Measuring Intentional Manipulation: A Structural Approach

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March 30, 2013

Abstract

Using a sample of about 1,500 CEOs in the post-Sarbanes-Oxley Act of 2002 period, I estimate the extent of undetected intentional manipulation in earnings and managers' manipulation costs using a dynamic finite-horizon structural model. The model features a risk-averse manager, who receives cash and equity compensation and maximizes his terminal wealth. I find that the expected cost of manipulation is low. The probability of detection is estimated to be 9%, and the average misstatement results in an 11% loss in the manager's wealth if the manipulation is discovered. According to the estimated parameters, the implied fraction of manipulating CEOs is 66%, and the value-weighted bias in the stock price across manipulating CEOs is 15.5%. At the same time, the value-weighted bias in the stock price across all CEOs is 6%. Finally, I find that out-of-sample, the model-implied measure of intentional manipulation performs at least eight times better in terms of the root mean squared error than any of the five proxies for earnings management that have been used in the extant literature.

*I thank my dissertation committee at the Stanford Graduate School of Business - Anne Beyer, David Larcker (co-advisor), Maureen McNichols, Joseph Piotroski, and Peter Reiss (co-advisor) - for their invaluable guidance and support. I acknowledge the University of Chicago Research Computing Center (RCC) for support of this study. I am grateful to John Johnson, Hakizumwami Birali Runesha (RCC), Andy Wettstein (RCC), Darren Young and, especially, Ravi Pillai and Robin Weiss (RCC) for their help with computing resources. I learned about computational issues from discussions with Che-Lin Su, Kenneth Judd and Stefan Wild. I extensively discussed the institutional details of restatements with Dennis Tanona and Olga Usvyatsky from Audit Analytics, Inc. I am grateful to Gaizka Ormazabal, Alan Jagolinzer, Christopher Armstrong, and Allan McCall for their insights into executive compensation data and to Mary Barth, Bill Beaver, Jean-Pierre Dube, Arthur Korteweg, Sergey Lobanov, John Lazarev, Pedro Gardete, Jesse Shapiro, Stephan Seiler, Ilya Strebulaev, Chad Syverson, Maria Ogneva, and Anita Rao for many helpful comments and suggestions. I would like to thank Carol Shabrami and Sarah Kervin for editorial help. I also benefited from the comments of the seminar participants at the Stanford Graduate School of Business, the Wharton School of Business, the Columbia Business School, the University of Chicago Booth School of Business, the Yale School of Management, the NYU Stern School of Business, the London Business School, and the 2013 FARS Midyear Meeting. I thank the Neubauer Family Foundation for financial support.

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1. Introduction

This paper attempts to estimate managers' costs of lying about earnings and the extent of undetected manipulation in the post-Sarbanes-Oxley Act of 2002 (post-SOX) period. In this period, approximately 4.2% of the companies presently listed on the NYSE, the Amex, or NASDAQ restated their financial statements, with about 70% of the restatements affecting net income [Cheffers et al., 2011]. Although a majority of companies attribute restatements to innocuous internal company errors [Plumlee and Yohn, 2010], questions about whether these restatements reverse the intentional manipulation decisions made by management and the extent of undetected manipulation remain. The major difficulty researchers face in addressing these issues lies in the imperfect ability of outside parties to detect intentional manipulation [e.g., Feroz et al., 1991, Correia, 2009, Dechow et al., 2010]. If, in fact, a substantial amount of undetected manipulation exists, it is important to ascertain its magnitude and potential impact on shareholder value. These insights would allow investors, boards of directors, regulators and researchers to make informed decisions about resources that should be invested in the detection and prevention of manipulation.

This paper implements a structural model of a manager's manipulation decision, which follows an economic approach to crime [Becker, 1968] by incorporating the manager's costs and benefits of manipulation. The structural model allows for the possibility that manipulation is not detected perfectly. It also allows for an estimation of his manipulation cost parameters, as well as an inference about the bias in the stock price induced by the manipulation. The manipulation decision is modeled as a solution to an optimization problem of a risk-averse manager in a dynamic finite-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

[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.

[e.g., Bergstresser and Philippon, 2006, Harris and Bromiley, 2007, 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.

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 with 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 bias in net assets) and that the benefit depends on the amount of manipulation in current earnings (i.e., the difference in consecutive biases in net assets) implies that the existing bias in net assets acts as a constraint on the manipulation decision.[2] This feature is the *valuation* effect which states that the manager chooses a higher bias in net assets in the current period if the existing bias in net assets is also high. Another feature of the model is the *wealth* effect, which implies that a risk-averse manager with greater total wealth chooses a smaller bias since he does not value the additional dollar of manipulation as much and, at the same time, the manipulation cost for him is higher. Finally, the manager's manipulation decision exhibits income-smoothing.[3]

In contrast to the common approach in the literature, the structural approach allows the estimation of the manipulation cost parameters, such as the probability of detection and the loss in wealth using the data on detected misstatements. Furthermore, estimates of these parameters permit the recovery of the incidence and magnitude of overall undetected manipulation. However, using the structural approach comes at a cost, because it imposes strong assumptions on the data related to the functional form of the manager's objective function. For instance, I assume that the manipulation incentives are primarily determined by the relative importance of the manager's equity holdings in the firm and his cash wealth;

[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].

[3]The phenomenon of smoothing by managers has received substantial attention in the theoretical literature. For example, it is derived as a result of smoothing consumption in an agency setting [e.g., Lambert, 1984, Dye, 1988] or a non-agency setting [e.g., Sankar and Subramanyam, 2001], to lower the perceived probability of bankruptcy [e.g., Trueman and Titman, 1988], and/or to maximize the manager's tenure in the firm [e.g., Fudenberg and Tirole, 1995].

then, I use observed equilibrium compensation and earnings pricing multiples to solve the manager's dynamic optimization problem with respect to manipulation. While these assumptions are strong and can be relaxed in future research, they allow me to estimate the model and provide useful descriptive evidence about executives' manipulation decisions.

Because the structural model described here does not allow for a closed-form solution to the manager's optimization problem, I use the Simulated Method of Moments (SMM) to estimate the costs of manipulation parameters.[4] In this approach, I solve the individual optimization problem for each executive in my sample of about 1,500 CEOs. This method allows me to incorporate heterogeneity into manipulation decisions, which is assumed to be primarily determined by differences in the structure of the executives' compensation packages. The estimation uses observed data on restatements that are included in the category of non-technical and nontrivial restatements from the Audit Analytics Advanced Restatement database over the post-SOX period.

The data on restatements define four moment conditions which I use to identify three parameters: the probability of detection, the loss in wealth, and the sensitivity of the loss in wealth to the magnitude of manipulation. The four moment conditions are the fraction of restating firms, the mean bias in net assets in the first restated period, the mean product of biases in net assets in the first two restated periods, and the mean ratio of cash wealth to the value of inflating earnings by one dollar. The probability of detection and the loss in wealth are primarily identified from the fraction of restating firms and the mean ratio of cash wealth to the value of inflating earnings by one dollar because these parameters determine the manager's binary decision to manipulate. The sensitivity parameter is primarily identified from the two moments which utilize the magnitude of bias in net assets.

One of this paper's major findings is that the expected cost of manipulation is low. Specifically, the estimated probability of the manipulation being detected is 9%. If detected, the average misstatement results in a 11% loss in the manager's wealth for the non-technical restatement sample. According to the estimated model, the fraction of executives who manipulate during their tenure is 66%. This number is similar in magnitude to the 78% of

[4]The use of the SMM is common in structural corporate finance studies [Strebulaev and Whited, 2012].

executives reporting that they would sacrifice long-term value to smooth earnings [Graham et al., 2005]. In addition, two recent studies by Gerakos and Kovrijnykh [2013] and Dyck et al. [2013] provide a conservative estimate for the fraction of misreporting executives and fraud. According to Gerakos and Kovrijnykh [2013], the lower bound on the fraction of misreporting firms is about 22%, whereas according to Dyck et al. [2013], a conservative estimate for undetected fraud in any given year is 14.5%, assuming that the probability of fraud detection has increased substantially following the Arthur Andersen collapse.

At the same time, the value-weighted inflation in the stock price among manipulating executives is 15.5%, and the equally weighted inflation in the stock price is 24% for the non-technical restatements sample. The difference between value-weighted and equally weighted inflation implies that manipulation is primarily concentrated among small stocks. These estimates are similar to Dyck et al. [2013], who estimate the cost of fraud to investors to be around 22% of firm value. These estimates are also of the same order of magnitude as a negative 25% mean annual return in the year in which a firm restates its earnings. The value-weighted inflation in the stock price across all firms is 6%, which is two times higher than the 3% estimated by Dyck et al. [2013] for fraud cases.

Finally, based on the out-of-sample tests, the model-implied measure of manipulation is at least eight times better at predicting the magnitude of manipulation in earnings than the commonly used measures of discretionary accruals[5] [e.g., Jones, 1991, Dechow et al., 1995, Kasznik, 1999, Kothari et al., 2005] in terms of the root mean squared error. This finding implies that finance and accounting researchers should be cautious about using discretionary accruals as a proxy for earnings management, and, instead, carefully consider the benefits and costs of misreporting specific to their research setting.

While there is an extensive literature on earnings management[6] and on the relationship

[5] A measure of discretionary accruals is a residual from a regression of total accruals on the determinants of normal accruals. These measures are biased to the extent that the model does not use the true determinants of normal accruals [see the discussion in McNichols, 2000] and ignores the incentives behind the manipulation decision. Consequently, previous research indicates that measures of discretionary accruals do not predict actual cases of manipulation, such as severe restatements and fraud [e.g., Dechow et al., 2011, Price et al., 2011, Larcker and Zakolyukina, 2012].

[6] For a review of the empirical research, see Healy and Wahlen [1999], Dechow and Skinner [2000], and Dechow et al. [2010]. For a review of the theoretical research, see Lambert [2001] and Ronen and Yaari

between earnings management and equity incentives[7], this is the first study to estimate earnings management using a structural model. Moreover, this study represents the first attempt to fit an economic model to data on restatements and executive compensation and to evaluate the manager's manipulation costs. Although the model is stylized, its specification is detailed enough to capture important features of the data such as the partial observability of manipulation decisions.

The remainder of the paper consists of five sections. Section 2 discusses why the structural approach is particularly suitable in studying earnings manipulation. Section 3 outlines the model and presents the intuition using a manager's decision in the last period. 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. Structural estimation

I use the structural approach to estimate the expected cost of manipulation in earnings because it allows model-specific parameters that cannot be observed directly to be quantified. Such parameters determine the manager's decision about what earnings number to report and include the probability of detection and, if detected, the manager's loss in wealth. To estimate these parameters, I fit the model to the data on detected manipulation. I then use the model to infer the magnitude of undetected manipulation in reported earnings.

