Uncertainty and the Decision to Manipulate Reported Performance

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ABSTRACT
We consider the role of forecast uncertainty in whether an attempt to manipulate reported performance is made and the magnitude of any attempt. We present a model of manager behavior, given a desired performance target and level of forecast uncertainty. Implications of the model suggest that, all else equal, as a manager becomes more certain, more attempts will be made to manipulate reported performance, using smaller magnitude adjustments. These results suggest that bias in internal and external reporting of performance is a function of the manager’s information setting (e.g. information system quality, experience, competitive environment, etc.). Further, earnings management, which is already difficult to detect, becomes more challenging to identify as managerial uncertainty decreases.
1. INTRODUCTION

We explore whether the decision to manage reported performance is a function of certainty about performance forecasts, assuming incentives to achieve a particular performance target (i.e. analyst forecast or contract requirements). As Das, et. al. (2007) note with respect to earnings, any adjustments “…are likely to be made when the excess or shortfall from the target becomes known”. In order to identify this variance from the target, and determine the corresponding amount of manipulation necessary, the manager must first forecast future reported (expected) performance. If expected performance is better than the target, no manipulation is necessary.\(^1\) If expected performance is worse than the target, the manager can then weigh the benefits of achieving the target against the likelihood of detection (and the associated costs), given the amount of manipulation deemed necessary.

Extant research has identified and explored myriad drivers of performance reporting manipulation. The earnings management literature has considered the importance of many managerial objectives and targets, including meeting analyst forecasts (e.g. Abarbanell, and Lehavy 2003; DeGeorge et al. 1999; Kasznik 1999), avoiding losses or achieving earnings targets (e.g. Burgstahler and Dichev 1997), reducing tax exposure (e.g. Adiel 1996; Beatty, Chamberlain, and Magliolo 1995), smoothing earnings (Trueman and Titman 1988), affecting stock price (Graham et al. 1995).

\(^1\) Das et. al. (2007) do find that at least a quarter of firms reporting a small increase in EPS appear to manage accruals down to just beat the target, suggesting that manipulation could go both directions. While we recognize that there are some instances where managers have incentives to manage performance down (e.g. 'big bath', smoothing or political scrutiny), we assume that the average incentive for managers is to increase earnings. This is likely especially true in broader internal performance reporting settings where the reversing pattern seen in accrual manipulation may not be as apparent.
and catering to the capital markets appetite for ‘surprise’ (Rajgopal et al. 2007). Existing studies explore incentives to maximize personal wealth (e.g. Healy 1985; DeAngelo 1988; Dechow et al. 1995; Holthausen et al. 1995; Bartov and Mohanram 2004; Cheng and Warfield 2005), to satisfy contracting requirements (e.g. DeFond and Jiambalvo 1994; Collins et al. 1995; Sweeney 1994) and to attract or avoid political scrutiny (e.g. Jones 1991; Key 1997).

Existing research has also investigated manipulation of internal reporting. Among others, studies have explored the creation of budget slack as a function of concerns for reputation and ethics (Stevens 2002), as well as the determinants of honest reporting of costs to a manager (see Evans et al. 2001, Zhang 2008). Other studies have considered the gaming of nonfinancial measures (Smith 2002) and how managers respond to the risk of gaming (Gibbs et al. 2004). Collectively these studies have broadly documented that greater opportunity and greater incentives are associated with greater reporting manipulation.

We augment this opportunity and incentive story by introducing the information environment faced by the manager as a potential factor. We argue that for any of the determinants in the existing literature to apply, a manager must first identify the need for manipulation - a difference between expected and desired performance. Further, not all managers have the same ability to forecast future reported performance.

Differences in forecast accuracy may derive from various sources. For instance, the ability of any given manager likely affects forecast accuracy. An individual who is particularly skilled will be able to generate superior predictions relative to an individual
not so talented. Related, managers with greater expertise in their area will likely be able to produce more accurate forecasts than those who are less experienced.²

The information systems at the disposal of the manager may yield a forecast of greater or lesser precision. Firms possessing information systems that provide integration within the value chain and across the supply chain are more likely to produce accurate forecasts than firms in which information systems operate as isolated silos (Bacheldor 2004; Colkin and Whiting 2002; Colkin and Maselli 2002; Fliedner 2003; Sullivan 2004; Whiting 2002). These integrated information systems are superior tools for forecasting (Colkin and Maselli 2002; Fliedner 2003; Whiting 2002) and may affect the certainty of the forecasts provided to the managers.³

Firm characteristics, such as size and the extent to which the firm operates across heterogeneous systems, are known to affect uncertainty associated with forecasts (Goldberg and Heflin 1995; Reeb, Kwok, and Baek 1998; Duru and Reeb 2002; Herrmann et al. 2008). Firms operating in varied geographic regions are exposed to numerous risks (currency fluctuations, political risk, government regulations, etc.) that make their environment more complex and more volatile (Goldberg and Heflin 1995; Reeb et al. 1998), making forecasting more challenging.

² Trueman (1986) argues that such managerial expertise may be signaled to the market with the disclosure of earnings forecasts.

