investors)' expectation of their opponent's reliance (adjustment), calculated from the optimal response to their own strategies. The significance levels for the main and interaction effects are computed using repeated-measures ANOVA analysis. All associated p-values are two-tailed.

Panel A: Average payoff losses due to expectation errors and average absolute expectation errors.

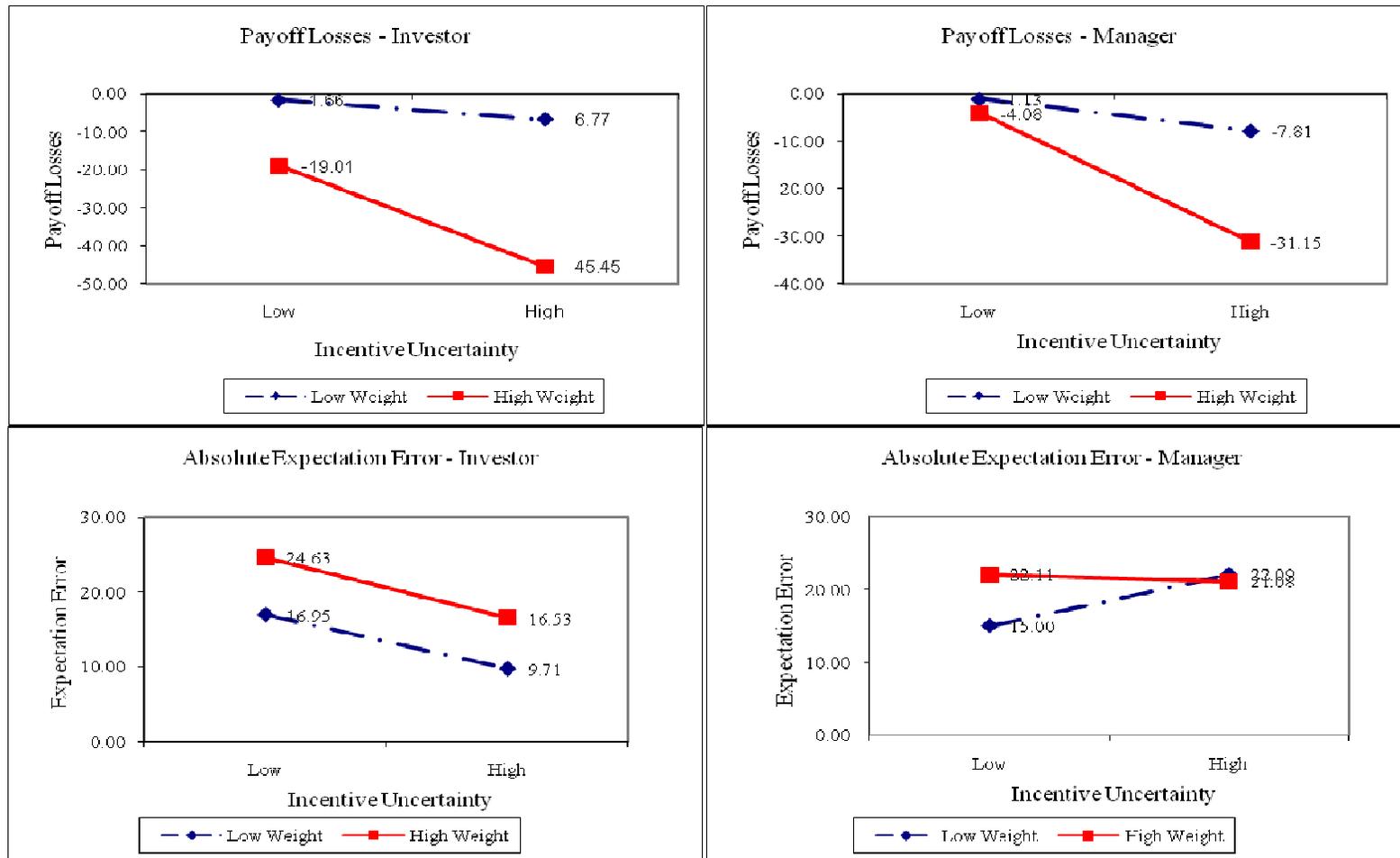


FIGURE 1.3 (Continued)

Panel B: Statistics of the main and interaction effects

Variable	Effect	F-statistics	p-value
PayLossInv	Weight	15.72	0.00
	Incentive Uncertainty	7.75	0.02
	Weight x IU	5.97	0.03
PayLossMA	Weight	6.09	0.03
	Incentive Uncertainty	5.34	0.04
	Weight x IU	5.85	0.03
ExpAdj-Adjustment	Weight	6.13	0.03
	Incentive Uncertainty	7.64	0.02
	Weight x IU	0.67	0.43
ExpRel-Reliance	Weight	0.57	0.47
	Incentive Uncertainty	0.02	0.90
	Weight x IU	0.91	0.36

across the conditions of incentive uncertainty and weight. Panel B of Figure 1.3 presents the main and interaction effects of weight and incentive uncertainty on payoff losses and expectation errors.

Consistent with H1, the welfare consequences of expectation errors are all statistically significant and in the predicted direction. For the investors, increasing in weight reduces investors' average payoff relative to their best payoffs possible by 28.01 (p-value < 0.01) and increasing in incentive uncertainty decreases the investors' average payoff relative to their best payoffs possible by 15.78 (p-value = 0.02)⁶. For the managers, increasing in weight reduces the managers' average payoff by 13.15 (p-value = 0.03) and increasing in incentive uncertainty decreases their average payoff by 16.88 (p-value = 0.04). The interaction between weight and incentive uncertainty is highly significant for both the managers and investors (p-values = 0.03 for both the managers and investors). The simple means of subjects' payoff losses further reveal that the interaction effect is driven by the much higher payoff losses in the high strategic dependence scenario. In contrast, payoff losses are relatively small when either weight or incentive uncertainty is low. These results strongly support H1.

Measuring absolute errors in expectations (rather than the payoff effect of those errors) reveals a slightly different story. Neither the effect of weight nor the effect of incentive uncertainty significantly influences managers' absolute expectation errors (p-value = 0.47 and p-value = 0.90 respectively). Weight significantly reduces investors' absolute expectation errors (p-value = 0.03), but incentive uncertainty actually decreases investors' expectation errors (p-value = 0.02).

As discussed in Section II, the weak effect of incentive uncertainty on expectation errors may arise because players do not choose arbitrarily from within the set of

⁶ All p-values presented in the paper are two-sided, unless otherwise indicated.

feasible strategies remaining after iterated deletion of dominated strategies. I test this explanation after presenting evidence for hypotheses H2 and H3.

H2 states that strategic dependence reduces the predictive power of the rational expectations equilibrium. Similar to the analysis for H1, I compute two types of measures to test this hypothesis: the absolute deviations of their payoffs from the equilibrium payoffs and the absolute deviations of subjects' strategies from the equilibrium values. Both measures are averaged over the last 8 rounds in each scenario.

The results are reported in Figure 1.4. Consistent with H2, subjects' payoffs deviate more from the equilibrium payoffs when strategic dependence is higher. An increase in weight significantly increases the deviation of the investors' payoff (managers' payoff) from the equilibrium payoff with a p-value of 0.01 (p-value < 0.01), and an increase in incentive uncertainty significantly increases the deviation of the investors' payoff (managers' payoff) with a p-value of 0.01 (p-value < 0.01). The interaction between weight and incentive uncertainty is significant for the managers (p-value = 0.01) and marginally significant for the investors (p-value = 0.07, one-sided). Overall, the evidence is consistent with H2, which predicts that strategic dependence reduces the predictive power of the REE.

Figure 1.4 also shows the results on the absolute deviations of subjects' strategies from equilibrium behavior. An increase in weight increases both the absolute deviations of the investors' reliance and the managers' adjustment from equilibrium (p-value < 0.01 and p-value = 0.01 respectively). However, similar to the findings on the absolute expectation errors in Figure 3, the effect of incentive uncertainty is insignificant for either the absolute deviation of the investors' reliance (p-value = 0.15) or the absolute deviations of the managers' adjustment (p-value = 0.37).

H3 predicts that subjects' strategies fluctuate more when strategic dependence is

FIGURE 1.4

Predictive Power of Rational Expectations Equilibrium

Panel A displays the average deviations of subjects' payoffs from the equilibrium payoffs and the average absolute deviations of Reliance and Adjustment from the rational expectations equilibrium over the last eight rounds in each of the four scenarios. Panel B displays the main and interaction effects of weight and incentive uncertainty for each of the four variables. The variable Payoff* represent the equilibrium payoff. The variables Reliance* and Adjustment* denote the equilibrium reliance and adjustment. Significance levels for all interactions and main effects are computed using repeated-measures ANOVA analysis. All associated p-values are two-tailed.

Panel A: Average absolute deviations of payoffs and strategies from equilibrium

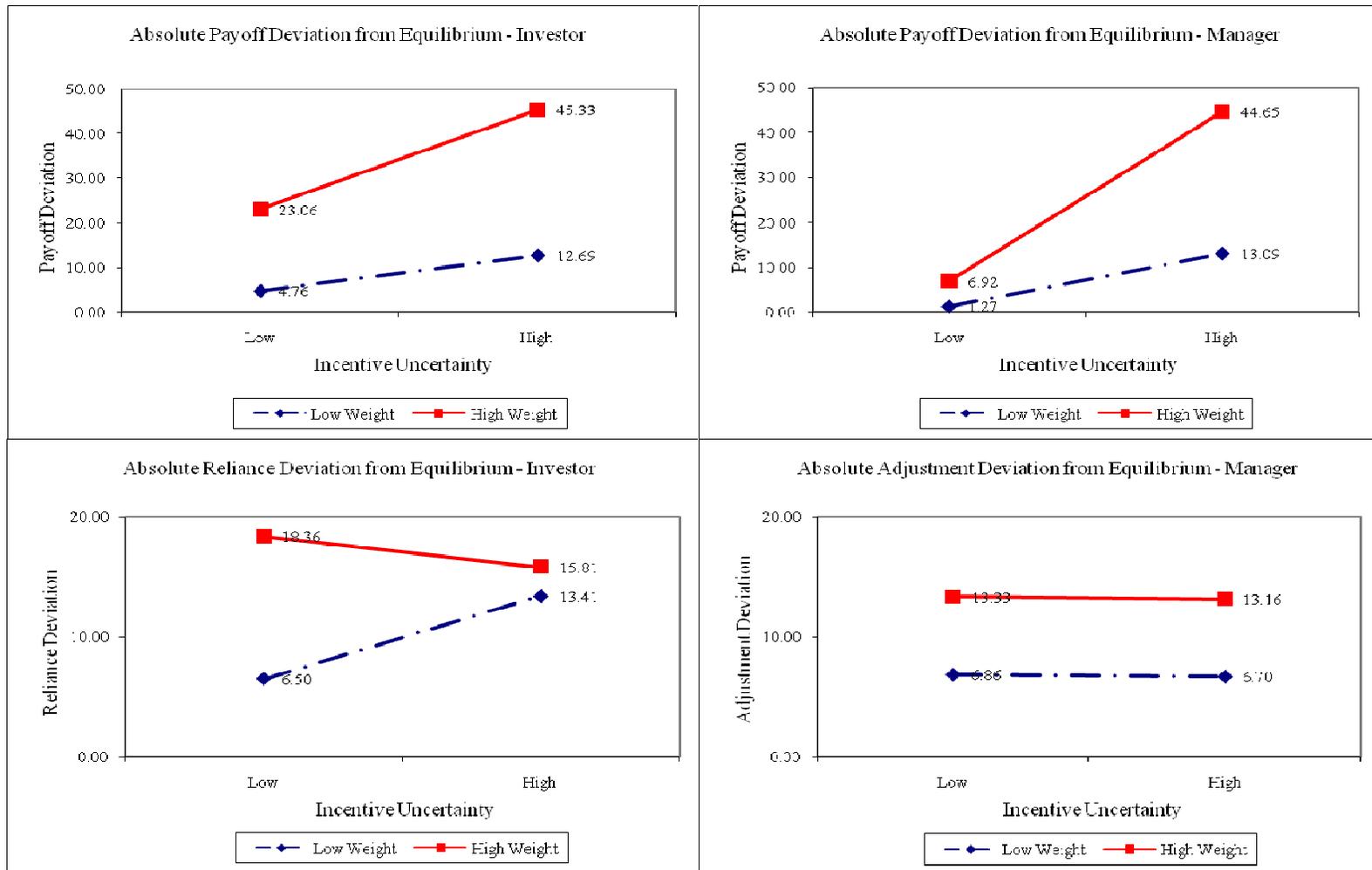


FIGURE 1.4 (Continued)
 Panel B: Statistics for the main and interaction effects

Variable	Effect	F-statistics	p-value
Payoff - Payoff* (Investor)	Weight	10.27	0.01
	Incentive Uncertainty	5.92	0.01
	Weight x IU	2.60	0.14
Payoff - Payoff* (Manager)	Weight	16.10	0.00
	Incentive Uncertainty	19.03	0.00
	Weight x IU	11.66	0.01
Reliance - Reliance*	Weight	58.79	<.0001
	Incentive Uncertainty	2.40	0.15
	Weight x IU	2.37	0.15
Adjustment - Adjustment*	Weight	9.11	0.01
	Incentive Uncertainty	0.87	0.37
	Weight x IU	0.13	0.73

higher. Support for H3 rules out the possibility that inaccurate expectations and deviations from equilibrium arise because players settle on a consistent disequilibrium outcome. The effects of strategic dependence on the standard deviations of reliance and adjustment are shown in Figure 1.5. Panel A presents the charts of the cell means of the standard deviations. Panel B summarizes the main and interaction effects of weight and incentive uncertainty. The effects of weight on the standard deviations of both reliance and adjustment support H3. An increase in weight significantly increases the standard deviation of investors' reliance and the standard deviation of managers' adjustment. However, the effect of incentive uncertainty is only significant on the variation of investors' reliance in the predicted direction, but is significant in the opposite direction to the hypothesis on the variation of managers' adjustment.

To check whether high variations are indeed driven by strategies varying round by round, I calculate the absolute changes in investors' reliance and managers' adjustment in consecutive rounds over round 3 to round 10. Results are displayed in panel B of Figure 1.5. The behaviors of the absolute changes in reliance and adjustment confirm that the higher standard deviations in subjects' strategies are mostly driven by fluctuation in their strategies. High weight is associated with greater absolute changes in both reliance and adjustment. And high incentive uncertainty induces greater absolute change in reliance. Consistent with the explanation of payoff sensitivity, high incentive uncertainty is associated with lower absolute change in adjustment.⁷

⁷ To ensure that absolute deviations from equilibrium are not due to subjects consistently playing strategies lower or higher than the equilibrium, I also analyze time-averaged strategy choices. If the deviations are driven by differences in subjects' ability to develop accurate expectations, time-averaged behaviors should be closer to the equilibrium predictions. Specifically, I compare subjects' time-averaged payoffs and time-averaged strategies over the last 8 rounds in each scenario to the equilibrium strategies and payoffs. Except for the reliance in the high incentive uncertainty scenarios, the average strategies over the last 8 rounds are statistically indistinguishable from the equilibrium strategies. Even in the high incentive uncertainty scenarios, the average deviation from equilibrium accounts for only a small portion of investors' payoff losses relative to equilibrium.

FIGURE 1.5

Time-Averaged Behavior

Panel A displays the average deviations of subjects' payoffs from the equilibrium payoffs and the average deviations of Reliance and Adjustment from the rational expectations equilibrium over the last eight rounds in each of the four scenarios. Panel B displays the main and interaction effects of weight and incentive uncertainty for each of the four variables. The variable Payoff* represent the equilibrium payoff. The variables Reliance* and Adjustment* denote the equilibrium reliance and adjustment. Significance levels for all interactions and main effects are computed using repeated-measures ANOVA analysis. All associated p-values are two-tailed.