The structural approach has frequently been used in economics, particularly to study industrial organization [e.g., Reiss and Wolak, 2007, Einav and Levin, 2010] and consumer choices [e.g., Nevo and Whinston, 2010, Keane, 2010]. Structural estimation also provides useful insights into corporate finance [e.g., Whited, 1992, Hennessy and Whited, 2005, Morellec et al., 2012, Nikolov and Whited, 2009, Taylor, 2010, Matvos and Seru, 2013, Strebulaev and Whited, 2012]. It allows the estimation of theoretical parameters and provides a better understanding of the precise economic mechanisms behind the decisions made by managers and firms. It is often possible to test how well the model explains the data within this

[2008].

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

framework. However, the core feature of structural models is their potential in examining counterfactuals, i.e., extrapolating from observed responses to predict responses under an environment that has not yet been observed.

To infer undetected manipulation in this study, I analyze the primitives of the manager's decision problem, which differs from the extant studies that typically measure manipulation using discretionary accruals. Discretionary accruals are defined as residuals from a linear regression of some measure of total accruals on the *ad hoc* determinants of normal accruals. However, measuring manipulation via discretionary accruals is problematic because they are correlated with firms' characteristics that are unrelated to manipulation, such as, for instance, growth [McNichols, 2000]. Furthermore, such statistical models do not incorporate the costs and benefits of manipulation to the manager. Therefore, only by estimating the model of the manager's decision to lie about earnings can the managers' manipulation costs and the magnitude of unobserved manipulation be assessed, which is done in this paper.

3. Model

3.1 Model outline

The model features a risk-averse manager who maximizes the utility of his wealth when he leaves the firm. His terminal wealth depends on both the manager's equity holdings in the firm and cash. At each period, the manager can strategically distort the reported earnings in order to inflate the stock price and, hence, the value of his equity holdings.[8]

The firm's stock price deviates from the firm's intrinsic value by an amount proportional to the bias in earnings, which equals the difference in the biases in net assets. This specification accommodates various potential rates of accrual reversal because the manager can always bias net assets by an additional dollar to compensate for any reversal rate. This is possible because the cost of manipulation is assumed to depend only on the total bias in

[8] A number of theoretical papers consider the rational expectations equilibrium when the market 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 since incorporating rational expectations into a multi-period setting is a difficult theoretical problem that lies beyond the scope of this paper.

net assets rather than on the incremental bias introduced in each period. Therefore, when selecting the bias in net assets in the current period, the manager considers the bias in net assets in the previous period as well as the effect his choice of current-period bias in net assets will have on future optimal bias levels.

The manager's choices of bias determine the value of his wealth when he leaves the firm. The manager can leave the firm for the following three reasons. First, the manager can leave the firm for reasons unrelated to manipulation with a certain probability. This 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 voluntarily, will arise. Second, the manager can be forced to resign when manipulation is detected, and the firm restates its financial statements. Third, the manager must leave the firm when he reaches a retirement age; thus, his dynamic optimization problem has a finite horizon. That is, irrespective of the reason for which the manager leaves, his utility is a function of the value of his equity holdings and cash at that time.

The composition of the manager's compensation, as captured by the relative magnitudes of his equity holdings and cash, determines his manipulation decision. The manager benefits from the manipulation by increasing the stock price and, as a result, the value of his equity holdings. At the same time, he expects to incur a loss in his wealth once the manipulation is detected. Because the manager receives a new grant of shares and periodic cash compensation, his wealth changes every period. However, the terminal value of the manager's wealth depends on whether he manipulates and whether his manipulation is detected.

If he has never manipulated before, the manager can decide whether to manipulate in each period. Once he has decided to manipulate, he chooses the optimal amount of the bias in net assets in every future period before the manipulation is detected or he leaves the firm. The optimal amount of manipulation in the future periods could be zero, depending on the firm's current intrinsic value (because this value affects the future distribution of the manager's equity wealth) as well as the existing bias. If he manipulated before, he also faces the probability of detection in each future period. Then, if the manipulation is detected, the restatement is made, and the manager can be forced to resign. Restatement corrects the bias; thus, the stock price equals the intrinsic value subsequent to the detection. However, if the manager is not terminated after the detection, he can never manipulate again, because the board significantly improves its monitoring.

The board can also force the manager to resign, in which case the manager incurs a loss proportional to his wealth. I assume that the loss is a convex function of the bias in net assets as well as that either positive or negative misstatements are equally costly to the manager. As a result of the forced resignation, the manager suffers a loss in his wealth, the loss of non-vested equity holdings[9] in addition to the loss of the future compensation that he would have earned had he stayed with the firm. The solution to the multi-period problem and the formal description of the model are presented in Appendix A.

3.2 Final period decision

Each period, the manager decides whether to manipulate and by how much by solving the finite-horizon problem. A finite horizon implies that the manager's optimal decision depends on the number of periods remaining until the final date T. In addition, his decision is determined by the path of his future wealth and equity holdings as well as by the distribution of the future intrinsic firm value. To simplify the explanation, I demonstrate the intuition underlying the manager's decision using the optimization problem he solves at the final date T. This intuition will carry over to the earlier periods.

At the final date T, the manager privately observes the realization of the intrinsic firm value, p_T; and, if he has manipulated in the previous periods, the magnitude of the existing bias in net assets, b_{T-1}. If the manager has manipulated before, he chooses an amount of manipulation that is a function of the intrinsic firm value and the existing bias in net assets, $b_T(p_T, b_{T-1})$. However, if the manager has not manipulated before, he can decide to manipulate, in which case he chooses a magnitude of manipulation, which is a function of the intrinsic firm value only because the existing bias is zero by definition, $b_T(p_T)$.

If the manager manipulates, his payoff depends on whether his manipulation is detected

[9] This idea is consistent with the common feature of compensation contracts in the sense that the manager automatically loses his non-vested equity if he is terminated.

and whether he is terminated as a result of this detection. If the manipulation is not detected, the manager receives his wealth valued at the stock price distorted by the manipulation. However, if manipulation is detected and the manager is terminated, the manager receives only a fraction of his wealth, valued at the intrinsic price. This fraction decreases with the magnitude of manipulation; therefore, higher levels of manipulation imply that the manager receives less wealth. Finally, if manipulation is detected and the manager is not terminated, the manager receives his wealth valued at the intrinsic price, which equals the wealth he would have received if he had been honest. Denote the wealth the manager would have received if he had been honest by $\widetilde{w}_T = w_T + n_T p_T$ (where w_T is the manager's cash holdings, $n_T = n_T^v$ is his vested equity holdings[10]), then his expected payoff at T becomes:

$$\max_{b_T}(1-g)\underbrace{U\Bigg(\widetilde{w}_T + n_T\beta(b_T - b_{T-1})\Bigg)}_{not\ detected} + \\ + g\phi\underbrace{U\Bigg(\widetilde{w}_T\Bigg(1-\kappa_1-\frac{\kappa_2}{2}(\beta b_T)^2\Bigg)\Bigg)}_{detected,\ terminated} + g(1-\phi)\underbrace{U\Bigg(\widetilde{w}_T\Bigg)}_{detected,\ not\ terminated}, \quad (1)$$

where g is the probability of detection; ϕ is the probability of termination if the manipulation is detected; κ_1 is the loss in the manager's wealth if he has ever manipulated; κ_2 is the sensitivity of the loss in the manager's wealth to the magnitude of manipulation; β is the price-to-earnings multiple; and $U(.)$ is a constant relative risk aversion utility.

The optimal choice of bias $b_T^*(p_T, b_{T-1})$ satisfies the first-order condition:

$$(1-g)U'\Bigg(\widetilde{w}_T + n_T\beta(b_T^* - b_{T-1})\Bigg)n_T = g\phi U'\Bigg(\widetilde{w}_T\Bigg(1-\kappa_1-\frac{\kappa_2}{2}(\beta b_T^*)^2\Bigg)\Bigg)\kappa_2\beta b_T^*. \quad (2)$$

If the manager has not manipulated before, he decides to manipulate if the payoff he receives from manipulating, $b_T^*(p_T)$, is strictly greater than the payoff he would have received

[10] To simplify the notation, I set his non-vested equity holdings to zero.

if he had not been manipulating:

$$(1-g)U\left(\widetilde{w}_T + n_T\beta b_T^*\right) + g\phi U\left(\widetilde{w}_T\left(1-\kappa_1-\frac{\kappa_2}{2}(\beta b_T^*)^2\right)\right) + \\ + g(1-\phi)U\left(\widetilde{w}_T\right) > U\left(\widetilde{w}_T\right). \quad (3)$$

For the general case of the constant relative risk aversion utility, this problem cannot be solved analytically. Therefore, I solve the problem numerically. Fig. 1 depicts the optimal magnitude of manipulation when the manager manipulates for the first time, $b_T^*(p_T)$, and the optimal magnitude of manipulation if the manager continues to manipulate, $b_T^*(p_T, b_{T-1})$, at the terminal date T.

The manager trades off the benefit he receives from distorting the stock price and the cost that is incurred if his manipulation is detected and he is terminated. The cost is proportional to the manager's wealth; hence, wealthier managers may not start manipulating in the final period because the cost of termination for them at that time is higher. However, if the manager manipulates in the final period, he will always manipulate a positive amount because there is no future benefit to downwards distortion. On the other hand, it can be optimal for a wealthier manager to distort the stock price downwards in previous periods. This downwards distortion provides the manger with the reserve of manipulation that can be reversed to inflate earnings in future periods. This practice is well known as a "cookie jar" reserve, and the manager uses it to smooth the value of his wealth.[11]

The optimal magnitude of manipulation, $b_T^*(p_T, b_{T-1})$ generally decreases with the intrinsic value, p_T, which I label the *wealth* effect, and increases with the existing bias, b_{T-1}, which I label the *valuation* effect (Fig. 1). According to the *wealth* effect, the wealthier managers have a lower magnitude of manipulation because they benefit less from manipulation, but, at the same time, manipulation is still costly for them, as can be seen from the first-order condition (2). This effect arises because the manager is risk-averse, and the cost of manipulation is proportional to his wealth. Accordingly, his marginal benefit of manipulation decreases

[11]Income-smoothing has been derived in extant theoretical literature in a number of settings [see, for instance, Lambert, 1984, Dye, 1988, Fudenberg and Tirole, 1995].

more rapidly than his marginal cost when the wealth of the manager increases (under the non-zero cost of manipulation parameters, (κ_1, κ_2)).