³ The adoption of integrated information systems does not necessarily lead to improved forecasting accuracy and increased manager confidence in results. This will depend on the firm’s experience during the pre and post-implementation phase. As Markus et al. (2000) have shown, the implementation of such integrated systems whose effects span geographical and organizational areas is not without problems. Frequently users fail to grasp cross-functional business processes and the ramifications of business record quality in an integrated system. In many cases “End-users and line managers are unwilling to trust and use systems if they do not trust the data and reports.” (Markus et al. 2000: p. 262). While recognizing these potentialities, we operate on the assumption that, on average, integrated information systems do yield improvements.
Finally, looking outside the firm itself, the overall competitive environment will have an effect on the ability of managers to forecast performance. Firms today face intense competition in an increasingly turbulent and dynamic global market (D’Aveni 1994; Sambamurthy 2000). This manifests in higher volatility of earnings, increased incidents of “performance slumps” among Fortune 500 companies, and stories of companies with superior past performance record having difficulty delivering consistently superior earnings in recent years (Hamel and Välikangas 2003). The ability to generate high quality forecasts also likely varies by industry, suggesting that firms in volatile industries, or operating in multiple industries, face lower certainty in forecasted performance.

If one accepts the premise that there is variance in forecasting ability, we argue that it must affect the managers' perception of the need to manipulate performance (i.e. the excess or shortfall from the performance target). In turn, consistent with the existing research on manipulating performance reports, managers will respond by differently adjusting the drivers that are likely to bring the expected level in line with the targeted level. This is the main research question of this study: how does forecast certainty affect whether and to what degree reported performance is manipulated?

We develop a model that captures the performance reporting manipulation behavior of managers who maximize their payoffs as a function of forecast certainty and detection risk associated with manipulation. Our results indicate that as the uncertainty (variance) associated with a prediction of future performance decreases, the economically optimum strategy becomes increasingly frequent manipulations of smaller magnitude.
These findings suggest avenues for the empirical investigation of the effects of managerial skill, information system quality, industry and other proxies of uncertainty on bias in performance reporting. In addition, while it has been repeatedly pointed out in the earnings management literature that the state of the art methods for identifying earnings management are inadequate (e.g. Das et al. 2007), the inferences from this model suggest that the problem becomes more severe as managerial certainty increases.

2. MODELING THE ROLE OF CERTAINTY

Our model starts at the beginning of a period with a manager considering whether to manipulate reported performance and, if so, by how much. This consideration reflects an evaluation of risks and rewards as part of the manager’s decision process to maximize her payoffs from manipulation. A rational manager’s decision process will go through the following three stages:

1. Awareness – the manager becomes aware of excess or shortfall from the performance target
2. Options/Persuasion – the manager considers and collects information that will be used in the evaluation of the options (manipulation versus inaction or no-manipulation).
3. Decision – manager will select the level of manipulation that produces the maximum payoffs (maximum distance between expected rewards and expected risks).

The level of manipulation signals the managers’ decision to manipulate (level of manipulation is different than zero) or not (level of manipulation is zero). Rewards take the form of increased compensation for achieving the target. Risk takes the form of a potential negative audit outcome.\(^4\) In this decision the manager will consider the

\(^4\) In our setting, a ‘negative audit outcome’ refers to an auditor observing the amount of adjustment and deeming it unsupportable or an attempt at fraud, either of which imposes costs on the manager. We assume that the auditor can observe the amount of the adjustment itself with certainty. As such, the increasing
following information/general setting.

There is a level \( G \) of targeted performance at time \( t_1 \), which is the level of performance specified contractual requirement (or, in the case of public reporting, expected by financial analysts) and represents the manager’s goal. The expectations were formed at \( t_0 \); thus we treat \( G \) as a fixed known value at time \( t_0 \), and it should be understood as the minimal expectation. \( E_a \) denotes performance at the time \( t_1 \), which at the time \( t_0 \), is a random variable. This will be the level of reported without any manipulation. \( E_a = \mu + \epsilon \), where \( \mu \) is the expected (most likely) level of performance without any manipulation and \( \epsilon \) is an error (random variable) with \( \mathbb{E}(\epsilon) = 0 \). We denote with \( m \) the level of manipulation. This is the value to be determined by a rational manager who is trying to maximize her payoff at time \( t_1 \). We treat \( m \) as a deterministic quantity. In other words, we assume that the manager can specify an exact amount of manipulation. Let \( E_r \) be the level of reported performance at time \( t_1 \). This will be the level of reported performance with manipulation. \( E_r = m + E_a \).

Let \( R \) be the reward to the manager if the level of reported performance \( (E_r) \) is greater or equal than the expected level \( (G) \) and the manipulation is undetected. We introduce an auxiliary random variable \( W \in [0,1] \) to describe the probability of a reward situation: \( W = 1 \) if \( G \leq E_r \) or \( G - m \leq E_a \); and \( W = 0 \) if \( G > E_r \) or \( G - m > E_a \). However, there is the risk of a penalty \( (P) \) if manipulation is detected. We assume that the audit result (detection or not-detection) follows a Bernoulli process and we introduce a random variable \( Z \in [0,1] \) to denote the auditing result: \( Z = 1 \) if the manipulation is detected (with probability \( p \)), and \( 0 \) if the manipulation is undetected (with probability \( 1 - p \)).

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*probability of a negative audit outcome associated with larger adjustments is a function of the size of the adjustment, not the auditor’s ability to identify an adjustment or the quality of the information system itself.*
The selection of a model for \( p \) is significant for this analysis and it should meet the following criteria: (1) \( p \) is increasing function of \( m \); the larger the amount of manipulation, the higher the likelihood that the manipulation might be detected.\(^5\) (2) \( p = 0 \) if \( m = 0 \) since no manipulation can be detected if there is in fact no manipulation. (3) \( p \) should approach 1 when \( m \) is sufficiently large. Such convergence can be attained with a log-reciprocal function, for simplicity approximated by \( p = \frac{m}{m + C} \). In this model, \( C \) is a detection parameter and a proxy for effectiveness of internal controls. Values of \( C \) approaching zero indicate that internal controls are very effective and, as a result, the probability of detection is very high. On the other hand, high \( C \) values indicate that internal controls are ineffective thus probability of detection is minimal.