Panel A: Average deviations of payoffs and strategies from equilibrium

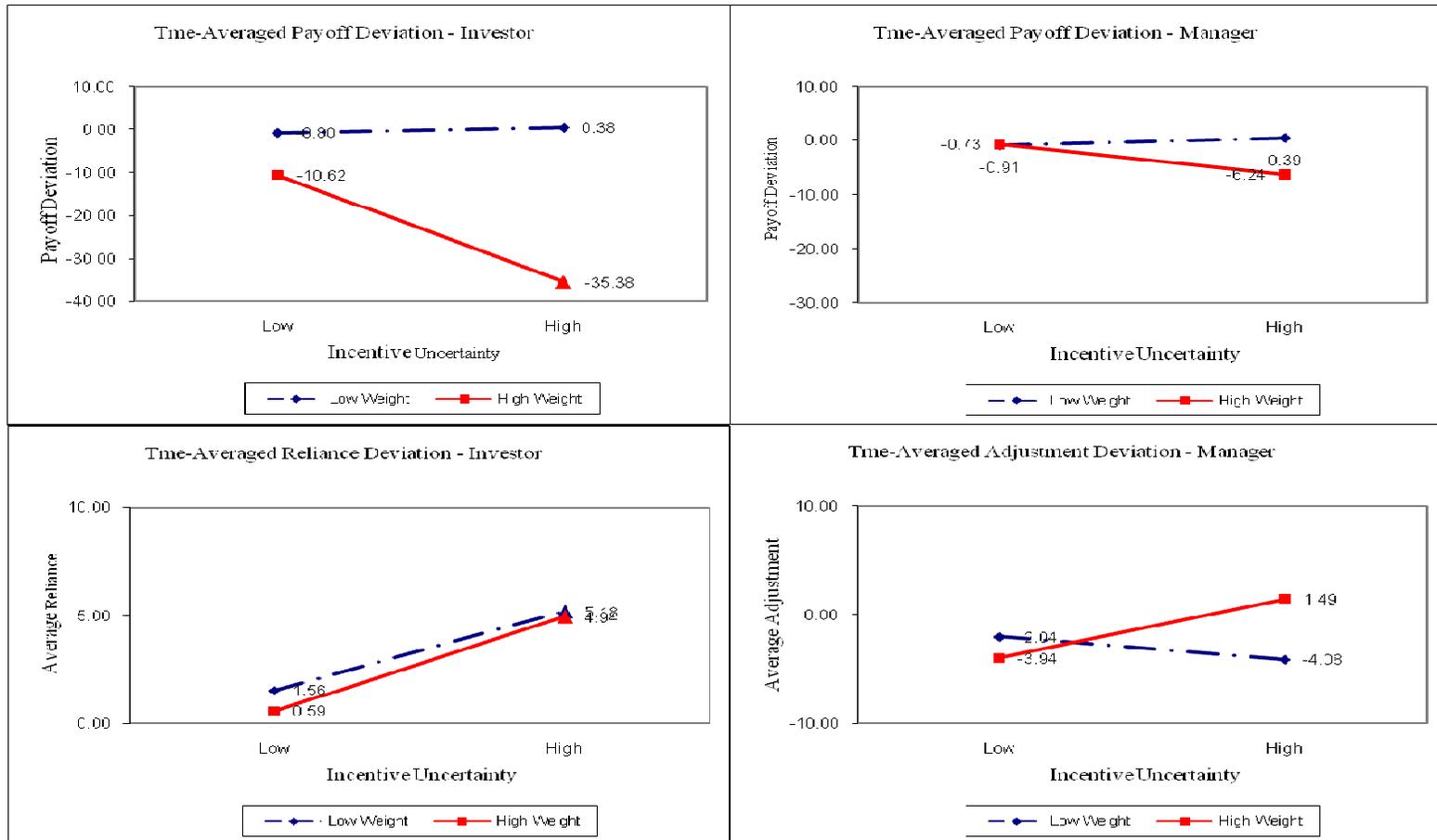


FIGURE 1.5 (Continued)

Panel B: Statistics of the main and interaction effects of weight and incentive uncertainty

Variable	Effect	F-statistics	p-value
Payoff - Payoff* (Investor)	Weight	7.67	0.02
	Incentive Uncertainty	4.45	0.06
	Weight x IU	7.05	0.02
Payoff - Payoff* (Manager)	Weight	0.28	0.61
	Incentive Uncertainty	0.60	0.45
	Weight x IU	0.13	0.73
Reliance - Reliance*	Weight	0.09	0.77
	Incentive Uncertainty	6.42	0.03
	Weight x IU	0.67	0.43
Adjustment -Adjustment*	Weight	0.38	0.55
	Incentive Uncertainty	1.19	0.30
	Weight x IU	5.74	0.04

Overall, the evidence supports H3 that subjects adapt to past strategies and change their strategies over time, and more so when strategic dependence is higher and payoff sensitivity is lower. High variations in strategies make it harder for subjects to converge to equilibrium due to noisier performance feedback. The following section investigates these anomalous results in more details.

Analysis of Anomalous Results

My hypotheses assumed that players chose strategies arbitrarily among those that survive at least two iterations of rationalization. In this analysis, I examine whether the weak effect of incentive uncertainty on expectation errors arises because players avoid strategies with high payoff risk, even though they may be consistent with several iterations of rationalization.

To test this conjecture, I calculate the average sensitivity of the players' payoffs to their opponents' strategies for each level of their own strategy, and also calculate the range of strategies consistent with second-order rationalization (B_2 and H_2).⁸ The average sensitivity of both players' payoffs for all four scenarios is depicted as solid lines in Figure 1.6, superimposed over a histogram indicating the average frequencies of players' strategies for each level, shown as light grey bars.

The graphs show that strategies inconsistent with second-order rationalization are rarely selected. Within the remaining strategies, those with very high payoff sensitivity are also rarely selected, particularly in the scenarios with high payoff uncertainty. To formally establish this tendency, I conduct a regression analysis on the frequency of strategies. The independent variables include a binary variable with a value of 1 if the strategy satisfies second-order rationalization and a value of 0 otherwise (The analysis based on zero-order or first-order rationalization gives similar

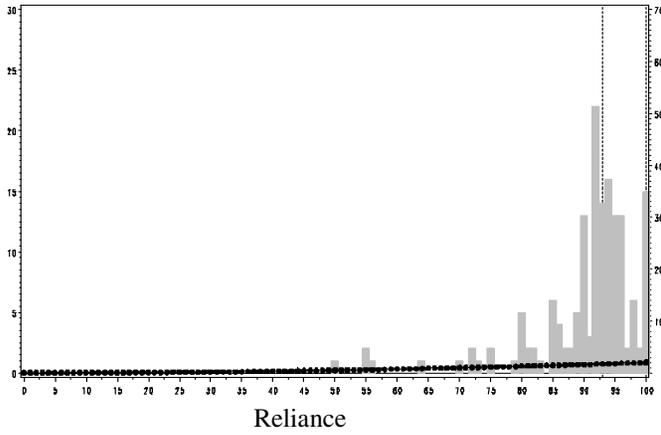
⁸ The players' payoffs are monotonic in their opponent's strategy for each level of their own strategy. Specifically, investors' payoff decreases monotonically in the manager's manipulation and the manager's payoff increases monotonically in investors' reliance, *ceteris paribus*.

FIGURE 1.6

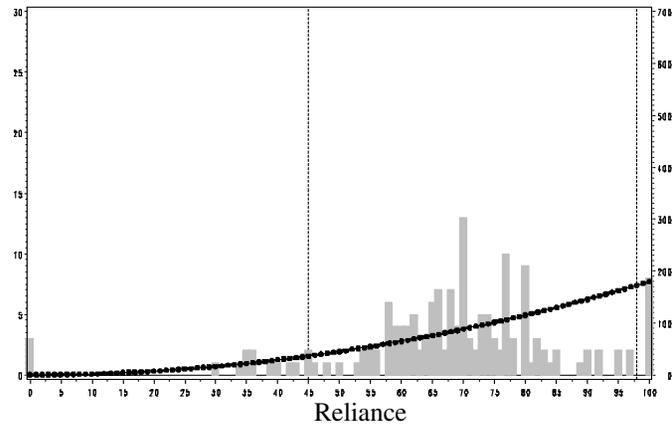
Average Frequency of Strategies and Payoff Sensitivity

This figure shows the average frequency of players' strategies and players' average payoff sensitivity to their opponents' strategies. Panel A to Panel D show for all 4 scenarios the average frequency of investors' reliance, depicted as grey vertical bars, and the investors' average payoff sensitivity to the manager's manipulation, depicted as black dotted lines. Panel E to Panel H show the average frequency of the manager's manipulation and average payoff sensitivity to investors' reliance. The frequency of strategies is displayed on the left vertical axis and the payoff sensitivity is displayed on the right vertical axis. The two dashed lines indicate the range of strategies that survive the second-order rationalization.

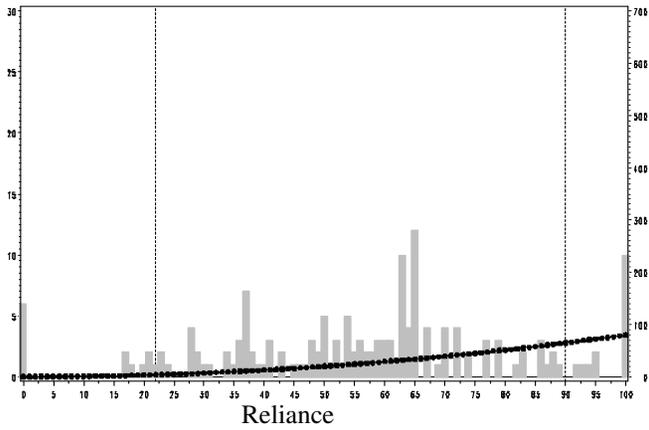
Panel A: Low Weight, Low Incentive Uncertainty



Panel B: Low Weight, High Incentive Uncertainty



Panel C: High Weight, Low Incentive Uncertainty



Panel D: High Weight, High Incentive Uncertainty

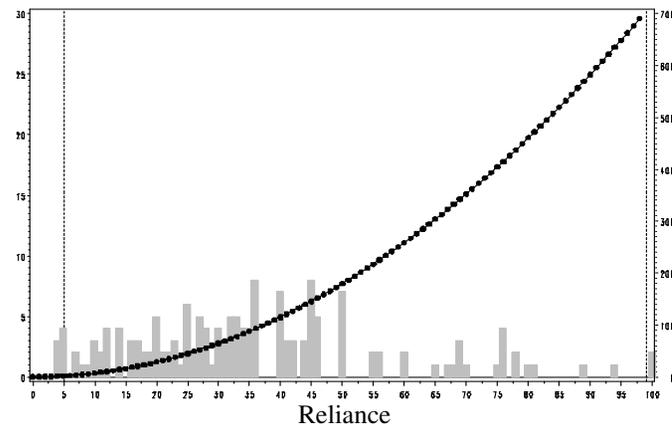
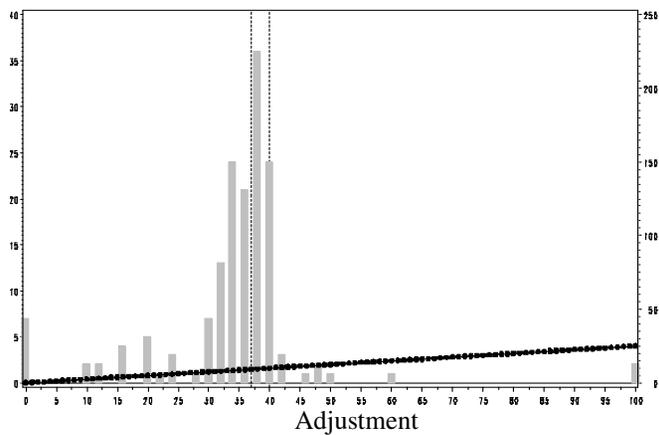
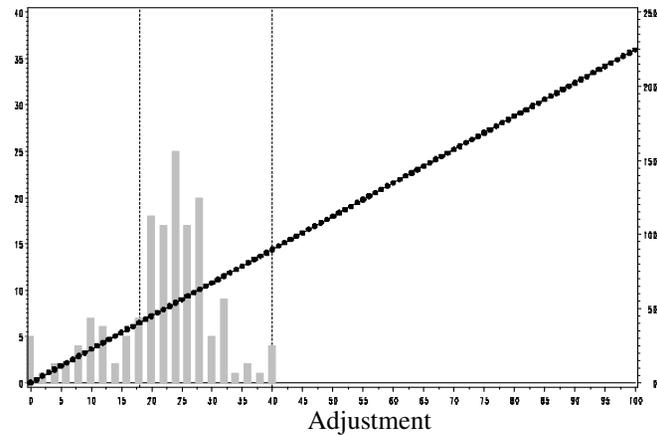


FIGURE 1.6 (continued)

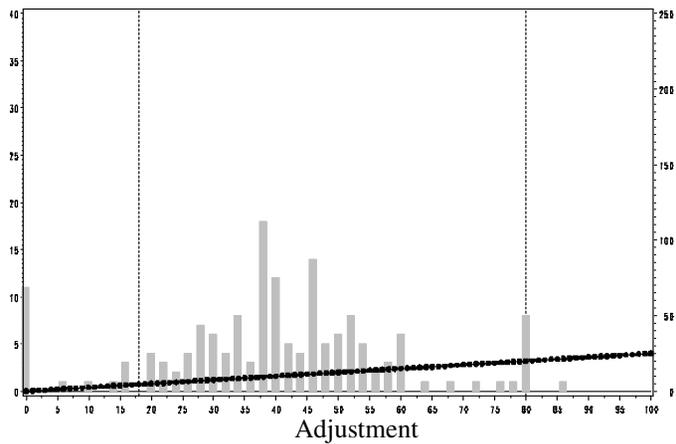
Panel E: Low Weight, Low Incentive Uncertainty



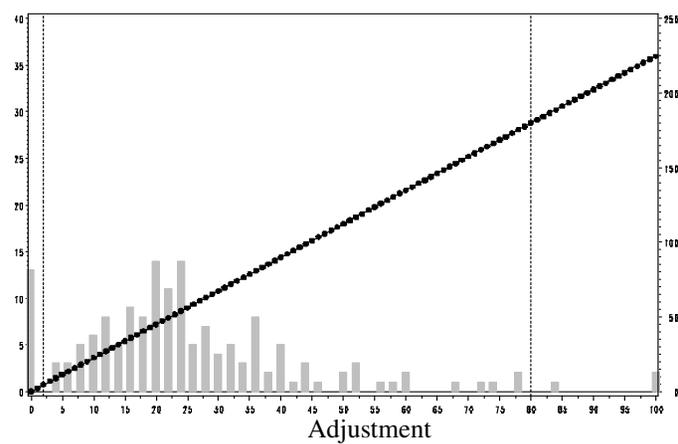
Panel F: Low Weight, High Incentive Uncertainty



Panel G: Low Weight, Low Incentive Uncertainty



Panel H: Low Weight, High Incentive Uncertainty



results), payoff sensitivity, and an interaction between payoff sensitivity and the binary variable. Results shown in Table 1.2 provide evidence consistent with the hypothesis. Players are more likely to choose strategies that satisfy second-order rationalization (both p-values < 0.01), and among those strategies, are less likely to choose strategies that result in highly variable payoffs (p-value < 0.01 and p-value = 0.05 for the frequencies of reliance and adjustment respectively).

TABLE 1.2
Influence of Rationalizability and Payoff Sensitivity on Strategy Choice

This table presents the regression analysis of the frequency of strategies. The independent variables include a binary variable (Dummy) with a value of 1 if the strategy satisfies second-order rationalization and a value of 0 otherwise, payoff sensitivity (Pay Sensitivity), and an interaction between the binary variable and payoff sensitivity. Payoff sensitivity is calculated as the average sensitivity of players' payoffs to their opponents' strategies for each level of their own strategy.

The regression model: $\text{Frequency} = \alpha + \beta_1 \cdot \text{Dummy} + \beta_2 \cdot \text{Pay Sensitivity} + \beta_3 \cdot (\text{Pay Sensitivity} \cdot \text{Dummy})$

Dependent Variable	α	β_1	β_2	β_3	Adjusted R ²
Frequency of Reliance	0.653	2.296	0.005	-0.011	0.127
<i>P-value</i>	0.001	<0.0001	0.101	0.003	
Frequency of Adjustment	1.136	2.785	-0.006	-0.014	0.086
<i>P-value</i>	0.001	<0.0001	0.060	0.049	

The result indicates that an increase in incentive uncertainty also increases players' payoff sensitivity to their opponents' strategies, which motivates players to respond strongly to their incentives and to avoid risky strategies. Therefore, increasing management incentive uncertainty dampens the effect of strategic dependence by increasing players' payoff sensitivity.