According to the *valuation* effect, the optimal bias in net assets in the current period increases with the existing bias in net assets. This effect ensues because the manager is risk-averse and reported earnings (possibly distorted by the difference in the biases in net assets, $b_T - b_{T-1}$) are used by investors to price shares. The manager's risk aversion is important for this effect to occur because his marginal benefit of manipulation increases in the existing bias, whereas his marginal cost depends only on the current-period bias. For instance, suppose that the manager biased net assets by $10 in the previous period compared to a $1 bias. In this case, the manager has greater incentives to misreport because if he did not bias net assets in the current period, his firm's earnings would be lower by $10; whereas the earnings would be lower by just $1 if the bias in the previous period was $1.

Finally, manipulation is a convex function of wealth (Fig. 1). Manipulation by less wealthy managers declines more rapidly as his wealth increases compared to the case of wealthier managers. This effect is the result of the manager being risk-averse; thus, less wealthy managers become more sensitive to the changes in their wealth caused by manipulation.

To summarize, the optimal level of manipulation is determined by three effects. First, the *wealth* effect implies that wealthier managers manipulate less. Managers' manipulation pattern smooths the value of their wealth. Second, the *valuation* effect implies that the optimal bias in net assets in the current period increases with the existing bias in net assets. Third, manipulation is a convex function of wealth. The intuition behind the results established in the final period carries over to the multi-period case.

4. Estimation

4.1 Data

The model estimation requires data on executive compensation, CEO turnover, restatements, and the parameters of the intrinsic value process. To be consistent with the model, I only consider restatements that are fully covered by the CEO's tenure and have a non-zero effect on net income. Restatements may be issued for a variety of reasons and may not be intentional; whereas this model hypothesizes that the manager chooses manipulation optimally, expecting that it may be detected with some probability. Accordingly, manipulation in the model has two features: first, it should represent non-GAAP accounting that, if detected, should be restated; second, the misstatement should be intentional. To satisfy the first criterion, I consider only restatements that are due to accounting errors. However, it is difficult to satisfy the second criterion; therefore, some discretion is unavoidable. I try to deal with this issue by allowing for different definitions of an "intentional" misstatement and estimating the model with two groups of restatements: non-technical and nontrivial.[12]

Data on CEO compensation are obtained from the comprehensive database on executive compensation collected from annual proxy filings (DEF 14A) provided by Equilar, Inc. The Equilar database coverage is more than double the coverage of Compustat Execucomp. This database includes the CEO resignation date, but does not list the date on which the CEO leaves the firm. These two dates can be different, for instance, because the CEO could resign, but remain with the firm as a member of the board. I obtained the date on which the CEO left from the BoardEx database, which provides the employment histories of individual executives. Data on restatements originate from the Audit Analytics Advanced Restatement database, which contains data from the restatement footnotes for firms traded on the NYSE, the Amex, or NASDAQ at the end of 2007 or any time thereafter. Accordingly, there are two groups of executives in my sample depending on whether the firm has restated its financial statements. The first group comprises executives who had no restatements during their tenure and became CEOs between August 1, 2002 and December 31, 2007. The second group of executives represents those who issued a restatement during their tenure if they became CEOs before December 31, 2007; and, the restated periods for them began after August 1, 2002. As a result, the sample represents an intersection of the Equilar and BoardEx data sets

[12] I have also estimated the model using the data on restatements that involve allegations of fraud, formal and informal SEC investigations, or class-action lawsuits. There are only 28 instances of such restatements in my sample; as a result, I found that the model is rejected, probably because not enough variation exists in the detected misstatements in this case.

with the additional restriction that the firm be listed on the NYSE, the Amex, or NASDAQ as of December 31, 2007 or any time thereafter.

The industry composition based on Standard & Poor's Global Industry classification groups of the sample firms is almost identical to the industry composition of firms in Compustat. The industries comprising a larger percentage of firms include capital goods (7%), health care equipment and services (7%), banks (9%), and software and services (8%). The industries below 1% include food and staples retailing and household and personal products. 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 the return on assets and profit margins), sales growth, and capital structure (as measured by the book-to-market ratio, leverage, and free cash flows) (Table 2).

I attempt to exclude extraneous restatements by considering two groups of restatements: non-technical and nontrivial.[13] This strategy represents a tradeoff between the likelihood of these restatements being intentional and the amount of variation in the data. Having only a few restatements can be a problem in my setting. Indeed, the number of restatements decreases by half as the criteria for the seriousness of a restatement become more restrictive (Table 3). First, non-technical restatements (165 cases) exclude lease-related restatements[14], restatements related to SAB 108 and FIN 48 implementation because these restatements do not provide a complete time-line for the misreporting and are likely to be non-intentional. Second, nontrivial restatements (99 cases) are non-technical restatements that exclude accounting issues that do not trigger a significant negative market reaction according to Scholz [2008]. These restatement groups differ in the characteristics that are hypothesized by previous research to capture the severity of a misstatement [Palmrose et al., 2004, Scholz, 2008]. Specifically, nontrivial restatements contain more misstatements related to revenue recognition, core expenses, and correct a greater number of accounting issues. The

[13]The recent paper by Karpoff et al. [2012] caution researchers that commonly used restatement databases, including Audit Analytics, contain potentially extraneous restatements that are not necessarily related to misconduct.

[14]See http://www.sec.gov/info/accountants/staffletters/cpcaf020705.htm

mean annual return in the year in which the restatement was disclosed equals negative 25% for both groups of restatements (Table 3). Accordingly, I estimate two models of intentional manipulation when these two groups of restatements are classified as "intentional."

Executives' total wealth (the sum of outside and firm-specific wealth) is unobserved; however, it is usually approximated as being a multiple of firm-specific wealth comprised of cash compensation and the value of equity holdings [e.g., Core and Guay, 2010, Conyon et al., 2011]. For instance, it is often assumed that a CEO's firm-specific wealth is between 50% and 67% of his total wealth. Accordingly, I assume that a CEO's initial outside wealth (or initial cash wealth) equals his firm-specific wealth in the first period. In addition, I assume that his periodic cash compensation adds to his cash wealth and that he earns a risk-free rate of 2% on his cash wealth every year.

The finite horizon of the problem requires an assumption about the terminal date; I assume that the manger leaves the firm with certainty at the age of 85. I make this assumption because some executives stay in the firm after they have reached the age of 80. However, not all the executives stay in the firm until they are 85; hence, I must extrapolate the manager's compensation until that age. Specifically, I assume that cash compensation and equity holdings for each executive grow at an annual rate equal to the median growth in industry-revenue groups. Before that age, an executive could leave the firm for restatement-related or other reasons. I assume that his departure is restatement-related if he departs between the end of the restated period and within one year following the restatement filing date.[15]

Industry-specific parameters are defined based on Standard & Poor's Global Industry classification groups.[16] These parameters include the price-to-earnings multiple and parameters corresponding to the firm's intrinsic value process. I set the price-to-earnings multiple equal to the median price-to-earnings multiple across firms in the same industry in order to avoid unusually large or small firm-specific values that are unlikely to persist over time. Similarly, I assume that firms in the same industry group experience a similar evolution of

[15] The extant studies use various assumptions about the time-window for restatement-related turnover that ranges from six months as in Hennes et al. [2008] and three years as in Srinivasan [2005].

[16] I use the classification in which the number of industries is 24.

intrinsic value because they are likely to have similar investment opportunities, technologies, and markets. Accordingly, the intrinsic value parameters are set to their corresponding industry medians.

I measure the bias as the difference between the initially-reported basic earnings per share (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 sum of the bias in earnings and the lagged bias in shareholders' equity in the first restated period.[17] The second-period bias in net assets is the sum of the bias in net assets in the first period and the bias in EPS in the second restated period.

Table 1 lists the parameter definitions. Descriptive statistics are presented in Table 4. The sample for which an intentional misstatement is defined as a non-technical (nontrivial) restatement contains $1,513$ $(1,462)$ CEOs. Because the two samples have virtually identical summary statistics, I discuss these statistics only for the sample of non-technical restatements. The mean cash wealth scaled by the value of CEOs' equity holdings in the first period is 191% with a large standard deviation of 141%. The mean of the number of vested shares as a fraction of the number of total shares in the first period is 99%, and the mean of the number of non-vested shares as a fraction of the number of total shares in the first period is 35%. The median age of a CEO is 53 years old, and he is observed in the sample for four years. The mean annual probability of leaving the firm for reasons unrelated to restatements is relatively low at 7%. The parameters for the intrinsic value process are the expected annual return with a mean of 8% and a standard deviation with a mean of 39%, which is comparable 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 21, which is consistent with the sample period being expansionary.

Although the summary statistics are similar across the two samples, the restatement rates differ. The sample in which an intentional misstatement is defined as non-technical (nontrivial) is associated with 11% (7%) of firms restating. The corresponding mean bias in net assets in the first restated period scaled by the stock price before a CEO joins a firm

[17] In most cases, the lagged bias in shareholders' equity in the first restated period is zero.

among restating firms is 1% (1%). The mean magnitude of bias in net assets in the second restated year is 0.66% (0.77%). The second period bias is lower because not all firms restate both periods.

4.2 Identification

I estimate three parameters that determine the expected cost of manipulation: the probability of manipulation being detected, g, the loss in the manager's wealth, κ_1, and the sensitivity of the loss in the manager's wealth to the magnitude of the manipulation, κ_2. These parameters are estimated using a structural model and are assumed to be constant across executives. Accordingly, I restrict my sample to the post-SOX period because SOX has increased criminal penalties and the CEO's exposure to liability for financial misreporting [Karpoff et al., 2008], and, hence, changed the cost of the manipulation parameters. It is certainly plausible that these parameters can be a function of managers' and firms' characteristics.[18] However, the rare nature of restatements does not allow me to incorporate such variation into the model.

These three parameters are identified from four moment conditions: the fraction of restating firms in the overall population (the population of manipulating CEOs is unobserved[19]); the mean bias in the first restated period, the covariance of biases in the first and second restated periods, and the mean ratio of cash wealth to the value of inflating earnings by one dollar. I use the biases in the first two restated periods because the firm restates its financial statements upon detection of manipulation; and an overwhelming majority of restatements corrects only two annual reports [Cheffers et al., 2011].

Managers have different incentives to manipulate. The heterogeneity in manipulation decisions arises from time and cross-sectional variation in the composition of the manager's wealth and in the amount of time remaining until retirement in addition to cross-sectional

[18] The paper by Schrand and Zechman [2012] suggests that the expected cost of misreporting earnings can vary across executives because differences in the degree of overconfidence may result in differing assessments of the probability of detection. In addition, the probability of detection can depend on the analyst following [Yu, 2008] and corporate governance [Hazarika et al., 2012].