Finally, if we let \( B \) denote the total payoff the manager will get at time \( t_1 \), we have: \( B = (1-Z) \cdot W \cdot R - Z \cdot P \). Once the manager has collected all information that will be used in the evaluation of the options (manipulation versus inaction or no-manipulation), she is ready to proceed in the final stage; selection of the level of manipulation that produces the maximum payoffs (maximum distance between expected rewards and expected risks). Table 1 summarizes the combination of all possible results at the end of period \( (t_1) \).

<Insert Table 1 about here>

In order to calculate expected payoffs, we make the following assumptions: (1) performance error \( \varepsilon \) is normally distributed, i.e., \( \varepsilon = N(0, \sigma^2) \). (2) For simplicity and

\(^5\) If we consider the detecting probability is dependent on the relative magnitude of earnings manipulation \( (m) \) with respect to the level of reported earnings \( (E_r) \), then \( p \) is increasing function of \( m/E_r \).
without loss of generality we assume that the reward $R$ and the penalty $P$ are constant.\(^6\)

Based on these assumptions, we can compute the expected rewards at time $t_1$ as:

$$
E[(1 - Z) \cdot W \cdot R] = E[E[(1 - Z) \cdot W \cdot R | E_t]] = 
$$

$$
\left(1 - \frac{m}{m + C}\right) \cdot R \cdot E(W) = \frac{C \times R}{m + C} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx,
$$

and expected risk (penalty) as $E[ZP] = \frac{mP}{m + C}$. So we have that the expected payoff, which is the difference between expected rewards, and expected risk (penalty) is given by

$$
B(m) = \frac{CR}{m + C} \left(1 - \Phi\left(\frac{G - \mu - m}{\sigma}\right)\right) - \frac{mP}{m + C} \quad (1)
$$

A rational manager will choose the level of $m$ that maximizes the payoff function. Implicitly, this means that the manager will have to perform two tasks. First, find whether there is a non-trivial (non-zero) maximum value of the payoff function. Second, determine the level of manipulation ($m$) that will deliver the desired optimum level of payoffs.

In order to find the optimum value of the payoff, we take the first derivative of (1) with respect to $m$ and find the value of $m$ at which this is equal to zero [$B'(m) = 0$] and see if the second derivative of (1) is less than zero [$B''(m) < 0$]. If we let $m^*$ denote the global optimum solution for the optimization problem $B(m^*) = \sup_{m \geq 0} \{B(m)\}$, we have the following theorem about the optimum solution $m^*$:

**Theorem 1.a.** If $m^* > 0$, then $m^* > G - \mu$

[See Appendix A – A1. Proof for Theorem 1.a]

\(^6\) It can be shown that the main results of our analysis would be the same if we were to assume that $R$ is function of $E_t$ and $G$, and $P$ is a function of $E_t$ and $m$. 
In other words rational managers can attain the maximum payoff either without manipulation \((m^* = 0)\) or with manipulation \((m^* > 0)\). However, if they decide to manipulate, the amount of manipulation will be greater than the difference between the targeted and the expected (most likely) level of performance, \(m^* > G - \mu\)

The intuition and a logical explanation behind the statement \((m^* > G - \mu)\) can be traced to two of our assumptions. First, we have made a dichotomous assumption regarding the reward. The manager will receive (all) reward if performance is greater or equal to the expected level. There is no reward if performance is below expected level, i.e., there is no partial reward for coming close(r) to the target. Second, the random variable component \((\varepsilon)\) in performance volatility is normally distributed. This means that the probability of getting the reward \((1 - \Phi)\) is less than 50%, when \(m^* > \theta\) and in the range \([0, G - \mu]\).\(^7\) Knowing that even after manipulation you are not getting better than the odds of pure chance is enough to deter a risk neutral manager, even if you don’t account for the risk of detection.

**Theorem 1.b.** If \(m^* > 0\) and \(\frac{P}{R} \geq \frac{C}{\sigma \sqrt{2\pi}} \left(1 - \Phi \left(\frac{G - \mu}{\sigma}\right)\right)\), then \(B(m=0) \geq B(m^*)\).

[See Appendix A – A2. Proof for Theorem 1.b].

In other words rational managers will avoid trivial solutions. More specifically, if \(m^* > 0\) and \(\frac{P}{R} \geq \frac{C}{\sigma \sqrt{2\pi}} \left(1 - \Phi \left(\frac{G - \mu}{\sigma}\right)\right)\) the payoffs associated boundary solution \(B(m=0)\) are better than the payoffs associated with positive optimum solution \(B(m^*)\) and the manager will avoid manipulation. The intuition behind this statement is that the typical manager is assumed to be risk neutral and will not engage in manipulation unless it has

\(^7\) Recall that the probability of getting the reward, when \(m^* > \theta\), is given by \(1 - \Phi \left(\frac{G - \mu - m}{\sigma}\right)\)

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the potential to produce a payoff that is higher than the risk-free inaction; i.e., the manager will not manipulate unless \( B(m^*) > B(m = 0) \). We can interpret the term
\[
\frac{C}{\sigma \sqrt{2\pi}} \left( 1 - \Phi\left( \frac{G - \mu}{\sigma} \right) \right)
\]
as the prohibitive threshold of relative penalty \((P/R)\) that will deter the manager from engaging in manipulation. Managers have no incentive to engage in manipulation if the relative penalty is above or equal to this threshold. The threshold relaxes as the right hand part of the condition is increased, making it more likely that managers will engage in manipulation. The threshold relaxes, under the following conditions: (1) Managers operate in environment of ineffective internal controls, i.e., \( C \) is high. (2) Managers have higher degree of certainty, i.e., \( \sigma \) is low. (3) Managers realize that the distance from the expected level of performance is large, thus the probability of receiving the reward without any manipulation is small, i.e., \( 1 - \Phi\left( \frac{G - \mu}{\sigma} \right) \) is small.

