Measure of Intentional Manipulation: A Structural Approach

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Abstract

Using a sample of over 1,800 CEOs in the post-SOX period, I estimate the extent of intentional manipulation and manipulation costs using a dynamic structural model that features a risk-averse manager who receives cash and equity compensation. I find that the expected cost of manipulation is low. The probability of detection is 9%, and the average misstatement results in a 1.5% loss in the manager's wealth. According to the estimated parameters, the implied fraction of manipulating firms is around 63% and the value-weighted bias in the stock price is 2.8%. Among five proxies for earnings management used in the extant literature, only performance-matched discretionary accruals have a positive association with the model-implied measure of intentional manipulation.

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1. Introduction

From 2001 to 2010, approximately 4.2% of companies presently listed on the NYSE, Amex, or NASDAQ restated their financial statements, with about 70% of restatements affecting net income (AuditAnalytics [May 2011]). Although a majority of companies attribute restatements to innocuous internal company errors (Plumlee and Yohn [2010]), questions about whether these restatements reverse intentional manipulation decisions by management and the extent of undetected manipulation remain. The main difficulty researchers face in addressing these questions lies in the imperfect ability of outside parties to detect intentional manipulation (e.g., Feroz et al. [1991], Correia [2009], Dechow et al. [2010a]). If there is indeed a substantial amount of undetected manipulation, it is important to ascertain its magnitude and potential impact on shareholder value.

This paper attempts to estimate the incidence and magnitude of firm-specific intentional manipulation of financial statements using a structural model. The structural model allows one to incorporate the possibility that manipulation is not detected perfectly, to estimate manipulation cost parameters perceived by the manager, and to estimate the bias in the stock price induced by manipulation. The manipulation decision is modeled as a solution to an optimization problem of a risk-averse manager in a dynamic infinite-horizon setting. The manager's wealth depends on cash compensation and his holdings in the firm's equity. Because the firm's stock price depends on reported earnings, the manager has incentives to misreport earnings to increase the value of his equity holdings as suggested by the popular press[1] and extant literature (e.g., Harris and Bromiley [2006], Erickson et al. [2006], Armstrong et al. [2010]). Misreporting is introduced as the bias in net assets, with the bias in earnings equal to the difference in consecutive biases in net assets. This specification adds a dynamic dimension to the manager's optimization problem and avoids specific assumptions about the rate at which discretionary accruals reverse.

[1] Olive, David (2002) "Many CEOs richly rewarded for failure - They didn't suffer as stocks tanked in new economy", The Toronto Star, August 25, A01. Kilzer, Lou, David Milstead, and Jeff Smith (2002) "Qwest's rise and fall; Nacchio exercised uncanny timing in selling stock", Rocky Mountain News, June 03, 1C. Haddad, Charles (2003) "Too good to be true - Why HealthSouth CEO Scrushy began deep-frying the chain's books", BusinessWeek, April 14, 70.

The manager trades off the benefits of misreporting against the cost of manipulation. I assume that the cost is a fraction of the manager's wealth and that this fraction increases in the magnitude of manipulation, which is the bias in net assets. The assumption that the cost depends on the cumulative amount of manipulation in earnings (i.e., the existing bias in net assets) and that the benefit depends on the amount of manipulation in current earnings implies that the bias in net assets acts as a constraint on the manipulation decision.[2] This is because the manager will avoid an abrupt reduction in the bias in net assets in order to avoid a decline in the stock price.

I find that the optimal manipulation decision is determined by two effects, namely, the *wealth* effect and the *valuation* effect. The *wealth* effect captures the fact that a risk-averse manager with a greater ratio of cash wealth to equity holdings chooses a smaller bias as his marginal benefit of manipulation decreases more rapidly than his marginal cost under a sufficiently high cost of manipulation. The *valuation* effect captures the fact that the manager chooses a higher bias in net assets in the current period if the existing bias in net assets is also high. Because the benefit depends on the bias in current earnings and the cost depends on the existing bias in net assets, it follows that the marginal benefit of the current period's bias in net assets increases in the existing bias whereas the marginal cost does not depend on the existing bias as it depends on the current period's bias only.

In contrast to the common approach in the literature (i.e., the reduced-form approach), the structural approach allows one to explicitly articulate the economic mechanism that gives rise to manipulation. Using the estimated structural model, it is possible to explore counterfactuals and quantify the effects of the change in policy parameters. For instance, the structural model helps address the question of how much the fraction of manipulating firms would decrease if the probability of detection doubles. However, use of the structural approach comes at a cost, as it imposes strong assumptions on the data. In this paper, the critical assumptions are as follows: compensation is exogenous to the manipulation decision, the market does not form rational expectations about manipulation and mechanically prices

[2]This is similar to the notion of the balance sheet as an earnings management constraint (e.g., Barton and Simko [2002], Baber et al. [2011]).

reported earnings, and the magnitude of observed restatements is primarily determined by the structure of compensation. While these assumptions are strong and can be relaxed in future research, as a first attempt they allow me to estimate the model and provide useful descriptive evidence about executives' manipulation decisions.

Because the structural model here does not allow for a closed-form solution of the manager's optimization problem, I use Simulated Method of Moments (SMM) to estimate the costs of manipulation as perceived by the manager. Under this approach, I solve the individual optimization problem for each executive in my sample of over 1,800 CEOs. This allows me to incorporate heterogeneity in manipulation decisions, which is assumed to be determined by differences in the structure of the executives' compensation packages. The estimation uses observed data on restatements that involve executive turnover from Audit Analytics Advanced Restatement database over the post-SOX (Sarbanes-Oxley Act of 2002) period.

One of the paper's main findings is that the expected cost of manipulation is low. In particular, the estimate of the probability of manipulation being detected is 9%, and the average misstatement results in a 1.5% loss in the manager's wealth in the case of detection.[3] According to the estimated model, the fraction of executives who manipulate during their tenure is 63%. A recent study by Gerakos and Kovrijnykh [2011] estimates that for approximately 74% of firms, there is evidence consistent with misreporting. These numbers are of similar magnitude as the 78% of executives reporting that would sacrifice long-term value to smooth earnings (Graham et al. [2005]). Although my estimate of the share of manipulating firms is relatively high, the value-weighted inflation in the stock price[4] is 2.8% and the median inflation in the stock price is 5.64%. The model-implied median inflation in the stock price is of the same order of magnitude as the median return for fraud restatements of -4% at the restatement announcement for the post-SOX period (Scholz [2008], Table 8).

While there is a large literature on earnings management[5] and on the relation between

[3]The average misstatement (cost impact of bias) is 11.57% (Table 6).

[4]Value-weighted inflation in the stock price is computed as the value-weighted difference between the observed stock price and the model-implied intrinsic value of the firm divided by the observed stock price for firm-years in which the executive misreports according to the model.

[5]For a review of the empirical research, see Healy and Wahlen [1999], Dechow and Skinner [2000], and

earnings management and equity incentives[6], this is the first study to estimate earnings management using a structural model. Further, this study represents the first attempt to fit economic model to data on restatements and executive compensation and to evaluate manipulation costs perceived by the manager. Although the model is stylized, its specification is detailed enough to capture important features of the data such as partial observability of manipulation decisions. As an empirical study, this work does not make a theoretical contribution; instead, it estimates a structural model where a manipulation decision is the solution to an executive's optimization problem.

The approach suggested in this paper differs substantially from the common approach of measuring manipulation using discretionary accruals (e.g., Jones [1991], Dechow et al. [1995], Kasznik [1999], Kothari et al. [2005]). The idea behind this approach is to estimate a model of normal accruals and to use the residual from that model as a measure of earnings management (manipulation). These measures are biased to the extent that the model does not use the true determinants of normal accruals[7] and ignores incentives behind the manipulation decision. As a consequence, prior research finds that measures of discretionary accruals are not predictive of actual cases of manipulation such as severe restatements and fraud (e.g., Dechow et al. [2010b], Price et al. [2010], Larcker and Zakolyukina [2010]).

In the structural model, the optimal misreporting decision also exhibits income-smoothing, which arises because of the linearity of the manager's payoff in the earnings bias, risk aversion, and stochastic evolution of the firm's intrinsic value. The phenomenon of smoothing by managers has received substantial attention in the theoretical literature, which proposes it can be a result of smoothing consumption in the agency setting (e.g., Lambert [1984], Dye [1988]) or non-agency setting (e.g., Sankar and Subramanyam [2001]), or smoothing to lower the perceived probability of bankruptcy (e.g., Trueman and Titman [1988]), and smoothing to maximize the manager's tenure in the firm (e.g., Fudenberg and Tirole [1995]).

The remainder of the paper consists of five sections. Section 2 discusses structural mod-

Dechow et al. [2010a]. For a review of the theoretical research, see Lambert [2001] and Ronen and Yaari [2008].

[6]See, for example, a short review in Armstrong et al. [2010].

[7]See the discussion in McNichols [2000].

eling relative to the reduced-form approaches typically used in accounting research. Section 3 outlines the model and highlights the intuition using a three-period setting. Section 4 discusses data, identification considerations, and the estimation method. The results are presented in Section 5. Section 6 discusses limitations and provides concluding remarks.

2. *Background on structural estimation*

The structural approach used in this paper is relatively new to the accounting literature. However, it is common in economics, particularly in macroeconomics, industrial organization, and marketing (e.g., Nevo and Whinston [2010], Keane [2010]). Several recent papers also apply structural estimation in corporate finance (e.g., Morellec et al. [2009], Nikolov and Whited [2009], and Taylor [2010]).

In contrast to reduced-form regressions, the structural approach fits economic models directly to the data. If the model describes the decisions made by managers and firms, it is possible to estimate theoretical parameters and provide insights into economic choices (e.g., how equity incentives affect the managerial decision to manipulate financial reports). In contrast to vague stories often used to motivate reduced-form regressions, structural estimation can answer specific questions about economic mechanisms. The structural model hypothesizes causality. However, unlike a reduced-form approach in which the causal mechanism is unclear, a structural approach is only possible when precise theoretical causal links are specified.

The core feature of structural models that differentiates them from reduced-form modeling is their potential to extrapolate from observed responses to predict responses under the environment not yet observed, i.e., to examine counterfactuals (Nevo and Whinston [2010]). For example, counterfactuals of interest in this paper could include whether increasing penalties on managers found to have manipulated leads to less manipulation or whether increasing managers' equity holdings leads to more or less manipulation.

Randomized experiments appear to be an attractive alternative to the structural approach, but they are not a panacea for resolving the problems that arise when economic agents make choices. Sims [2010] notes that "[...] economics is not an experimental science and cannot be. 'Natural' experiments and 'quasi' experiments are not in fact experiments, any more than are Prescott's 'computational' experiments." He further observes that economists have to face the difficulty of non-experimental inference, with restrictive assumptions used in cases in which there exists agreement and less restrictive assumptions used when the data have the potential to resolve disagreement. Keane [2010] similarly notes that even experimental studies rely on some untestable assumptions that might not be as well articulated as in structural models. Finally, true natural experiments are quite rare in economics, which limits the research questions that can be examined using this approach.

Some researchers are cautious about the structural approach. For example, Angrist and Pischke [2010] express the concern that under "elaborate superstructure", a specific functional form may drive results rather than the data. To avoid this, there are (at least) four hurdles that any econometric model (including reduced-form models) should pass before interpreting the statistical results (e.g., Welch [2011]). First, the theory needs to make sense. Second, the structural model implied by the theory needs to fit the data as a first (in-sample) approximation. Another way to express these first two concerns is that the model should articulate first-order effects and capture the most important observed economic correlations. Third, the estimated model should have some ability to predict out-of-sample. This is a distinctive feature of the well-specified structural model. Finally, the model should be able to predict outcomes during quasi-experiments (e.g., during changes in regulation).

This paper attempts to address the first two hurdles. First, I develop a stylized model that captures first-order effects that determine the manager's manipulation decision. Second, I estimate the model and provide a test of in-sample fit. The out-of-sample test is more difficult to implement in my setting because restatements are rare events. However, indirect evidence of model fit out-of-sample can be provided using data that are not directly used in the model estimation. Finally, as an extension of this paper, I plan to compare estimates of the model based on pre-SOX data with similar estimates based on post-SOX data. Such analysis will assess model performance around an important regulatory change.

3. Model

3.1 Assumptions

The model features a manager who maximizes his utility of wealth at the time he leaves the firm (e.g., Lambert et al. [1991], Murphy and Zimmerman [1993]). Terminal wealth depends on the manager's equity holdings in the firm and cash wealth. In every period, the manager can strategically bias earnings reported to the market in order to inflate the stock price and the value of his equity holdings.

The firm's intrinsic value, P_t, follows a log-normal process and the stock price equals the intrinsic value of the firm whenever earnings are not inflated by the manager:

$$ln\left(\frac{P_{t+1}}{P_t}\right) \sim N\left(\mu - \frac{\sigma^2}{2}, \sigma^2\right). \tag{1}$$

However, when the manager biases his report, the realized price deviates from the firm's intrinsic value by an amount proportional to the bias in earnings. I assume that the market prices earnings mechanically using the price-to-earnings multiple β. In this model, I ignore the possibility that investors may adjust the manager's earnings report by the amount of manipulation they expect to occur in equilibrium. This simplifying assumption avoids the difficulty of solving for the strategic interaction between the manager and the market in a dynamic setting.[8]

I adopt a balance-sheet perspective. Each period the manager decides on the magnitude of the bias in current-period net assets, B_t. The earnings reported to the market are biased by $B_t - B_{t-1}$ and the stock price, $\widehat{P}_t$, becomes

$$\widehat{P}_t = P_t + \beta(B_t - B_{t-1}). \tag{2}$$

[8] A number of theoretical papers consider the rational expectations equilibrium when the market rationally incorporates the manager's manipulation decision into the pricing function (e.g., Fischer and Verrecchia [2000], Sankar and Subramanyam [2001]). I do not follow this approach here as incorporating rational expectations in a multi-period setting is a difficult theoretical problem that lies beyond the scope of this paper.