[19] We do not observe all CEOs who manipulate in the data; instead, we only observe detected manipulation.

variation in the parameters of the intrinsic value process and in price-to-earnings multiples. Instead of modeling a general equilibrium, I assume that we observe the equilibrium path comprising managers' wealth and pricing multiples in the data. These values can perhaps incorporate the expectation about how much the manager would manipulate; however, when the manager solves his optimization problem, he takes these equilibrium values as being given.

I model the probability of detection and termination as exogenous although they could be a function of the bias.[20] Instead, I assume that the loss in wealth increases with the bias. This assumption allows the expected cost of manipulation to increase with the bias through the increased loss of wealth, rather than through the increased probability of detection or termination.[21]

The four moment conditions are selected based on their sensitivity to parameter changes. The first moment condition is the frequency of restatements. The changes in the probability of detection and the loss-in-wealth parameters affect the number of restatements differently. Once the probability of detection is held fixed, the number of restating firms decreases as the loss in wealth parameters increases. In contrast, the change in the probability of detection plays a dual role. On the one hand, as the probability of detection increases, the expected cost of manipulation increases; hence, fewer managers find it optimal to manipulate, which results in fewer restatements. On the other hand, once the loss in wealth is sufficiently low, as the probability of detection increases, the number of restatements may also increase.

[20] A model of optimal monitoring would imply that the probability of detection and termination should be higher when the cost of manipulation is low. However, I do not find that the firms in which the manager is more likely to manipulate have corporate governance features that are hypothesized to be related to better monitoring of the manager. Alternatively, monitoring by employees of the firm plays a role in fraud detection [Dyck et al., 2010]. It is not clear whether the intensity of monitoring by employees would be higher if the manager faces a lower cost of manipulation.

[21] I have also estimated the model in which the probability of detection depends on the bias. The parameters are not well identified and the model has a poor fit. The identification can be more difficult in this case because the manager has direct control over the probability of detection. The larger bias would imply a higher probability of detection, and hence, more restatements. At the same time, the larger bias would imply a higher expected cost of manipulation, and, hence, fewer manipulating managers and fewer restatements. Thus, an increase in the bias would have two opposing effects on the restatement rate, which makes it difficult to identify parameters. On the other hand, if the probability of detection is modeled as exogenous and only the loss in wealth depends on the bias, the effect of an increase in the bias is one-directional. Specifically, the larger bias would imply a higher expected cost of manipulation, and, as a result, fewer manipulating managers and fewer restatements.

The second moment condition is the mean first-period bias. This bias declines as the expected cost of manipulation increases. The third moment condition is the mean product of manipulation in the first and second periods. The bias in the second period decreases as the expected cost of manipulation increases, but it is less sensitive to parameter changes if the bias in the first period is large. This finding is a manifestation of the *valuation* effect: the second-period manipulation is more valuable if the first-period manipulation is large.

The fourth moment condition is the mean ratio of cash wealth to the value of inflating earnings by one dollar. The mean is taken over all future periods after the manager manipulates for the first time. This moment is particularly sensitive to changes in the probability of the manipulation being detected and to a loss in the manger's wealth because these parameters primarily affect the manager's decision to start manipulating. Indeed, the manager's manipulation can be detected and he can suffer a loss in his wealth anytime after he has manipulated once.

One parameter that is difficult to identify is the relative risk aversion parameter, γ. The difficulty associated with estimating the relative risk aversion parameter is well recognized in the macroeconomics and finance literatures. A risk aversion parameter equal to 2 or 3 is generally argued to be plausible and has been used in the prior empirical studies on executive compensation [e.g., Conyon et al., 2011]. I follow the literature by setting its value to 2 for the main result and set its value equal to 3 in the robustness test.[22] The probability f with which the manager can leave the firm for reasons other than a restatement is set to be equal to the annual turnover rate across CEOs with the same tenure.[23] The probability ϕ of the manager leaving the firm as a result of a restatement (i.e., the probability of termination) is set to be equal to a fraction of the restatement-related turnovers among restating firms.

[22]Alternatively, I could estimate the risk aversion parameter. However, the difficulty of the joint estimation of a discount factor and a risk aversion parameter is well recognized in the literature. This issue is relevant in my setting because I estimate the probability of detection, which acts like a discount factor when the manager starts manipulating. The literature usually deals with this issue by setting one parameter to a plausible value and estimating the other parameter. Similar to the extant literature, I fix the risk aversion parameter and estimate the probability of detection. The economic interpretation of a risk aversion parameter is provided in Ljungqvist and Sargent [2004] and Cochrane [1997].

[23]I assume that this probability equals 10% after ten years with the firm.

4.3 Estimation method

To estimate the expected cost of manipulation, I use the method of moments in which I closely match the moments from the data with the moments from the model. As discussed in Section 4.2, I use four moment conditions to estimate three cost-of-manipulation parameters. The closed-form expressions for these moment conditions cannot be obtained analytically; therefore, I use the Simulated Method of Moments (SMM). The objective function of the SMM is similar to that of the Generalized Method of Moments (GMM). Specifically, 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 to calculate the model-implied moments. In contrast, in the SMM, the model-implied moments are obtained using simulation. I provide details regarding the SMM estimation in Appendix B.

Since the number of moment conditions exceeds the number of parameters (four moment conditions are used to estimate three parameters), I can apply the test of overidentifying restrictions to assess the model fit. If the test is rejected, the SMM estimator is inconsistent. The rejection implies that a particular specification of the model, including all of the underlying assumptions about functional forms and distributions, is rejected. However, the test does not provide information about which specific moment does not hold.

5. *Results*

5.1 Parameter estimates

Parameter estimates for the structural model are presented in Table 5. For the sample of non-technical restatements, I find that the probability of the manipulation being detected is 9%, which is arguably low. The estimate of κ_1, the loss in the manager's wealth in the event that past manipulation is detected, whereas current financials are unbiased, is small at 0.03% 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 relatively small.

The estimate of κ_2, the sensitivity of the loss in the manager's wealth to the bias in net assets, can best be 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 a percentage of the manager's wealth loss when he inflates the stock price by 1%.[24] The marginal effect for the sample of non-technical restatements is 0.51, which implies that a 1% inflation in the stock price is associated with a 0.51% loss in the manager's wealth. As is the case with the probability of detection, the marginal wealth loss is also low. However, the average misstatement for the sample of non-technical restatements is higher and results in a 11% loss in the manager's wealth.[25] Because the manager's perceived costs of manipulation are not directly observable, there are no previous studies against which to benchmark these estimates. In fact, the ability to make inferences about unobserved theoretical parameters is the distinctive feature of my approach.

As a robustness check, I also estimate the structural model for the sample in which a detected intentional misstatement is defined as a nontrivial restatement. I find that the estimates are qualitatively similar. However, because of the lower frequency of restatements, the estimated perceived probability of manipulation being detected is 7%. Since the sample mean of the biases in net assets for this sample's first two periods is similar to that for the non-technical sample,[26] the estimated loss in the manager's wealth in the event of detection is similar, e.g., the marginal effect of manipulation is 0.42[27] versus 0.51 in the non-technical restatements sample. Similarly, for the sample of nontrivial restatements κ_1, the loss in the manager's wealth in the event that past manipulation is detected, whereas current financials are unbiased, is not statistically significant and equals 8%. Accordingly, the average

[24] The loss in the manager's wealth that is sensitive to the magnitude of manipulation is $\frac{\kappa_2}{2}(\beta b_t)^2$, 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 in the sample of non-technical restatements is 0.4329 (Table 8) and the estimate of κ_2 is 1.17 (Table 5), which implies that $\kappa_2 \overline{\beta b}_t \approx 0.51$

[25] The average wealth loss is computed as $\frac{\kappa_2}{2}(\beta b_t)^2\Big|_{\beta b_t = 0.4329} + \kappa_1 = 1.17 * (0.4329)^2/2 + 0.0003 \approx 0.11$.

[26] The bias in net assets in the first (second) restated period is 1% (0.65 %) in the non-technical sample and 1% (0.76%) in this sample.

[27] Here, I apply the same formula for the marginal effect, $\kappa_2 \overline{\beta b}_t = 0.96 * 0.4405 \approx 0.42$.

cost of manipulation in this sample is higher and equals 17%.[28] The sample of nontrivial restatements implies that manipulation is perceived by the manager as being more costly when detected, despite the fact that it has a lower probability of detection compared to the sample of non-technical restatements.

5.2 Model fit

The test of overidentifying restrictions, which is a formal test of whether the model actually explains the data, is reported in Table 5. The model is not rejected for either sample at conventional significance levels. The magnitude of the J-test (0.03 for the sample of non-technical restatements and 1.67 for the sample of nontrivial restatements) implies that the model is not rejected, including the choice of the moment conditions.

Following Taylor [2010], I study the Monte Carlo simulation results to assess the differences between empirical and simulated moments. Under this approach, the distribution of moments is obtained by simulating 10,000 samples of CEOs, assuming that the model parameters are equal to the estimates presented in Table 5. The p-values for the moment differences are reported in Table 6. All moments for the non-technical restatement sample are not significantly different from the simulated moments at the 5% significance level, whereas for nontrivial restatements, two moments (the mean product of biases in the first and second periods and the average ratio of cash wealth to the value of a dollar increase in manipulation) are reliably different from the simulated moments at the 1% significance level. However, empirical and simulated values are very similar in terms of their magnitudes.

5.3 Model-implied measure of manipulation

I use the structural model and estimated parameters to infer the implied extent of undetected manipulation from stock prices. To infer manipulation, stock prices have to be known in each period because the optimal manipulation decision in the current period depends on the

[28]The average wealth loss is computed as $\frac{\kappa_2}{2}(\beta b_t)^2\Big|_{\beta b_t=0.4405} + \kappa_1 = 0.96 * (0.4405)^2/2 + 0.0788 \approx 0.17$.

manipulation decision in the previous periods.[29] I utilize the price at the end of the third month following the end of the fiscal year as the current period price because it generally already incorporates the information in reported earnings.

For each firm in my sample, the model specifies what the stock price should be for a specific realization of the intrinsic value as well as the manager's manipulation incentives. I can then utilize the time-series of stock prices, the time-series of compensation and the structural model to infer the unobserved time-series of intrinsic values and manipulation decisions. This inference is possible because according to the model, the stock price is the sum of the intrinsic value and the product of the price-to-earnings multiple with the optimal bias in earnings. At the same time, the optimal bias in earnings is a function of the intrinsic value if the manager just started to manipulate; or, if the manager has manipulated before, the optimal bias is a function of the intrinsic value and the existing bias. Therefore, if the manager just began to manipulate, the stock price is solely a function of the intrinsic value; hence, I can infer the intrinsic value and the corresponding bias from the stock price. Furthermore, if the manager has already manipulated, the stock price is solely a function of the intrinsic value and the existing bias; hence, I can infer the intrinsic value and the corresponding bias from the stock price and the existing bias.