**Necessary and sufficient conditions:** The optimum solution \( m^* \) is positive if and only if \( m^* \) satisfies the following conditions: \( f(m^*) = 0, m^* > G - \mu \), (necessary conditions) and
\[
\frac{C}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2} \geq 1 + \frac{P}{R} - \Phi\left( \frac{G - \mu}{\sigma} \right) \quad \text{(sufficient condition)}.
\]

[See Appendix A – A3. Proof for Necessary and Sufficient conditions]

3. REPORTED PERFORMANCE MANIPULATION MODEL: PROPOSITIONS

In order to evaluate a manager’s propensity to manipulate performance we will look at the conditions for positive optimum solutions under three difference scenarios: 1. Targeted level of performance is below expected level. 2. Targeted and expected level are equal. 3. Targeted is higher than the expected level. Table 2 summarizes these conditions. [See Appendix A – A4. Proof for Proposition 1]
In all three cases, we see that the relative penalty threshold that will deter managers from engaging in manipulation is relaxing, as \( \frac{C}{\sigma \sqrt{2\pi}} \) is getting bigger. Thus we conclude, that the likelihood that a manager would engage in manipulation is proportional to \( C \) and inversely proportional to \( \sigma \). In other words, anything that contributes to either a decrease in the probability of detection (recall that higher values of \( C \) are a proxy for ineffectiveness of internal controls) or a reduction of the uncertainty around predicted performance (\( \sigma \)), increases the likelihood that a rational manager who maximizes her payoff will engage in manipulation. While the former of these findings was expected, the latter is new and leads to the first proposition of our model.

**Proposition 1:** Ceteris paribus, an increase in manager’s ability to forecast future performance is likely to lead to an increase in propensity to engage in performance manipulation.

The following corollaries will provide us with some insight regarding the magnitude of manipulation and the implications of a targeted level of performance that is far beyond the expected level.

**Corollary 1.a** Assuming a given level of reward, penalties and expected performance are in place, there is a threshold of targeted level of performance that makes the manipulation undesirable to the risk–neutral manager. The manager will not manipulate performance if \( G - \mu > \frac{CR}{P} \); under these conditions there is no optimum solution. [See Appendix A – A5. Proof for Corollary 1.a]
This corollary complements the findings from theorem 1.b. Recall that in 1.b we found that the relative penalty threshold that will deter managers from engaging in performance manipulation relaxes as managers realize that the distance from the expected level of performance is large. Thus the probability of getting the reward without any manipulation is small, i.e., \(1 - \Phi \left( \frac{G - \mu}{\sigma} \right)\) is small. The implication of 1.a is that a rational manager will avoid manipulation when the targeted level of performance \(G\) is too far beyond the expected level \(\mu\). This makes sense considering the fact that the magnitude of the distance between targeted and expected performance \((G - \mu)\) defines the lower boundary (minimum) level of manipulation \(m\) needed to reach the maximum payoff, and, at the same time, the risk of being audited increases with the level of manipulation. However, what is perceived as a prohibitively distant target will depend on the ratio of rewards and penalties.

**Corollary 1.b** If there is a positive optimum solution \(m^*\), then the boundaries of this optimum solution (upper and lower limit) will fall within the following range:

\[
G - \mu \leq m^* \leq G - \mu + \sigma \sqrt{\frac{2\ln \frac{CR}{\sigma P \sqrt{2\pi}}}{\sigma P \sqrt{2\pi}}}
\]

The implication of corollary 1.b is that the level of manipulation increases with \(\sigma\). In the extreme case of zero uncertainty \((\sigma = 0)\) in the prediction of future performance, the manager will select the minimum level of manipulation \((m^* = G - \mu)\) that will secure the desired level of reward \(B(m^*)\). This is consistent with our prior observation regarding managers’ risk neutrality and, when combined with our first proposition, leads to our second and more general proposition.
**Proposition 2:** Ceteris paribus, an increase in a manager’s ability to forecast future performance is likely to lead to an increase in propensity to engage in manipulation, while the level of manipulation will decrease. [See Appendix A – A6. Proof for Corollary 1.b. (Proposition 2)]

4. DISCUSSION

We conclude from our model that increasing forecast certainty will lead to more attempts of smaller magnitude. The intuition behind this result is not controversial and can be followed by considering two identical independent managers operating in similar firms within the same industry. Both of them face an expected performance ($\mu$), which is equivalently short of the desired target ($G$), but they differ in terms of their degree of certainty regarding their forecasting accuracy ($\sigma_{\text{Low}}=1\%$ versus $\sigma_{\text{High}}=1.8\%$).

Variations in their performance forecasting accuracy could be attributed in the differences in terms of managerial experience or the availability and/or ability to extract value from the firm’s information systems. For example, if we assume that the first manager has several years of experience in the firm and industry, it is reasonable to expect that she can combine internal and external information more effectively in order to generate more accurate forecasts of future performance ($\sigma_{\text{Low}}$) than her less experienced counterpart ($\sigma_{\text{High}}$). An equivalent alternative scenario could be to assume similar experience in both managers, but grant one of them a superior information system that produces more accurate forecasts.