This specification does not make any assumptions about the rate at which discretionary accruals (as reflected in the bias in net assets) reverse and hence accommodates various potential rates of accrual reversal. Instead, the formula reflects the assumption that the stock price is a multiple of earnings and as a result varies with the change in the bias in net assets. Therefore, the manager optimally considers the bias in net assets in the previous period when choosing the bias in net assets in the current period, as well as the effect his choice of current-period bias in net assets will have on optimal bias levels in the future. Alternatively, one could assume that the stock price is a multiple of book value, and as a result the manager's optimal decision is independent of the existing bias. However, this would imply that the manager's utility is not tied to the firm's reported earnings - an assumption that seems unrealistic considering extensive evidence to the contrary.

I assume that the manager leaves the firm with fixed probability f. The probabilistic exit captures the notion that the manager is uncertain about when he will be terminated or when an exogenous employment opportunity prompting him to leave the firm voluntarily will arrive. At the time the manager leaves the firm, if he has ever manipulated earnings, he incurs the cost of manipulation with probability g (the probability of manipulation being detected).

For simplicity, I assume that the manager's equity holdings, $\overline{n}$, and cash compensation, $\overline{C}$, are constant throughout his tenure in the firm. I introduce a multiple $\lambda > 1$ on the manager's cash compensation to capture the manager's non-equity wealth because his overall cash wealth is likely to be greater than his annual cash compensation. Thus, the overall wealth of the manager is $\overline{n}\widehat{P}_t + \lambda\overline{C}$. The assumption that cash compensation and equity holdings do not vary over time reduces the dimensionality and computational complexity of the manager's problem.[9]

The cost of manipulation is proportional to the manager's wealth and has two components: the fixed proportional cost, κ_1, and the sensitivity of the cost of the manager's

[9] I will allow equity holdings and cash compensation to depend on price performance in future research. This change will make the manipulation decision more nuanced, because the sensitivity of the manager's equity holdings and cash compensation with respect to manipulation will add another incentive for the manager to manipulate.

wealth to the magnitude of manipulation, κ_2. Specifically, the manager loses a fraction $\kappa_1 + \frac{\kappa_2}{2}\left(\frac{\beta B_{t-1}}{P_0}\right)^2$ of his wealth if manipulation is detected. The fixed proportional cost, κ_1, allows for the possibility that the manager suffers a cost if he manipulated, irrespective of the magnitude of the detected bias. At the same time, non-zero κ_2 ensures an interior solution.[10]

At each point in time, the manager can be in one of two states, which I label *non-manipulative* and *manipulative*. In the *non-manipulative* state ($s_t = nm$), the manager makes the discrete decision $d_t(P_t) \in \{0, 1\}$ to manipulate ($d_t(P_t) = 1$) or not ($d_t(P_t) = 0$). If the manager decides to manipulate, he enters the *manipulative* state forever. In the *manipulative* state ($s_t = m$), the manager makes the continuous decision $B_t(P_t, B_{t-1})$ about the magnitude of manipulation. Intuitively, the manager starts in the firm with zero intentional manipulation, i.e., $B_0 = 0$. If the manager manipulates, he faces the probability of incurring the cost related to manipulation in each future period. The decision to manipulate and the amount of manipulation are functions of the firm's current intrinsic value because this value affects the future distribution of the manager's equity wealth. Because the manager is uncertain about when he will leave the firm, his optimization problem becomes an infinite-horizon problem with the discount rate equal to the probability of staying with the firm up to a particular point in time.

The manager's payoffs in the *manipulative* and *non-manipulative* states are as follows. In the *manipulative* state, the manager decides the magnitude of the bias in current-period net assets, B_t. Thus, his expected per-period payoff in the *manipulative* state becomes

$$gU\left((\overline{n}P_t + \lambda\overline{C})\underbrace{\left(1 - \kappa_1 - \frac{\kappa_2}{2}\left(\frac{\beta B_{t-1}}{P_0}\right)^2\right)}_{proportional\ loss}\right) + (1-g)U\left(\overline{n}\underbrace{(P_t + \beta(B_t - B_{t-1}))}_{\widehat{P}_t} + \lambda\overline{C}\right). \quad (3)$$

Here, I assume that if manipulation is detected, the stock price equals the firm's intrinsic value, P_t.[11]

[10] Loosely speaking, the proportional loss can be interpreted as a reputation loss. For instance, the manager's wealth can reflect his ability, and higher-ability managers experience greater damage from reputation loss. In other words, the reputation loss is equivalent to a reduction in the value of future employment opportunities, and the value of future employment opportunities is assumed to be positively associated with the manager's ability.

[11] There are two interpretations of the probability of manipulation being detected, g. The first interpreta-

In the *non-manipulative* state, the manager decides every period whether to manipulate. If he does not manipulate, he reports earnings truthfully and, as a result, the stock price equals the intrinsic value of the firm. If he manipulates, I assume that the first attempt to manipulate cannot be detected. One of the reasons for this assumption is that, empirically, it is difficult to identify cases in which the manager is terminated for the first attempt to manipulate when he never (successfully) misreported earnings.

The manager is assumed to exhibit constant relative risk aversion (e.g., Lambert et al. [1991], Hall and Murphy [2002]).[12] Specifically, the manager's utility function is given by

$$U(c) = \frac{c^{1-\gamma}}{1-\gamma}, \tag{4}$$

where γ is the relative risk aversion coefficient. For convenience, I scale the manager's optimization problem by $\overline{n}P_0$ and denote the corresponding parameters of the model with lower-case letters as follows:

$$\left\{ p_t = \frac{P_t}{P_0}, b_t = \frac{B_t}{P_0}, \overline{c} = \frac{\overline{C}}{\overline{n}P_0} \right\}. \tag{5}$$

3.2 Three-period model

To simplify the exposition, I first discuss a three-period model. The three-period model cannot be solved analytically and thus I solve it numerically. However, the same analytical results under additional simplifying assumptions about the manager's utility function and the firm's intrinsic value are presented in Appendix A.

Initially, the manager is in the *non-manipulative* state and has zero intentional manipulation ($b_0 = 0$). The manager might decide to manipulate in periods one and two. If the

tion is that g is the probability that manipulation is detected at the time the manager leaves the firm. In this case, when the manager leaves the firm, the stock price equals the firm's intrinsic value. The second interpretation is that g is the probability that manipulation is detected during the manager's tenure, and the cost is incurred only when the manager leaves the firm. The second interpretation requires assuming that the manager cannot manipulate after the manipulation is detected for the first time and, as a result, the stock price equals the firm's intrinsic value when the manager leaves the firm.

[12] The managers cannot diversify their stock holdings in the firm and it is common to assume that the manager's risk aversion is decreasing in the manager's wealth (e.g., Lambert et al. [1991]).

manager decides to manipulate, he enters the *manipulative* state and remains in that state. I constrain the bias in net assets to be zero in the third period to avoid infinite manipulation in net assets being optimal in the final period of the finite-horizon game. This issue does not arise in the infinite-horizon model because there is no "final" decision to manipulate.

Two effects, which I label the *wealth* and *valuation* effects, are captured by the model. According to the *wealth* effect, the optimal bias in net assets decreases in the ratio of the manager's cash compensation to equity holdings. In particular, a manager whose ratio of cash compensation to equity holdings is higher optimally biases net assets in the current period to a lesser extent because his marginal benefit of manipulation decreases more rapidly than his marginal cost under sufficiently high cost of manipulation parameters, (κ_1, κ_2). According to the *valuation* effect, the optimal bias in net assets in the current period is increasing in the existing bias in net assets. This effect arises because the marginal benefit increases in the existing bias while the marginal cost does not depend on the existing bias, as it depends only on the current-period bias. For instance, if the manager biased net assets by \$2 in the previous period (compared to if he biased net assets only by \$1 in the previous period), the manager has greater incentives to bias net assets in the current period because if he did not bias net assets in the current period his firm's earnings would be lower by \$2 (compared to just \$1) and the stock price would drop accordingly.

Figure 1 presents plots of the optimal manipulation in the first period $b_1(p_1)$ and the optimal manipulation in the second period $b_2(p_2, b_1)$. Consistent with the *valuation* effect, the second period bias, $b_2(p_2, b_1)$, increases in the first period bias, b_1. In addition, in the second period, the manager gradually reduces the bias in net assets when the intrinsic value of the firm is high because the cost of manipulation is proportional to the bias.

At the same time, the manipulation in both periods, $b_1(p_1)$ and $b_2(p_2, b_1)$, decreases in the intrinsic value of the firm, which is consistent with income-smoothing (i.e., the manager inflates his earnings report if the intrinsic value is low and biases his report downwards if the intrinsic value is high).[13] Income-smoothing arises because the manager is risk-averse,

[13] Income-smoothing is obtained in extant theoretical literature in a number of settings (see, for instance, Lambert [1984], Dye [1988], Fudenberg and Tirole [1995]).

his terminal wealth is linear in his earnings report, and the evolution of the firm's intrinsic value is stochastic.

For instance, if the volatility of the firm's intrinsic value is relatively low ($\sigma = 0.3$), the manager biases his earnings report upwards when intrinsic value is low and does not bias his report if intrinsic value is high. However, as the volatility of the firm's intrinsic value increases ($\sigma = 0.55$), in addition to biasing his report upwards when intrinsic value is low, the manager biases his earnings report downwards when the realization of the intrinsic value in the current period is high. The higher volatility of intrinsic value makes the low realization of the value more likely in the future and thus the future bias becomes more valuable and induces the manager to save in the current period by manipulating his report downwards.

To summarize, the optimal level of manipulation is determined by three effects. First, the *wealth* effect implies that managers with a higher ratio of cash compensation to equity holdings manipulate net assets to a lesser extent. Second, the *valuation* effect implies that the optimal bias in net assets in the current period is increasing in the existing bias in net assets. Third, the manipulation pattern is consistent with income-smoothing. The intuition behind the results established in the three-period model extends to the infinite-horizon case. The solution to the infinite-horizon model is described in Appendix B.

4. Estimation

4.1 Data

The model estimation requires data on executive compensation, CEO turnover, and restatements. To be consistent with the model, I only consider restatements that are fully covered by the CEO's tenure, have non-zero effect on net income in the first restated period, and involve the CEO leaving the company between the end of the restated period and within the fixed window of the restatement filing date. Consistent with prior literature, the fixed window is defined as either six or 36 months after the restatement disclosure (e.g., Hennes et al. [2008], Srinivasan [2005]). I assume that the CEO is more likely to incur the manipulation cost if he leaves after the restatement is filed.

Data on CEO compensation are obtained from the comprehensive database on executive compensation collected from annual proxy filings (DEF 14A) provided by Equilar, Inc. Equilar database coverage is more than double the coverage of Compustat Execucomp. This database has the CEO resignation date but does not have the date when the CEO leaves. I obtain the date when the CEO leaves from the BoardEx database, which provides employment histories of individual executives. Data on restatements come from the Audit Analytics Advanced Restatement database, which contains data from the restatement footnotes for firms traded on NYSE, Amex, or NASDAQ at the end of 2007 or any time thereafter. As a result, the sample is an intersection of the Equilar and BoardEx datasets with the additional restriction that the firm be listed on NYSE, Amex, or NASDAQ as of December 31, 2007 or anytime thereafter. The industry composition of sample firms is almost identical to the industry composition of firms in Compustat.[14] While the sample firms are significantly larger than the Compustat sample in terms of market capitalization, total assets, and sales, they are not significantly different from the Compustat sample in terms of profitability (as measured by return on assets and profit margin), sales growth, and capital structure (as measured by book-to-market ratio, leverage, and free cash flows).

In my structural estimation, I assume that the manipulation cost parameters are constant across executives and over time. Because SOX changed the cost of manipulation through increased criminal penalties and the CEO's exposure to liability for financial misreporting (Karpoff et al. [2008]), I restrict my sample to the post-SOX period. Further, to solve the problem for every executive, it is necessary to know whether he is in the *manipulative* state or the *non-manipulative* state and the magnitude of existing intentional bias when he enters the sample. The sample consists of executives who had no restatements during their tenure and became CEO between August 1, 2002 and December 31, 2007 because, by definition, they have zero intentional manipulation when they enter the sample. Additionally, I include executives who had a restatement during their tenure if they became CEO before December 31, 2007 and the restated periods for them start after August 1, 2002. Assuming that a restatement uncovers the complete history of misreporting, the latter executives were in the

[14]The comparison with the Compustat universe is untabulated.

non-manipulative state with zero intentional manipulation as of August 1, 2002 because the restated period for them starts after that date.