I infer undetected manipulation in three steps. First, I compute what the stock price should be given a specific realization of intrinsic value when the manager has never manipulated before. Second, I compute what the stock price should be given a specific realization of intrinsic value and the existing bias when the manager has already manipulated. Third, I use the time-series of stock prices to infer whether the manager manipulates and by how much. I constructed the sample in such a way that executives do not manipulate when they enter the sample. Therefore, for each executive, I can take the stock price in the first period and map it into his first-time manipulation decision in the first period. Next, if the stock price in the first period corresponds to the executive not manipulating, I take the second

[29]The price data are obtained from the Center for Research in Security Prices (CRSP). I omit executives for whom the stock price at 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, since the stock price process for these firms may deviate substantially from the process assumed in the model.

period price and map it into his first-time manipulation decision in the second period, and so on. However, if the stock price in the first period corresponds to the executive manipulating, I find the optimal bias in the first period and map the second period stock price and the first period bias (i.e., existing bias) into his manipulation decision to find the intrinsic value and the optimal bias in the second period, and so on.

The model-implied measures of manipulation are reported in two tables. Table 7 reports the descriptive statistics computed using all CEO-years; whereas Table 8 reports the descriptive statistics computed using only the CEO-years after the CEO has misreported once. According to the model, misreporting occurs in 45% (37%) of the CEO-years (Table 7) and 66% (59%) of the CEOs decide to manipulate sometime during their tenure in the non-technical (nontrivial) sample (Table 8). These numbers are similar in magnitude to the 78% of executives who report that they would sacrifice long-term value to smooth earnings [Graham et al., 2005]. In addition, two recent studies by Gerakos and Kovrijnykh [2013] and Dyck et al. [2013] provide a conservative estimate for the fraction of misreporting and fraud. According to Gerakos and Kovrijnykh [2013], a lower bound on the fraction of misreporting firms is 22%, whereas according to Dyck et al. [2013], a conservative estimate for the undetected fraud in any given year is 14.5%.

For all CEO-years, equally weighted bias in price is 11% (11%) and the value-weighted bias in price is 6% (5%) of the observed stock price in the non-technical (nontrivial) sample. The difference between equally weighted and value-weighted bias implies that manipulation is concentrated among small stocks. This result still holds for the sample of CEO-years when the CEO misreports (Table 8). The estimated equally weighted bias in price among misreporting CEOs is 24% (29%), and the value-weighted bias in price is about 15.5% (19%) of the observed stock price for the non-technical (nontrivial) sample. This indicates that although the incidence of manipulation is high, the actual amount of manipulation is not as high on a value-weighted basis. The model-implied mean inflation in the stock price is about two times higher than the mean return for fraudulent restatements of negative 13% at the two-day restatement announcement window for 1997 - 2006 [Scholz, 2008, Table 8]. The two-day return may not fully incorporate the impact of a restatement. Indeed, I find that the mean annual return at the restatement announcement year is negative 25%, which is consistent with the model-implied equally weighted bias in price. Dyck et al. [2013] estimate that among the fraud-committing firms the mean cost of a fraud is about 22% of firm value, which aligns with my estimate of the mean inflation in the stock price among manipulating firms.

Although the estimate of the share of manipulating firms is relatively high, the average bias in net assets and earnings is low. Among manipulating firms, the bias in net assets as a percentage of the lag of total assets is 2%, and the bias in earnings as a percentage of the lag of total assets is 1% (Table 8).

5.4 Out-of-sample performance of model-implied manipulation and discretionary accruals

I evaluate the out-of-sample performance of the model-implied manipulation and the commonly used measures of earnings management. Accounting and finance researchers traditionally measure earnings management using discretionary accruals. Both the discretionary accruals and the structural model-implied manipulation 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 real world. Nevertheless, both approaches attempt to capture a very complex misreporting decision. Therefore, it is instructive to compare the out-of-sample performance of these measures. I use only 90% of the executives in my sample to estimate parameters (i.e., the estimation sample) and hold out a randomly chosen 10% (i.e., the holdout sample).[30] The sample is split in such a way that the fraction of restatements in the estimation sample and in the holdout sample is the same. The out-of-sample performance can be computed only for the firms that restated their financial statements because I observe the complete path of their manipulation, i.e., in which periods executive manipulated as well as the extent of the misreporting.[31]

[30] The probability of leaving the firm for reasons unrelated to manipulation and the probability of termination are estimated using the full sample.

[31] For non-restating firms, it is ambiguous whether they manipulated and were not detected or whether they did not manipulate; hence, such firms cannot be used for this test.

For each executive who restates in the holdout sample, I compute the model-implied measure of bias in earnings as well as the bias in earnings implied by five discretionary accruals models defined in Table 9. These models are the total accruals as in Hribar and Collins [2002], the comprehensive accruals of Richardson et al. [2005], the Jones model discretionary accruals as in Jones [1991], the modified Jones model discretionary accruals as in Dechow et al. [1995], and the performance-matched discretionary accruals as in Kothari et al. [2005]. I perform a parametric bootstrap to compute the model-implied probability of detection and the bias in earnings: (1) generate 100 random draws from the asymptotic distribution of the parameter estimates[32]; (2) for each parameter draw, infer the manipulation path as in Section 5.3; (3) compute the model-implied estimate of the probability of manipulation and the bias in earnings by averaging over draws for every CEO-year. This procedure produces the model-implied probability of manipulation for every CEO-year, whereas discretionary accruals models do not provide such a measure. For discretionary accruals, I assume that an executive manipulates when a measure of discretionary accruals is not zero, i.e., the discretionary accruals-implied probability of manipulation can only be zero or one.

Next, I compute out-of-sample performance statistics for the probability of manipulation and the bias in earnings. These statistics include the bias, the mean absolute deviation, the median absolute deviation and the root mean squared error (RMSE). I compute these statistics by taking the difference between the true value observed in the holdout sample and the estimate (i.e., deviation). The bias is defined as the mean deviation and the formula for the RMSE is

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(x_{(n)} - \widehat{x}_{(n)}\right)^2}, \tag{4}$$

where $x_{(n)}$ is the true observed value for the observation n which represents a CEO-year (e.g., the misreporting in earnings observed in the data) and $\widehat{x}_{(n)}$ is the estimate for the observation n. The statistics for the probability of manipulation are computed using all

[32] If a parameter lies outside of the theoretical bounds (e.g., the probability of detection is negative), I repeat the draw.

CEO-years for executives who restate in the holdout sample because, under the assumption that a restatement uncovers the complete path of manipulation, for these executives the periods in which they manipulated are known; hence, each period can be coded as zero or one depending on whether the executive manipulated. At the same time, the statistics for the magnitude of misreporting are computed using only CEO-years in which an executive actually misreports in the holdout sample. These statistics are summarized in Table 10.

Both the model-impled probability and the discretionary accruals-implied probability predict that CEOs manipulate in the periods in which they *actually* do not manipulate. The model-implied probability is slightly better than discretionary accruals-implied probability in terms of the mean deviation and the RMSE statistics; the improvement for the mean deviation is 29.5% (38.5%) and for the RMSE is 1% (5.5%) for non-technical (nontrivial) restatements. For the bias in earnings, the model-implied measure performs significantly better than discretionary accruals. For instance in terms of the RMSE for the sample of non-technical restatements, the model-implied measure has a RMSE equal to 1%, which is eight times better than the next best measure of the performance-matched discretionary with a RMSE equal to 8%. Similarly, in terms of the RMSE for the sample of nontrivial restatements, the model-implied measure has a RMSE equal to 2%, which is about five times better than the next best measure of modified Jones model discretionary accruals with a RMSE equal to 11%.

Overall, the results in Table 10 suggest that the model-implied measure of manipulation performs significantly better out-of-sample than the commonly used measures of discretionary accruals. The problems with using discretionary accruals as a proxy for earnings management are well-recognized in extant research [e.g., McNichols, 2000, Dechow et al., 2010]. These models are *ad hoc* statistical models; hence, the discretionary accruals measures depend on various firm characteristics and incentives to misreport. Therefore, researchers should be cautious about using discretionary accruals as a proxy for earnings management and, instead, carefully consider the benefits and costs of misreporting specific to their research setting.

5.5 Robustness

There are three parameters that are set to specific values: the risk aversion parameter, γ, the retirement age, T, and the multiple on firm-specific wealth that is used in computing the managers' outside wealth, η. The main specification in the paper utilizes $\gamma = 2, T = 85, \eta = 1$. It is important to evaluate the robustness of the results to the assumptions about these parameters. To evaluate robustness, I vary the parameters one at a time and report the results in Tables 11 through 14. Three alternative specifications are considered: (1) $\gamma = 3, T = 85, \eta = 1$; (2) $\gamma = 2, T = 65, \eta = 1$; and (3) $\gamma = 2, T = 85, \eta = 0.5$. I follow the literature in selecting these parameters. First, researchers in macroeconomics and finance argue that the plausible values for the risk aversion parameter are $\gamma = 2$ or $\gamma = 3$ [e.g., Ljungqvist and Sargent, 2004]. Second, extant studies on executive compensation assume that the manager's firm-specific wealth is 50% or 67% of his total wealth [e.g., Conyon et al., 2011] which implies $\eta = 1$ or $\eta = 0.5$. Finally, the mandatory retirement age for executives in some firms is set at 65.

The qualitative conclusions about parameter estimates are similar for all specifications (Table 11). The point estimates for the probability of detection range from 8% (6%) to 9% (7%); and the marginal effects of a 1% inflation in the stock price on the loss in the manager's wealth range from 0.26% (0.30%) to 0.56% (0.55%)for the sample of non-technical (nontrivial) restatements.[33] The loss in wealth parameter is not statistically significant for the sample of non-technical restatements; however, it is statistically significant in some specifications for the sample of nontrivial restatements. For the sample of non-technical restatements, the costs of manipulation parameters tend to be lower for the specification in which the retirement age is set at 65; they tend to be higher for the specification in which the firm-specific wealth comprises 67% of the manager's total wealth (i.e., $\eta = 0.5$). In contrast, for the sample of nontrivial restatements, I do not find the same pattern for the probability of detection; however, the sensitivity of the loss in wealth to manipulation is once

[33] For comparability, I compute these effects for the average cost impact of bias (βb_t) among manipulating executives in the respective samples of non-technical (i.e., $\beta b_t = 0.4329$) and nontrivial (i.e., $\beta b_t = 0.4405$) restatements from Table 8.

again the lowest for the specification with the retirement age set at 65 and the highest for $\eta = 0.5$. The finding for the shortest horizon (i.e., $T = 65$) can be explained by the manager's lower tendency to manipulate, because there is a lower likelihood that he will benefit from manipulation in the future. Therefore, the lower sensitivity parameter is sufficient to match the empirical moments. However, if the manager's total wealth is lower (i.e., $\eta = 0.5$), he will have a greater tendency to manipulate; therefore, the sensitivity parameter should be higher to preclude him from manipulating. Finally, according to the J-test, almost none of the specifications are rejected at conventional significance levels, except for the specification in which $\gamma = 2, T = 65, \eta = 1$ for non-technical restatements.