Contrasting these two managers as they decide whether to manipulate reported performance (i.e. $m^*\neq0$ or $m^*=0$) in a way that maximizes their expected payoffs $B(m^*)$
leads to the following observations. First, in the absence of any action \((m=0)\), the manager with higher uncertainty \((\sigma_{\text{High}})\) will always have a greater probability of exceeding the desired performance target via nature, translating into a higher payoff. If we treat this payoff associated with no action as an opportunity cost, the relative benefit of not manipulating is higher for the manager with higher forecasting uncertainty. As a result, all else equal, the optimum strategy will be ‘no manipulation’ more often for the manager with the high uncertainty predictions than for the manager with low uncertainty predictions.

Second, under the assumption that the reward is in the form of all or nothing and there is no partial compensation for coming closer to the goal; small positive manipulations \((0<m<G-\mu)\) are not a desirable action for either one of these managers. Small manipulations, which are less than the distance between the desired target \((G)\) and expected performance \((\mu)\), will fail to increase the probability of receiving the reward to more than the 50:50 odds of pure chance. A small amount of manipulation does not raise the expected reward high enough to compensate for the increase in the expected risk.

Third, by this point both managers realize that if they are going to manipulate and expect that this manipulation will have an incremental impact on their payoffs, the manipulation will have to be at least more that the difference between the desired target \((G)\) and expected performance \((\mu)\). This realization has its own implication regarding their relative payoffs and the amount of manipulation needed to reach their respective maximum payoff levels. The former of these implications is as follows: In this range \((m^*>G-\mu>0)\), and as long as the distance between the desired target \((G)\) and expected
performance ($\mu$) is not too large, the probability of receiving the reward reverses and becomes higher for the manager with the more accurate forecast (i.e. the more seasoned manager or the manager who can leverage the company’s information systems). This translates into a higher payoff for the manager with the higher forecasting certainty. While both managers can maximize their respective payoffs with positive manipulation, the manager with the higher forecasting accuracy ($\sigma_{\text{Low}}$) can attain a higher level of expected payoff than the manager with lower forecasting accuracy ($\sigma_{\text{High}}$): \[ \text{Max } B(m^*) \text{ with low } \sigma > \text{Max } B(m^*) \text{ with high } \sigma. \]

Alternatively, we can treat this payoff associated with positive manipulation as the opportunity cost; the expected benefit, which these managers will have to forfeit if they decide to refrain from manipulation. If we assume that both managers are equally averse towards manipulation, the benefit and thus the incentive to manipulate is stronger for the manager with the higher forecasting accuracy. Thus we conclude that, in relative terms, the more experienced manager or the manager who can leverage the company’s information system to produce more accurate forecasts is more likely to engage in manipulation than the less certain manager.

The second implication associated with positive manipulation and in the range of $m^* > G - \mu > 0$ is that the manager with higher forecasting accuracy ($\sigma_{\text{Low}}$) will maximize her payoff with a lower level of manipulation than will a manager with lower forecasting accuracy ($\sigma_{\text{High}}$): \[ m^* \text{ for Max } B(m^*) \text{ with low } \sigma < m^* \text{ for Max } B(m^*) \text{ with high } \sigma. \] This comes as a logical extension of the fact that the manager who can produce more accurate forecasts, regardless of the reason, holds an advantageous position. Having to select the

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8 See corollary 1.a.
optimum level of manipulation while working with a more tight distribution of possible results allows her to be more precise and select the minimum possible level of manipulation needed. This observation, when coupled with our previous observation regarding the opportunity cost of no manipulation, further reinforces the propositions yielded from the model.

Taken together, the manager with more accurate forecasts is tempted first by the fact that the opportunity cost of not manipulation is relatively higher and, second, by the fact that this can be done with smaller manipulation than her counterpart. Again, if we assume that both managers are equally reluctant to manipulate, the manager with higher forecast accuracy is more likely to engage in manipulation reported performance, and do so with smaller levels of manipulation.⁹

5. CONCLUSION

This study provides two primary contributions. First, we introduce a heretofore-unexamined determinant of a manager’s decision to manipulate reported performance - the ability to forecast performance - developing a model of economically efficient manager behavior. Second, the inferences from our model suggest that greater certainty in forecast accuracy leads to more attempts to manipulate; however, these attempts will be of smaller magnitude. As such, we offer empirically testable implications of behavior as a function of proxies for forecast certainty (e.g. information system quality, manager ability, industry characteristics). Further, while it has been repeatedly pointed out in the

⁹ Note that a similar story could be told in a time-series setting. Rather than two different managers with different levels of experience, we could compare the same manager with herself over time. Alternatively, we could compare manager behavior pre- and post-implementation of an information system with superior forecasting abilities.
earnings management literature that the state of the art methods for identifying earnings managers are inadequate (e.g. Das et al. 2007), the inferences from this model suggest that the problem of earnings manipulation detection will in fact become worse as a result of managerial certainty.

The current model has limitations that suggest future research. We assume that we are dealing with rational managers who can evaluate the expected rewards associated with reported (manipulated) performance, which are above a certain target, and the expected risks of a negative audit outcome. This leaves open the question of whether managers would actually behave as economically rational actors. For instance, in some conditions might the noise provided by greater variance in the forecast be perceived as an asset, prompting more attempts? Conversely, might a low variance forecast be perceived as a loss of plausible defense for any manipulation, prompting fewer or smaller magnitude attempts? Future research should investigate this setting.