The manipulation decision of the manager depends on a number of parameters that can be measured directly. Executive-specific parameters are the initial value for the firm's intrinsic value process P_0, equity holdings in the firm $\overline{n}$, and cash compensation $\overline{C}$. The initial value for the intrinsic value process is assumed to be equal to the stock price at the fiscal year-end before the CEO joins the firm because it is not affected by the incoming manager's reporting decision. As noted earlier, I assume that CEO equity and cash compensation are constant, and I set them equal to the average equity holdings and cash compensation over the CEO's tenure.

Industry-specific parameters are based on the 49 Fama-French industry classification. These parameters include the probability that the manager leaves the firm within a year, f, the price-to-earnings multiple, β, and parameters corresponding to the firm's intrinsic value process, (μ, σ). The probability that the manager leaves the firm, f, is the mean annual turnover rate across firms in the same industry. The price-to-earnings multiple is the mean price-to-earnings multiple across firms in the same industry. I use industry statistics for the price-to-earnings multiple to avoid unusually large or small firm-specific values that are not likely to persist over time (i.e., they are expected to revert to the industry mean). Similarly, I assume that firms in the same industry group have a similar evolution of intrinsic value because they are likely to have similar investment opportunities, technologies, and markets. Accordingly, the intrinsic value parameters, (μ, σ), are set to their corresponding industry means.

I measure the bias as the difference between the initially reported basic EPS and subsequently restated basic EPS. I adjust firms' EPS for stock splits to make them comparable with data from Equilar. The bias in net assets in the first manipulative period is the bias in earnings in the first restated period. This is consistent with my assumption that the manager starts with zero intentional manipulation and that a restatement fully corrects for the manipulation. Under the balance-sheet perspective of earnings, the second-period bias in net assets is the sum of the biases in EPS in the first two restated periods.

Table 1 contains the parameter definitions. Descriptive statistics are presented in Table 2. The sample for which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within six (36) months of the restatement filing date contains $1,815$ ($1,850$) CEOs. Because the two samples have virtually identical summary statistics, I discuss these statistics just for the sample of CEOs who left within six months of the restatement filing date. The mean cash compensation scaled by the value of CEOs' equity holdings, $\bar{c}$, is around 14.56% and has a large standard deviation of 16.36%. The mean probability of leaving the firm is relatively low at 7.77%. The parameters for the intrinsic value process are the expected annual return with a mean of 9.21% and the standard deviation with a mean of 42.19%, which is relatively high compared to the historical mean of about 30% for large publicly traded companies from the previous decade (Hall and Murphy [2002]). The mean price-to-earnings multiple is 29.97, which is consistent with the sample period being expansionary.

Although the summary statistics are similar across the two samples, the restatement rates and magnitudes of bias differ. The sample in which an intentional misstatement is defined as a restatement when the CEO leaves the firm within six (36) months of the restatement filing date is associated with 2.09% (4.38%) of firms restating. The corresponding mean bias in net assets in the first restated period scaled by the stock price among restating firms is 0.43%(0.54%). The mean magnitude of bias in net assets in the second restated year is greater than the mean bias in the first restated year.

4.2 Identification

This subsection introduces moment conditions that identify the parameters estimated using the model. I also provide intuition for the choice of these moment conditions and various additional restrictions imposed on the model.

The parameters estimated from the model are assumed to be constant across executives. These are the expected cost of manipulation parameters: the probability of manipulation being detected, g, the proportional loss in the executive's wealth, κ_1, and the sensitivity of the loss in the executive's wealth to the magnitude of manipulation, κ_2. Ideally, the cost of manipulation parameters should be a function of observed firm characteristics. Unfortunately, the rare nature of restatements that involve executive turnover in the post-SOX period does not allow me to incorporate such variation in the model. However, the optimal manipulation decisions vary across executives with their compensation packages.

The extent of misstatement is only observed when manipulation is detected (i.e., when previously issued financial statements are restated), which is assumed to occur with probability g at the time the manager leaves the firm. In addition, the model assumes that the manager rationally expects to incur the cost of manipulation. Accordingly, I assume that the manager is more likely to incur the cost related to manipulation if he leaves the firm around the restatement filing date, and thus restatements that involve executive turnover are the primary focus of the model. An overwhelming majority of restatements correct only two annual financial statements (AuditAnalytics [May 2011]). This means that the restated bias is observed in net assets in the first two periods, (b^1, b^2). I use notation b^τ, where τ denotes the time the manager enters the manipulative state, i.e., b^1 is the first period in which the manager is in the manipulative state. This feature of the data suggests that the moment conditions discussed below only use data about the frequency of restatements and the biases in net assets for two restated periods.

I use four moment conditions to estimate three parameters (g, κ_1, κ_2). The most important criterion in selecting moments is their sensitivity to parameter changes. In other words, I am looking for the moments implied by the model that vary with the cost of manipulation parameters.[15] The first moment condition is the frequency of restatements. The frequency of restatements is determined by the manager's decision to manipulate, which depends on all three cost of manipulation parameters and is particularly sensitive to the probability of manipulation being detected, g. Intuitively, as the expected cost of manipulation increases, fewer managers will find it optimal to manipulate, and thus, controlling for the probability of manipulation being detected, the empirical frequency of restatements will be lower.

The second moment condition is the mean ratio of cash compensation to equity holdings,

[15]As a minimum requirement, the moment conditions should vary with parameters as implied by the theory. The identification of parameters in the data is an empirical question.

$\overline{c}$, multiplied by the indicator of restatement. This moment is particularly sensitive to changes in the probability of manipulation being detected, g, and in the fixed proportional cost of manipulation, κ_1. These parameters primarily affect the manager's decision to enter the *manipulative* state.

Figure 2 depicts how the magnitude of the first-period bias changes conditional on the ratio of cash compensation to equity holdings, $\overline{c}$, as the cost of manipulation parameters, g and κ_1, change. As can be seen from these plots, the mean ratio of cash compensation to equity holdings, $\overline{c}$, at which the manager decides to manipulate declines as the probability of manipulation being detected, g, and the fixed proportional cost of manipulation, κ_1, increase. For instance, at $g = 0.05$ it is optimal to manipulate at all three values of $\overline{c} \in \{0.1, 0.5, 1.5\}$, at $g = 0.15$ it is optimal to manipulate only at two values of $\overline{c} \in \{0.1, 0.5\}$, and at $g = 0.3$ it is optimal to manipulate only at the lowest value of $\overline{c} = 0.1$. The same pattern is observed for κ_1.

The third moment condition is the mean first-period bias, b^1. This bias declines as the expected cost of manipulation increases. The fourth moment condition is the mean product of manipulation in the first and second periods, $b^1 b^2$. The bias in the second period, b^2, decreases as the expected cost of manipulation increases, but it is less sensitive to parameter changes if the bias in the first period, b^1, is large. This is a manifestation of the valuation effect. Second-period manipulation is more valuable if first-period manipulation is large as the manager benefits from the differences in the consecutive biases in net assets. Indeed, as can be seen from Figure 3, the bias in the second period, b^2, has a steeper slope with respect to the cost parameters when the first-period bias, b^1, is low, and thus the valuation effect is weaker.

Two parameters that are unidentified are the relative risk aversion parameter, γ, and the multiple on cash compensation, λ. The difficulty associated with estimating the relative risk aversion parameter, γ, is well recognized in the macroeconomics and finance literatures. A risk-aversion parameter equal to two or three is generally argued to be plausible (e.g., Ljungqvist and Sargent [2004], Cochrane [1997]). I follow the literature by setting its value to two. Similarly, I do not estimate the multiple on the manager's cash compensation λ

using the structural model and instead set its value to ten. This assumption would roughly capture the non-equity wealth of a manager who has been CEO for about ten years.

4.3 Estimation details

Since closed-form expressions for the moments of interest cannot be obtained analytically, I estimate the cost of manipulation parameters $\theta = (g, \kappa_1, \kappa_2)$ using Simulated Method of Moments (SMM). The objective function of the SMM is similar to that of the Generalized Method of Moments (GMM). In particular, both methods minimize the weighted squared distance between the moments implied by the data and the moments implied by the model. The difference between the two methods is that the GMM uses the closed-form expressions for the model-implied moments. In contrast, in the SMM the model-implied moments are obtained using simulation.

In the SMM, the moment condition is defined as

$$m_n(\theta) = \frac{1}{n}\sum_{i=1}^{n}\left[h(x_i) - \frac{1}{S}\sum_{s=1}^{S} h(y_{is}(\theta))\right], \tag{6}$$

where n is the number of observations, S is the number of simulations per observation, $h(x)$ are the moment functions, θ is the parameter vector to be estimated, x_i is an *i.i.d.* data vector, and $y_{is}(\theta)$ is an *i.i.d.* simulated vector from simulation s for observation i. The SMM seeks to minimize the weighted squared distance between the moments implied by the data and the moments implied by the model:

$$\widehat{\theta} = arg\min_{\theta} m_n(\theta)'\widehat{W}_n m_n(\theta). \tag{7}$$

I provide details on SMM estimation in Appendix C. Since the number of moment conditions exceeds the number of parameters, the test of overidentifying restrictions can be applied to test the model fit. If the test is rejected, the SMM estimator is inconsistent for θ (i.e., a particular specification of the model including all underlying assumptions about functional forms and distributions is rejected). However, the test does not provide information about which moment in particular does not hold.

Under the assumption that the simulations are unbiased, the SMM estimator is consistent even if $S = 1$ (Cameron and Trivedi [2005]). However, the number of simulations is typically set to $S = 10$ or $S = 20$ (e.g., Michaelides and Ng [2000], Taylor [2010]). I use $S = 100$ in my simulations to provide enough variation in the paths of intrinsic value. To simulate the model, I first fix the set of independent random shocks for the intrinsic value process, turnover decision, and detection of manipulation. The random draws have to be fixed to avoid "chatter" (the noise introduced by using different random draws) when optimizing the SMM objective function (McFadden [1989]). Next, for every executive in my sample, I solve the optimization problem under fixed parameters. The solution of the optimization problem yields optimal decision rules about whether to manipulate and by how much depending on the intrinsic value of the firm and the existing bias.

Based on the set of random shocks and the optimal decision rules for every executive, I simulate the data according to the model. First, I simulate the intrinsic value paths.[16] Second, for every executive in every simulation I apply his optimal decision rule with respect to whether to manipulate depending on the firm's realized intrinsic value. Third, if it is optimal for the executive to manipulate, I apply the optimal decision rule about the magnitude of manipulation for the first time. Once the executive has manipulated, he enters the *manipulative* state. In every period in the *manipulative* state, I apply the optimal decision rule about the magnitude of manipulation depending on the firm's current intrinsic value and the existing bias. As a result of these steps, for each executive in each simulation I obtain a path for whether the executive is in the *non-manipulative* state or the *manipulative* state. If he is in the *manipulative* state, I also observe the manipulation in each period and whether he leaves the firm. Finally, if he leaves the firm, I observe whether the manipulation is detected.

I compute the simulated moments in the same way that I compute the moments from the actual data. In the empirical sample, the number of years that each executive is observed

[16] Because the model is normalized in such a way that all executives in the sample start with $p_0 = 1$, there is no need to choose a starting point for the intrinsic value process, and thus there is no need to employ a burn-in period to dissipate the effect of an arbitrary choice of starting point.

varies. To address the fact that different executives are observed for different lengths of time in my sample, I use the simulation outcomes from the first t simulated periods for the executive that I observe for t years in the empirical sample. Thus, in the simulated sample, the restatement corresponds to an executive leaving the firm with manipulation being detected within the time interval during which I observe him in the empirical sample. Next, I sample the simulated biases in the first two restated periods in the same way they are observed in the data.[17] Finally, I use the restatement events and the biases in the first two periods from the simulated sample to compute the moments.

The structural estimation involves the optimization of the SMM objective function. For every guess of parameters (g, κ_1, κ_2), it is necessary to solve the optimization problem for every executive, simulate the data, and compute moments based on the simulated data. I constrain the parameters to lie in the following intervals: $g \in [0,1], \kappa_1 \in [0.0001, 0.5], \kappa_2 \in [0,2]$.[18] Solving the optimization problem for every executive is computationally intensive. For example, it takes about 330 seconds on a 64-processor cluster to evaluate the SMM objective function once.[19]

I use a genetic algorithm (Holland [1992]) to select starting values for the deterministic directional search. The genetic algorithm incorporates the principles of biological evolution and selects the candidate points by keeping the best ones without any change and replacing

[17]According to Audit Analytics, firms commonly provide restated figures only for the last five years for the annual restated periods. For instance, if the firm restates ten annual financial statements it would commonly disclose only the last five years of restated data. In this case, the restated figures are not observed for the first two years of the restated period. Accordingly, if in the simulated sample the length of the restated period exceeds five years, I assume that the first two years of the restated data are not observed.

[18]The interval for the probability of manipulation being detected, g, is straightforward. The fixed proportional cost of manipulation, κ_1, is the cost of manipulation that the manager incurs if he has ever manipulated before irrespective of his current bias in net assets. Since κ_1 is the fixed proportional loss in overall wealth, this parameter is expected to be low and I constrain it to $\kappa_1 \in [0.0001, 0.5]$. The sensitivity of the proportional loss in overall wealth to the magnitude of manipulation, κ_1, is constrained to $\kappa_2 \in [0,2]$. The maximum value of two corresponds to the manager losing all his wealth when he inflates the stock price by 100%.