Similarly, the conclusions about the in-sample model-implied measure of manipulation do not change significantly, except for the specification when executives retire at 65 (Tables 12 and 13). The fraction of CEO-years when CEO manipulates ranges from 34% (29%) to 47% (39%) for non-technical (nontrivial) restatements with the lowest fraction for the specification with $T = 65$ and the highest fraction for the specification with $\gamma = 3$. Similarly, the unconditional value-weighted bias in stock price ranges from 5% (4%) to 6% (6%) for non-technical (nontrivial) restatements with the lowest fraction for the specification with $T = 65$ and the highest fraction with $\gamma = 3$. This result is consistent with more risk-averse managers (i.e., $\gamma = 3$) trying to smooth the stock price by manipulating more. Similarly, the fraction of manipulating CEOs is the highest for the specification with $\gamma = 3$ and equals 67% (61%), whereas the fraction of manipulating CEOs is the lowest for the specification with $T = 65$ and equals 54% (51%) for non-technical (nontrivial) restatements (Table 13).

Interestingly, there is a tradeoff between how well the model captures the probability of detection and how well it fits the magnitude of manipulation out-of-sample (Table 14). The specification in which the manager has the shortest horizon (i.e., $T = 65$) fits the probability of manipulation out-of-sample better than any other model. At the same time, this specification has the highest out-of-sample error in fitting the magnitude of manipulation. In contrast, the other three specifications have virtually identical out-of-sample performance and capture the magnitude of manipulation better than the specification with a shorter horizon.

6. Conclusions

In this paper, I suggest a structural model of a manager's manipulation decision that allows me to estimate his costs of manipulation and to infer the amount of undetected intentional manipulation for each executive in my sample. The model follows the economic approach to crime [Becker, 1968] and incorporates the costs and benefits of manipulation decisions. The model is a dynamic finite-horizon problem in which the risk-averse manager maximizes his terminal wealth. The manager's total wealth depends on his equity holdings in the firm and his cash wealth. The model yields three predictions. First, according to the *wealth* effect, managers having greater wealth manipulate less. Second, according to the *valuation* effect, the current-period bias in net assets increases in the existing bias. Third, the manager's risk aversion, the linearity of his terminal wealth in reported earnings, and the stochastic evolution of the firm's intrinsic value produce income-smoothing. Furthermore, the structural approach allows partial observability of manipulation decisions in the data; hence, I can estimate the probability of detection as well as the loss in the manager's wealth using the data on detected misstatements (i.e., financial restatements).

I contribute to the literature by providing estimates of the manager's manipulation costs and the extent of undetected intentional manipulation. I find that the costs of manipulation are low: the probability of detection is 9%, and the marginal loss in wealth for inflating the stock price by 1% is 0.51% for non-technical restatements. These costs result in high estimates of the incidence of undetected manipulation. Specifically, the model predicts that about 66% of executives manipulate at least once with a value-weighted bias in the stock price of 15.5%. At the same time, the unconditional rate of manipulation is lower: CEOs bias their earnings reports in 45% of CEO-years, and a value-weighted bias in the stock price is 6% across all CEO-years. Finally, I find that the model-implied measure of manipulation performs significantly better than the commonly used measures of discretionary accruals out-of-sample. Therefore, researchers should exercise caution in relying on such measures as proxies for earnings management and, instead, should carefully consider the costs and benefits of manipulation that are relevant to their particular setting.

These findings can be useful for investors, boards of directors, regulators and researchers. The estimated cost of manipulation parameters can be utilized in calculating the cost to a CEO of misreporting earnings by 1% or by a given amount. The only data that this calculation requires is the firm's price-to-earnings multiple and the hypothetical level of bias per share, scaled by the stock price before a CEO joins a firm.[34] In addition, the model can be applied to the time-series of stock prices and the time-series of executive compensation to infer the extent of undetected manipulation in a manner similar to that described in Section 5.2.

The structural approach can be used to analyze counterfactuals. For instance, one can evaluate how an increase in the probability of detection changes the extent of manipulation. However, to make sensible counterfactual predictions, one has to consider how investors would react to a change in the policy parameters. For instance, if the costs of manipulation increase, fewer managers would find it optimal to manipulate; in equilibrium, investors may place greater weight on reported earnings; thus, price-to-earnings multiples would increase, which, in turn, increase the manager's incentives to manipulate. These issues can be addressed by explicitly modeling an equilibrium interaction between the manager's reporting choices and investors' inferences about manipulation.

An analysis of counterfactuals can also be useful in helping regulators to decide about the resources that should be invested in detection and the punishment for misreporting. For instance, similar expected costs of manipulation can be achieved by adjusting the probability of detection or the punishment for misreporting. However, the relative sensitivities of the manipulation decision to the probability of detection and punishment can differ depending on whether an executive is risk-averse or risk-loving. If an executive is risk-averse, then the increase in the punishment for manipulation would have a greater effect on reducing misstatements than an equivalent change in the probability of detection, whereas if an executive

[34] The percentage of an executive's wealth loss when he inflates the stock price by 1% equals $\kappa_2 \beta b_t$, where κ_2 is the sensitivity parameter reported in Table 5, β is the firm's price-to-earnings multiple (or the median industry multiple to avoid extreme firm-specific values) and b_t is a hypothetical bias in net assets per share, expressed as a fraction of the stock price right before the executive joins the firm. The total wealth loss can be computed as $\kappa_1 + \frac{\kappa_2}{2}(\beta b_t)^2$, where κ_1 is the loss parameter estimated in Table 5, and other parameters are defined above.

is risk-loving, an increase in the probability of detection would have a greater effect than an equivalent change in the punishment for manipulation [Becker, 1968].

A structural approach involves trade-offs between restrictive assumptions that make estimation feasible and sufficient flexibility to capture the patterns observed in the data. In my analysis, I make a variety of important assumptions; these choices represent limitations to my results. 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 regarding the optimal compensation contract. In doing so, I avoid solving a difficult multi-period problem that lies beyond the scope of this paper. Another limitation of this paper and a 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 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 here may be biased to the extent that other incentives to misreport are also important. Future research can provide further evidence on the relative importance of the various incentives to misreport.

A. *Solving the manager's problem*

This appendix provides the formal description of the model and explains how I solve the manager's dynamic manipulation problem. The definitions of variables can be found in Table 1. There are five state variables that the manager observes in the beginning of the period t:

$$S_t = \{P_t, B_{t-1},\ Detect_{t-1},\ Manip_{t-1},\ Left_{t-1}\}, \tag{5}$$

$$P_t \in (0, +\infty),\ B_t \in (-\overline{B}, \overline{B}),\ Detect_t \in \{0, 1\},\ Manip_t \in \{0, 1\},\ Left_t \in \{0, 1\}. \tag{6}$$

The two state variables – the existing bias in net assets B_{t-1} and the indicator for whether the manager has manipulated in previous periods $Manip_{t-1}$ – are controlled by the manager. In contrast, the intrinsic firm value P_t, the indicator for whether the manager has been detected in previous periods, $Detect_{t-1}$, and the indicator for whether the manager has left the company $Left_{t-1}$, are random and, therefore, not directly controlled by the manager.

The manager is assumed to privately observe the firm's intrinsic value without error. The firm's intrinsic value P_t follows a log-normal process,[35] and the stock price equals the intrinsic value of the firm whenever the manager does not distort financial statements. The time subscript denotes either his year t in the firm or a period in the model:

$$ln\left(\frac{P_{t+1}}{P_t}\right) \sim N\left(\mu - \frac{\sigma^2}{2}, \sigma^2\right). \tag{7}$$

The firm's intrinsic value P_t is a state variable because its distribution in the subsequent periods and, hence, the distribution of the value of the manager's equity holdings depends on P_t.

I define manipulation as the bias in net assets B_t and assume that the market relies

[35] It is common to assume that the stock prices follow the log-normal distribution in the literature on executive compensation [e.g., Lambert et al., 1991, Hall and Murphy, 2002]. It is certainly plausible that the evolution of the intrinsic value depends on the manager's characteristics and his effort; however, I ignore the moral hazard and adverse selection problems in this paper. Instead, I assume that the data on return distribution and executive compensation are generated in equilibrium, and I use these data to infer the manger's manipulation decision.

on the reported earnings to price firm's shares.[36] Because net assets are biased by B_t, the reported earnings are biased by $B_t - B_{t-1}$, and the stock price $\widehat{P}_t$ becomes

$$\widehat{P}_t = P_t + \beta(B_t - B_{t-1}), \tag{8}$$

where β is the price-to-earnings multiple. The existing bias in net assets B_{t-1} is a state variable because the stock price depends on the bias in earnings; hence, the manager considers how the current period bias in net assets would affect his future wealth. I assume that the manager maximizes the utility of his terminal wealth, which is consistent with extant literature [e.g., Lambert et al., 1991, Hall and Murphy, 2002].

Each period t consists of several stages. If the manager has not manipulated previously ($Manip_{t-1} = 0$), the stages are as follows: (1) the manager decides whether to manipulate; (2) if he does not manipulate ($Manip_t = 0$), he can leave the firm with probability f_t (he leaves the firm for certain if $t = T$); (3) if he decides to manipulate ($Manip_t = 1$), he chooses the bias in net assets B_t and (3a) his manipulation can be detected with probability g, in which case he can be terminated with probability ϕ or, (3b) if his manipulation is not detected, he can leave the firm with probability f_t; (4) if the manager is not terminated and does not leave the firm for other reasons, he continues into the next period. If the manager has manipulated before (i.e., $Manip_{t-1} = 1$), the stages are identical to (3). If the manager has manipulated once, he can always be detected. Suppose the manager manipulates at $\bar{t}$ for the first time, then

$$Manip_t = \begin{cases} 0, & \forall t < \bar{t} \\ 1, & \forall t \geq \bar{t} \end{cases}. \tag{9}$$

Once the manager has manipulated ($Manip_t = 1$) and before he leaves the firm, his manipulation can be detected with probability g.[37] I assume that his manipulation can be

[36] In this paper, I ignore the possibility that the manager may make a mistake in his reporting that will be later classified as manipulation. To be consistent in applying this assumption, I carefully select the sample of restatements, such that they include possibly intentional misstatements rather than mere technical errors.