Supplementary Analysis

While the theory of rationalization assumes that players base their strategy choices on an analysis of best response functions, the predictions of rationalization are very similar to the long-run predictions that would be derived from analysis of “adaptive” processes that assume that players alter their strategies in response to prior experience in the game (see Moulin 1984; Samuelson and Zhang 1992). Adaptive processes also predict learning behavior in the short run. I now conduct exploratory analyses of short-term learning behavior, which may shed light on how the actual reliability of financial reports (as determined by managers’ adjustment factors) and their perceived reliability (as determined by investors’ reliance) may vary over time.

To examine the speed of convergence, I estimate the following regression model for both expectation errors and absolute deviations from equilibrium:

$$DV = \alpha + SDdummy + \beta_1 Round + \beta_2 (Round \times SDdummy),$$

where DV denotes appropriate dependent variable, $Round$ is the number of rounds elapsed in the scenario, and $SDdummy$ is an indicator that takes a value of 1 for the low strategic dependence scenario (Low-Weight, Low-Incentive Uncertainty) and 0 for the high strategic dependence scenario (High-Weight, High-Incentive Uncertainty). A significant negative coefficient on the third term in the regression model, β_2 , would suggest a faster convergence in the low strategic dependence scenario. As Table 1.3 shows, the results on the absolute deviations from equilibrium and investors’ expectation errors are all consistent with this hypothesis.⁹ The coefficient β_2 is negative and statistically significant in all four models. The evidence strongly supports the strategic dependence argument that subjects learn faster and converge to equilibrium at a higher speed when strategic dependence is lower.

⁹ The results are similar when only the first block of scenario D is included in the regressions.

TABLE 1.3
Time Series Properties of Strategies

This table presents the results of the regression models that compare the speed of convergence of the four variables between the low and high strategic dependence scenarios (scenarios A and D). Round is the number of rounds elapsed in the scenario. SDdummy is an indicator that takes a value of 1 for the low strategic dependence scenario. All three blocks of the high strategic dependence scenario are included in the regression analysis.

The regression model: $DV = \alpha + SDdummy + \beta_1 * Round + \beta_2 * (Round * SDdummy)$

Dependent Variable	α	SDdummy	β_1	p-value	β_2	p-value	Adjusted R ²
ExpRel-Reliance	24.243	11.627	-0.307	0.001	-2.663	<0.000	0.053
ExpAdj-Adjustment	19.846	8.356	-0.354	<0.0001	-1.321	0.001	0.058
Reliance - Reliance*	16.337	-5.024	-0.118	0.046	-0.588	0.062	0.063
Adjustment - Adjustment*	15.629	-0.276	-0.300	<0.000	-0.888	0.001	0.069

To examine how actual and perceived reliability change over time, I estimate the following regression models for investors and managers in each of the four scenarios:

For investors:

$$Reliance_t - Reliance_{t-1} = \alpha + \beta_1(ExpAdj_{t-1} - Adj_{t-1}) + \beta_2(ExpRel_{t-1} - Reliance_{t-1}) + \beta_3(Reliance_{t-1} - Reliance_{t-2}) + \beta_4(Adj_{t-1} - Adj_{t-2})$$

For managers:

$$Adj_t - Adj_{t-1} = \alpha + \beta_1(ExpRel_{t-1} - Reliance_{t-1}) + \beta_2(ExpAdj_{t-1} - Adj_{t-1}) + \beta_3(Adj_{t-1} - Adj_{t-2}) + \beta_4(Reliance_{t-1} - Reliance_{t-2})$$

where Adj, Reliance, ExpAdj and ExpRel are defined as in Figure 3. The regression results are presented in Table 4. The adjusted R²s range from 0.39 to 0.57 explaining about half of subjects' changes in strategies. For Investors (managers), β_1 is positive (negative) and statistically significant for all scenarios. A positive (negative) β_1 for investors (managers) suggests that when managers' adjustment (investors' reliance) in

the previous round was lower than expected investors (managers) are likely to increase (reduce) their reliance (adjustment) in current round. This is consistent with players moving toward their best responses in the previous round. β_2 in the investor regression model is positive and statistically significant in all four scenarios, suggesting that when managers' adjustment in the previous round was higher than optimal investors increase their reliance in current round. Similarly, β_2 in the manager regression model is significantly positive in scenarios C and D, suggesting that when investors' reliance in the previous round was lower than optimal, managers increase their adjustment in current round. The evidence shows that subjects anticipate their opponents' actions and act accordingly. Both β_3 and β_4 are either insignificant or significantly negative. This suggests subjects tend to reverse the changes in their strategies in the previous round and react to changes in their opponents' strategies.

These analyses suggest that perceived and actual reliability are likely to change in predictable ways over time, particularly when strategic dependence is high. It would therefore be an oversimplification to assume accounting manipulation and investors' reliance are at the equilibrium levels, especially when managers have great discretion on financial reports and face greater uncertainty in reporting incentives.

V. CONCLUSION

This paper modifies Dye and Sridhar's [2004] framework for examining the optimal trade-off between relevance and reliability when the manager can provide relevant but potentially manipulable (and therefore unreliable) information to accounting reports. An equilibrium analysis shows that the optimal incorporation of the manager's claims decreases as investors become more uncertain about the manager's reporting incentives. A disequilibrium analysis further shows that equilibria are less likely to be attained—to the detriment of investors—when the

accounting report places greater weight on the manager's claims and when investors are less certain about the manager's incentives. A laboratory experiment largely confirms this prediction, and shows that such characteristics of the reporting environment significantly reduce investor welfare.

The results have implications for regulators, given the current movement toward extending the use of fair value measurements in financial reports. Fair value measurements are often considered to be more relevant but less reliable due to measurement errors and manipulation. My results show that failing to consider the uncertainty in management reporting incentives may result in overstating the degree to which fair value or other manipulable estimates should be incorporated into accounting reports. Moreover, incorporating more fair value measurements may have an unintended consequence in making the actual reliability of financial reports more variable and less predictable for investors by increasing the strategic dependence between the manager and investors. The welfare analysis indicates that investors' interest is likely to be harmed when management reporting incentives are uncertain.

Supplementary analyses suggest that the market-perceived reliability of financial reports does not always equal the actual reliability, and that both may vary over time. Therefore, value-relevance studies that assume an efficient market are likely to misestimate the actual relevance and reliability of the accounting information under examination. Aboody, Hughes, and Liu (2002) recognize this issue and propose to incorporate information in delayed future market reactions in estimating value-relevance coefficient.

To the extent that management investment decisions are based on expected market reactions, unpredictable market use of financial reports is likely to cause inefficient investment decisions. This concern is shared by Liang and Wen (2005) and Plantin, Sapra, and Shin (2005). Liang and Wen show analytically that an increase in

accounting noise and manipulation induces greater market mispricing, and consequently, causes a less efficient investment decision. Plantin et al. argue that shifting toward fair value accounting may cause excessive artificial volatility that degrades the informational value of market prices and induces less efficient investment decisions.

Certain characteristics of the experiment may limit the generalizability of the results to real markets. In the experiment, I use a two-player game to test the effect of strategic dependence on the predictive power of equilibrium. Analyses on time-averaged strategies (untabulated) show that the rational expectations equilibrium has fairly good predictive power on players' time-averaged behaviors. If investors' beliefs are uncorrelated, the law of large numbers may allow investor reliance to reach a steady state. In addition, other market and institutional factors not captured in the current experimental setting, such as the existence of arbitrageurs and auditing services, are also likely to have an impact on the manager-investors interaction. Alternatively, the addition of more players (and therefore more strategic uncertainty) may make equilibrium even more difficult to achieve.

APPENDIX

I: Proofs

A. Proof of Theorem 1

Proof: Given the valuation model, $\omega_e(r) = a + br$ and realizations $(m, \omega, \varepsilon_\omega)$ of $(\tilde{m}, \tilde{\omega}, \tilde{\varepsilon}_\omega)$, the manager chooses ω_m to maximize

$$m(a + br) - \frac{c}{2}(\omega_m - \omega_f)^2$$

The first order condition with respect to ω_m implies: $\omega_m(\omega, \varepsilon_\omega) = \frac{mb\lambda}{c} + \omega + \varepsilon_\omega$

Since $\omega_h = \omega + \delta$, we can write the aggregated report r as:

$$\begin{aligned} r &= \lambda\omega_m(\omega, \varepsilon_\omega) + (1 - \lambda)\omega_h \\ &= \omega + \lambda\left(\frac{mb\lambda}{c} + \varepsilon_\omega\right) + (1 - \lambda)\delta \end{aligned}$$

Therefore, applying a method of standard linear regression, we have:

$$E[\tilde{\omega} | r] = \bar{\omega} + \frac{\sigma_\omega^2}{\sigma_\omega^2 + \lambda^2 \text{var}(v) + \lambda^2 \sigma_\varepsilon^2 + (1 - \lambda)^2 \sigma_\delta^2} (r - \bar{\omega} - \lambda E[v])$$

where v is the amount of manipulation in the manager's report. In the equilibrium,

v has the following properties: $E[v] = \frac{b\lambda}{c} E[m] = \frac{b\lambda}{c} \bar{m}$ and $\text{var}(v) = \left(\frac{b\lambda}{c}\right)^2 \sigma_m^2$

From this, it is clear that the expression for b in the valuation model is

$$b = \frac{\sigma_\omega^2}{\sigma_\omega^2 + \lambda^2 \left(\frac{b\lambda}{c}\right)^2 \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1 - \lambda)^2 \sigma_\delta^2} \quad (\text{A1})$$

The constant a has the following form in equilibrium: $a = (1 - b)\bar{\omega} - b\lambda \frac{b\lambda\bar{m}}{c}$

When $\bar{\omega}$ and \bar{m} are zero, it is clear that equilibrium a is zero.

B. Derivation of the optimal λ that maximizes b

Define the optimal λ , denoted λ^* , as the aggregator that maximizes the information value of the aggregated report, i.e. b . We can rewrite equation A1 as:

$$b\sigma_\omega^2 + b\lambda^2 \left(\frac{b\lambda}{c}\right)^2 \sigma_m^2 + b\lambda^2 \sigma_\varepsilon^2 + b(1-\lambda)^2 \sigma_\delta^2 - \sigma_\omega^2 = 0 \quad (\text{B1})$$

Solving for λ^* using implicit differentiation, we get:

$$\begin{aligned} \sigma_\omega^2 \frac{\partial b}{\partial \lambda} + 3 \frac{b^2 \lambda^4}{c^2} \sigma_m^2 \frac{\partial b}{\partial \lambda} + 4 \frac{b^3 \lambda^3}{c^2} \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 \frac{\partial b}{\partial \lambda} + 2b\lambda \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2 \frac{\partial b}{\partial \lambda} - 2b(1-\lambda) \sigma_\delta^2 &= 0 \\ \frac{\partial b}{\partial \lambda} (\sigma_\omega^2 + 3 \frac{b^2 \lambda^4}{c^2} \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2) - 2b\sigma_\delta^2 + 4 \frac{b^3 \lambda^3}{c^2} \sigma_m^2 + 2b\lambda(\sigma_\varepsilon^2 + \sigma_\delta^2) &= 0 \\ \frac{\partial b}{\partial \lambda} &= \frac{2b\sigma_\delta^2 - 4 \frac{b^3 \lambda^3}{c^2} \sigma_m^2 - 2b\lambda(\sigma_\varepsilon^2 + \sigma_\delta^2)}{\sigma_\omega^2 + 3 \frac{b^2 \lambda^4}{c^2} \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2} \end{aligned}$$

Since the denominator is always greater than zero, setting $\frac{\partial b}{\partial \lambda}$ to zero implies the numerator must be zero:

$$\sigma_\delta^2 - 2 \frac{b^2 \lambda^3}{c^2} \sigma_m^2 - \lambda(\sigma_\varepsilon^2 + \sigma_\delta^2) = 0 \quad (\text{B2})$$

We also know that λ^* and the maximum b satisfy equation B1. Therefore, λ^* and the maximum b can be determined by equations B1 and B2.

Due to the complexity of the terms involved, λ^* and the maximum b cannot be solved explicitly. However, we can define λ' as the optimal λ when σ_m^2 is zero, which corresponds to the case in Dye and Sridhar [2004]. When σ_m^2 is zero, the optimal λ can be determined from the following equation:

$$\sigma_\delta^2 - \lambda(\sigma_\varepsilon^2 + \sigma_\delta^2) = 0 \quad (\text{B3})$$

Given σ_δ^2 and σ_ε^2 , equations B2 and B3 imply that:

$$\lambda'(\sigma_\varepsilon^2 + \sigma_\delta^2) - 2\frac{b^2\lambda^{*3}}{c^2}\sigma_m^2 - \lambda^*(\sigma_\varepsilon^2 + \sigma_\delta^2) = 0$$

$$(\lambda' - \lambda^*)(\sigma_\varepsilon^2 + \sigma_\delta^2) - 2\frac{b^2\lambda^{*3}}{c^2}\sigma_m^2 = 0$$

Since $2\frac{b^2\lambda^{*3}}{c^2}\sigma_m^2 > 0$, it follows that λ' has to be greater than λ^* .

More formally, we can show that $\frac{\partial\lambda^*}{\partial\sigma_m^2}$ is negative. Applying implicit

differentiation on equation B2, we get:

$$2\frac{b^2\lambda^3}{c^2} + 6\frac{b^2\lambda^2}{c^2}\sigma_m^2\frac{\partial\lambda}{\partial\sigma_m^2} + 4\frac{b\lambda^3}{c^2}\sigma_m^2\frac{\partial b}{\partial\lambda}\frac{\partial\lambda}{\partial\sigma_m^2} + (\sigma_\varepsilon^2 + \sigma_\delta^2)\frac{\partial\lambda}{\partial\sigma_m^2} = 0$$

$$\frac{\partial\lambda}{\partial\sigma_m^2} = \frac{-2\frac{b^2\lambda^3}{c^2}}{6\frac{b^2\lambda^2}{c^2}\sigma_m^2 + 4\frac{b\lambda^3}{c^2}\sigma_m^2\frac{\partial b}{\partial\lambda} + (\sigma_\varepsilon^2 + \sigma_\delta^2)} = \frac{-2\frac{b^2\lambda^3}{c^2}}{6\frac{b^2\lambda^2}{c^2}\sigma_m^2 + (\sigma_\varepsilon^2 + \sigma_\delta^2)}$$

The last equality follows because $\frac{\partial b}{\partial\lambda}$ is zero when λ is chosen to maximize b . It

is clear that $\frac{\partial\lambda}{\partial\sigma_m^2}$ is negative, therefore, the optimal λ decreases in σ_m^2 .

This result indicates that the optimal λ when incentive uncertainty is present is lower than the optimal λ documented in Dye and Sridhar [2004]. Ignoring the uncertainty in management reporting incentives may cause λ to be set higher than equilibrium and reduce the informational value of accounting reports.