[19]Simulated annealing is commonly used to optimize the objective function (e.g., Rust [1994], Taylor [2010]) to deal with the function being non-smooth and to avoid local minima. At each iteration, simulated annealing randomly generates a candidate point. That makes it inefficient in optimizing the objective function in my setting because, by the nature of the problem, there is a large parameter region over which no executive finds it optimal to manipulate and a relatively narrow parameter region over which the expected cost of manipulation is relatively low and some executives manipulate. As a result, the simulated annealing routine can consume extensive computational time in the large parameter region where no executive manipulates.

the rest of the population by combining the best points (i.e., performing crossover) and adding random mutations. At each of the two steps of the SMM optimization, I run the genetic algorithm for ten generations with the number of points in each generation being 20 (this implies 220 function evaluations including the evaluation of the initial generation). I tune the genetic algorithm parameters in such a way that the algorithm has enough random components to have a chance of finding a better point without spending too much time in the region where it is not optimal to manipulate).[20] After the genetic algorithm finds a region that potentially contains the global minimum, I refine the point using another global optimization algorithm, the pattern search, which searches the points around the current point in pre-specified directions. I run the pattern search until convergence.

5. *Results*

5.1 Parameter estimates

Parameter estimates for the structural model are presented in Table 3. For the sample of CEOs who left the firm within six months after the restatement filing date I find that the probability of manipulation being detected is 9.17%, which is arguably low. The estimate of κ_1, the fixed proportional loss in the manager's wealth in the event that manipulation is detected, is small at 0.46% and not statistically significant. This finding indicates that the cost of restatements that do not impact current financials is perceived by the manager to be negligible.

The estimate of κ_2, the sensitivity of the loss in the manager's wealth to the bias in net assets, can be best interpreted by considering the marginal impact of manipulation on the wealth loss evaluated at the average magnitude of manipulation among manipulating firms. It seems natural to express this magnitude as the percentage of the manager's wealth loss when he inflates the stock price by 1%.[21] The marginal effect is 0.17, which implies that

[20] The specific settings for the genetic algorithm that I use in Matlab are: gaoptions.EliteCount = 3; gaoptions.CrossoverFraction = 0.7; gaoptions.CrossoverFcn = @crossoverheuristic; gaoptions.MutationFcn{1} = @mutationadaptfeasible; gaoptions.MutationFcn{2} = 0.35; gaoptions.MutationFcn{3} = 0.75; and gaoptions.Generations = 10.

[21] The proportional loss in the manager's wealth that is sensitive to the magnitude of manipulation is

a 1% inflation in the stock price is associated with a 0.17% loss in the manager's wealth. As with the probability of detection, the marginal wealth loss is also low. Similarly, the average misstatement results in a 1.47% loss in the manager's wealth.[22] There are no prior studies that I can benchmark these estimates against because the manager's perceived costs of manipulation are not directly observable. The ability to make inferences about unobserved theoretical parameters is the distinctive feature of this approach.

As a robustness check, I also estimate the structural model for the sample in which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within 36 months of the restatement filing date. I find that the estimates are qualitatively similar. However, because of the higher frequency of restatements, the estimated perceived probability of manipulation being detected is 17.41%, which is almost twice as large as the estimate obtained using the other sample. Since the sample mean of the biases in net assets for this sample's first two periods is similar to that for the main sample,[23] the estimated loss in the manager's wealth in the event of detection is smaller, e.g., the marginal effect of manipulation is 0.12[24] versus 0.17 in the main sample.

5.2 Model fit

The test of overidentifying restrictions, which is a formal test on whether the model actually explains the data, is reported in Table 3. The model is rejected for the sample of CEOs who left within 36 months of the restatement filing date at the 1% significance level and for the sample of CEOs who left the firm within six months at the 5% significance level. Although the model is statistically rejected for both samples, this rejection is not surprising as I am fitting the same stylized model to over 1,800 CEOs. The magnitude of the J-test (5.21 for the six-month sample and 10.03 for the 36-month sample) implies that the model is better

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$\frac{\kappa_2}{2}(\beta b_t)^2$, where βb_t is expressed as a fraction of the stock price P_0. Therefore, the magnitude in question is $100\left(\frac{\partial \frac{\kappa_2}{2}(\beta b_t)^2}{\partial \beta b_t 100}\right) = \kappa_2 \beta b_t$. The estimate of the average cost impact of bias (βb_t) among manipulating executives is 0.1157 (Table 6) and the estimate of κ_2 is 1.51 (Table 3), which implies that $\kappa_2 \overline{\beta b}_t = 0.17$

[22] The average wealth loss is computed as $\frac{\kappa_2}{2}(\beta b_t)^2\Big|_{\beta b_t = 0.1157} + \kappa_1 = 1.51 * (0.1157)^2/2 + 0.46/100 = 0.0147$.

[23] The bias in net assets in the first restated period is 0.43% in the main sample and 0.54% in this sample.

[24] Here, I apply the same formula for the marginal effect, $\kappa_2 \overline{\beta b}_t = 0.60 * 0.1951 = 0.12$ (Table 6).

specified (and not rejected marginally at the 1% significance level) in the sample that uses the six-month turnover criterion to identify intentional misstatements, which agrees with the extant literature (e.g., Hennes et al. [2008]).

Following Taylor [2010], I study the Monte Carlo simulation results for the difference between empirical and simulated moments. Under this approach, the distribution of moments is obtained by simulating 10,000 samples of CEOs assuming that the parameters of the model are equal to the estimates presented in Table 3. The p-values for the moment differences are reported in Table 4. For both samples, the empirical moments are greater than the simulated moments; e.g., the model implies a lower restatement rate and lower first-period bias. However, these two moments still exhibit relatively good fit. The two other empirical moments, the average re-scaled cash compensation and average product of the biases in two periods, are reliably different from the simulated moments at the 1% level, which is consistent with the results of the J-test.

5.3 Counterfactual experiments

A distinct advantage of a structural approach is the ability to study the effects of parameter changes on optimal managerial decisions. In Table 5 I present counterfactual experiments on changes in the cost of manipulation. Specifically, I increase (decrease) a particular cost of manipulation parameter holding the other parameters constant. In each counterfactual experiment, I simulate 10,000 samples of CEOs with the same number of CEOs in the simulated sample as in the data under different parameter choices (which imply different optimal managerial decisions) to obtain 10,000 simulated samples. In the baseline simulation, I use the parameter estimates reported in Table 3. I then change the parameters one at a time to obtain simulations for the counterfactual samples.

Hypothetically, suppose that the SOX regulation has not changed the reputational costs of misstating earnings, but it has significantly increased the detection rate because of heightened scrutiny from regulators, auditors, and boards. Further, suppose that the probability of detection has doubled. The structural model allows one to analyze the effect of this change on the fraction of manipulating firms and the bias in the stock price. Under a lower probability of detection, the rate of manipulating firms increases from 59.13% under $g = 9.17\%$ to 71.35% under $g = 5\%$ while the restatement rate declines by only 1%. The equally weighted bias in the stock price conditional on manipulation does not change qualitatively.

To illustrate the power of the model, I also consider what would occur if the policy change were to increase the costs of manipulation substantially. As the expected cost of manipulation, (g, κ_1), increases, I find that fewer managers find it optimal to manipulate. However, changes in these two parameters have different implications for the equally weighted bias in price conditional on manipulation. On the one hand, the equally weighted bias in price decreases from 6.16% for $g = 9.17\%$ to 5.30% for $g = 25\%$. On the other hand, the equally weighted bias in price almost doubles from 6.16% for $\kappa_1 = 0.46\%$ to 12.02% from $\kappa_1 = 10\%$. As κ_1 increases, only the executives with a relatively low ratio of cash compensation to equity holdings misstate, and the magnitude of their misstatement is higher. This results in a higher value for the equally weighted bias in price conditional on manipulation. At the same time, as g increases, the magnitude of bias conditional on manipulation becomes slightly lower as a dollar of bias in net assets becomes more costly in expectation. The magnitudes of the results in Table 5 imply that significant policy changes are required to achieve qualitative shifts in the extent of manipulation.

5.4 Model-implied measure of manipulation

For each firm in my sample, I use the structural model and the estimated parameters to infer the unobserved decision to manipulate and the magnitude of manipulation from the path of the firm's stock price. The stock price has to be known in every period as the optimal manipulation decision in the next period depends on the optimal manipulation decision in the current period. This requirement reduces my sample of executives by approximately one-third.[25] I take the price at the end of the second month after the earnings announcement date as the current period price, $\widehat{P}_t$. This price is likely to incorporate the information in

[25]The price data are from CRSP. I omit executives for whom the stock price at the time zero is in the "penny stock" category (i.e., the stock price is under \$2). It is common in corporate finance studies to eliminate penny stocks as the stock price process for these firms may deviate substantially from the process assumed in the model.

reported earnings fully as the post-earnings announcement drift lasts about two months (e.g., Foster et al. [1984], Bernard and Thomas [1989]).

Consistent with the estimated expected cost of manipulation being low, the rate of manipulating executives is relatively high in my sample (Table 6). According to the model, about 63.23% of CEOs decide to manipulate sometime during their tenure. The mean bias in the stock price is primarily determined by small stocks as the estimated equally weighted bias in price is 12.96% and the value-weighted bias in price is about 2.77% of the stock price. This indicates that although the incidence of manipulation is high, the actual amount of manipulation is moderate on a value-weighted basis. The median inflation in the stock price is 5.64%, which is of the same order of magnitude as the median return for fraud-related restatements of around -4% at the restatement announcement for the post-SOX period (Scholz [2008], Table 8). As the estimated expected cost of manipulation is lower for the sample of CEOs for which an intentional misstatement is defined as a restatement in which the CEO left the firm within 36 months of the restatement filing date, the estimated rate of manipulating CEOs and the biases in stock price are higher in that sample.

The estimated rate of manipulating firms in my same is similar to the estimate obtained by Gerakos and Kovrijnykh [2011], who find evidence consistent with misreporting for 74% of firms. These numbers are also similar in magnitude to the 78% of executives reporting that they would sacrifice long-term value to smooth earnings (Graham et al. [2005]). Although my estimate of the share of manipulating firms is relatively high, the average bias in net assets and earnings is low. Among manipulating firms,[26] the bias in net assets as a percentage of the lag of total assets is 0.52%, and the bias in earnings as a percentage of the lag of total assets is 0.19% (Table 6).

[26] Manipulating executives are the executives in the manipulative state, i.e., the executives who have manipulated before, irrespective of the magnitude of the bias in net assets.

5.5 Association between the model-implied measure of manipulation and discretionary accruals

The accounting literature traditionally proxies for earnings management using measures of discretionary accruals. Both discretionary accruals and the structural model-implied measure of manipulation likely measure true unobserved manipulation with some error. The discretionary accruals models are ad hoc statistical models, whereas the structural model represents a stylized view of the world. Yet both approaches attempt to capture very complex intentional misreporting decision. Therefore, it is instructive to examine the association between traditional measures of earnings management and the model-implied manipulation measure. I examine the association between these measures on the pooled sample of CEO-years when it is optimal for the CEO to manipulate according to my model. This association is expected to be positive as all these proxies are designed to capture earnings manipulation.

I consider five measures of discretionary accruals: the total accruals measure as in Hribar and Collins [2002], the comprehensive measure of accruals of Richardson et al. [2005], the Jones model discretionary accruals measure as in Jones [1991], the modified Jones model discretionary accruals measure as in Dechow et al. [1995], and the performance-matched discretionary accruals measure as in Kothari et al. [2005]. To be consistent with prior literature, I omit financial firms from these tests (SIC between 6000 and 6999) because statistical discretionary accruals models are likely to be misspecified for these firms. To avoid the effect of outliers, I drop observations with manipulation measures being more than three standard deviations away from their respective means.

The sample mean of the model-implied measure of manipulation is comparable to some measures of discretionary accruals (Table 8). However, the model-implied measure of manipulation in earnings has a lower standard deviation and takes a tighter range of values compared to the discretionary accruals measures I consider.

The unconditional association between the model-implied measure and discretionary accruals is positive and statistically significant only for performance-matched discretionary accruals (Table 9). The model-implied measure is significantly negatively associated with the comprehensive measure of accruals as in Richardson et al. [2005].

The incorrect sign on the association with the comprehensive measure of accruals and the absence of an association with other accruals measures may be explained by not conditioning on the firm's expected earnings growth. On the one hand, it is plausible that firms with greater expected earnings growth have grater accruals as these firms incorporate growth expectations (McNichols [2000]). On the other hand, firms with greater earnings growth would have greater intrinsic value and as a result of the optimal manipulation decision, the bias in earnings would be lower. Hence, omitting the expected growth in earnings will result in a downward bias in the coefficient on the model-implied measure of manipulation in earnings.

Consistent with extant research, I proxy for the expected growth in earnings using the median analyst long-term growth forecast from I/B/E/S. As can be seen from Table 9, qualitative conclusions about the association between discretionary accruals and the model-implied measure of manipulation in earnings do not change - only performance-matched discretionary accruals are significantly positively associated with the model-implied measure of intentional manipulation.