[37] I do not model the probability of detection g as a function of bias or the number of periods the manager

detected only once, i.e., if the manager is caught, he cannot manipulate again:

$$
Detect_t = \begin{cases} 0, & t < \bar{t} \\ 0, & \text{with prob. } 1-g, \forall t \geq \bar{t} \\ 1, & \text{with prob. } g, \forall t \geq \bar{t} \\ 1, & \text{if } Detect_{t-1} = 1 \end{cases}. \quad (10)
$$

The evolution of $Left_{t-1}$ is stochastic as well as contingent on whether the manipulation was detected:

$$
Left_t = \begin{cases} 0, & \text{with prob. } 1-f_t, \text{ if } Detect_t = 0 \\ 0, & \text{with prob. } 1-\phi, \text{ if } Detect_{t-1} = 0, Detect_t = 1 \\ 1, & \text{with prob. } f_t, \text{ if } Detect_t = 0 \\ 1, & \text{with prob. } \phi, \text{ if } Detect_{t-1} = 0, Detect_t = 1 \\ 1, & \text{if } Left_{t-1} = 1 \end{cases}, \quad (11)
$$

where f_t is the probability for the manager to leave for reasons unrelated to manipulation; ϕ is the probability for the manager to be terminated when the manipulation is detected.[38] When $Left_t = 0$ and $Left_t = 1$, the manager receives his terminal wealth and leaves the firm at the end of period t.

The manager is assumed to exhibit constant relative risk aversion; hence, his utility is

$$
U(c) = \frac{c^{1-\gamma}}{1-\gamma}, \quad (12)
$$

where γ is the relative risk aversion parameter.

Under the constant relative risk aversion utility, it is possible to re-scale the argument

manipulates because it is difficult to identify this functional form from the data on rare restatements.

[38] As is the case with the probability of detection, I do not model the probability of termination as a function of bias, again, because it is difficult to identify this functional form from the data on rare restatements. Instead, I assume that the expected cost of manipulation increases by means of the increased wealth loss when the manager is caught. If caught, the managers who manipulate more will lose more of their wealth.

of the utility function without affecting the manager's optimal decision. Since the problem is executive-specific, it is convenient to re-scale the problem for every executive by $N_1 P_0$ (where N_1 denotes the total number of shares the manager holds in the first period, and P_0 denotes the stock price at the end of the third month after the fiscal year end before the manager joins the firm). Re-scaled variables are denoted by lower-case letters as follows:

$$\left\{ p_t = \frac{P_t}{P_0}, b_t = \frac{B_t}{P_0}, n_t = \frac{N_t}{N_1}, w_t = \frac{W_t}{N_1 P_0} \right\}, \tag{13}$$

where P_t represents the firm's intrinsic value at time t; B_t represents the bias in net assets per share at time t; N_t represents the number of shares the manager holds at time t; and W_t denotes the manager's total cash wealth at time t.

At the beginning of the period one, the state is

$$S_1 = \{P_1, 0, 0, 0, 0\}. \tag{14}$$

This state evolves depending on whether the manager manipulates, whether his manipulation is detected, and whether he is terminated or leaves the firm for reasons unrelated to manipulation.

The manager's terminal payoff depends on the state S_t, and the manager receives it when $Left_{t-1} = 0$ and $Left_t = 1$:

$$\widetilde{w}_t^{total} = \begin{cases} w_t + (n_t^v + n_t^{nv}) p_t, \text{if } Manip_t = 0 \\ w_t + (n_t^v + n_t^{nv}) p_t, \text{if } Manip_t = 1, Detect_{t-1} = 1, Detect_t = 1 \\ w_t + (n_t^v + n_t^{nv}) \underbrace{\left(p_t + \beta (b_t - b_{t-1}) \right)}_{\hat{p}_t, distorted\ price}, \text{if } Manip_t = 1, Detect_{t-1} = 0, Detect_t = 0 \\ \left(w_t + n_t^v p_t \right) \left(1 - \kappa_1 - \frac{\kappa_2}{2} (\beta b_t)^2 \right), \text{if } Manip_t = 1, Detect_{t-1} = 0, Detect_t = 1 \end{cases}, \tag{15}$$

where w_t is the manager's cash holdings, and $n_t = n_t^v + n_t^{nv}$ represents his equity holdings of vested n_t^v and non-vested n_t^{nv} shares.

I solve the manager's problem using backwards induction in three steps because there are three value functions. First, I solve for the value $V_{pd,t}(p_t)$ which the manager expects to receive in the state $S_t = (p_t, 0, 1, 1, 0)$ for each time t until he retires (where pd represents *post-detection* state). Next, I solve for the value $V_{m,t}(p_t, b_{t-1})$ and the optimal bias $b_t(p_t, b_{t-1})$ in the state $S_t = (p_t, b_{t-1}, 0, 1, 0)$ (where m represents the *manipulative* state). Finally, I solve for the value $V_{nm,t}(p_t)$ in the state $S_t = (p_t, 0, 0, 0, 0)$ (where nm reflect the *non-manipulative* state).

In the *post-detection* state, the manager can leave only for reasons unrelated to manipulation. Accordingly, the manager's value function in the *post-detection* state at time t is

$$V_{pd,t}(p_t) = \underbrace{f_t U\left(w_t + (n_t^v + n_t^{nv})p_t\right)}_{\text{detected at } \bar{t}<t, \text{ leaves at } t} + \delta(1 - f_t) \underbrace{\mathbb{E}_t\left[V_{pd,t+1}(p_{t+1})\middle| p_t\right]}_{\text{detected at } \bar{t}<t, \text{ stays in pd state}}, \tag{16}$$

where δ is the time-discount factor which is assumed to be equal to $1/(1 + r_f)$ with r_f being a risk-free rate.

The manager can leave the *manipulative* state at time t under three scenarios: (1) the manipulation is not detected and the manager leaves at time t for other reasons; (2) the manipulation is detected at time t, and the manager is terminated; (3) the manipulation is detected, but the manager is not terminated and transitions into a *post-detection* state. Accordingly, the manager's value function in the *manipulative* state at time t is

$$\begin{aligned} V_{m,t}(p_t, b_{t-1}) = \max_{b_t(p_t, b_{t-1})} & \underbrace{(1 - g) f_t U\left(w_t + (n_t^v + n_t^{nv})\widehat{p}_t\right)}_{\text{not detected, leaves at } t} + \underbrace{g\phi U\left((w_t + n_t^v p_t)\left(1 - \kappa_1 - \frac{\kappa_2}{2}(\beta b_t)^2\right)\right)}_{\text{detected at } t\text{,leaves at } t} + \\ & + \delta \underbrace{(1 - g)(1 - f_t)\mathbb{E}_t\left[V_{m,t+1}(p_{t+1}, b_t)\middle| p_t\right]}_{\text{not detected at } t, \text{ stays in } m} + \delta \underbrace{g(1 - \phi)\mathbb{E}_t\left[V_{pd,t+1}(p_{t+1})\middle| p_t\right]}_{\text{detected at } t, \text{ transitions to pd}} \end{aligned} \tag{17}$$

In the *non-manipulative* state, the manager decides whether to manipulate at each period, and his value function is

$$V_{nm,t}(p_t) = f_t U\Big(w_t + (n_t^v + n_t^{nv})p_t\Big) + \\ + \delta(1-f_t)\mathbb{E}_t\Big[\max_{d(p_t)\in\{0,1\}}\Big\{V_{nm,t+1}(p_{t+1}), V_{m,t+1}(p_{t+1},0)\Big\}\Big|p_t\Big]. \quad (18)$$

I compute these three value functions via backwards induction [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 the intrinsic value, the grid ranges from 0 to 10 with increments that correspond to a 5% stock return. Because the intrinsic value is defined on a grid of points, I can use a transition matrix for the price process to compute the expectation of the future value with respect to p_t. The intrinsic value grid is the same for all executives because the data are normalized such that $p_0 = 1$. For the bias, the grid includes 100 points and the support of the grid is determined by the extent of the manipulation observed empirically.[39]

For each value function, I compute the value at terminal time T when the manager retires and iterate backwards to compute values for all previous periods. Specifically, once the manager enters the *post-detection* state, he remains there until he leaves the firm. Therefore, I can calculate the value function for the *post-detection* state, $V_{pd,t}(p_t)$, independently of the value function in the *manipulative* or *non-manipulative* states by iterating on the following equation:

$$V_{pd}^t(p_t) = f_t U\Big(w_t + (n_t^v + n_t^{nv})p_t\Big) + \delta(1-f_t)\mathbb{E}_t\Big[V_{pd}^{t+1}(p_{t+1})\Big|p_t\Big], \quad (19)$$

starting with the terminal value in the *post-detection* state, $V_{pd}^T(p_T)$.

Next, if the manager enters the *manipulative* state, he remains there until he either leaves the firm or transitions to the *post-detection* state. Therefore, I can find the value function for the *manipulative* state, $V_{m,t}(p_t, b_{t-1})$, once I know the value function in the *post-detection*

[39]The maximum value of the grid is set to the maximum manipulation observed in the data multiplied by 1.1.

state, $V_{pd,t}(p_t)$, by iterating on the following equation:

$$V_m^t(p_t, b_{t-1}) = \max_{b_t(p_t,b_{t-1})} \underbrace{(1-g)f_t U\bigg(w_t + (n_t^v + n_t^{nv})\widehat{p}_t\bigg)}_{\textit{not detected, leaves at } t} + \underbrace{g\phi U\bigg((w_t + n_t^v p_t)\bigg(1 - \kappa_1 - \frac{\kappa_2}{2}(\beta b_t)^2\bigg)\bigg)}_{\textit{detected at } t\textit{,leaves at } t} +$$

$$+\,\delta\, \underbrace{(1-g)(1-f_t)\mathbb{E}_t\bigg[V_m^{t+1}(p_{t+1}, b_t)\bigg|p_t\bigg]}_{\textit{not detected at } t\textit{, stays in } m} + \delta\, \underbrace{g(1-\phi)\mathbb{E}_t\bigg[V_{pd}^{t+1}(p_{t+1})\bigg|p_t\bigg]}_{\textit{detected at } t\textit{, moves to } pd}, \quad (20)$$

starting with the terminal value in the *post-detection* state, $V_{pd}^T(p_T)$, and the *manipulative* state, $V_m^T(p_T, b_{T-1})$.