C: Proof of increasing local measure of strategic dependence with incentive uncertainty

Recall that the best response functions for the manager and investors are:

$$\theta^*(b) = \frac{b\lambda}{c}$$

$$b^*(\theta) = \frac{\sigma_\omega^2}{\sigma_\omega^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2 + \lambda^2 \sigma_m^2 \theta^2}$$

The slopes of the best response functions at the equilibrium can be obtained by taking derivative with respect to the argument of each equation, and then evaluating the derivatives at the equilibrium values.

$$\left. \frac{\partial \theta^*}{\partial b} \right|_{\theta_{RE}, b_{RE}} = \frac{\lambda}{c}$$

$$\left. \frac{\partial b^*}{\partial \theta} \right|_{\theta_{RE}, b_{RE}} = \frac{-2\theta\lambda^2 \sigma_m^2 \sigma_\omega^2}{(\sigma_\omega^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2 + \lambda^2 \sigma_m^2 \theta^2)^2} \Big|_{\theta_{RE}, b_{RE}} = \frac{-2b^3 \lambda^3 \sigma_m^2}{c \sigma_\omega^2} \Big|_{\theta_{RE}, b_{RE}}$$

To show that the local measure of the degree of strategic dependence is increasing in σ_m^2 , it is equivalent to show $\left| \left. \frac{\partial \theta^*}{\partial b} \right|_{\theta_{RE}, b_{RE}} \times \left. \frac{\partial b^*}{\partial \theta} \right|_{\theta_{RE}, b_{RE}} \right|$ is increasing in σ_m^2 . Since

$\left. \frac{\partial \theta^*}{\partial b} \right|_{\theta_{RE}, b_{RE}}$ is independent of σ_m^2 , we only need to consider $\left. \frac{\partial b^*}{\partial \theta} \right|_{\theta_{RE}, b_{RE}}$, or simply

$b^{*3} \sigma_m^2$, as a function of σ_m^2 .

$$\frac{\partial(b^{*3} \sigma_m^2)}{\partial \sigma_m^2} = 3b^{*2} \sigma_m^2 \frac{\partial b^*}{\partial \sigma_m^2} + b^{*3}$$

$\frac{\partial b^*}{\partial \sigma_m^2}$ can be derived by using implicit differentiation on equation B1 with respect

to σ_m^2 as follows:

$$\sigma_\omega^2 \frac{\partial b^*}{\partial \sigma_m^2} + 3 \frac{b^{*2} \lambda^4}{c^2} \sigma_m^2 \frac{\partial b^*}{\partial \sigma_m^2} + \frac{b^{*3} \lambda^4}{c^2} + \lambda^2 \sigma_\varepsilon^2 \frac{\partial b^*}{\partial \sigma_m^2} + (1-\lambda)^2 \sigma_\delta^2 \frac{\partial b^*}{\partial \sigma_m^2} = 0$$

$$\frac{\partial b^*}{\partial \sigma_m^2} = \frac{-\frac{b^{*3} \lambda^4}{c^2}}{\sigma_\omega^2 + 3 \frac{b^{*2} \lambda^4}{c^2} \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2}$$

Since b^* is at the equilibrium value, using equation B1 to simplify the expression, we get:

$$\frac{\partial b^*}{\partial \sigma_m^2} = \frac{-\frac{b^{*4} \lambda^4}{c^2}}{2 \frac{b^{*3} \lambda^4}{c^2} \sigma_m^2 + \sigma_\omega^2}$$

Plug it into $\frac{\partial(b^{*3} \sigma_m^2)}{\partial \sigma_m^2}$,

$$\begin{aligned} \frac{\partial(b^{*3} \sigma_m^2)}{\partial \sigma_m^2} &= 3b^{*2} \sigma_m^2 \frac{-\frac{b^{*4} \lambda^4}{c^2}}{2 \frac{b^{*3} \lambda^4}{c^2} \sigma_m^2 + \sigma_\omega^2} + b^{*3} \\ &= b^{*3} \left(1 - \frac{3 \frac{b^{*3} \lambda^4}{c^2} \sigma_m^2}{2 \frac{b^{*3} \lambda^4}{c^2} \sigma_m^2 + \sigma_\omega^2} \right) \\ &= b^{*3} \left(\frac{\sigma_\omega^2 - \frac{b^{*3} \lambda^4}{c^2} \sigma_m^2}{2 \frac{b^{*3} \lambda^4}{c^2} \sigma_m^2 + \sigma_\omega^2} \right) \end{aligned}$$

Therefore, to show $\frac{\partial(b^{*3} \sigma_m^2)}{\partial \sigma_m^2}$ is positive, we only need to show the numerator is

greater than zero, i.e. σ_ω^2 is greater than $\frac{b^{*3} \lambda^4}{c^2} \sigma_m^2$. This follows easily from equation

B1. Since $\frac{b^{*3}\lambda^4}{c^2}\sigma_m^2 + b^*\sigma_\omega^2 + b^*\lambda^2\sigma_\varepsilon^2 + b^*(1-\lambda)^2\sigma_\delta^2 = \sigma_\omega^2$ and

$b^*\sigma_\omega^2 + b^*\lambda^2\sigma_\varepsilon^2 + b^*(1-\lambda)^2\sigma_\delta^2$ is strictly greater than zero, it follows that σ_ω^2 is greater

than $\frac{b^{*3}\lambda^4}{c^2}\sigma_m^2$.

D: Proof of increasing strategic dependence with weight

To show that the product of the two best response functions at equilibrium is

increasing in λ , it is equivalent to show $\left.\frac{\partial\theta^*}{\partial b}\right|_{\theta_{RE}, b_{RE}} \times \left.\frac{\partial b^*}{\partial\theta}\right|_{\theta_{RE}, b_{RE}}$ is increasing in λ .

From Appendix I.C., we know $\left.\frac{\partial\theta^*}{\partial b}\right|_{\theta_{RE}, b_{RE}} \times \left.\frac{\partial b^*}{\partial\theta}\right|_{\theta_{RE}, b_{RE}} = \left.\frac{2b^3\lambda^4\sigma_m^2}{c^2\sigma_\omega^2}\right|_{\theta_{RE}, b_{RE}}$ and

$$\partial(b^3\lambda^4)/\partial\lambda = 3b^2\lambda^4\frac{\partial b}{\partial\lambda} + 4b^3\lambda^3.$$

$$\text{Plug } \frac{\partial b}{\partial\lambda} = \frac{2b\sigma_\delta^2 - 4\frac{b^3\lambda^3}{c^2}\sigma_m^2 - 2b\lambda(\sigma_\varepsilon^2 + \sigma_\delta^2)}{\sigma_\omega^2 + 3\frac{b^2\lambda^4}{c^2}\sigma_m^2 + \lambda^2\sigma_\varepsilon^2 + (1-\lambda)^2\sigma_\delta^2} \text{ into above equation:}$$

$$\begin{aligned} & \partial(b^3\lambda^4)/\partial\lambda \\ &= b^3\lambda^3 \frac{6\lambda\sigma_\delta^2 - 12\frac{b^2\lambda^4}{c^2}\sigma_m^2 - 6\lambda^2(\sigma_\varepsilon^2 + \sigma_\delta^2) + 4\sigma_\omega^2 + 12\frac{b^2\lambda^4}{c^2}\sigma_m^2 + 4\lambda^2\sigma_\varepsilon^2 + 4(1-\lambda)^2\sigma_\delta^2}{\sigma_\omega^2 + 3\frac{b^2\lambda^4}{c^2}\sigma_m^2 + \lambda^2\sigma_\varepsilon^2 + (1-\lambda)^2\sigma_\delta^2} \\ &= 2b^3\lambda^3 \frac{-\lambda\sigma_\delta^2 - \lambda^2(\sigma_\varepsilon^2 + \sigma_\delta^2) + 2\sigma_\omega^2 + 2\sigma_\delta^2}{\sigma_\omega^2 + 3\frac{b^2\lambda^4}{c^2}\sigma_m^2 + \lambda^2\sigma_\varepsilon^2 + (1-\lambda)^2\sigma_\delta^2} \\ &= 2b^3\lambda^3 \frac{2\sigma_\omega^2 + (2-\lambda-\lambda^2)\sigma_\delta^2 - \lambda^2\sigma_\varepsilon^2}{\sigma_\omega^2 + 3\frac{b^2\lambda^4}{c^2}\sigma_m^2 + \lambda^2\sigma_\varepsilon^2 + (1-\lambda)^2\sigma_\delta^2} \end{aligned}$$

The local measure of strategic dependence would be increasing in λ if

$2\sigma_\omega^2 + (2 - \lambda - \lambda^2)\sigma_\delta^2 - \lambda^2\sigma_\varepsilon^2$ is positive. Since $2 - \lambda - \lambda^2$ is always positive, a sufficient condition is

$2\sigma_\omega^2 - \lambda^2\sigma_\varepsilon^2 > 0$, which implies a sufficient condition is $\sigma_\omega^2 > \frac{\sigma_\varepsilon^2}{2}$. This condition can

also be expressed as $2 > \frac{\sigma_\varepsilon^2}{\sigma_\omega^2}$. The ratio $\frac{\sigma_\varepsilon^2}{\sigma_\omega^2}$ indicates the relative noisiness of the

manager's signal. The more noise the manipulable signal contains and the less variability the value of net assets has, the higher the ratio. The result indicates that the degree of strategic dependence increases with the relative informativeness of the manager's signal. Intuitively, the more informative the manager's signal, the higher the investors should rely on the aggregated report in equilibrium. Therefore, an increase in the weight on the manager's report increases the sensitivity of investors' reliance to the manager's manipulation.

E. Analysis on investors' equilibrium welfare in relation to weight and incentive uncertainty

I first show how investors' equilibrium welfare changes with weight.

The investors' welfare at the equilibrium is:

$$\begin{aligned}
 E[V_{inv}] &= E[-(br - \omega)^2] \\
 &= E[-(b(\omega + \lambda \frac{mb\lambda}{c} + \lambda\varepsilon + (1-\lambda)\delta) - \omega)^2] \\
 &= -E[(b(\lambda \frac{mb\lambda}{c} + \lambda\varepsilon + (1-\lambda)\delta) - (1-b)\omega)^2] \\
 &= -b^2[(\frac{b\lambda^2}{c})^2 \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2] - (1-b)^2 \sigma_\omega^2
 \end{aligned}$$

Take derivative with respect to λ :

$$\begin{aligned}
& \frac{\partial E[V_{inv}]}{\partial \lambda} \\
&= -[2 \frac{\partial b}{\partial \lambda} (2b(\frac{b\lambda^2}{c})^2 \sigma_m^2 + b\lambda^2 \sigma_\varepsilon^2 + b(1-\lambda)^2 \sigma_\delta^2 - (1-b)\sigma_\omega^2)] \\
&\quad - 2b^2 [2 \frac{b^2 \lambda^3}{c} \sigma_m^2 + \lambda \sigma_\varepsilon^2 - (1-\lambda) \sigma_\delta^2] \\
&= -2b(\frac{b\lambda^2}{c})^2 \sigma_m^2 \frac{\partial b}{\partial \lambda} - 2b^2 [2 \frac{b^2 \lambda^3}{c} \sigma_m^2 + \lambda(\sigma_\varepsilon^2 + \sigma_\delta^2) - \sigma_\delta^2]
\end{aligned}$$

Since $\frac{\partial b}{\partial \lambda} = \frac{2b\sigma_\delta^2 - 4\frac{b^3\lambda^3}{c^2}\sigma_m^2 - 2b\lambda(\sigma_\varepsilon^2 + \sigma_\delta^2)}{\sigma_\omega^2 + 3\frac{b^2\lambda^4}{c^2}\sigma_m^2 + \lambda^2\sigma_\varepsilon^2 + (1-\lambda)^2\sigma_\delta^2}$ holds in equilibrium, the above

equation can be written as:

$$\begin{aligned}
& \frac{\partial E[V_{inv}]}{\partial \lambda} \\
&= -2b(\frac{b\lambda^2}{c})^2 \sigma_m^2 \frac{\partial b}{\partial \lambda} + b[\sigma_\omega^2 + 3\frac{b^2\lambda^4}{c^2}\sigma_m^2 + \lambda^2\sigma_\varepsilon^2 + (1-\lambda)^2\sigma_\delta^2] \frac{\partial b}{\partial \lambda} \\
&= b[\sigma_\omega^2 + \frac{b^2\lambda^4}{c^2}\sigma_m^2 + \lambda^2\sigma_\varepsilon^2 + (1-\lambda)^2\sigma_\delta^2] \frac{\partial b}{\partial \lambda} \\
&= \sigma_\omega^2 \frac{\partial b}{\partial \lambda}
\end{aligned}$$

The last equality comes from the equilibrium b being

$$\frac{\sigma_\omega^2}{\sigma_\omega^2 + \lambda^2(\frac{b\lambda}{c})^2 \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2}. \text{ Since } \frac{\partial E[V_{inv}]}{\partial \lambda} \text{ has the same sign as } \frac{\partial b}{\partial \lambda}, \text{ when}$$

λ is chosen to maximize b , i.e. $\frac{\partial b}{\partial \lambda} = 0$, investors' welfare is also maximized.

Now I show investors' equilibrium welfare decreases in incentive uncertainty.

Take derivative with respect to σ_m^2 :

$$\begin{aligned}
& \frac{\partial E[V_{inv}]}{\partial \sigma_m^2} \\
&= -\left[2 \frac{\partial b}{\partial \sigma_m^2} \left(2b \left(\frac{b\lambda^2}{c}\right)^2 \sigma_m^2 + b\lambda^2 \sigma_\varepsilon^2 + b(1-\lambda)^2 \sigma_\delta^2 + b\sigma_\omega^2 - \sigma_\omega^2\right)\right] - \frac{b^4 \lambda^4}{c^2} \\
&= -\left[2 \frac{\partial b}{\partial \sigma_m^2} \left(b \left(\frac{b\lambda^2}{c}\right)^2 \sigma_m^2 + \sigma_\omega^2 - \sigma_\omega^2\right)\right] - \frac{b^4 \lambda^4}{c^2} \\
&= -2b \left(\frac{b\lambda^2}{c}\right)^2 \sigma_m^2 \frac{\partial b}{\partial \sigma_m^2} - \frac{b^4 \lambda^4}{c^2} \\
&= 2b \left(\frac{b\lambda^2}{c}\right)^2 \sigma_m^2 \frac{\frac{b^4 \lambda^4}{c^2}}{2 \frac{b^3 \lambda^4}{c^2} \sigma_m^2 + \sigma_\omega^2} - \frac{b^4 \lambda^4}{c^2} \\
&= \frac{-\sigma_\omega^2 \frac{b^4 \lambda^4}{c^2}}{2 \frac{b^3 \lambda^4}{c^2} \sigma_m^2 + \sigma_\omega^2}
\end{aligned}$$

Since $-\sigma_\omega^2 \frac{b^4 \lambda^4}{c^2}$ is always negative, it shows investors' welfare decreases with the uncertainty in management reporting incentives.

F. Proof of the optimality of a linear valuation model

From Appendix I.A., we know $r = \omega + \lambda \left(\frac{mb\lambda}{c} + \varepsilon_\omega\right) + (1-\lambda)\delta$. ω , m , ε_ω , and δ are independently and normally distributed. Therefore, (r, ω) are bivariate normal. Specifically,

$$(r, \omega) \sim \text{bivariate normal} (\mu_r, \mu_\omega, \sigma_r^2, \sigma_\omega^2, \rho_{r\omega}), \text{ where } \mu_r = \bar{\omega} + \frac{\bar{m}b\lambda^2}{c}, \mu_\omega = \bar{\omega},$$

$$\sigma_r^2 = \sigma_\omega^2 + \lambda^2 \left(\frac{b\lambda}{c}\right)^2 \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2, \sigma_\omega^2 = \sigma_\omega^2, \text{ and}$$

$$\rho_{r\omega} = \frac{\sigma_\omega^2}{\sigma_\omega \sqrt{\sigma_\omega^2 + \lambda^2 \left(\frac{b\lambda}{c}\right)^2 \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2}}.$$

Given the normality assumption, the best predictor of ω given investors' quadratic loss function is simply $E[\omega|r]$.

$$\begin{aligned} \omega_e = E[\omega|r] &= (\mu_\omega - \rho_{r\omega} \frac{\sigma_\omega}{\sigma_r} \mu_r) + \rho_{r\omega} \frac{\sigma_\omega}{\sigma_r} r \\ &= \bar{\omega} + \frac{\sigma_\omega^2}{\sigma_\omega^2 + \lambda^2 \left(\frac{b\lambda}{c}\right)^2 \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2} \left(r - \bar{\omega} - \frac{\bar{m}b\lambda^2}{c} \right) \end{aligned}$$

This proves that the best valuation function is linear in r . Moreover, when $\bar{\omega}$ and

\bar{m} are zero, $E[\omega|r]$ is simplified to $\frac{\sigma_\omega^2}{\sigma_\omega^2 + \lambda^2 \left(\frac{b\lambda}{c}\right)^2 \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2} r$.