6. *Conclusions*

In this paper, I develop a measure of intentional manipulation that is estimated using a structural model. The economic model is a dynamic infinite-horizon setting in which the manager maximizes his wealth at the time he leaves the firm which is random. The manager's wealth depends on his equity holdings in the firm and his cash wealth. The model yields the following results. First, according to the *wealth* effect, managers with greater cash compensation relative to equity holdings manipulate less. Second, according to the *valuation* effect, the current-period bias in net assets increases in the existing bias. Finally, the manager's risk aversion, the linearity of the terminal wealth in reported earnings, and the stochastic evolution of the firm's intrinsic value produce income-smoothing.

I contribute to the literature by providing estimates of manipulation costs perceived by a manager and the extent of intentional manipulation implied by these estimates. I find that the costs of manipulation are low. This results in high estimates of the incidence of latent manipulation. At the same time, the magnitude of manipulation is moderate. In contrast to the reduced-form approach, the structural approach applied in this study also allows one to conduct counterfactual experiments. I find that only a significant policy adjustment that increases the expected cost of manipulation can meaningfully alter the qualitative pattern of manipulation. The approach taken in this paper is also flexible enough to allow for partial observability of manipulation decisions.

In this paper, intentional manipulation is estimated under theoretical restrictions explicitly articulated by the model. This model can potentially be used in two ways by future research. First, it can be used to test whether analysts, investors, and boards learn about manipulation and incorporate this information into their decisions. Second, while executives' equity holdings provide the only incentive to manipulate according to my model. Many incentives can cause a manager to misstate (e.g., career concerns, debt covenants, etc.). Future research can use the estimate obtained in this paper to extract the part of accruals that is due to equity incentives alone in order to analyze the remaining incentives.

A structural approach involves trade-offs between restrictive assumptions that make estimation feasible and sufficient flexibility to capture patterns observed in the data. As a first attempt, I make a number of simplifying assumptions. First, I do not model a rational expectations equilibrium that involves the market anticipating the manager's reporting choices. Second, I do not incorporate the strategic decision of the board about the optimal compensation contract. In doing so, I avoid solving a difficult multi-period theoretical problem that lies beyond the scope of my empirical paper. Finally, as a first pass, I assume that the compensation structure is fixed. I plan to relax this assumption in future research.

Another limitation of this paper, and potential area for future research in structural estimation, relates to my assumption that only executives' equity holdings provide an incentive to misreport earnings. Other incentives to misreport include reputation management, career concerns (e.g., Fudenberg and Tirole [1995], DeFond and Park [1997], Dechow and Sloan [1991], Murphy and Zimmerman [1993]), bonuses (e.g., Healy [1985]), and debt covenants (e.g., DeFond and Jiambalvo [1994], Sweeney [1994]). Consequently, the measure of intentional manipulation suggested in this paper may be biased to the extent that the other incentives to misreport are also important.

In future research I will conduct the following two extensions of the current study. First, I will accommodate time-varying cash compensation and equity holdings. Second, I will compare the cost of manipulation in the pre- and post-SOX periods to quantify the change in the manipulation cost parameters induced by this policy shift.

A. *Analytical results*

The dynamic infinite-horizon model with stochastic evolution of the firm's intrinsic value cannot be solved analytically. In Section 3, I present a three-period problem that keeps all assumptions of the main model but assumes a finite horizon. In this appendix, I discuss analytical results that can be derived under more restrictive assumptions. The optimal bias can be obtained analytically under the assumptions of a linear utility function and constant intrinsic value. This case gives rise to the optimal bias level, which does not depend on the existing bias. Next, under the assumption of constant intrinsic value, I discuss the Euler equation for the case of a concave utility function.

A.1 Linear utility and constant intrinsic value

The simplest form of the dynamic optimization problem is the linear quadratic problem, which in some instances can be solved explicitly (e.g., Ljungqvist and Sargent [2004]). Under a linear utility function and constant intrinsic value, the problem takes the linear-quadratic form (the evolution of the bias is linear and the objective function is quadratic). The optimal solution is to maintain a constant bias in net assets irrespective of the existing bias. The optimal bias is given by

$$b^* = \frac{f(1-g)}{(1-f)g(p+\lambda\overline{c})\kappa_2\beta}. \tag{8}$$

Intuitively, the risk-neutral manager decides the optimal magnitude of bias and introduces this bias in the first period. As a result, first-period earnings will have the maximal bias, and there will be no bias in subsequent earnings.

The comparative statics for the optimal bias b^* are intuitive. First, b^* is increasing in the probability of leaving the firm, f, because the likelihood of benefiting from manipulation increases in f. Second, b^* is decreasing in the probability of manipulation being detected, g. Finally, b^* is decreasing in $(p+\lambda\overline{c})\kappa_2\beta$ as this expression reflects the cost of manipulation if it is detected. If the existing bias is very large, the manager will return to the optimal bias b^* by introducing a negative bias into current earnings.

A.2 Concave utility and constant intrinsic value

For simplicity, I assume that the firm's intrinsic value is constant. In this case, the optimal choice of the bias, b_t, should satisfy the deterministic Euler equation (as there is no uncertainty in the intrinsic value process)(Ljungqvist and Sargent [2004]):

$$f(1-g)U'\Big(p+\beta(b_t-b_{t-1})+\lambda\bar{c}\Big) = (1-f)f\Big[gU'\Big((p+\lambda\bar{c})\Big(1-\kappa_1-\frac{\kappa_2}{2}(\beta b_t)^2\Big)\Big)(p+\lambda\bar{c})\kappa_2\beta b_t+ \\ +(1-g)U'\Big(p+\beta(b_{t+1}-b_t)+\lambda\bar{c}\Big)\Big]. \quad (9)$$

The the expression on the left represents the marginal benefit and the expression on the right represents the marginal cost of current-period manipulation, b_t.

The Euler equation provides a number of intuitive insights regarding the optimal choice of manipulation, some of which also hold in the main model described in Section 3. From the formula above, it is easy to derive the following two effects. First, the manipulation level b_t decreases in the ratio of cash wealth to equity holdings because his marginal benefit of manipulation decreases more rapidly than his marginal cost under a sufficiently high costs (κ_1, κ_2). This feature of the model I label the *wealth* effect. Second, the optimal manipulation level b_t increases in b_{t-1} as the marginal costs do not depend on b_{t-1}, while the marginal benefit of manipulation increases in b_{t-1}. This feature of the model I label the *valuation* effect. Similar to the linear utility case, the magnitude of the bias, b_t, is decreasing in the probability of manipulation being detected, g, and increasing in the probability of leaving the firm, f. As expected, the extent of manipulation is decreasing in the cost parameters (κ_1, κ_2).

B. *Solving the infinite-horizon model*

The manager's value function in the *manipulative* state is

$$V_m(P_\tau, B_{\tau-1}) = \max_{B_\tau(P_\tau, B_{\tau-1})} \mathbb{E}_\tau \sum_{t=\tau}^{\infty} (1-f)^{t-\tau} f \Bigg\{ gU\Bigg((\overline{n}P_t + \lambda\overline{C}) \Bigg(1 - \kappa_1 - \frac{\kappa_2}{2}\Bigg(\frac{\beta B_{t-1}}{P_0}\Bigg)^2\Bigg)\Bigg) + \\ + (1-g)U\Bigg(\overline{n}(P_t + \beta(B_t - B_{t-1})) + \lambda\overline{C}\Bigg)\Bigg\}. \quad (10)$$

In the *non-manipulative* state ($B_{\tau-1} = 0$ by definition), the manager decides whether to manipulate every period and his value function is

$$V_{nm}(P_\tau) = fU(\overline{n}P_\tau + \lambda\overline{C}) + (1-f)\mathbb{E}_\tau\Bigg[\max_{d(P_\tau)\in\{0,1\}} \Bigg\{V_{nm}(P_{\tau+1}), V_m(P_{\tau+1}, 0)\Bigg\}\Bigg| P_\tau\Bigg]. \quad (11)$$

Under constant relative risk aversion utility, it is possible to re-scale the argument of the utility function without affecting the manager's optimal decision. It is convenient to re-scale the problem for every executive by $\overline{n}P_0$ since the problem is executive-specific. Re-scaled variables are denoted by lower-case letters as follows:

$$\Bigg\{p_t = \frac{P_t}{P_0}, b_t = \frac{B_t}{P_0}, \overline{c} = \frac{\overline{C}}{\overline{n}P_0}\Bigg\}. \quad (12)$$

I solve the manager's optimization problem numerically in two steps because there are two value functions. One value function corresponds to the *manipulative* state, $V_m(p_t, b_{t-1})$, and the other to the *non-manipulative* state, $V_{nm}(p_t)$. I compute these two functions via a value function iteration (e.g., see Ljungqvist and Sargent [2004]) using a two-dimensional grid for the firm's intrinsic value p_t and the existing bias b_{t-1}. For intrinsic value, the grid ranges from zero to ten with increments that correspond to a 5% stock return. The intrinsic value grid is the same for all executives because the data are normalized such that $p_0 = 1$. For the existing bias, the grid includes 100 points and the support of the grid is determined by the extent of the manipulation observed empirically.[27] For the value function iterations,

[27]The maximum value of the grid is set to the maximum manipulation observed in the data multiplied by

I assume that a value function has converged when its change in consecutive iterations is lower than 10^{-4}.

Once the manager enters the *manipulative* state, he remains there until he leaves the firm. As a consequence, I can find the value function for the *manipulative* state, $V_m(p_t, b_{t-1})$, independent of the value function in the *non-manipulative* state, $V_{nm}(p_t)$, by iterating on the following equation:

$$V_m^{j+1}(p_t, b_{t-1}) = \max_{b_t} \Bigg\{ fgU\Bigg((p_t+\lambda\bar{c})\Bigg(1-\kappa_1-\frac{\kappa_2}{2}(\beta b_t)^2\Bigg)\Bigg)+f(1-g)U\Bigg(p_t+\beta(b_t-b_{t-1})+\lambda\bar{c}\Bigg)+ \\ + (1-f)\mathbb{E}[V_m^j(p_{t+1}, b_t)|p_t, b_t]\Bigg\} \quad (13)$$

with respect to iteration j. Theoretically, a guess of the initial value, V_0, does not affect the convergence result and I start iterations assuming that V_0 equals the value of staying in the *non-manipulative* state forever.

Next, I use the value function $V_m(p_t, b_{t-1})$ from the previous step to find $V_{nm}(p_t)$ from the following equation, which I iterate with respect to j:

$$V_{nm}^{j+1}(p_t) = fU(p_t + \lambda\bar{c}) + (1-f)\mathbb{E}\Bigg[V_{nm}^j(p_{t+1}), V_m(p_{t+1}, 0)\Bigg| p_t\Bigg]. \quad (14)$$

As a by-product of value function iterations, I obtain the manager's optimal decisions with respect to whether to manipulate and to what extent.

1.1.

C. Simulated Method of Moments estimation details

In the SMM, the moment condition is defined as

$$m_n(\theta) = \frac{1}{n}\sum_{i=1}^{n}\left[h(x_i) - \frac{1}{S}\sum_{s=1}^{S}h(y_{is}(\theta))\right], \tag{15}$$

where n is the number of observations, S is the number of simulations per observation, $h(x)$ are the moment functions, θ is the parameter vector to be estimated, x_i is an *i.i.d.* data vector, and $y_{is}(\theta)$ is an *i.i.d.* simulated vector from simulation s for observation i. The SMM seeks to minimize the weighted squared distance between the moments implied by the data and the moments implied by the model

$$\widehat{\theta} = arg\min_{\theta} m_n(\theta)'\widehat{W}_n m_n(\theta). \tag{16}$$

Similar to the traditional two-step GMM, I obtain the SMM estimate of θ in two steps. In the first step, the weighting matrix is set to a symmetric and positive definite matrix that produces a consistent (but not necessarily efficient) estimator $\widehat{\theta}$. It is common to set the first weighting matrix to the identity matrix. However, to avoid numerical issues with the optimization that are caused by restatements being rare events and the restated bias being small, I scale the diagonal elements of the identity matrix in such a way that each moment has one significant digit before the decimal point. In the second step, the weighting matrix is set to the inverse of the variance-covariance matrix of the moments estimated in $\widehat{\theta}$. The variance-covariance matrix of the moments of the SMM estimator is inflated by $\left(1+\frac{1}{S}\right)$ and equals $V_{SMM}(m_n(\theta)) = \left(1+\frac{1}{S}\right)V(m_n(\theta))$ because the moments are simulated, i.e., $\widehat{W}_{opt} = \frac{S}{1+S}V(m_n(\widehat{\theta}))^{-1}$, where $V(m_n(\widehat{\theta}))$ is the variance-covariance matrix of the moments $m_n(\theta)$ (McFadden [1989], Cameron and Trivedi [2005], Dave and Dejong [2007]) . The second step produces the consistent and asymptotically efficient estimator $\widehat{\theta}_{SMM}$.