The current version of the model assumes that all uncertainty is internally controlled. In other words, two companies with identical information systems (i.e. same internal resources) will produce forecasts with a similar degree of accuracy. However, this assumption ignores the major role of environmental factors, such as industry structure and the competitive environment in general. Firms today face intense competition (hypercompetition) in an increasingly turbulent and dynamic (hypercompetitive) global market (D’Aveni 1994; D’Aveni 1995; Bettis and Hitt 1995; Sambamurthy 2000). This manifests in higher volatility of performance, increased incidents of “performance slumps” among Fortune 500 companies, and stories of companies with superior past performance record having difficulty delivering
consistently superior earnings in recent years (Hamel and Välikangas 2003). In general, we expect that, all else being equal, firms operating in more dynamic environments will not be able to produce as accurate predictions of performance as firms that operate in a more stable environment. A future study might examine the role of environmental uncertainty in affecting the results of the current model.10

Rapid technological changes and globalization are among the major factors behind the increased turbulence in the modern economic competitive environment. Both of these factors have been associated with the entry to the network era or the commercialization of the Internet (mid nineties). Interestingly enough, during the same period we had several high profile scandals (e.g Enron, Tyco and WordCom) as well as an increase in the absolute and relative numbers of smaller scale, less dramatic incidents.

“\textit{The General Accounting Office (GAO) in 2002 identified 919 financial restatements by 845 public companies from January 1, 1997, to June 30, 2002, that involved accounting irregularities resulting in material misstatements of financial results. Such restatements occur when a company, either voluntarily or prompted by its auditors or regulators, revises previously reported public financial information. Of the companies, 645 were publicly traded. The number of identified restatements rose from 92 in 1997 to 225 in 2001. “The proportion of listed companies on NYSE, Amex, and NASDAQ identified as restating their financial reports tripled from 0.89 percent in 1997 to 2.5 percent in 2001,” the GAO concluded. “From January 1997 through June 2002, about 10 percent of all listed companies announced at least one restatement.” Moreover, later restatements involved larger firms: The average market capitalization of restating companies quadrupled between 1997 and 2002, from $500 million to $4 billion, while the average size of listed companies increased only about 60 percent over the same period.”} (Kedia and Philippon 2006).

\begin{footnote}
10 Related, there is reason to believe that internal and external sources of uncertainty will not be perceived equivalently. For instance, uncertainty that results from overall noise in industry performance may be easier to recognize and incorporate than is and equivalent amount of uncertainty from a personal lack of experience. If so, this suggests that the source of forecast uncertainty is an important variable to consider.
\end{footnote}
Hence, an opportunity exists for an archival study which looks at the association of the adoption of integrated information systems and earnings management behavior over the period of the mid-1990’s to present.\(^\text{11}\)

Another limitation and opportunity for future research is that this is a single period model that does not explicitly or implicitly account for the effect of prior years of manipulation reversals. It is very likely that a manager who fails to reach a goal in consecutive years may lose her job or otherwise lose valuable future opportunities. How is this going to affect her behavior? As our current model is single-period in nature, we do not yet capture the effects of manipulation reversals across time. Extending the model to multiple periods, one in which information from prior periods affects current choices, and incorporating the effect of reversals on managers’ optimum strategy is a potentially interesting and valuable exploration.

\(^{11}\)Brazel and Dang (2008) provide some empirical evidence potentially related to our setting. They consider the behavior of abnormal discretionary accruals in firms pre- and post-adoption of an ERP system. They document that earnings management behavior appears to increase in a narrow period following the ERP system ‘go live’ date. To be consistent with our setting, instead of using a pre-event model to predict post-event behavior as in Brazel and Dang, the analysis would have to be based on two independent models considered in isolation. This is because there is substantial reason to believe that the definitions of “normal” and ”abnormal” accruals will be significantly different before and after an ERP adoption due to the changes to process and structures that typically occur simultaneously (Wilcocks and Sykes 2000).
REFERENCES


--------., and R. Whiting. 2002. Fast-track financials. The SEC wants quicker financial information, but some companies aren't ready. *InformationWeek* (Feb. 18.).


Whiting, R. 2002. Crystal-ball glance into fiscal future" *InformationWeek* (July 22)

Table 1: Possible actions and results at the end of period \( t_1 \)

<table>
<thead>
<tr>
<th>End Result</th>
<th>Manipulation</th>
<th>Audit Result</th>
<th>Reward Status</th>
<th>Payoff</th>
</tr>
</thead>
<tbody>
<tr>
<td>( G \leq E_r )</td>
<td>( m = 0 ) No manipulation</td>
<td>N/A</td>
<td>( W = 1 ) (Awarded)</td>
<td>( B &gt; 0 )</td>
</tr>
<tr>
<td>( G &gt; E_r )</td>
<td>( m &gt; 0 ) Manipulation</td>
<td>( Z = 1 ) Detected</td>
<td>( W = 0 ) (Not Awarded)</td>
<td>( B &lt; 0 )</td>
</tr>
<tr>
<td>( G &gt; E_r )</td>
<td>( m = 0 ) No manipulation</td>
<td>N/A</td>
<td>( W = 0 ) (Not Awarded)</td>
<td>( B = 0 )</td>
</tr>
<tr>
<td>( G &gt; E_r )</td>
<td>( m &gt; 0 ) Manipulation</td>
<td>( Z = 1 ) Detected</td>
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</tr>
<tr>
<td>( G &gt; E_r )</td>
<td>( m = 0 ) No manipulation</td>
<td>N/A</td>
<td>( W = 0 ) (Not Awarded)</td>
<td>( B = 0 )</td>
</tr>
</tbody>
</table>
Table 2: Conditions for positive optimum solution

<table>
<thead>
<tr>
<th>Targeted Level</th>
<th>Targeted Level</th>
<th>Targeted Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below Expected</td>
<td>Equal to Expected</td>
<td>Above Expected</td>
</tr>
<tr>
<td>$G &lt; \mu$</td>
<td>$G = \mu$</td>
<td>$G &gt; \mu$</td>
</tr>
</tbody>
</table>
| \[
\frac{P}{R} \leq \frac{C}{\sigma \sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{G-\mu}{\sigma}\right)^2\right) \left(1 - \Phi\left(\frac{G-\mu}{\sigma}\right)\right)
\] | \[
\frac{P}{R} < \frac{C}{\sigma \sqrt{2\pi}} - \frac{1}{2}
\] | \[
\frac{P}{R} \leq \frac{G - \mu + C}{\sigma \sqrt{2\pi}} - \frac{1}{2}
\] |