The variance of the best predictor is

$$\begin{aligned} \text{Var}(\omega_e | r) &= \sigma_\omega^2 (1 - \rho_{r\omega}^2) \\ &= \frac{\sigma_\omega^2 (\lambda^2 \left(\frac{b\lambda}{c}\right)^2 \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2)}{\sigma_\omega^2 + \lambda^2 \left(\frac{b\lambda}{c}\right)^2 \sigma_m^2 + \lambda^2 \sigma_\varepsilon^2 + (1-\lambda)^2 \sigma_\delta^2} \end{aligned}$$

II: Instructions

Introduction

This experiment is about economic decision making. You will be paired with another subject to play a two-person game for 10 rounds per scenario in many different scenarios. Some scenarios may be played multiple times, while some other scenarios will only be played once or not at all. You will always know which scenario you are in. There are 64 rounds in total including 4 practice rounds. At the end of the session, we will ask you a series of questions about your experience. The total session lasts about 80 minutes. You will gain ‘laboratory dollars’ in this experiment. Your gains in laboratory dollars will be converted to US dollars after you complete the experiment.

Overview

There are two types of players: reporter and appraiser. Half of the subjects will be randomly picked to play the role of reporter and the other half will play the role of appraiser for the entire session. A reporter will be randomly paired with an appraiser at the beginning of the session and will play with the same appraiser throughout the session. Players’ identities are kept anonymous throughout the experiment.

The reporter learns a **base value**, and reports a number to the appraiser. The appraiser estimates the base value based on the reported number. The appraiser always earns more by estimating the base value more accurately. The reporter sometimes earns more by getting the appraiser to overestimate the base value, and sometimes earns more by getting the appraiser to underestimate the base value, depending on a random number called an **incentive multiplier**.

Reporter’s Task

The base value is a random variable with mean zero and standard deviation 10. The incentive multiplier indicates how his/her payoff will be linked to the appraiser’s

estimate of the base value. The standard deviation of the multiplier will be different in different scenarios. A higher standard deviation means the realized incentive multiplier is more likely to be farther away from zero.

The reporter's task is to choose an **adjustment factor** which will be multiplied with the incentive multiplier to determine the reporter's total adjustment for each report. The percentage of the adjustment that is added to base value will be different in different scenarios. A higher weight on the total adjustment means the reported value is influenced more by the reporter's adjustment.

In summary, the report is determined by the equation:

$$\textit{Reported Value} = \textit{Base Value} + \textit{Weight} \times (\textit{Incentive Multiplier} \times \textit{Adjustment Factor})$$

- If the reporter chooses an adjustment factor of 0, the reported value is always equal to the base value.
- Greater adjustment factors make the report *lower* than the base value if the incentive multiplier is *negative*. Greater adjustment factors make the report *higher* than the base value if the incentive multiplier is *positive*.
- The greater the adjustment factor, the more the report is *increased* (for *positive* incentive multipliers) or *decreased* (for *negative* incentive multipliers), other things equal.

The reporter is also charged a fee for the total adjustment. The fee increases with the total adjustment.

100 Reports in Each period

Rather than choose a different adjustment factor every time, reporters choose a single adjustment factor that is applied to 100 different reports. Every report has its own randomly-chosen base value and its own randomly-chosen incentive multiplier. Your computer screen will show the average payoff for the entire set of 100 reports.

Appraiser's Task

The appraiser's task is to estimate the base value for each report as accurately as possible. Specifically, the appraiser is charged based on the square of the difference between the estimate and the base value. For example, if the appraiser estimates a value of 14, and the base value is 9, the charge will be $(14 - 9)^2 = 25$.

Instead of choosing different estimate for each report, the appraiser chooses a single number, called "**reliance**," to come up with an estimate. For each report, the appraiser's estimate is determined by this equation:

$$\textit{Appraiser's Estimate} = \textit{Reliance} \times \textit{Reported Value}$$

- If the reporter has chosen an adjustment factor of 0, the appraiser's best choice is select reliance of 100%, because the report is exactly equal to the base value.
- The higher the reporter's adjustment factor, the less reliant the appraiser should be, because high reports probably indicate that the reporter adjusted upward, and low reports probably indicate that the reporter adjusted downward.

Payoff Calculation

The reporter's laboratory payoff for each round is the average payoff of all 100 reports. The reporter's laboratory payoff for each report is determined by the equation:

$$\textit{Reporter's Payoff} = \textit{Incentive Multiplier} \times \textit{Appraiser's Estimate} - \textit{Cost of Adjustment}$$

The appraiser's laboratory payoff for each round is also the average payoff of all 100 reports. The appraiser's laboratory payoff for each report is determined by the equation:

$$\textit{Appraiser's Payoff} = - (\textit{Appraiser's Estimate} - \textit{Base Value})^2$$

Your screen shows the average *expected* payoff calculated based on your *expectation* of the other player's strategy and on your own choice in the same way as the actual payoff calculation of all 100 reports (shown in yellow at the bottom of your

decision making screen).

You can use the dropdown menus to select different combinations of the other player’s strategy you expect and your own strategy to see how your *expected* payoff is affected. However, your *expected* payoff is calculated based on your *expectation* of the strategy of the other player, which may deviate from the *actual* strategy played out by the other player that determines your *actual* payoff.

Converting laboratory payoffs into US dollars

Your total laboratory payoffs will be converted into US dollars according to the following conversion rule:

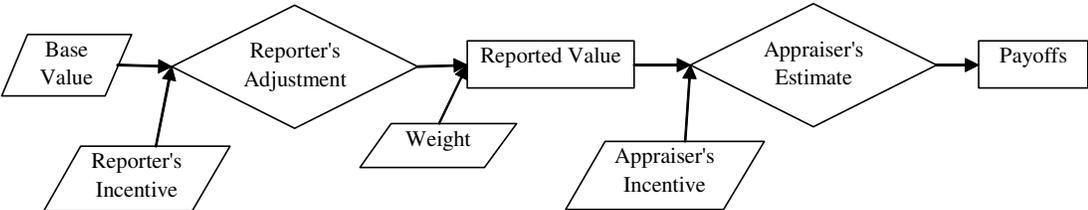
$$USD\ Winnings = Exchange\ Rate \times (Your\ Laboratory\ Payoffs + "Adjustment")$$

You will not learn the exact exchange rate and adjustment. However, there are a few facts you can learn. First, the exchange rate is positive, meaning that the more laboratory dollars you win, or the fewer you lose, the more USD you get. Second, the exchange rate is set to be independent of the performance of the other player in your pair. Third, “adjustment” will be different for reporters and appraisers. The exchange rate and ‘adjustment’ are set so that the average winnings will be approximately US\$25 for each person for the session. You will also receive \$5 in cash for participation when you finish the experiment.

Summary

The flow of information and decision making is summarized in Figure 1 below:

Figure 1: Flow of Information and Decision Making



III: Screen Shots

A. Decision screen for investors

You are an APPRAISER		Scenario C	
Decision Making Panel:		This is Round #	3
Reporter's Adjustment Factor You Expect 2.1 (Please Choose)		Weight on Adjustment is	80 %
Your Choice of Reliance 17 % (Please Choose)		S.D. of Multiplier is	15
Your Expected Payoff -88.4		Past Decisions:	
		Your	Reporter's
		Round	Reliance (%)
		Adj. Factor	Your
		Actual Payoff	
		Last Round	10
		2 Rounds Ago	20
		3 Rounds Ago	
		4 Rounds Ago	
		5 Rounds Ago	
			0.8
			3.4
			-86.8
			-125.3
Submit Decision			

B. Decision screen for managers

You are a REPORTER		Scenario C	
Decision Making Panel:		This is Round #	3
Appraiser's Reliance You Expect 56 % (Please Choose)		Weight on Adjustment is	80 %
Your Choice of Adjustment Factor is 2.1 (Please Choose)		S.D. of Multiplier is	15
Your Expected Payoff 103.2		Past Decisions:	
		Your	Appraiser's
		Round	Reliance (%)
		Adj. Factor	Your
		Actual Payoff	
		Last Round	0.8
		2 Rounds Ago	3.4
		3 Rounds Ago	
		4 Rounds Ago	
		5 Rounds Ago	
			10
			20
			0.3
			-123.5
Submit Decision			

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CHAPTER II

Investor Affect and the Credibility of Management Disclosures

I. INTRODUCTION

The credibility of management disclosures is an important determinant of investor reactions to the disclosures (Jennings, 1987). For instance, Kothari (2006) has documented that lower credibility of management disclosures is associated with higher cost of capital of firms (Kothari, 2006). Given the significant impact of the credibility of management disclosures on the financial market, it is of great interest to both researchers and practitioners to understand the factors that influence the credibility of management disclosures. Mercer (2004) defines disclosure credibility as “investors’ perceptions of the believability of a particular disclosure”. However, the existing literature has focused primarily on the characteristics of management and disclosures, but left out the characteristics of investors as an important input into the perceived credibility of management disclosures. The goal of this paper is to investigate how investor affect influences their credibility assessments of management disclosures. Affect is broadly used here to refer to an evaluative reaction to a stimulus that has either positive or negative valence (Fiske and Taylor, 1991). In this study, I look at how investor affect influences their choice of information processing strategies and information base in judgments and how investor affect interacts with management reporting incentives in influencing investors’ information processing and perceived disclosure credibility.

Drawing upon the extant psychology literature on affect and the accounting literature on disclosure credibility, I predict that investors will use their affect as a

source of information and adopt a heuristic information-processing strategy in a positive affective state and a systematic information-processing strategy in a negative affective state. In a management earnings disclosure context, this prediction leads to a high credibility assessment of a good news disclosure when investors are in a positive affective state and vice versa. The awareness of management reporting incentives is likely to induce investors to pay more attention to the disclosure and switch to a systematic information-processing strategy, which will mitigate the effect of a positive affect on information processing. When investors are in a negative affective state, the awareness of management reporting incentives will not have an additional effect because investors in a negative affective state process information systematically.

I test the predictions in a pilot experiment where 57 accounting master's students and undergraduate seniors assess the credibility of a positive management earnings forecast. Archival research that uses naturally-generated data is unable to detect the effects of affect on investor credibility assessments due to the unobservability of investor affect and credibility judgments, a lack of control of disclosure content and inherent credibility of disclosure, and the self-selection problem. Experimentation allows me to control for management disclosure contents and the self-selection problem by holding them constant across treatments, to examine the effects of affect and management reporting incentives by varying them, and to measure and collect process variables that are unobservable in naturally-generated data.

The experiment manipulates management incentives to misreport and experimental payment to participants in a 2X2 between-subjects design. I vary experimental payments to participants to induce positive affect in participants who receive higher payments and negative affect in participants who receive lower payments. The results of the pilot experiment provide some support to the predictions. Specifically, I find that participants assess management as more truthful when the

management incentive to misreport is low. However, inconsistent with my predictions and prior experimental evidence, I find that lower assessments of management truthfulness do not result in lower credibility assessments of the management earnings forecast. I also find that, contrary to the results in prior psychology literature, positive affective states are associated with less heuristic processing of information.

The pilot study raises several interesting questions to be answered in future research. First, the payment manipulation successfully induced certain affective states, but not all affective states. Watson and Tellegen (1983) identify two fundamental dimensions of affect, strong engagement/disengagement and pleasantness/unpleasantness. According to the two-dimensional framework of affect, the manipulated affective states locate primarily along the dimension of strong engagement/disengagement. My result contradicts prior evidence on the effects of affect on information processing, and instead shows that positive affective states are associated with more systematic information processing. Given the affect manipulation result, it is not clear whether the experiment results indicate that prior psychological findings do not generalize in a management disclosure setting or that the findings do not generalize to all dimensions of affects. Second, the results do not support the general perception that higher management situational incentives lead to lower credibility of management disclosures. The results call for more research on the interactive effects of the factors that influence the credibility of management disclosures. I discuss my future plans to revise the experiment to address the raised questions in the conclusion and discussion section.

Provided that the follow-up experiment answers the above questions, I expect the study to contribute to the accounting research on the credibility of management disclosures in two ways. First, the paper identifies investor affect as another factor that influences the perceived credibility of management and their disclosures. Second, it

shows that that investors' awareness of management incentives to misreport could potentially mitigate the effects of positive affects that cause investors to accept management disclosures at face value. I also expect the study to contribute to the psychology literature by showing that the findings in prior psychology studies do not generalize to all dimensions of affect. The paper calls for a more refined theory on the effects of affect.

The rest of the paper is organized as follows. Section II reviews relevant literature in both psychology and accounting and develops the hypotheses. Section III presents an experiment that tests the hypotheses. Section IV discusses the experimental results. The last section concludes and discusses future plans to revise and improve the current study.

II. LITERATURE REVIEW AND HYPOTHESES

Literature on Affect

Affect may influence thinking and judgments in two ways: by biasing the informational source and by influencing the information-processing strategies (See Clore, Schwarz, and Conway, 1994; Wyer, Clore, and Isbell, 1999; Forgas, 2000, for reviews).

On the informational role of affect, a few studies show that affect facilitates the recall and use of mood-congruent information. To explain the findings, affect-priming theories propose an associative network model of memory and assume that the greater availability of mood-related memories, constructs, and associations will influence top-down interpretive processes in thinking and judgments (Bower, 1981; Isen, 1987). The priming of affect-congruent information will, in turn, facilitate affect-congruent materials, focus attention on mood-congruent details, help the recall of mood-consistent details learned in a matching mood, and help the mood-congruent

interpretation of ambiguous information. All these effects lead to mood-congruent biases in the informational basis of thinking and judgments.

In a management disclosure situation, the proposed direct and indirect informational roles of affect suggest that investors in a positive affective state will focus on positive information, interpret information in a positive way, and recall positive aspects of the management and disclosure from their memory. The informational consequence of positive affect is likely to lead to an overly optimistic credibility assessment of management disclosures. On the contrary, negative affect is likely to lead to a pessimistic credibility assessment of management disclosures.

In addition to the informational role, affect is also shown to influence the choice of the information-processing strategies. The traditional view proposes a processing dichotomy of positive versus negative affect. Positive affect typically leads to a simplified, heuristic processing strategy as people seek to maintain their good mood (Clark and Isen, 1982). Bad moods are associated with a systematic processing strategy as required to repair moods. Consistent with this view, Bless et al. (1990) find that happy subjects were equally persuaded by strong and weak arguments, unless explicitly instructed to pay attention to the content of the message, while sad subjects were more influenced by strong arguments than by weak arguments. When subjects were given a distracting task, the differential persuasive power of strong versus weak arguments to sad subjects was mitigated. The results lead to the conclusion that subjects in a good mood are less likely to engage in message elaboration than subjects in a bad mood.

Further studies provide findings contradicting this simple view of dichotomy. Bless and Fiedler (1995) argue that positive affect does not necessarily lead to impairment in processing efficacy. This argument is supported by evidence showing that tasks requiring creativity and generative thinking are often facilitated by positive

affect (Isen, 1987). Bless proposes that positive affect also promotes a general schematic way of thinking and the use of general knowledge and reduces the tendency to focus on piecemeal information.

Forgas (1995), in an attempt to reconcile the contradictory evidence on the effects of affect, proposes a multi-process theory, the Affect Infusion Model (AIM). Affect infusion refers to the process whereby affective loaded information exerts an influence on, and becomes incorporated into cognitive and judgmental processes. Forgas argues that people are likely to use heuristic processing strategy when neither stored responses nor a motivational goal can guide judgments, and people seek to compute a constructive response with minimal effort. Substantive processing strategy is used when people need to select, learn, and interpret novel information and relate this information to their preexisting knowledge structures in order to construct a response. Consistent with his arguments, Clark and Isen (1982) show that negative affect may trigger motivated processing in the service of mood repair. In AIM, the relationship between information processing strategies and affect infusion is not unidirectional. Affect can influence the processes being adopted. Negative moods are associated with vigilant, systematic attention to stimulus details, which, in turn, tends to reduce or even eliminate judgmental biases (Forgas, 1998). In contrast, positive affect tends to increase the likelihood of cognitive mistakes, such as attribution error and memory mistakes.