According to McFadden [1989], the asymptotic distribution of $\widehat{\theta}_{SMM}$ is

$$\sqrt{n}(\widehat{\theta}_{SMM} - \theta) \longrightarrow^d N(0, \Omega) \tag{17}$$

$$\widehat{\Omega} = \left(1 + \frac{1}{S}\right)\left(\frac{\partial m_n(\widehat{\theta}_{SMM})}{\partial \theta'} V(m_n(\widehat{\theta}_{SMM}))^{-1} \frac{\partial m_n(\widehat{\theta}_{SMM})}{\partial \theta}\right)^{-1}. \tag{18}$$

The four moment functions $h(x_i)$ that define moment conditions are

$$h_1(x_i) = \mathbf{1}(restate_i) \tag{19}$$

$$h_2(x_i) = \mathbf{1}(restate_i)\bar{c}_i \tag{20}$$

$$h_3(x_i) = b^{1i}\mathbf{1}(restate_i) \tag{21}$$

$$h_4(x_i) = b^{2i}b^{1i}\mathbf{1}(restate_i). \tag{22}$$

The test of overidentifying restrictions can be applied to test the model fit when the number of moment conditions exceeds the number of parameters,

$$J = \frac{nS}{1+S} m_n(\widehat{\theta}_{SMM})' V(m_n(\widehat{\theta}_{SMM}))^{-1} m_n(\widehat{\theta}_{SMM}) \sim \chi^2(1). \tag{23}$$

The test of overidentifying restrictions is a general model specification test that equals the optimal SMM objective function evaluated at $\widehat{\theta}_{SMM}$. The null hypothesis is that the model is well identified, or $H_0 : E[h(x_i, \theta)] = 0$. If the test is rejected then the SMM estimator is inconsistent for θ (i.e., a particular specification of the model including all underlying assumptions about functional forms and distributions is rejected). However, the test does not provide information about which moment in particular does not hold.

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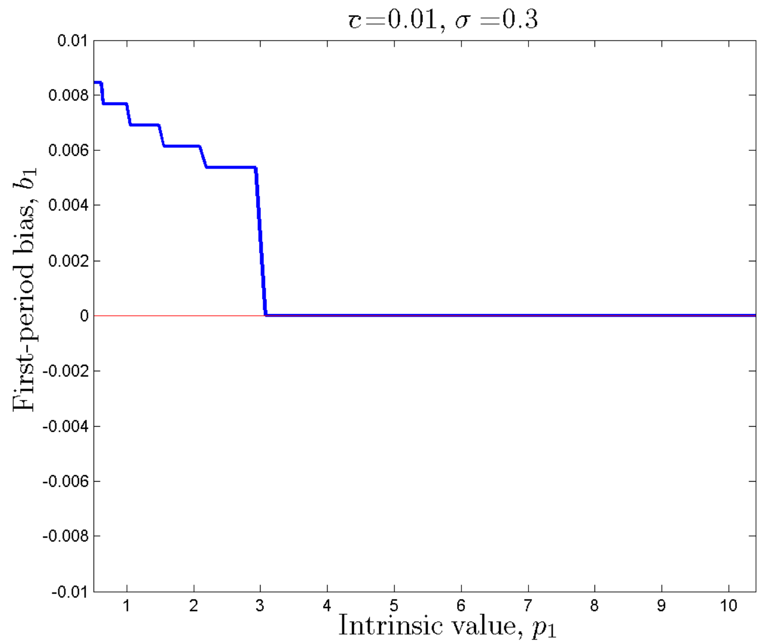
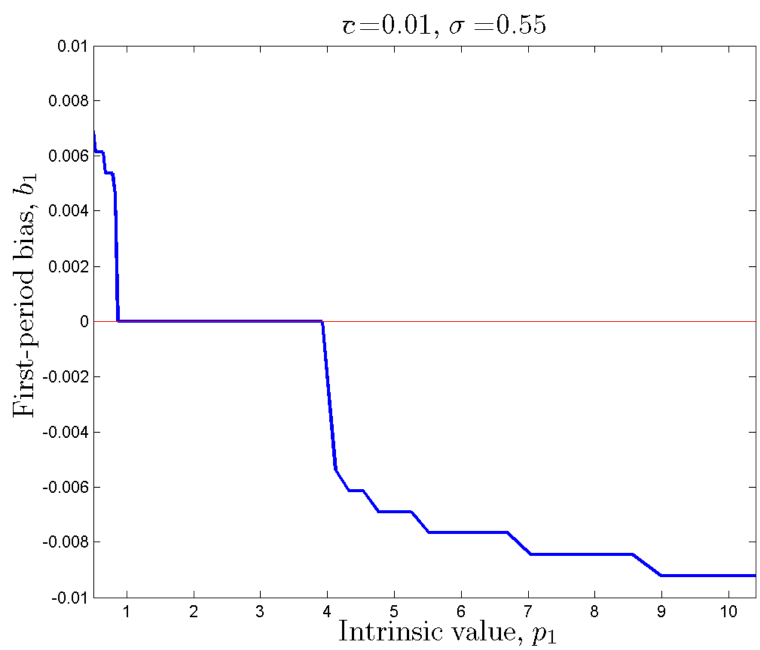
Figure 1: Optimal magnitude of bias in net assets in the first two periods

This figure shows the optimal magnitude of manipulation in the first period $b_1(p_1)$ and the optimal magnitude of manipulation in the second period $b_2(p_2, b_1)$ for the three-period model described in Section 3. For parameters common to all executives, I assume $\gamma = 2$, $g = 0.09$, $\kappa_1 = 0.005$, $\kappa_2 = 1.5$, and $\lambda = 10$. I set the executive-specific parameters (except for $\bar{c}$) to their sample means, that is, $f = 0.08, \beta = 30$, and $\mu = 0.10$.





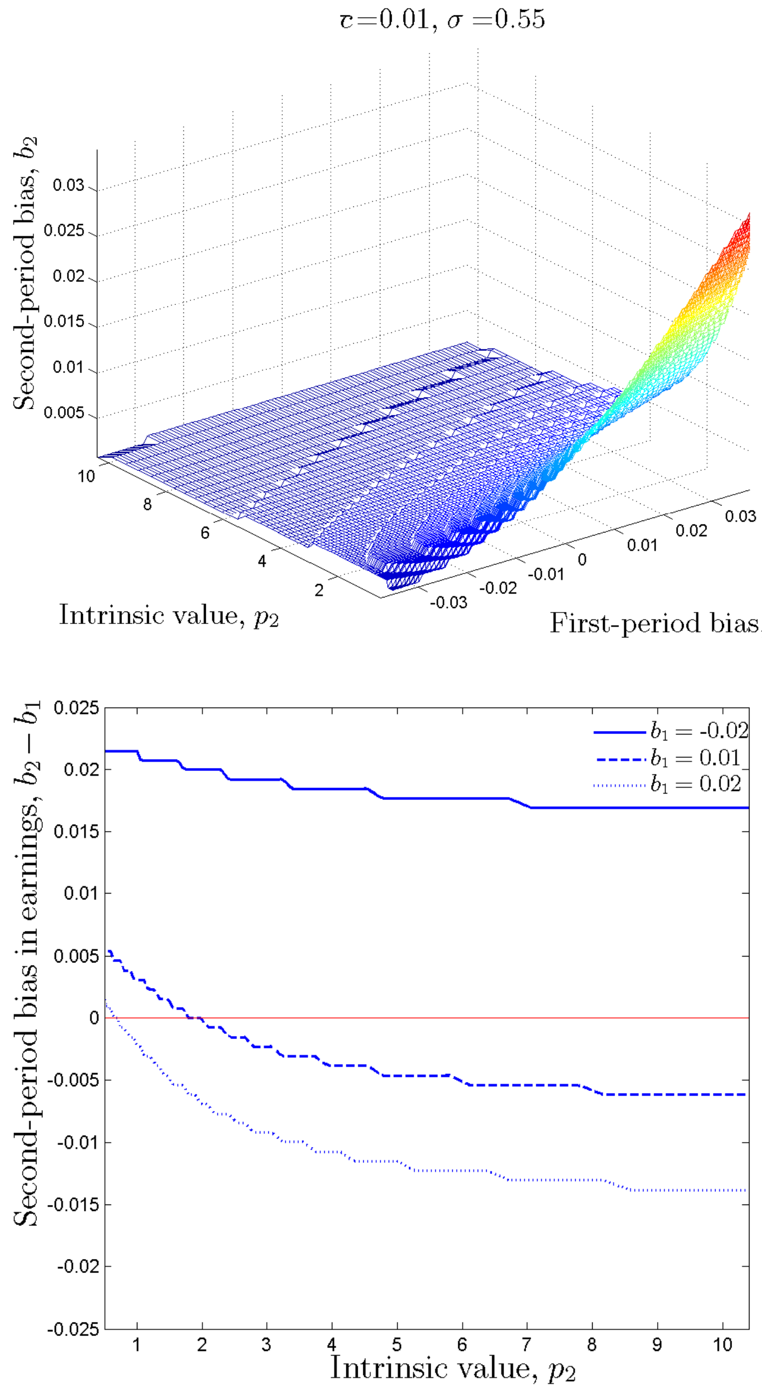

c=0.01, σ =0.55
Second-period bias, b_2
0.03
0.025
0.02
0.015
0.01
0.005
10
8
6
4
2
Intrinsic value, p_2
-0.03
-0.02
-0.01
0
0.01
0.02
0.03
First-period bias
Second-period bias in earnings, $b_2 - b_1$
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
-0.02
-0.025
b_1 = -0.02
b_1 = 0.01
b_1 = 0.02
1
2
3
4
5
6
7
8
9
10
Intrinsic value, p_2

Figure 2: Optimal magnitude of bias in net assets in the first period: comparative statics

This figures depict how the magnitude of the bias in net assets in the first period, b_1, changes with respect to the cost of manipulation parameters, g and κ_1, for different levels of the ratio of cash compensation to equity holdings, $\bar{c}$. The plots correspond to the three-period model described in Section 3. For parameters common to all executives, I assume $\gamma = 2, g = 0.05, \kappa_1 = 0.05, \kappa_2 = 0.05$, and $\lambda = 1$. I set the executive-specific parameters (except for $\bar{c}$) to their sample means, that is, $f = 0.08, \beta = 30, \mu = 0.10$, and $\sigma = 0.42$.

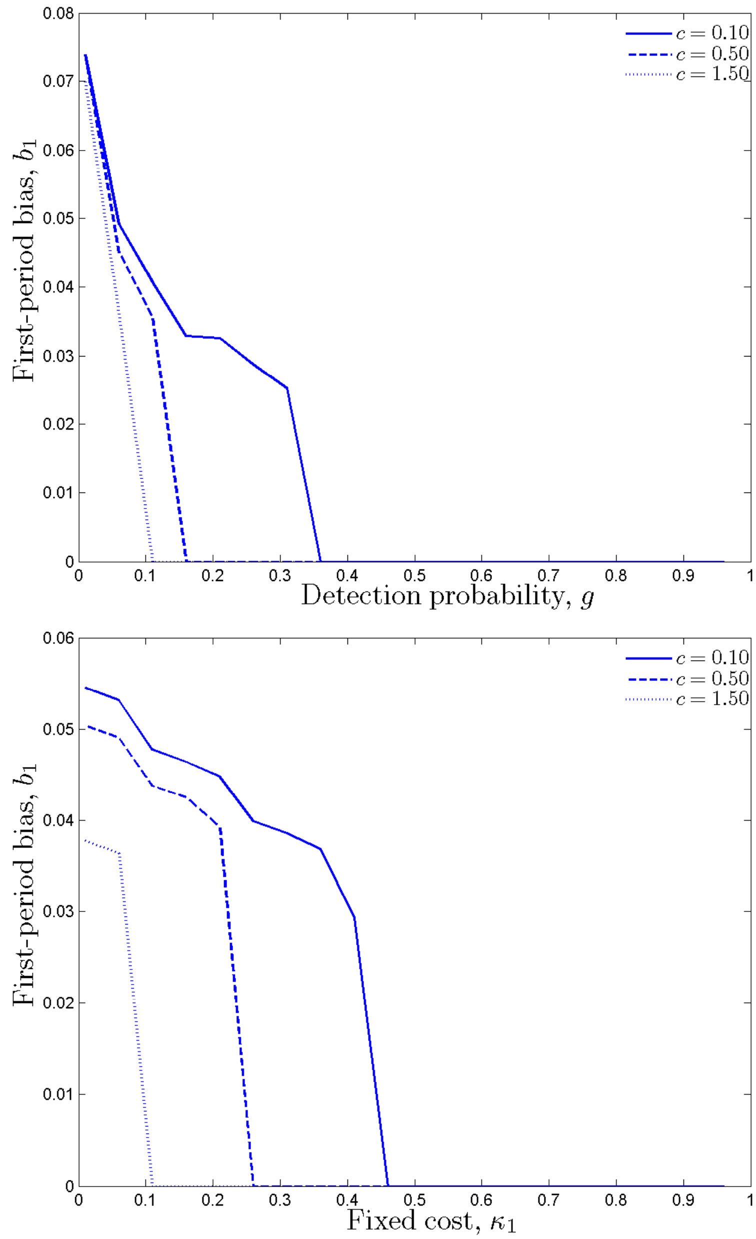
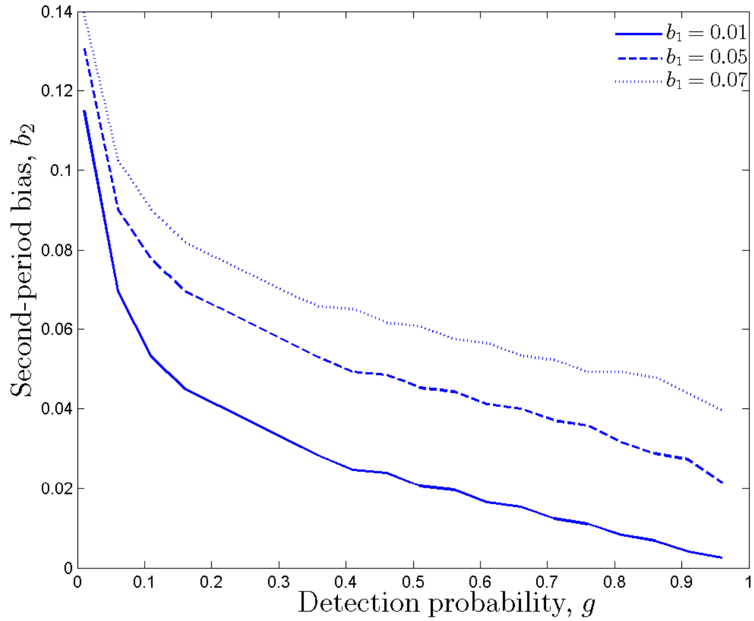


Figure 3: Optimal magnitude of bias in net assets in the second period: comparative statics

This figures depict how the magnitude of the bias in net assets in the first period, b_1, changes with respect to the cost of manipulation parameters, g and κ_2, for different levels of the ratio of cash compensation to equity holdings, $\bar{c}$. The plots correspond to the three-period model described in Section 3. For parameters common to all executives, I assume $\gamma = 2, g = 0.05, \kappa_1 = 0.05, \kappa_2 = 0.05$, and $\lambda = 1$. I set the executive-specific parameters (except for $\bar{c}$) to their sample means, that is, $f = 0.08, \beta = 30, \mu = 0.10$, and $\sigma = 0.42$.