12 Notice that this condition is not likely to hold unless the $C$ is extremely large, i.e. the probability to be detected is very small. This implies that the manager should avoid manipulation if expected earning already exceeds the targeted level ($G < \mu$).
APPENDIX A

A1. Proof for Theorem 1.a

In order to find the optimum value of the payoff, we take the first derivative of

\[ B(m) = \frac{CR}{m+C} \left(1 - \Phi \left( \frac{G - \mu - m}{\sigma} \right) \right) - \frac{mP}{m+C} \]  

(1)

with respect to \( m \) and find the value of \( m \) at which this is equal to zero \( [B'(m) = 0] \) and see if the second derivative of (2.1) is less than zero \( [B''(m) < 0] \).

\[ B'(m) = \frac{Cf(m)}{(m+C)^2} \]  

(2)

Where

\[ f(m) = \frac{R(m+C)}{\sigma \sqrt{2\pi}} e^{\frac{-1}{2}(\frac{G-\mu-m}{\sigma})^2} + R\Phi \left( \frac{G - \mu - m}{\sigma} \right) - R - P \]  

(3)

Differentiating (3), we have:

\[ f'(m) = \frac{R(m+C)(G - \mu - m)}{\sigma^3 \sqrt{2\pi}} e^{\frac{-1}{2}(\frac{G-\mu-m}{\sigma})^2} \]  

(4)

And

\[ B''(m) = \frac{Cf'(m)}{(m+C)^2} - \frac{2Cf(m)}{(m+C)^2} \]  

(5)

Since \( m^* \) is the optimum solution, if \( m^* > 0 \), then \( B'(m^*) = 0, \quad B''(m^*) < 0 \)

If \( B'(m^*) = 0 \) then \( f(m^*) = 0 \). Based on this (5) will become:

\[ B''(m^*) = \frac{Cf'(m^*)}{(m^*+C)^2} - \frac{2Cf(m^*)}{(m^*+C)^2} < 0 \quad \iff \]

\[ = \frac{Cf'(m^*)}{(m^*+C)^2} < 0 \quad \iff \]

\[ = \frac{CR}{(C+m^*)}(T - \mu - m^*) e^{\frac{1}{2}(\frac{T-\mu-m^*}{\alpha})^2} < 0 \]

Since the term \( \frac{CR}{(C+m^*)} \) and \( e^{\frac{1}{2}(\frac{T-\mu-m^*}{\alpha})^2} \) are greater than zero, the equation will only hold if \( (G-\mu-m^*) < 0 \). Therefore, if \( m^* \) is the non-negative optimum solution of the manager’s optimization problem then \( G-\mu < m^* \). **QED.**

---

1 Notice that if \( f(m) \) is equal to zero, this means that the first order (necessary) condition for the maximization of the payoff function is met.

2 Remember that \( \Phi \left( \frac{T - \mu - m}{\sigma} \right) = -\frac{1}{\sigma \sqrt{2\pi}} e^{\frac{-1}{2}(\frac{T-\mu-m}{\alpha})^2} \)
A2. Proof for Theorem 1.b.
If \( m^* \) is the optimum solution and \( m^* > 0 \), then \( f(m^*) = 0 \) and by (3) we have

\[
\Phi\left( \frac{G - \mu - m^*}{\sigma} \right) = 1 + \frac{P}{R} - \frac{C + m^*}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2} \iff
\]

\[
1 - \Phi\left( \frac{G - \mu - m^*}{\sigma} \right) = -\frac{P}{R} + \frac{C + m^*}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2}
\]

Substitute above into (1), we have

\[
B(m^*) = \frac{CR}{m^* + C} \left( -\frac{P}{R} + \frac{C + m^*}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2} \right) - \frac{Pm^*}{m^* + C}
\]

\[
= -\frac{CP}{m^* + C} + \frac{CR}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2} - \frac{Pm^*}{m^* + C}
\]

\[
= -P + \frac{CR}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2} = \frac{CR}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2} - P
\]

However, one of the requirements for a meaningful optimum solution should be that the optimum solution \( B(m^*) \) should be better than the boundary solution \( B(0) \), i.e., \( B(m^*) > B(0) \). If the boundary solution \( (m=0) \) generates payoffs that are higher than the optimum solution \( (m^*) \), it will be irrational for a manager to engage in earnings manipulation. Therefore,

\[
B(m^*) > B(m = 0) \iff \frac{CR}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2} - P > R \left( 1 - \Phi\left( \frac{G - \mu}{\sigma} \right) \right)
\]

But \( e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2} > 1 \), so

\[
\frac{CR}{\sigma \sqrt{2\pi}} - P > R \left( 1 - \Phi\left( \frac{G - \mu}{\sigma} \right) \right)
\]

Which implies \( \frac{CR}{\sigma \sqrt{2\pi}} - \left( 1 - \Phi\left( \frac{G - \mu}{\sigma} \right) \right) > \frac{P}{R} \) QED.


Looking at equation (4) \( f'(m) = \frac{R(m + C)(G - \mu - m)}{\sigma^3 \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m}{\sigma} \right)^2} \), it is clear that its sign depends on the term \((G - \mu - m)\). All other terms are greater than zero. \( f'(m) \) is positive when \( m < G - \mu \) and negative when \( m > G - \mu \). Therefore \( f(m) = 0 \) could have at most one solution which is larger than \( G - \mu \).