In summary, psychology research on affect in general suggests that affect may influence people's credibility judgment of a persuasive communication through their assessments of the logical coherence of the arguments and the set of knowledge that is retrieved and used to assess the plausibility of these arguments. Positive affect is often associated with heuristic processing of information and activation of positive information. People in a positive affective state are thus more likely to overlook

logical inconsistencies in the arguments and assess a higher level of credibility. In contrast, negative affect is often associated with more systematic information processing and a more thorough evaluation of information. People in a negative affective state are less likely to overlook logical inconsistencies in the arguments.

Literature on Management Disclosure Credibility

Investors' reactions to management disclosures are a function of both the magnitude of the news contained in the messages and the credibility of the disclosures (Jennings, 1987). Due to the importance of the credibility of management disclosures, researchers have devoted much effort to identifying the determinants of the credibility of management disclosures. Mercer (2004) defines disclosure credibility as "investors' perceptions of the believability of a particular disclosure". This definition emphasizes the distinction between management credibility and investors' perceived credibility of management disclosures. The former refers to the inherent credibility of management, yet the latter focuses on investors' perceptions of management disclosures, which is the focus of this paper. Mercer synthesizes the existing literature and identifies four factors that influence the perceived credibility of management disclosures (see Mercer, 2004, for a review on the credibility of management disclosures): 1. management's situational incentives at the time of the disclosure; 2. management's credibility; 3. the degree of external and internal assurance; 4. various characteristics of the disclosure, including its precision, venue, timing, amount of supporting information, and inherent plausibility.

Evidence on management situational incentives suggests that investors are sensitive to the incentives of management when assessing disclosure credibility. When the messages are consistent with the incentives of management, investors are less likely to believe the messages. Koch (1999) examines analysts' reliance on management earnings forecasts of financially distressed firms and finds that analysts

rely less on the forecasts as the firm's financial distress increases. Similarly, investors are more skeptical about management credibility when positive disclosures are provided than when negative disclosures are provided. Hutton et al. (2003) find a larger stock price reaction to management disclosures that contain negative news. Hassell et al. (1998) document that bad news disclosures result in larger analyst forecast revisions. In an experiment, Hirst et al. (2007) show that investors assess a lower level of credibility with positive news disclosures from management than with negative news disclosures, and this tendency is greater when investors know that the management has greater incentives to report optimistically.

Prior studies that examine the characteristics of disclosures find that the precision of disclosures and the amount of supporting information in the disclosures influence investors' perception of the disclosure credibility. Several studies argue and find support that investors perceive precise forecasts to be more credible compared to imprecise forecasts. Hirst et al. (1999) vary the precision of management forecasts (point vs. range) in an experiment and find that investors are more confident when relying on more precise forecasts. Management explanations to support their disclosures also increase the credibility of disclosures for various reasons. Supporting information could be a costly signal to increase investors' confidence in the credibility of the information. Supporting information also increases the ex post verifiability of the disclosure and reduces management's ability to manipulate information ex ante (Lundholm, 1999; Hutton, Miller, and Skinner, 2003).

Hypotheses

The review of the literature on the credibility of disclosures leads to the following hypothesis on the effect of management incentives on the credibility of management disclosures.

H1: Investors assess lower credibility of management good-news disclosures in

the presence of management incentives than they do in the absence of management incentives.

Surprisingly, given how important investors' *perceptions* of disclosure credibility are, prior research on the credibility of management disclosures has not considered the characteristics of investors, affective states in particular, as inputs into the credibility judgments. The implicit assumption seems to be that investor affect does not influence credibility judgments systematically.

The psychology literature on affect suggests that investor affect could be an important factor that influences their perceptions of disclosure credibility. As Forgas (1995) points out, affective states serve as an important and independent source of functional information and input into realistic judgmental and information-processing tasks, rather than merely as a source of noise. However, the effects of affect in a management setting cannot be presumed. In particular, research has identified two primary dimensions of affect, pleasantness/unpleasantness and strong engagement/disengagement (Watson and Tellegen, 1985). The two primary dimensions of affect categorize affective states into four groups: high positive affect, low positive affect, high negative affect, and low negative affect. Several studies (Lewinsohn and Mano, 1993; Mano, 1997) suggest that the two affective dimensions may have differential effects on information processing. However, prior literature often uses the term affect loosely to refer to various affective states and dimensions. It is unclear whether the effects of affect documented in psychology and accounting literature can be generalized in a management disclosure setting. Due to a lack of guidance on potentially differential effects of affective states and dimensions, I use the general term affect in the hypotheses and the rest of the paper.

In the absence of management incentives to misreport, any difference in investor assessments of management disclosure credibility is only attributed to the influences

of affect on the information base and the information-processing strategy used in investor judgments. The effects of affect predict that investors are likely to use their affective state as a source of information, which leads to higher credibility assessments of disclosures when investors are in a positive affective state than when they are in a negative affective state. It also predicts that investors in a positive affective state are likely to adopt a heuristic processing strategy, as opposed to a systematic processing strategy by investors in a negative affective state. Using a heuristic processing strategy weakens investors' ability to detect logical inconsistencies in management arguments and leads investors to overly accepting the messages in management disclosures. The discussion leads to the following hypothesis on the effect of investor affect on the credibility assessment of management disclosure.

H2: In the absence of management incentives to misreport, investors assess management good-news disclosures as more credible in a positive affective state than in a negative affective state.

In the presence of management incentives to misreport, however, the awareness of management incentives will urge investors to seek more information and to scrutinize the disclosure more. This effect is likely to mitigate the processing bias due to positive affect and restore investors' sensitivity on the strength and plausibility of management disclosures. In a negative affective state, because investors will adopt a systematic processing strategy, the awareness of management reporting incentives is unlikely to further increase the amount of information processed and improve the accuracy of credibility assessment. This leads to the third hypothesis on the interactive effect of affect and management reporting incentives.

H3: The presence of management incentives to misreport reduces investors' assessments of the credibility of good-news disclosures in a positive affective state more than it reduces investors' assessments in a negative affective state.

The hypotheses on the effects of affect and management incentives on the credibility of management disclosures are summarized in Figure 2.1.

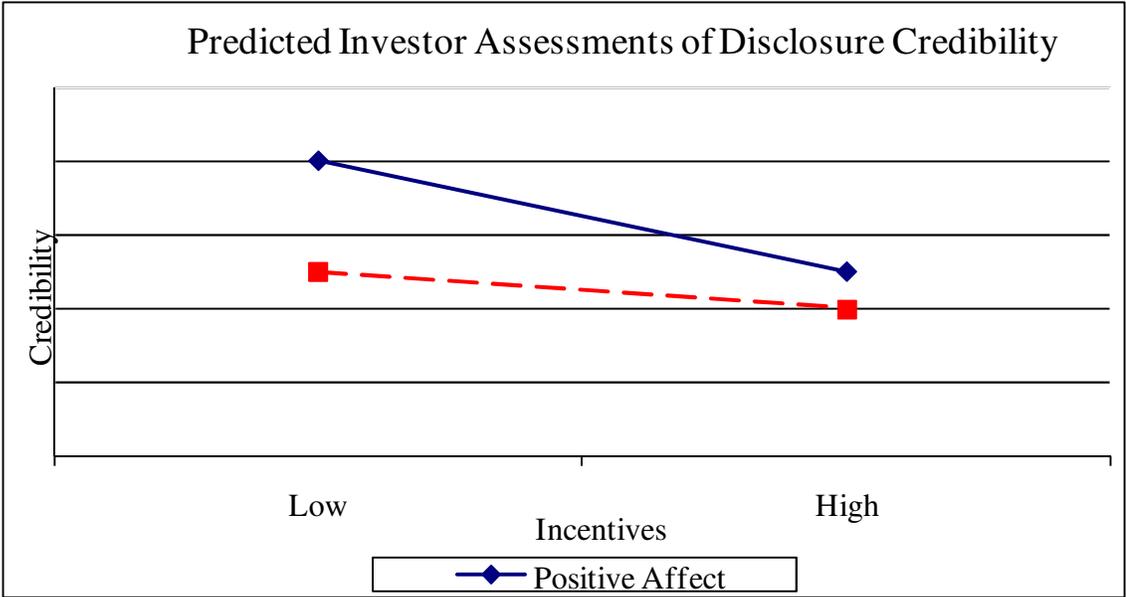


FIGURE 2.1
 Predicted Effects of Management Compensation Scheme and Investor Affect on the Credibility of Management Good-news Disclosures

This figure summarizes the predicted effects of management reporting incentives and investor affect on investors' perceptions of management disclosure credibility. The horizontal axis refers to management reporting incentives. The vertical axis records investors' credibility assessments. The solid blue line represents predicted credibility assessments of investors in positive affective states. The red dashed line represents predicted credibility assessments of investors in negative affective states.

III. EXPERIMENT

To test these hypotheses, I conducted a pilot experiment with 57 master's students and undergraduate seniors enrolled in accounting programs at a large state university. The participants were recruited via classroom announcements. On average, the participants had taken over seven accounting and finance classes. Sufficient evidence indicates that the subject pool has the necessary knowledge to understand management

reporting incentives, which is required for the manipulation to have the intended effects.

Experimental Design and Task

The experiment uses 2 x 2 between-subjects design that varies management incentives to misreport (low versus high), and investor affect (positive versus negative). I focus on good-news forecasts in the experiment because good-news forecasts are consistent with management's general tendency to report optimistically and are, therefore, more likely to suffer from credibility issues. In contrast, bad-news forecasts are inherently more credible and as a consequence are less affected by management situational incentives.

Using an experiment to examine the effect of investor affect on management disclosure credibility has several advantages. First, through experimentation, I am able to hold constant information content, forecasting accuracy, and other confounding variables that potentially influence disclosure credibility. This would be hard to achieve with naturally-generated data where the effects of these confounding variables and the effects of affect and management reporting incentives are hard to disentangle. Second, experimentation allows me to manipulate investor affect and draw clear inferences on the effects of affect on the credibility of management forecasts. In the real world, investors' emotional states are not observable and the sources of their emotional states may be correlated with other factors that affect disclosure credibility. Therefore, it is very difficult, if not impossible, to test the effect of investor affect on information processing and decision making with naturally-generated data. Third, experimentation allows me to measure investor credibility judgments separately from valuation judgments and to collect processing data from investors, which are necessary in order to draw clear inferences on the causal relationship between affect and credibility assessments. Finally, experimentation also gives me an opportunity to

create scenarios that are rarely observed in the real world (Libby, Nelson, and Bloomfield, 2002). Real management disclosures are unlikely to be entirely independent from management reporting incentives. By creating scenarios where disclosures are not affected by management reporting incentives, I can disentangle the effects of affect and management incentives.

I manipulate investor affect by varying the relative payments of investors in the experiment. I randomly assigned participants either positive or negative shares of a fictitious company, company A, as their starting share balances. They were then informed that the market price of the stock drops. Their positions were closed out at the reduced market price. This procedure results in half of the participants receiving positive balance of laboratory dollars and the other half receiving negative balance of laboratory dollars. All participants were informed that higher balances of laboratory dollars translate to higher cash payments at the end of the experiment. The payment differences between low and high payment groups averaged 15USD for a thirty-minute session. The participants who received positive balances were likely to be in a more pleasant mood compared to the participants who received negative balances. Compared to the traditional ways of inducing affect using mood-laden statements or music in the psychology literature, this manipulation resembles more closely what investors experience in the real world, and yet still holds other factors, such as self-efficacy, constant. Participants' self-efficacy is unlikely to be affected because their gains or losses are due to random assignment of shares as opposed to their own investment decisions.

Following the affect manipulation but before measuring participants' affect, participants then assumed the role of investors. They were provided with information about Overland Storage, a company that provides data protection solutions. Participants in each affect group were randomly assigned to one of two conditions:

low management incentives to report favorably and high management incentives to report favorably. Participants in the low management incentives setting were informed that the management team of Overland Storage is compensated based on a fixed-salary scheme and the compensation does not depend on the company's net income or stock price performance. Participants in the high management incentives setting were informed that the management team of Overland Storage is compensated based on a bonus scheme, where 80% of their compensation depends on the company's net income and stock price performance. In the real world, there could be many other situational incentives management may have that could lead them to manipulate financial information. I assume that participants' beliefs about other management incentives will not affect results directionally due to random assignment of participants to different treatments (Libby, Nelson, and Bloomfield, 2002).

The materials presented to participants are based on a real company, Overland Storage Inc. The company is chosen based on several criteria. First, the company provides a management earnings forecast that contains good news disclosed in a relatively wide range. Prior research shows that earnings forecasts in a range format are considered to be less credible than forecasts in a point format (Hirst, Koonce, and Miller, 1999). Second, the company is a small capitalization company that does not have significant news in recent business presses. This reduces the possibility that participants might recognize the company and use their information about the company from outside of the experiment in the task. In choosing the company, I use the First Call database for 2006 January reports that contain quarterly good-news earnings forecasts in a range format.

Each participant was given the background information about Overland Storage Inc. and the management earnings forecast. After reading the earnings forecast, participants could choose to read the risk factors involved in Overland's business and

the key variables of the company before they proceeded to answer questions.

Following the materials, participants provided assessments of the credibility of the earnings forecast, assessments of the management credibility, estimated true earnings, and responses about their cognitive processing.

As manipulation checks, they then answered questions about their affective states and their awareness of the management incentive schemes. I assess participants' affect by asking them to rate their current affective states using mood-descriptive words on provided scales. The mood-descriptive words are adopted from the Positive and Negative Affect Schedule (PANAS) developed by Watson, Clark and Tellegen (1988). The PANAS consists of two 10-item scales for positive affect and negative affect, respectively. Watson and Clark (1994) later expanded the PANAS to measure more affective states (the PANAS-X). The PANAS can be used in a cropped version (Watson and Clark, 1988). I select 15 items from the PANAS-X to measure participants' affective states. Among the 15 items, 8 items reflect positive emotions: Alert, Attentive, Confident, Concentrating, Excited, Happy, Interested, and Proud; 7 items reflect negative emotions, Angry at self, Dissatisfied with self, Irritable, Nervous, Sad, Tired, and Upset¹⁰.

I measure affect after the experimental task for several reasons. First, measuring participants' affect before the task introduces the risk of participants realizing the purpose of manipulation. Prior research has shown that when people identify the source of their mood that is unrelated to the current task, the effect of mood is removed (e.g., Gorn, Goldberg, and Basu, 1993; N. Schwarz and Clore, 1983). Second, studies show that transient emotions induced in experiments fade in about 45

¹⁰ The 15 words can be further classified to represent sub-categories of emotions including hostility, sadness, joviality, self-assurance, and attentiveness, of which the first two constructs are considered as basic negative emotions and the latter three constructs are considered as basic positive emotions.

minutes. The experimental task is designed so that participants should finish the main task within 20 minutes. If the manipulation is successful, measuring affect after the task should allow me to detect any difference between treatment groups. However, measuring affect after the experimental task might distort participants' ratings of their affective states. First, the manipulated affects may fade after the experimental task and reduce the power of detecting a difference. Second, Kida and Smith (1995) argue that investors' affective reactions toward an event are encoded in memory. Therefore, participants' affective states after the experimental task might be affected by both the affect manipulation and the valence of earnings forecast. The second is less of a concern because participants' affective reactions to the valence of the earnings forecast should not cause a differential reaction by participants in different treatments.

Before participants were dismissed, they answered a number of demographic questions about their prior coursework, investment experience, ethnicity, and gender.

Dependent Variables

To measure investors' assessments of the credibility of the earnings forecast, I follow Hirst et al. (2007) to ask participants to assess the credibility and believability of the earnings forecast. To gain more insights into the mechanism through which affect influences investor judgments, I also ask participants questions about the determinants of disclosure credibility identified in Mercer (2004). Specifically, I ask participants to assess management credibility, the precision of the earnings disclosure, and the amount of supporting information demonstrated by the management. On management credibility, I use four questions adapted from Mercer (2005) to measure participants' perceptions of management's competence, knowledge, trustworthiness, and truthfulness.