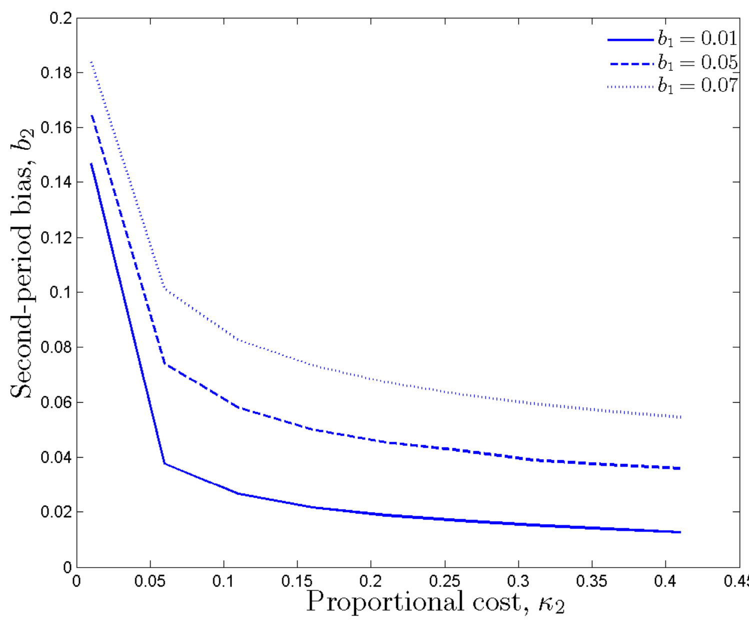


Table 1. Variable definitions

This table contains definitions of variables and parameters used in estimation. To measure industry-specific parameters, I use the Fama-French 49 industry classification and take the average of the variable defined at an annual frequency over the period from January 1, 2002 to December 31, 2007.

	Definition	Source
	Executive-specific parameters	
P_0	Stock price in the beginning of the fiscal year when the CEO joins the firm or, if not available, the earliest available stock price.	Equilar
$\overline{n}$	Mean equity holdings over the CEO's tenure in the firm, defined as $\overline{n}_{stock} + \overline{n}_{options} \times d$, where $\overline{n}_{stock}$ is the mean number of stocks over the CEO's tenure, $\overline{n}_{options}$ is the mean number of options over the CEO's tenure (irrespective of vesting status), and d is the mean stock option delta computed under the assumptions of Core and Guay [2002] for all firms in the same industry.	Equilar, CRSP
$\overline{C}$	Mean annual cash compensation over the CEO's tenure defined as the sum of salary and bonuses.	Equilar
$\overline{c}$	Re-scaled cash compensation $\overline{c} = \overline{C}/(\overline{n}P_0)$. This variable is winsorized at the 5th and 95th percentiles.	Equilar
	Industry-specific parameters	
f	Probability of the CEO leaving the firm, defined as the mean annual turnover rate across all firms in the same industry.	Equilar, Boardex
μ	Mean expected return across all firms in the same industry, under the assumption that CAPM holds, that is, $r_f + \beta_{CAPM}(r_m - r_f)$. I use β_{CAPM} provided by CRSP, which computes annual betas as in Scholes and Williams [1977]. Since betas are based on two portfolio types (NYSE/Amex and NASDAQ-only), I define r_m as the value-weighted return on the NYSE/Amex and NASDAQ-only portfolios. I use the one-year T-bill rate for r_f.	CRSP
σ	Mean standard deviaiton of continuously compounded returns across all firms in the same industry. The standard deviation is measured as the annualized standard deviation of daily returns provided by CRSP.	CRSP
β	Mean price-to-earnings multiple across all firms in the same industry. The price-to-earnings multiple is defined as the average of fiscal year-end stock prices $\widehat{P}_t$ and $\widehat{P}_{t+1}$ divided by net income for year t for firms with positive net income.	Equilar
	Fixed parameters	
$\gamma = 2$	Relative risk aversion parameter.	
$\lambda = 10$	Multiple on cash compensation to obtain the overall non-equity wealth of the CEO.	
	Variables observed in the case of restatements	
B_1	Correction of net income in the first restated period.	AuditAnalytics
$B_2 - B_1$	Correction of net income in the second restated period.	AuditAnalytics
b_1, b_2	Re-scaled bias in net assets: $b_t = B_t/P_0$. This variable is winsorized at the 5th and 95th percentiles.	
	Estimated parameters	
g	Probability of manipulation being detected at the time the CEO leaves the firm.	
κ_1	Fixed proportional loss in CEO wealth in the event that manipulation is detected.	
κ_2	Sensitivity of the proportional loss in CEO wealth to the magnitude of manipulation in the event manipulation is detected.	

Table 2: Descriptive statistics

Panel A contains summary statistics for the sample of 1,815 CEOs in which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within six months of the restatement filing date. Panel B contains summary statistics for the sample of 1,850 CEOs in which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within 36 months of the restatement filing date. Additional details on variable measurement are in Table 1.

Panel A: CEO left within six months (N = 1815)							
	Mean	Std dev	25th	50th	75th	Min	Max
Re-scaled cash compensation, $\overline{c}$ (%)	14.56	16.36	3.97	8.29	17.94	0.69	64.78
Probability of leaving the firm, f (%)	7.77	1.46	6.87	7.94	8.82	3.33	10.74
Expected return, μ (%)	9.21	1.55	8.51	8.94	9.76	6.53	16.73
Return volatility, σ (%)	42.19	8.91	36.03	42.06	49.02	26.22	56.51
Price-to-earnings multiple, β	29.97	7.23	25.36	29.44	37.21	17.26	48.49
Restatement indicator (%)	2.09	14.32	0.00	0.00	0.00	0.00	100.00
Bias in net assets for restating firms (N = 38)							
	Mean	Std dev	25th	50th	75th	Min	Max
Bias in net assets in $t = 1$, b_1 (0.01%)	43.63	108.25	-17.44	30.48	83.69	-156.18	350.02
Bias in net assets in $t = 2$, b_2 (0.01%)	82.21	226.65	0.00	0.00	89.12	-197.05	783.66
Panel A: CEO left within 36 months (N = 1850)							
	Mean	Std dev	25th	50th	75th	Min	Max
Re-scaled cash compensation, $\overline{c}$ (%)	14.47	16.32	3.93	8.24	17.82	0.58	64.68
Probability of leaving the firm, f (%)	7.78	1.46	6.87	8.17	8.82	3.33	10.74
Expected return, μ (%)	9.22	1.55	8.72	8.94	9.76	6.53	16.73
Return volatility, σ (%)	42.24	8.88	36.03	42.14	49.02	26.22	56.51
Price-to-earnings multiple, β	30.00	7.22	25.36	29.44	37.21	17.26	48.49
Restatement indicator (%)	4.38	20.47	0.00	0.00	0.00	0.00	100.00
Bias in net assets for restating firms (N = 81)							
	Mean	Std dev	25th	50th	75th	Min	Max
Bias in net assets in $t = 1$, b_1 (0.01%)	54.56	116.19	-3.39	25.43	86.73	-148.01	350.02
Bias in net assets in $t = 2$, b_2 (0.01%)	97.91	228.35	0.00	4.60	79.21	-148.01	854.05

Table 3: Parameter estimates

This table contains estimates of the cost of manipulation parameters for the model described in Section 3. The parameters are defined in Table 1. Panel A contains estimates based on the sample of 1,815 CEOs in which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within six months of the restatement filing date. Panel B contains estimates based on the sample of 1,850 CEOs in which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within 36 months of the restatement filing date. The parameters are estimated using SMM, as described in Section 4. The J-test is the test of overidentifying restrictions (distributed as $\chi^2(1)$ in this case, as described in Section 4), which is the specification test for how well the model explains the data; p-value is the p-value for the J-test. Standard errors are in parentheses.

Panel A: CEO leaves within six months				
Detection prob. g (%)	Fixed cost κ_1 (%)	Proport. cost κ_2	J-test	p-value
9.17	0.46	1.51	5.21	0.02
(3.68)	(3.26)	(0.004)		
Panel B: CEO leaves within 36 months				
Detection prob. g (%)	Fixed cost κ_1 (%)	Proport. cost κ_2	J-test	p-value
17.41	0.02	0.60	10.03	0.00
(2.70)	(1.12)	(0.02)		

Table 4: Empirical versus simulated moments

This table contains the results of Monte Carlo simulations of the distribution of simulated moments to test hypotheses about the equality of the moments computed from the data and simulated moments, as described in Section 5. The parameters are defined in Table 1. The choice of moments is discussed in Section 4. Panel A contains results for the sample of 1,815 CEOs in which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within six months of the restatement filing date. Panel B contains results for the sample of 1,850 CEOs in which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within 36 months of the restatement filing date. For each definition of an intentional misstatement, I simulate 10,000 samples of CEOs with the same number of CEOs in the sample as in the data under the estimated parameters reported in Table 3 to obtain 10,000 sets of simulated moments. The empirical values are moments computed using data. The simulated values are means across 10,000 sets of simulated moments. The standard error is the standard deviation of the 10,000 simulated moments; p-value is the p-value of the empirical moments based on the distribution of simulated moments, i.e., it is the p-value of the test for equality between the empirical moments and the simulated moments implied by the model.

Panel A: CEO leaves within six months				
	Empirical value	Simulated value	Standard error	p-value
Restatement rate (%)	2.09	1.72	0.30	0.10
Average $\bar{c}\mathbf{1}[restate]$ (%)	0.20	0.13	0.03	0.01
Average b_1 (0.01%)	0.91	0.60	0.19	0.05
Average b_2b_1 (0.01%)	0.043	0.004	0.001	0.00
Panel A: CEO leaves within 36 months				
	Empirical value	Simulated value	Standard error	p-value
Restatement rate (%)	4.38	3.50	0.42	0.02
Average $\bar{c}\mathbf{1}[restate]$ (%)	0.44	0.31	0.05	0.00
Average b_1 (0.01%)	2.39	2.30	0.38	0.40
Average b_2b_1 (0.01%)	0.077	0.017	0.004	0.00

Table 5: Counterfactual experiments

This table contains the results of counterfactual experiments in which I vary the cost of manipulation parameters as described in Section 5.3. The parameters are defined in Table 1. Panel A contains results for the sample of 1,815 CEOs in which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within six months of the restatement filing date. Panel B contains results for the sample of 1,850 CEOs in which an intentional misstatement is defined as a restatement in which the CEO left the firm between the end of the restated period and within 36 months of the restatement filing date. For each definition of an intentional misstatement, I simulate 10,000 samples of CEOs with the same number of CEOs in the sample as in the data under different choices of parameters to obtain 10,000 simulated samples. Each CEO is simulated for ten periods. In the baseline simulation, I use the parameters reported in Table 3. Next, I vary parameters one at a time to obtain a new set of simulated samples. For each simulated sample, I compute the rate of restatement, the rate of manipulating CEOs, and the equally weighted and value-weighted biases in the stock price (defined as the difference between the stock price and intrinsic value as a percentage of the stock price) over CEO-years in which the CEO manipulates according to the model. The reported values are means across 10,000 sets of simulated samples. The standard deviations of 10,000 simulated samples are in parentheses.