Now let \( m^* \) meet the necessary and sufficient conditions. Then the necessary conditions and (3) means that

\[
\Phi\left( \frac{G - \mu - m^*}{\sigma} \right) = 1 + \frac{P}{R} - \frac{(m^* + C)}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{G - \mu - m^*}{\sigma} \right)^2}
\]

Which implies \( B(m^*) > B(0) \) and therefore \( m^* \) is the optimum solution.
On the other hand, if \( m^* \) is the optimum positive solution, then \( f(m^*) = 0 \) and \( m^* > G - m \) is true and \( B(m^*) > B(0) \) which implies

\[
\frac{C}{\sigma \sqrt{2\pi}} e^{\frac{1}{2} \left( \frac{T - \mu - m^*}{\sigma} \right)^2} \geq 1 + \frac{P}{R} - \Phi \left( \frac{T - \mu}{\sigma} \right)
\]

A4. Proof for Proposition 1

Recall that we have introduced three conditions: \( G < \mu \), \( G = \mu \), and \( G > \mu \).

1) \( G < \mu \); in this case the expression \( f'(m) \) is always negative and \( f(m) \) decreases over the interval of \((0, \infty)\). The expression \( f(m) = 0 \) has solution only if \( f(0) > 0 \), which by (3) is equivalent to

\[
\frac{P}{R} \leq \frac{C}{\sigma \sqrt{2\pi}} e^{\frac{1}{2} \left( \frac{G - \mu}{\sigma} \right)^2} \left( 1 - \Phi \left( \frac{G - \mu}{\sigma} \right) \right). \quad QED
\]

Notice that this condition is not likely to hold unless the \( C \) is extremely large, i.e. the probability to be detected is very small. This implies that the manager should avoid manipulation if expected earning already exceeds the targeted level \((G < \mu)\).

2) \( G = \mu \); this is the case where expected earning (most likely earning level) is the same as the target. We have \( f(G - \mu) = f(0) = \frac{RC}{\sigma \sqrt{2\pi}} - \left( \frac{R}{2} + P \right) \) and \( f(m) \) is a monotonic function (decreasing) on the interval \((0, \infty)\) by (4). So \( f(m) = 0 \) has a positive solution only if \( f(0) > 0 \), which is equivalent to

\[
\frac{P}{R} \leq \frac{C}{\sigma \sqrt{2\pi}} e^{\frac{1}{2} \left( \frac{G - \mu}{\sigma} \right)^2} - \frac{1}{2}. \quad QED
\]

3) \( G > \mu \); since \( f'(m) < 0 \) in \((G - \mu, \infty)\), there is an optimum solution over this interval only if \( f(G - \mu) > 0 \), which based on (3) is equivalent to

\[
\frac{P}{R} \leq \frac{G - \mu + C}{\sigma \sqrt{2\pi}} - \frac{1}{2}. \quad QED
\]

A5. Proof for Corollary 1.a

We start by showing that there is no positive optimum solution when the following condition it true:

\[
G - \mu > \frac{CR \Phi \left( \frac{G - \mu}{\sigma} \right)}{P + R \left( 1 - \Phi \left( \frac{G - \mu}{\sigma} \right) \right)} \quad (6)
\]

If there is optimum solution, then

\[
C R \left( 1 - \Phi \left( \frac{G - \mu - m^*}{\sigma} \right) \right) - m^* P
\]

\[
B(m^*) = \frac{\left( G - \mu - m^* \right)}{m^* + C} > B(0) = R \left( 1 - \Phi \left( \frac{G - \mu}{\sigma} \right) \right)
\]

So \( CR - m^* \frac{P}{P} \geq (m^* + C) R \left( 1 - \Phi \left( \frac{G - \mu}{\sigma} \right) \right) \)
Which, together with $m^* > G - \mu$, implies that $G - \mu \leq m^* \leq \frac{CR\Phi\left(\frac{G - \mu}{\sigma}\right)}{P + R\left(1 - \Phi\left(\frac{G - \mu}{\sigma}\right)\right)}$

But the above condition could not hold when (6) is true.

At this point we look at the extreme values that the ratio $\frac{CR\Phi\left(\frac{G - \mu}{\sigma}\right)}{P + R\left(1 - \Phi\left(\frac{G - \mu}{\sigma}\right)\right)}$

can take. Given that $0 \leq \Phi\left(\frac{G - \mu}{\sigma}\right) \leq 1$, it is clear that $0 \leq \frac{CR\Phi\left(\frac{G - \mu}{\sigma}\right)}{P + R\left(1 - \Phi\left(\frac{G - \mu}{\sigma}\right)\right)} \leq \frac{CR}{P}$.

Hence, if $G - \mu > \frac{CR}{P}$ there is no optimum solution. QED

A6. Proof for Corollary 1.b (Proposition 2)

Based on Theorem 1.c (necessary and sufficient conditions for the existence of a positive optimum solution) we have that $\frac{C}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2}\frac{(G-\mu-m^*)^2}{\sigma^2}} > \frac{P}{R} \left(1 - \Phi\left(\frac{G - \mu}{\sigma}\right)\right) > \frac{P}{R}$

So $-\frac{1}{2} \left(\frac{G - \mu - m^*}{\sigma}\right)^2 > -\ln \frac{CR}{\sigma \sqrt{2\pi}}$. Notice $m^* > G - \mu$,

and $G - \mu \leq m^* \leq G - \mu + \sqrt{2\ln \frac{CR}{\sigma \sqrt{2\pi}}}$ follows. QED