To understand better how affect and management reporting incentives influence participants' decision making, I also measure participants' cognitive processing. First,

I ask participants to recall any information they remember from the earnings forecast and other information provided. I ask this question first to avoid contamination of the responses by the other questions. Second, I ask them to provide their subjective opinions on the amount of effort they spent on reading the materials and making the assessments. Third, I also record the amount of time participants spent on reading the forecast and related information, and the amount of time spent on making assessments. The three measures provide corroborative evidence on the cognitive effort participants exert in the task.

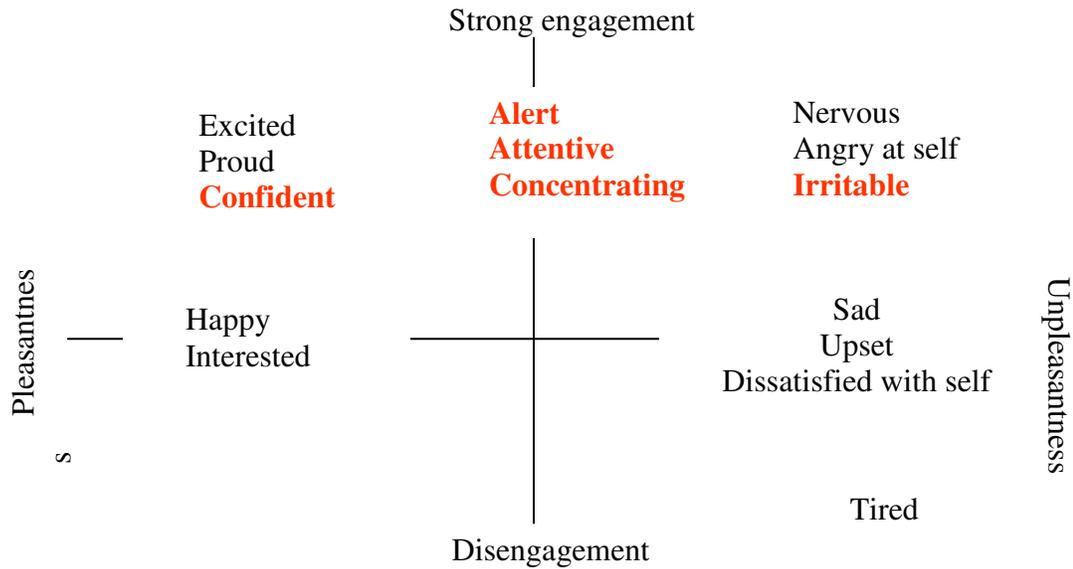
IV. RESULTS

Manipulation Checks

Responses to the manipulation check question on management incentive scheme indicate that all participants but one successfully identified the correct management incentive scheme. Excluding the participant who failed to recall management incentive scheme does not change any result reported.

Responses to questions about participants' affective states, however, do not generate significant differences overall between low and high payment groups. Further analysis on individual affective states indicates that low and high payment groups differ in participants' alertness, attentiveness, confidence, concentration, and irritability. The manipulated affective states are highlighted in bold red in Panel A of Figure 2.2. The statistics are presented in Panel B of Figure 2.2. This manipulation check was completed after participants performed the forecast credibility task. Several factors could have influenced the effectiveness of the manipulation check. First, subjects' affect was not measured immediately after the manipulation and could have dissipated after the completion of the task. Second, participants' affective states are likely to vary before participating in the experiment. Third, participants' affect could

Panel A: The two-dimensional framework of affect



Panel B: Statistics of successfully manipulated affective states

	High Payment group	Low Payment group	P-value (two-tailed)
Alert	4.034	3.250	0.001
Attentive	4.000	3.536	0.019
Confident	3.655	3.250	0.078
Concentrating	4.276	3.643	0.002
Irritable	1.241	1.607	0.076

FIGURE 2.2
Results of Affect Manipulation

This figure presents the results of the affect manipulation. Affect is measured based on participants’ responses to the 15 affect words selected from PANAS-X after they have finished the task of assessing disclosure credibility. In panel A, the 15 words are organized in the Watson and Tellegen (1985) framework of the two-dimensional affective space. The two dimensions are pleasantness/unpleasantness and strong engagement/disengagement. Participants were required to provide responses to each word on a scale of 1 to 5, with 1 = very slightly or not at all and 5 = extremely. The words highlighted in red are successfully manipulated. The statistics are presented in panel B. The p-values are all two-tailed.

have been influenced by the valence of management earnings forecast. The news valence of disclosures is shown to influence investors' affective evaluation of a company (Mercer, 2005). All three possibilities could reduce the statistical power to detect a difference between treatment groups.

Credibility Effects

Hypothesis 1 predicts that investors will assess lower credibility of good-news disclosures when management compensation is highly associated with the company's earnings performance. Hypothesis 2 predicts that investors who are in a positive affective state will assess higher credibility of good-news disclosures compared to investors who are in a negative affective state. The tendency to assess higher credibility in a positive affective state will be mitigated when the management compensation scheme is highly associated with the company's earnings performance, as predicted in hypothesis 3.

To test the predictions, I first conduct a two-way ANOVA with management compensation scheme (Incentive) and participants' payment group (Payment) as independent variables and participants' assessments of the believability and credibility of the earnings forecast as the dependent variables. The results are presented in Table 2.1. Surprisingly, the ANOVA result shows that there is no statistically significant difference on the credibility assessments of the earnings forecast between the two management compensation schemes. The result is inconsistent with prior evidence in the archival literature and other experimental studies that investors assess lower credibility of a management disclosure when the management has high situational incentives to distort the disclosure. Results on the effect of Payment and the interactive effect of Payment and Incentive do not generate statistical significance either.

TABLE 2.1
Effects of Management Compensation Scheme and Participants' Payment on
Credibility Assessments of Earnings Disclosure and Management

The table presents the effects of management compensation scheme (Incentive) and participants' payment (Payment) on the credibility assessments of the earnings forecast and management. The credibility assessments of the earnings forecast are based on participants' responses to two questions on the believability and credibility of the earnings forecast. Participants' responses to the two questions are summed to form a composite measure of disclosure credibility. To measure the credibility assessments of management credibility, I follow Mercer (2005) to collect subjects' responses to four questions on management's competence, knowledge, trustworthiness, and truthfulness. Responses were recorded and summed to form a composite measure of management's credibility.

	Low Payment	High Payment
Low Incentive		
Disclosure credibility	10.214	10.769
Management credibility	0.286	1.462
	Low Payment	High Payment
High Incentive		
Disclosure credibility	10.214	9.000
Management credibility	-2.286	-1.267

P-value	Payment	Incentive	Interaction
Disclosure credibility	0.697	0.298	0.298
Management credibility	0.506	0.112	0.962

To investigate the potential reasons for the lack of consistency of the results with the existing literature, I further look at the determinants of disclosure credibility identified in prior literature. Four groups of factors are identified to determine disclosure credibility (Mercer, 2004): management situational incentives, management credibility, external and internal assurance, and disclosure characteristics. In the experiment, I elicit participants' responses on their perceived precision of the earnings forecast, the amount of supporting information demonstrated by the management, and the perceived management credibility. I first examine whether the management compensation scheme and participants' payment group influence participants'

perceptions of the determinants of disclosure credibility. The participants provide assessments of four aspects of management credibility: management competence, knowledge, trustworthiness, and truthfulness. The four components are adopted from Mercer (2005). I use ANOVA to examine the effects of Incentive and Payment on the determinants of disclosure credibility. Results are shown in Table 2.2. Participants' perceived truthfulness of management is significantly lower when management compensation scheme is highly dependent on the firm's earnings performance. However, management compensation scheme does not have an effect on the other components of management credibility. Neither does it influence the perceived precision of the earnings forecast nor the amount of supporting information demonstrated in the forecast. Participants' payment group has no effects on any of the factors examined.

I further examine the possibility that variances in participants' perceptions prior to the experiment reduce the statistical power of detecting a difference. I conduct an ANCOVA with the credibility assessments of the earnings forecast as the dependent variable. In addition to Incentive and Payment, I include perceived precision, management's demonstration of supporting information, and perceived truthfulness of the management as additional independent variables to control for individual variances. The ANCOVA result is presented in Table 2.3. The result does not show significant effects of Incentive and Payment on the perceived credibility of the earnings forecast after controlling for individual variances in the other determinants of disclosure credibility. Consistent with Mercer's model, I find significant associations between the credibility assessments of the earnings forecast and the controlled variables. Credibility assessments are higher when participants believe the precision of the forecast is higher ($p = 0.0347$), when participants believe the management provides more supporting information ($p\text{-value} = 0.1484$), and when participants think

TABLE 2.2
Effects of Management Compensation Scheme and Participants' Payment on the
Determinants of Disclosure Credibility

This table reports the effects of management compensation scheme (Incentive) and participants' payment (Payment) on the determinants of disclosure credibility. The determinants of disclosure credibility examined include perceived management credibility, perceived precision in management information, and the amount of supporting information demonstrated by the management. The p-values are two-tailed.

	Low Payment	High Payment
Low Incentive		
Management truthfulness	4.857	4.462
Precision	4.429	4.462
Demonstration	3.571	3.923
High Incentive	Low Payment	High Payment
Management truthfulness	5.500	6.000
Precision	4.214	4.600
Demonstration	4.500	4.067

P-value	Payment	Incentive	Interaction
Management truthfulness	0.857	0.071	0.453
Precision	0.722	0.949	0.764
Demonstration	0.949	0.399	0.536

the management is more truthful (p -value = 0.0304).

TABLE 2.3
Analyses on the Determinants of Disclosure Credibility

Panel A presents the result of an ANCOVA analysis that examines the effects of management compensation (Incentive) and participants' payment (Payment) on participants' credibility assessments of the earnings forecast, after controlling for individual variations in the perceived precision of management's beliefs (Precision), the amount of supporting evidence to the disclosure (Demonstration), and the perceived truthfulness of the management (Truthfulness). Panel B presents a regression analysis that examines the association between credibility assessments of the earnings forecast and Precision, Demonstration, and Truthfulness.

Panel A: Results on the ANCOVA analysis

Dependent variable: the composite measure of disclosure credibility					
	Incentive	Payment	Precision	Demonstration	Truthfulness
P-value	0.4473	0.5510	0.0347	0.1484	0.0304

Panel B: Results on the regression analysis

Dependent variable: the composite measure of disclosure credibility			
	Precision	Demonstration	Truthfulness
Coefficient	0.409	0.233	0.402
P-value	0.0385	0.1761	0.0108

To provide additional assurance that the results of the ANOVA and ANCOVA analyses accurately portray the data, I also conduct a path analysis that tests the cause-and-effect relations among the variables simultaneously. The model I test is presented in Figure 2.3. In the model, I include three determinants identified in mercer (2004) that are relevant to this study. The three determinants are management situational incentives, management credibility, and certain disclosure characteristics. In addition to the three determinants identified in prior literature, I also hypothesize that investor affect may influence investors' perceived disclosure credibility directly or indirectly through influencing the other determinants. In Mercer's framework and prior studies, management credibility seems to be an exogenous variable that influences disclosure credibility. However, management prior forecast accuracy is determined by

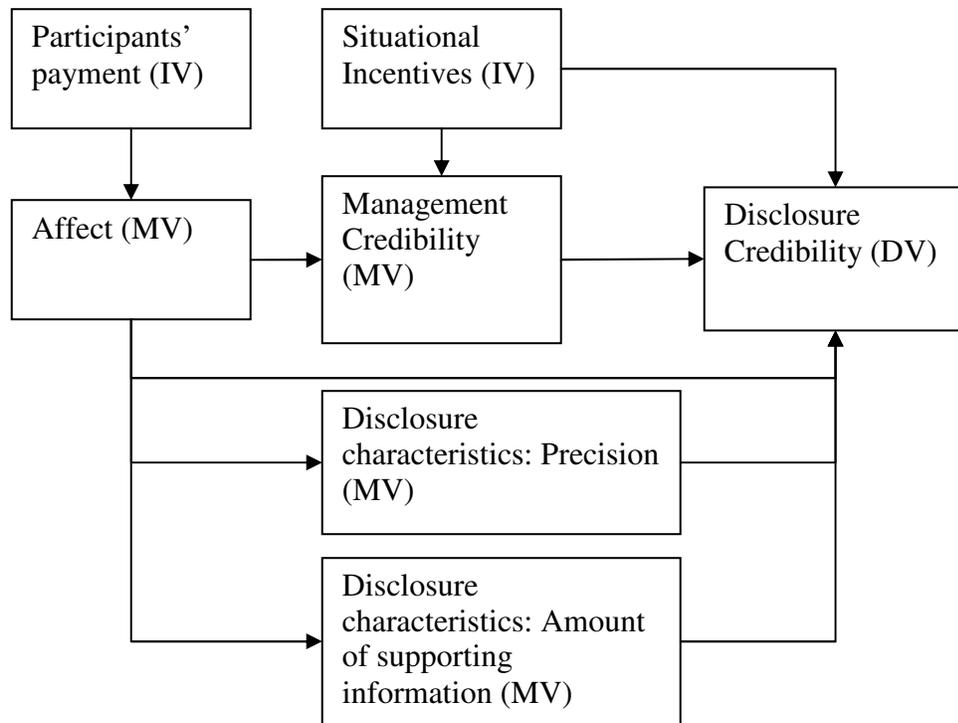


FIGURE 2.3
 Predicted Effects of Management Incentives and Participants' Payment on
 Disclosure Credibility

The following figure presents the hypothesized relationships among the manipulated variables (IV), mediating variables (MV), and primary dependent variable (DV). The model is adapted from Mercer (2004). As in Mercer (2004), disclosure credibility is determined by management situational incentives, management credibility, and various disclosure characteristics. In addition to the three determinants, I also hypothesize that investor affect may influence disclosure credibility directly or indirectly via its influences on the other determinants. In my study, I manipulate management reporting incentives and payments to participants and examine their direct and indirect effects on disclosure credibility.

management incentives over the long term. Thus, I predict the effect of management situational incentives may also influence disclosure credibility indirectly via its effect on management credibility. A test of the overall goodness of fit of the model generates a Goodness of Fit Index (GFI) of 0.9152. I confirm the model's goodness of fit with a Chi-Square test (P-value = 0.0004). The model's goodness-of-fit tests indicate that the model describes the data well.

The results of path analysis are consistent with the ANOVA and ANCOVA analyses, as presented in Figure 2.4. The affect manipulation is significantly associated with the variations in participants' affective states, but is not significantly associated with the perceived disclosure credibility either directly or indirectly through influencing participants' affect or other determinants of disclosure credibility. The management incentive manipulation is significantly associated with the perceived management credibility and the perceived management credibility is significantly associated with the perceived disclosure credibility. But the relationship between management reporting incentives and disclosure credibility is not significant. In addition, consistent with prior evidence, the perceived precision of the earnings forecast and amount of supporting information to the earnings forecast are positively correlated with the perceived disclosure credibility. However, the relationship between the perceived amount of supporting information and disclosure credibility is only weakly significant.