Panel A: CEO leaves within six months				
	Restatement rate (%)	Manipulation rate (%)	Equally weighted bias in price (%)	Value-weighted bias in price (%)
Estimated parameter values: $g = 9.17\%, \kappa_1 = 0.46\%, \kappa_2 = 1.51$				
	3.06	59.13	6.16	1.10
	(0.40)	(0.86)	(0.26)	(0.42)
Lower probability of detection: $g = 5\%, \kappa_1 = 0.46\%, \kappa_2 = 1.51$				
$g = 5\%$	2.09	71.35	6.96	1.42
	(0.33)	(0.78)	(0.25)	(0.45)
Higher probability of detection: $g = 25\%, \kappa_1 = 0.46\%, \kappa_2 = 1.51$				
$g = 25\%$	3.70	29.97	5.30	1.15
	(0.44)	(0.90)	(0.34)	(0.53)
Higher fixed cost: $g = 9.17\%, \kappa_1 = 10\%, \kappa_2 = 1.51$				
$\kappa_1 = 10\%$	0.76	18.00	12.02	1.05
	(0.20)	(0.72)	(0.76)	(1.08)

Panel B: CEO leaves within 36 months				
	Restatement rate (%)	Manipulation rate (%)	Equally weighted bias in price (%)	Value-weighted bias in price (%)
Estimated parameter values: $g = 17.41\%, \kappa_1 = 0.02\%, \kappa_2 = 0.60$				
	6.17	62.55	7.44	1.87
	(0.55)	(0.88)	(0.29)	(0.55)
Lower probability of detection: $g = 5.00\%, \kappa_1 = 0.02\%, \kappa_2 = 0.60$				
$g = 5\%$	2.50	83.02	10.34	2.96
	(0.36)	(0.59)	(0.30)	(0.68)
Higher probability of detection: $g = 25\%, \kappa_1 = 0.02\%, \kappa_2 = 0.60$				
$g = 25\%$	7.33	53.48	6.43	1.86
	(0.60)	(0.93)	(0.29)	(0.55)
Higher fixed cost: $g = 17.41\%, \kappa_1 = 10\%, \kappa_2 = 0.60$				
$\kappa_1 = 10\%$	0.74	10.40	20.67	4.36
	(0.19)	(0.61)	(1.36)	(3.00)

Table 6: Model-implied measure of manipulation

Panel A contains summary statistics for the model-implied bias computed under the cost parameter estimates obtained for the sample of 1,815 CEOs. This sample defines an intentional misstatement as the restatement in which the CEO left the firm between the end of the restated period and within six months of the restatement filing date. Panel B contains summary statistics for the model-implied bias computed under the cost parameter estimates obtained for the sample of 1,850 CEOs. This sample defines an intentional misstatement as a restatement in which the CEO left the firm between the end of the restated period and within 36 months of the restatement filing date. The details on bias estimation are in Section 5.4. I compute the rate of restatement, the rate of manipulating CEOs, and the equally weighted and value-weighted biases in the stock price (defined as the difference between the stock price and intrinsic value as a percentage of the stock price) over CEO-years in which the CEO manipulates according to the model. *Bias in net assets* is the bias in net assets scaled by the lag of total assets, i.e., $n_0\widehat{B}_t/AT_{t-1}$. *Bias in earnings* is the bias in earnings scaled by the lag of total assets, i.e., $n_0(\widehat{B}_t - \widehat{B}_{t-1})/AT_{t-1}$. *Bias in price* is the difference between the stock price and intrinsic value divided by the stock price, which is equivalent to $\beta(\widehat{B}_t - \widehat{B}_{t-1})/\widehat{P}_t$. *Cost impact of bias* is $\beta\widehat{b}_t$. The sample in Panel A contains 834 CEOs and 2,918 pooled CEO-years when CEO manipulates according to the model. The sample in Panel B contains 873 CEOs and 3,092 CEO-years in which CEO manipulates according to the model. *Bias in net assets*, *Bias in earnings*, and *Bias in price* are winsorized at the 5th and 95th percentiles.

Panel A: CEO left within six months							
	Manipulation rate (%)		Equally weighted bias in price (%)		Value-weighted bias in price (%)		
	63.23		12.96		2.77		
	Mean	Std dev	25th	50th	75th	Min	Max
Bias in net assets (%)	0.52	0.97	0.07	0.40	0.93	-1.34	2.84
Bias in earnings (%)	0.19	0.43	0.00	0.07	0.37	-0.59	1.29
Bias in price (%)	12.96	20.57	0.00	5.64	20.21	-9.08	71.63
Cost impact of bias (%)	11.57	20.71	6.32	17.50	23.34	-63.15	75.78
Panel B: CEO left within 36 months							
	Manipulation rate (%)		Equally weighted bias in price (%)		Value-weighted bias in price (%)		
	65.00		16.71		5.46		
	Mean	Std dev	25th	50th	75th	Min	Max
Bias in net assets (%)	0.83	1.16	0.19	0.61	1.32	-1.32	3.70
Bias in earnings (%)	0.27	0.55	0.00	0.08	0.47	-0.56	1.75
Bias in price (%)	16.71	25.63	0.00	5.77	26.87	-8.67	88.32
Cost impact of bias (%)	19.51	23.51	18.10	25.27	31.37	-82.59	96.35

Table 7. Definitions of discretionary accruals measures

Compustat XPF data items: AT is Assets - Total, SALE is Sales/Turnover (Net), RECT is Receivables Total, PPENT is Property Plant and Equipment - Total (Net), IBC is Income Before Extraordinary Items, XIDOC is Extraordinary Items and Discontinued Operations (Statement of Cash Flows), NI is Net Income (Loss), OANCF is Operating Activities - Net Cash Flow, LT is Liabilities - Total, PSTK is Preferred/Preference Stock (Capital) - Total, CHE is Cash and Short-Term Investments, IVST is Short-Term Investments - Total, ACT is Current Assets - Total, LCT is Current Liabilities - Total. The final variables are winsorized at the 1st and 99th percentiles.

	Abbreviation	Definition
Total accruals	ntac	Total accruals are measured following Hribar and Collins [2002] as $IBC_t - (CFO_t - XIDOC_t)$, and if missing as $NI_t - OANCF_t$ or as implied by the balance-sheet approach. This variable is scaled by lag of total assets.
Accruals as in Richardson et al. [2005]	rsst_acc	Accruals computed following Richardson et al. [2005] are calculated as the sum of the change in non-cash working capital, the change in net non-current operating assets, and the change in net financial assets. The formula simplifies to $(((AT_t - LT_t - PSTK_t) - (CHE_t - IVST_t)) - ((AT_{t-1} - LT_{t-1} - PSTK_{t-1}) - (CHE_{t-1} - IVST_{t-1})))$. This variable is scaled by lag of total assets.
Jones model discretionary accruals	nda	Accruals following the Jones [1991] model are given as the residuals from cross-sectional regressions (for every two-digit SIC code and fiscal year) of total accruals on a constant, the reciprocal of AT_{t-1}, $\Delta SALE_t$, and $PPENT_t$. All variables are scaled by lag of total assets, AT_{t-1}. Estimation requires at least ten observations per group.
Modified Jones model discretionary accruals	mnda	Accruals following the Dechow et al. [1995] model are given as the residuals from cross-sectional regressions (for every two-digit SIC code and fiscal year) of total accruals on a constant, the reciprocal of AT_{t-1}, $\Delta SALE_t - \Delta RECT_t$, and $PPENT_t$. All variables are scaled by AT_{t-1}. Estimation requires at least ten observations per group.
Performance-matched discretionary accruals	pmnda	The difference between Jones model discretionary accruals for firm i and mean Jones model discretionary accruals for the matched firms, where the matching is performed based on two-digit SIC code, fiscal year, and ROA_t for a matched firm within a 1% interval of firm i's ROA_{it}. Here, ROA_t is computed following Kothari et al. [2005] as NI_t/AT_{t-1}. Estimation requires at least two valid matches.

Table 8: Descriptive statistics for the variables used in the discretionary accruals tests

Panel A contains summary statistics for the variables used in the discretionary accruals tests where the model-implied bias is computed using the cost parameter estimates obtained from the sample of 1,815 CEOs. This sample defines intentional misstatement as a restatement in which the CEO left the firm between the end of the restated period and within six months of the restatement filing date. Panel B contains summary statistics for the variables used in the discretionary accruals tests where the model-implied bias is computed using the cost parameter estimates obtained from the sample of 1,850 CEOs. This sample defines intentional misstatement as a restatement in which the CEO left the firm between the end of the restated period and within 36 months of the restatement filing date. Details on bias estimation are in Section 5.4. Definitions of the discretionary accruals variables are in Table 7. *Bias in earnings* is the model-implied bias in earnings scaled by the lag of total assets, i.e., $n_0(\widehat{B}_t - \widehat{B}_{t-1})/AT_{t-1}$. *Long-term earnings growth* is the median analyst long-term growth forecast in the three months before and the three months after the fiscal year-end as reported by I/B/E/S (I set missing values equal to firm-specific means). The sample in Panel A contains 640 CEOs and 1,958 pooled CEO-year observations where the model-implied bias in net assets is non-zero. The sample in Panel B contains 658 CEOs and 1,982 pooled CEO-year observations where the model-implied bias in net assets is non-zero. I omit the observations with manipulation measures more than three standard deviations away from their respective means.

Panel A: CEO left within six months							
	Mean	Std dev	25th	50th	75th	Min	Max
Total accruals (%)	-7.07	7.66	-10.06	-5.95	-2.70	-43.01	24.00
Accruals as in Richardson et al. [2005] (%)	0.02	13.17	-5.52	1.10	5.98	-51.80	52.06
Jones model discr. accruals (%)	1.42	7.43	-1.85	1.77	5.65	-32.56	32.07
Modified Jones model discr. accruals (%)	1.29	7.47	-2.00	1.63	5.45	-32.64	31.95
Performance-matched discr. accruals (%)	-0.63	7.11	-4.08	-0.51	3.10	-27.61	26.13
Bias in earnings (%)	0.16	0.55	0.00	0.06	0.37	-2.30	2.82
Long-term growth (%)	14.27	11.29	9.00	13.00	17.61	-92.00	87.50
Panel B: CEO left within 36 months							
	Mean	Std dev	25th	50th	75th	Min	Max
Total accruals (%)	-7.14	7.75	-10.16	-5.95	-2.65	-43.01	24.00
Accruals as in Richardson et al. [2005] (%)	0.04	12.87	-5.29	1.10	5.99	-51.80	51.41
Jones model discr. accruals (%)	1.25	7.49	-1.99	1.56	5.56	-32.56	32.07
Modified Jones model discr. accruals (%)	1.12	7.53	-2.09	1.44	5.36	-32.64	31.95
Performance-matched discr. accruals (%)	-0.70	7.23	-4.13	-0.48	3.15	-27.61	26.13
Bias in earnings (%)	0.24	0.71	0.00	0.07	0.49	-2.98	3.64
Long-term growth (%)	14.27	11.99	8.83	13.00	17.50	-92.00	148.41

Table 9: Association between discretionary accruals and the model-implied measure of manipulation

Panel A reports the linear regression estimates for the model-implied bias in earnings, which is computed using the cost parameter estimates from Table 3 (Panel A). Panel B reports linear regression estimates for the model-implied bias in earnings, which is computed using the cost parameter estimates from Table 3 (Panel B). Details on bias estimation are in Section 5.4. Definitions of the discretionary accruals variables are in Table 7. *Bias in earnings* is the model-implied bias in earnings scaled by the lag of total assets, i.e., $n_0(\widehat{B}_t - \widehat{B}_{t-1})/AT_{t-1}$. *Long-term earnings growth* is the median analyst long-term growth forecast in the three months before and the three months after the fiscal year-end as reported by I/B/E/S. The model is estimated using the pooled sample of CEOs with a model-implied non-zero bias in net assets. I omit observations with manipulation measures more than three standard deviations away from their respective means. Standard errors clustered by executive are in parentheses.

Panel A: CEO left within six months										
	ntac	ntac	rsst_acc	rsst_acc	nda	nda	mnda	mnda	pmnda	pmnda
Intercept	-0.070***	-0.064***	0.005	0.003	0.014***	0.015***	0.013***	0.013***	-0.008***	-0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bias in earnings	-0.465	-0.135	-2.938***	-2.913***	-0.147	-0.023	-0.241	-0.043	0.958***	0.931**
	(0.39)	(0.53)	(0.74)	(0.89)	(0.37)	(0.47)	(0.37)	(0.47)	(0.37)	(0.44)
Long-term growth		-0.031		0.036		-0.010		-0.007		-0.003
		(0.03)		(0.03)		(0.03)		(0.03)		(0.02)
Adj.R2	0.001	0.001	0.014	0.014	-0.000	-0.002	-0.000	-0.002	0.005	0.004
Obs.	1861	1136	1861	1136	1861	1136	1861	1136	1861	1136
Panel B: CEO left within 36 months										
	ntac	ntac	rsst_acc	rsst_acc	nda	nda	mnda	mnda	pmnda	pmnda
Intercept	-0.071***	-0.064***	0.005	0.003	0.013***	0.013***	0.011***	0.012***	-0.009***	-0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bias in earnings	-0.327	-0.291	-1.900***	-1.531**	-0.018	-0.038	-0.111	-0.094	0.677**	0.711**
	(0.30)	(0.38)	(0.52)	(0.67)	(0.29)	(0.35)	(0.28)	(0.35)	(0.29)	(0.34)
Long-term growth		-0.032		0.036		-0.006		-0.004		-0.003
		(0.02)		(0.03)		(0.02)		(0.02)		(0.02)
Adj.R2	0.000	0.002	0.010	0.007	-0.001	-0.002	-0.000	-0.002	0.004	0.004
Obs.	1982	1197	1982	1197	1982	1197	1982	1197	1982	1197