One potential reason for failing to find statistical significance on the hypothesized results is that the experiment may not have enough power to detect statistical significance due to the data size. To investigate this possibility, I conduct a power analysis to arrive at the necessary sample sizes in order to achieve a significance level of 0.05 (one-tailed) and a power level of 0.7. The analysis indicates that given the specified significance and power levels the required sample size for detecting the

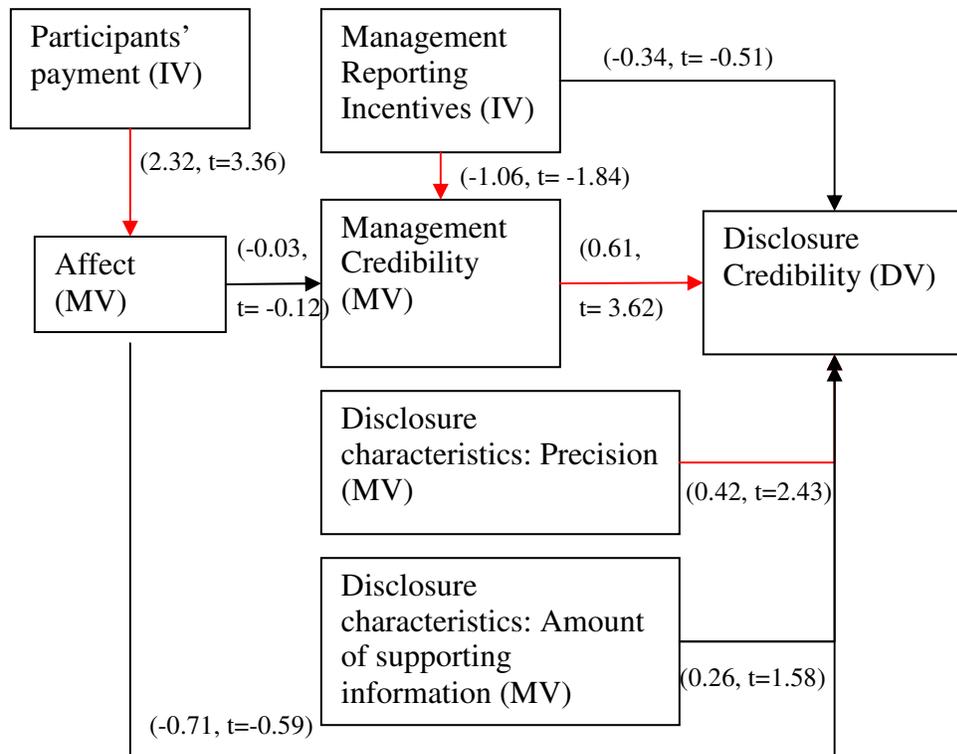


FIGURE 2.4
Results of Path Analysis on the Effects of Management Compensation Scheme and Participants' Payment on Disclosure Credibility

This figure presents the empirical results of a path analysis on the effects of management reporting incentives and participants' payment on disclosure credibility. A path analysis tests the cause-and-effect relationships simultaneously among the independent variables, mediating variables, and the ultimate dependent variable. The full predicted model is presented in Figure 1. The links between Affect and Disclosure Characteristics are omitted in the path analysis because of insignificance of the relationships. The coefficients and t-statistics of results are presented on the corresponding links. Statistically significant links are highlighted in red. The Goodness of Fit Index of this model is 0.9152, indicating an overall fit of the model. It is confirmed by a Chi-Square test with a p-value less than 0.0004.

effect of management reporting incentives on disclosure credibility is 250, and the required sample size for detecting the effect of participants' payment is over 1000. Varying required significance and power levels does not reduce the required sample sizes significantly. Therefore, it is possible that I do not find statistical significance of some of the tests due to limited sample size. I discuss a remedy for this issue in the discussion of future research plan in the conclusion and discussion section.

In addition to the power issue, there are two other possibilities for the lack of association between management compensation scheme and participants' credibility assessments of the earnings forecast. First, participants may have perceived the earnings forecast to be relatively precise and well supported. Therefore, management reporting incentives do not translate into management disclosure credibility. Hirst et al. (2007) show that management reporting incentives have a greater influence on investors' perceived credibility of disclosures when the management has greater opportunities to manipulate the disclosure. Specifically, they find that the perceived disclosure credibility is less affected when the disclosure is more disaggregated and supported by quantitative evidence.

Second, the inconsistency with prior experimental studies could be due to different experimental stimuli used in the experiment. I compare the information provided in my experiment with the materials used in Mercer (2005) that examines management disclosure credibility. Similar to my experiment, Mercer (2005) provided participants with the background information of the company including excerpts from management's discussion and analysis and historical financial statement data. Participants were informed of the consensus analyst forecast for the company. Participants then received a voluntary disclosure from management that includes a point earnings forecast higher than the current consensus analyst forecast. In my experiment, participants also received the background information of the company and

a voluntary disclosure from the management that includes a range earnings forecast higher than the current consensus analyst forecast. The major difference is that I also provided risk factors associated with Overland Storage's business. The original purpose of providing risk information is to warn participants of the possibility that the company might fail to achieve the earnings forecast in the future. To the extent that participants may view the risk information as part of the management's prior disclosures, the risk information may lend credibility to the earnings forecast and reduce the effects of the manipulations on the credibility assessments. I discuss my plans to revise the experiment in the conclusion and discussion section.

The results on the effects of affect do not support the hypotheses either. To gain more insights, I further look at the process variables in participants' information processing and decision making.

Processing Variables

The predictions in hypotheses 2 and 3 are based on the prior psychology studies on the effects of affect on information processing. The hypotheses predict that participants in the high payment group are likely to be in a positive affective state, and therefore, would be more likely to use a heuristic information processing style compared to the low payment group. A heuristic processing strategy is shown to be associated with a lower amount of effort and time spent on processing information and decision making. I test the predictions by examining the amount of time participants spent on reading the disclosure and related information, participants' subjective assessments of their efforts, and their decision time. I use an ANOVA with Payment and Incentive as independent variables and the total amount of time spent on reading the materials, subjective assessments of mental effort, and total amount of decision time as dependent variables.

The results are presented in Table 2.4. The ANOVA results indicate that the

TABLE 2.4
Effects of Management Compensation Scheme and Participants' Payment on
Information Processing

The table presents the effects of management compensation scheme and participants' payment on subjective effort level, total time spent on reading earnings disclosure and related company information (View Time), total time spent on making decisions (Decision Time), and the sum of View Time and Decision Time. Subjective effort level is measured based on participants' responses on an eleven-point Likert scale with endpoints labeled 1 = low effort and 11 = high effort. View time is measured as the sum of time participants spent on reading the general information about the company, the company's earnings disclosure, the key variables of the company, and the risk factors of the company. Total Time is measured as the total amount of time spent on reading information and answering questions. All p-values are two tailed.

	Low Payment	High Payment
Low Incentive		
Subjective effort	7.286	7.846
View time	261.411	282.459
Decision time	223.560	261.738
Total time	484.971	544.197
High Incentive	Low Payment	High Payment
Subjective effort	6.357	7.400
View time	301.420	348.589
Decision time	219.025	273.353
Total time	520.444	621.942

P-value	Payment	Incentive	Interaction
Subjective effort	0.063	0.110	0.570
Total time	0.071	0.886	0.745
View time	0.226	0.062	0.641
Decision time	0.066	0.886	0.745

participants in the high management compensation scheme spent 53 seconds more in processing the information compared to the participants in the low management compensation scheme (p-value = 0.062). The result is consistent with my prediction that high management reporting incentives will induce investors to use a systematic information processing strategy. The psychology literature provides evidence that participants in a positive affective state tend to avoid exerting much effort that could disrupt their positive affect. Contrary to the hypothesis, the results show that the participants in the high payment group report a higher level of mental effort compared to the participants in the low payment group (p-value = 0.063). The higher level of subjective effort in the high payment group could be attributed to two possibilities. The first possibility is that participants in a positive affective state have lower tolerance for effort. Therefore, they report a higher level of mental effort even when the objective level of effort could be no different than the amount of effort exerted by the participants in a negative affective state. The other possibility is that participants in a positive affective state indeed exert higher levels of effort than participants in a negative affective state. To distinguish between the two possibilities, I also compare the information processing time and the amount of decision time for the two payment groups.

The results on the information processing time and decision time are more consistent with the second possibility, with high payment group spending more time on processing the disclosure information and on making decisions (only the p-value for decision time is significant though). The analysis suggests that higher likelihood of the second possibility that participants in a positive affective state exert more effort and scrutinize more in processing the information and making decisions. The results contradict prior findings in the psychology literature.

Prior literature on the effects of affect on information processing and decision

making does not clearly differentiate between different dimensions of affective states. It is likely that the effects documented in prior studies are driven by certain dimensions of affect that are not manipulated in this pilot experiment. In particular, as Figure 3 shows, the affective states successfully manipulated in the experiment locate primarily along the dimension of strong engagement/disengagement. It is likely that prior evidence in psychology on the effects of affect requires an activation of certain dimensions of affect that are not manipulated in this experiment. If it is indeed the case, the results of this study call for a more refined theory on the effects of different affect dimensions on information processing and decision making.

V. CONCLUSION AND DISCUSSION

Conclusions

In this study, I conduct a pilot experiment to examine the effects of affect on investors' information processing and assessments of the credibility of management disclosures as well as the interaction of such effect with management reporting incentives. The hypotheses are based on the psychology literature on affect and the accounting literature on management disclosure credibility. I predict that investors in positive affective states use a heuristic information processing strategy and assess higher credibility of management disclosures, and that this JDM effect of affect is mitigated by the presence of management reporting incentives. In the pilot study, I successfully manipulated participants' alertness, attentiveness, confidence, concentration, and irritability by varying payments to participants. Inconsistent with my predictions, participants in the high payment group spent more time on information processing and decision making than participants in the low payment group. The difference in information processing strategies does not lead to a difference in the assessments of management disclosure credibility. Participants assess a lower

level of management truthfulness when management compensation scheme is highly associated with the earnings performance. However, inconsistent with the prediction and prior literature, lower assessments of management truthfulness do not result in lower assessments of management disclosure credibility.

The results indicate that prior literature on the differential effects of positive versus negative affects on information processing and decision making may not be generalizable to all dimensions of affect. Future research should refine the effects of specific dimensions of affect on information processing and decision making. The study extends the existing accounting literature on management disclosure credibility by showing that when the management has high incentives to misreport, investors do not simply discount the disclosures, but also scrutinize the disclosures more carefully.

The pilot experiment leaves several important questions unanswered. First, it is not clear whether the results indicate that the findings on affect in psychology do not generalize in a management disclosure setting or that the findings do not generalize to all dimensions of affect. Second, the results show that lower management credibility does not necessarily lead to lower credibility of management disclosures. It is not clear whether this result, contradictory to prior studies, is due to the effects of other determinants of disclosure credibility or due to a low statistical power to detect a difference.

Plans for Future Research

Given the results of the pilot study, I plan to make the following revisions in future research to achieve better experimental controls and address the questions raised.

One possible reason for failing to find statistical significance in the results is that there may be significant variances in participants' information processing styles and emotions before the experiment. To achieve better controls over individual variances in information processing and decision making, I plan to use a pretest-posttest design

where participants provide assessments about two disclosures, one before affect manipulation, and the other after the manipulation. A pretest-posttest design provides changes as dependent and independent variables that are less subject to variances between individuals, and therefore should increase statistical power.

Another issue raised in the pilot experiment is whether the exiting findings on affect in the psychology literature can be generalized to all affect dimensions. To test potential differential effects of different dimensions of affects on information processing, I plan to manipulate affect using both the method in the psychology literature and the payment method in this study. The method used in the psychology literature has been shown to successfully induce affective states primarily along the pleasantness/unpleasantness dimension and the payment method used in the pilot study is shown to influence primarily affective states along the strong engagement/disengagement dimension. By manipulating the activation of different dimensions of affect, I can examine whether different dimensions of affect have differential influences on information processing.

The pilot experiment fails to replicate the empirical finding that management reporting incentives are associated with investors' assessments of disclosure credibility. One possibility is that I provided supplementary information to the earnings disclosure. Providing supplementary information could have increased the credibility of the earnings disclosure despite management reporting incentives. Providing supplementary information could also have increased information load on participants and added noise in their responses. In the future experiment, I plan to follow more closely the prior experimental studies by providing only background information and earnings forecasts in order to increase comparability and consistency with prior studies.

APPENDIX

Experimental Materials

The appendix contains the materials about Overland Storage used in the experiment and some of the experimental questions. Each participant reviews the general information about Overland Storage and the Overland Storage's earnings forecast. The participants could choose whether to view the key variables and the risk factors of the company before they proceeded to answer questions.

1. General Information about Overland Storage

Overland Storage, Inc. (Overland) is a provider of data protection solutions designed for backup and recovery to ensure business continuity. The Company sells its products on an indirect basis, primarily through three channels or types of customers, such as original equipment manufacturers, distributors and value-added resellers. End-users of its products include small and midsize businesses, as well as divisions and operating units of large multi-national corporations, governmental organizations, universities and other non-profit institutions. Overland's products are used in a range of industry sectors, including financial services, healthcare, retail, manufacturing, telecommunications, broadcasting, and research and development. Its products are sold world-wide in the Americas, EMEA (Europe, Middle East, Africa) and Asia Pacific. Approximately 56.5% of the Company's revenue is generated internationally, primarily in Europe.

2. Overland Storage Earnings Forecast

On Jan. 10, 2006, Overland Storage raised financial guidance for Fiscal Years 2007 and 2008 to incorporate expected benefits of new OEM contracts.

Jan. 10, 2006 – Overland Storage, Inc. (NasdaqNM: OVRL) today raised financial

guidance for its fiscal years ending June 30, 2007 and 2008. Incorporated in this new guidance is the impact of two new OEM contracts: a software license agreement for REO Protection OSTM and a supply agreement for the company's new tape automation product currently under development.

Overland now expects fiscal 2007 revenue to be in the range of \$280 to \$285 million. Fiscal 2008 revenue is expected to be in the range of \$320 to \$330 million. GAAP earnings per diluted share are expected to be \$0.22 to \$0.27 in fiscal 2007 and \$0.62 to \$0.72 in fiscal 2008.

“Based on new OEM business, we are raising our earnings guidance for fiscal years 2007 and 2008, with expectations that results will almost double our previous non-GAAP earnings guidance for these periods. Additionally, we have taken a further step to reduce a portion of the execution risk in our model by lowering the expected revenue contributions from our new ULTAMUS™ product over the next 18 months. Our operations and engineering teams are working diligently to support these new customers and products, and it is critical that we make the necessary investments in fiscal 2006 to drive the business in subsequent years. We are also pursuing a number of other OEM opportunities that could provide incremental revenue and operating profit contribution and leverage our new product investments,” said Christopher Calisi, president and chief executive officer.

3. Some key variables of Overland Storage

Number of Employees: 360

Fiscal Year Ending Date: 6/30/06

Market Capitalization (in millions): \$55.07

Percent Owned by Institutions: 68.90%

Shares Outstanding (in millions): 12.84

Number of Institutional Shareholders: 68

4. Potential risks

The information contained in this news release consists of forward-looking statements that involve risks, uncertainties and assumptions that are difficult to predict. Such forward-looking statements are not guarantees of performance and the company's actual results could differ materially from those contained in such statements.

Factors that could cause or contribute to such differences include

- a. risks and uncertainties associated with the company's acquisition of Zetta Systems, Inc.,
- b. including possible integration difficulties and successful execution of the business plan related to the acquisition;
- c. possible delays in new product introductions and shipments by the company including the new ULTAMUS line and the new tape automation platform currently under development,
- d. including versions subject to the company's new OEM contracts;
- e. possible delays in enhancements to the company's REO line;
- f. market acceptance of the company's new product offerings;
- g. the timing and market acceptance of new product introductions by competitors;
- h. the speed at which HP transitions from the products it currently buys from the company to its next-generation products to be purchased from another vendor;
- i. delays, unbudgeted expenses, inefficiencies and production problems that may result from the transition of manufacturing to Sanmina-SCI;
- j. worldwide information technology spending levels; unexpected shortages of critical components;

- k. rescheduling or cancellation of customer orders; loss of a major customer;
- l. the timing and amount of licensing royalties;
- m. general competition and price pressures in the marketplace;
- n. the company's ability to control costs and expenses;
- o. and general economic conditions.

5. Experimental Questions:

- 1) The perceived credibility of the earnings forecast is measured with the following two questions.
 - a) Please indicate how *believable* the provided earnings forecast is.
 - b) Please indicate how *credible* the provided earnings forecast is.
- 2) The supporting information demonstrated in the earnings disclosure is measured with the following question.
 - a) Please indicate how clearly the management demonstrates how they would achieve the forecast.
- 3) The perceived precision of the earnings forecast is measured with the following question.
 - a) Please indicate how precise you think the management's beliefs are about the future performance of the company.
- 4) The perceived management credibility is measured with the following four questions. The four questions are adopted from Mercer (2005).

Please indicate to what extent each of the following 4 statements reflects your belief.

 - a) I believe that the management of Overland Storage is very competent at providing financial disclosures.

- b) I believe that the management of Overland Storage has little knowledge of the factors involved in providing useful disclosures.
- c) I believe that the management of Overland Storage is very trustworthy.
- d) I believe that the management of Overland Storage may not be truthful in their financial disclosures.

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