Finally, I utilize the value functions for the *post-detection* state, $V_{pd,t}(p_t)$, and the *manipulative* state, $V_{m,t}(p_t, b_{t-1})$, from the previous steps to find the value function for the *non-manipulative* state, $V_{nm,t}(p_t)$, from the following equation:

$$V_{nm}^t(p_t) = f_t U\bigg(w_t + (n_t^v + n_t^{nv})p_t\bigg) + \delta(1-f_t)\mathbb{E}_t\bigg[\max_{d(p_t)\in\{0,1\}} \bigg\{V_{nm}^{t+1}(p_{t+1}), V_m^{t+1}(p_{t+1}, 0)\bigg\}\bigg|p_t\bigg]. \quad (21)$$

starting with the terminal value in the *manipulative* state, $V_m^T(p_T, b_{T-1})$ and the *non-manipulative* state, $V_{nm}^T(p_T)$.

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.

B. *Simulated method of moments estimation details*

B.1 Simulated method of moments

In the SMM, the moment condition is defined as

$$m_n(\theta) = \frac{1}{n}\sum_{i=1}^{n}\left[h(x_i) - \frac{1}{S}\sum_{s=1}^{S} h(y_{is}(\theta))\right], \tag{22}$$

where n is the number of observations; S is the number of simulations per observation; $h(x)$ is the vector of 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

$$\widehat{\theta} = arg\min_{\theta} m_n(\theta)'\widehat{W}_n m_n(\theta), \tag{23}$$

where $\widehat{W}_n$ represents a positive-definite weighting matrix.

Similar to the traditional two-step GMM, the SMM estimate of θ can be obtained 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 an efficient) estimator $\widehat{\theta}$. It is common to set the first weighting matrix to the covariance matrix of empirical moments [Strebulaev and Whited, 2012]. In the second step, the weighting matrix is set to the inverse of the covariance matrix of the moments estimated in $\widehat{\theta}$. The 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 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 optimal $\widehat{\theta}_{SMM}$ is

$$\sqrt{n}(\widehat{\theta}_{SMM} - \theta) \longrightarrow^{d} N(0, \Omega) \tag{24}$$

$$\widehat{\Omega} = \left(1 + \frac{1}{S}\right)\left(\frac{\partial m_n(\widehat{\theta}_{SMM})}{\partial \theta'} V(m_n(\widehat{\theta}_{SMM}))^{-1} \frac{\partial m_n(\widehat{\theta}_{SMM})}{\partial \theta}\right)^{-1}, \tag{25}$$

whereas the covariance matrix for the first-stage estimator is

$$\widehat{\Omega} = \left(1 + \frac{1}{S}\right)\left(\frac{\partial m_n}{\partial \theta'} W \frac{\partial m_n}{\partial \theta}\right)^{-1}\left(\frac{\partial m_n}{\partial \theta'} W V(m_n) W \frac{\partial m_n}{\partial \theta}\right)\left(\frac{\partial m_n}{\partial \theta'} W \frac{\partial m_n}{\partial \theta}\right)^{-1}. \tag{26}$$

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

$$h_1(x_i) = \mathbf{1}(restate_i) \tag{27}$$

$$h_2(x_i) = b^{(1i)}\mathbf{1}(restate_i) \tag{28}$$

$$h_3(x_i) = b^{(2i)}b^{(1i)}\mathbf{1}(restate_i) \tag{29}$$

$$h_4(x_i) = \frac{1}{T - \bar{t}} \sum_{\bar{t}}^{T} c_{it}\mathbf{1}(restate_i), \tag{30}$$

where $\mathbf{1}(restate_i)$ is an indicator for whether the firm i restates its financial statements; $b^{(1i)}$ is the bias in net assets in the first restated period for the firm i; $b^{(2i)}$ is the bias in net assets in the second restated period for the firm i; $c_{it} = \frac{w_{it}}{(n_{it}^{v} + n_{it}^{nv})\beta_i}$ is the ratio of the scaled cash wealth to the value of one dollar inflation in reported earnings with the mean taken over all future periods, starting from the period when the manager manipulates for the first time $\bar{t}$.

The test of overidentifying restrictions can be applied to test the model fit when the number of moment conditions exceeds the number of parameters. This test has one degree of freedom because I use four moments to estimate three parameters:

$$J = \frac{nS}{1 + S} m_n(\widehat{\theta}_{SMM})' V(m_n(\widehat{\theta}_{SMM}))^{-1} m_n(\widehat{\theta}_{SMM}) \sim \chi^2(1). \tag{31}$$

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. If the test is rejected, then the SMM estimator is inconsistent for θ (i.e., a particular specification of the model including all the underlying assumptions about functional forms and distributions is rejected). However, the test does not provide information about which specific moment does not hold.

To compute standard errors, I must have a Jacobian of moment conditions. This Jacobian matrix is computed numerically by taking the forward difference for the small enough step size h:

$$f'(x) = \frac{f(x+h) - f(x)}{h}. \tag{32}$$

The optimal h for a smooth function is 10^{-6}. This value may not be appropriate for the function that is obtained via noisy simulations. Indeed, I find that with $h = 10^{-6}$ the Jacobian matrix is not stable when parameters change slightly. Instead of arbitrary choosing h, I choose it optimally via a method suggested by Moré and Wild [2012]. This method allows the computation of the optimal h for a function that is obtained via simulations. I find that the optimal step sizes are specific to the moment condition - parameter pair; these optimal step sizes are larger than the step size which is optimal for a smooth function.[40]

Under the assumption that the simulations are unbiased, the SMM estimator is consistent, even if $S = 1$ [Cameron and Trivedi, 2005]. However, this assumption may not hold in complex non-linear models. The model estimated in this paper is complex and non-liner in the simulation noise; therefore, the number of simulations can potentially have an effect on the bias and efficiency of an estimator. To evaluate the effect of the number of simulations, I perform a Monte Carlo study. The Monte Carlo study involves the following steps: (1) simulate 50 artificial samples of 530 CEOs (randomly selected) under a fixed cost of manipulation parameters ($g = 0.1, \kappa_1 = 0.01, \kappa_2 = 1$); (2) estimate parameters for each sample using the two-step SMM; (3) compute summary statistics of the estimates. These statistics include the bias, mean absolute deviation, median absolute deviation and root mean squared error (RMSE) of the point estimates as well as the percentage of the data sets for which the

[40] The optimal step size for κ_2 is about ten times larger than the optimal step size for g and κ_1.

point estimates reject the truth at the 90% (!CI90), 95% (!CI95) and 99% (!CI99) confidence level. I compute these statistics by calculating the difference between the true parameter value and the estimate (i.e., deviation). The bias is defined as the mean deviation and the formula for the RMSE is

$$RMSE = \sqrt{\frac{1}{50}\sum_{n=1}^{50}\left(\theta_0 - \widehat{\theta}_{(n)}\right)^2}, \tag{33}$$

where θ_0 is the true parameter value, and $\widehat{\theta}_{(n)}$ is the estimate from the simulated sample n. The confidence intervals are computed using the standard asymptotic formula. These statistics are summarized in the table below.

Panel A: First stage of SMM							
Probability of detection g (%)							
	Bias	Mean Abs Dev	Med Abs Dev	RMSE	!CI90	!CI95	!CI99
100	−2.33	2.51	2.62	3.28	34.00	18.00	8.00
300	−2.07	2.26	2.37	3.06	20.00	10.00	6.00
500	−2.25	2.40	2.68	3.13	26.00	8.00	2.00
1000	−2.31	2.42	2.67	3.16	28.00	10.00	4.00
3000	−2.23	2.36	2.60	3.14	28.00	4.00	2.00
Loss in wealth κ_1 (%)							
	Bias	Mean Abs Dev	Med Abs Dev	RMSE	!CI90	!CI95	!CI99
100	0.67	1.00	0.97	1.29	4.00	2.00	2.00
300	0.88	0.94	0.96	0.94	0.00	0.00	0.00
500	0.87	0.91	0.97	0.93	0.00	0.00	0.00
1000	0.89	0.93	0.97	0.94	0.00	0.00	0.00
3000	0.77	1.08	0.98	1.38	2.00	0.00	0.00
Sensitivity of loss in wealth to bias κ_2							
	Bias	Mean Abs Dev	Med Abs Dev	RMSE	!CI90	!CI95	!CI99
100	0.08	0.08	0.07	0.09	20.00	10.00	4.00
300	0.08	0.08	0.07	0.09	12.00	6.00	2.00
500	0.08	0.08	0.07	0.09	14.00	2.00	0.00
1000	0.08	0.08	0.07	0.09	8.00	2.00	0.00
3000	0.08	0.08	0.08	0.09	2.00	2.00	0.00

Panel B: Second stage of SMM							
Probability of detection g (%)							
	Bias	Mean Abs Dev	Med Abs Dev	RMSE	!CI90	!CI95	!CI99
100	−3.13	3.31	3.09	4.18	48.00	34.00	20.00
300	−2.86	3.04	2.78	3.92	42.00	20.00	10.00
500	−2.92	3.09	3.47	3.91	42.00	24.00	8.00
1000	−2.91	3.07	3.30	3.94	44.00	24.00	10.00
3000	−2.88	3.05	3.47	3.90	38.00	20.00	6.00
Loss in wealth κ_1 (%)							
	Bias	Mean Abs Dev	Med Abs Dev	RMSE	!CI90	!CI95	!CI99
100	0.75	1.01	0.98	1.23	4.00	4.00	2.00
300	0.93	0.94	0.98	0.95	0.00	0.00	0.00
500	0.91	0.94	0.98	0.95	2.00	2.00	2.00
1000	0.92	0.95	0.98	0.96	2.00	2.00	2.00
3000	0.92	0.97	0.99	0.97	0.00	0.00	0.00
Sensitivity of loss in wealth to bias κ_2							
	Bias	Mean Abs Dev	Med Abs Dev	RMSE	!CI90	!CI95	!CI99
100	0.09	0.09	0.08	0.10	22.00	18.00	8.00
300	0.09	0.09	0.08	0.10	14.00	6.00	4.00
500	0.09	0.09	0.08	0.10	18.00	6.00	6.00
1000	0.09	0.09	0.08	0.10	16.00	10.00	6.00
3000	0.09	0.09	0.08	0.10	14.00	4.00	4.00

There are three conclusions that can be drawn from this table. First, the SMM estimates are biased, and the bias does not decrease substantially as the number of simulations increases. This finding is consistent with the findings of Michaelides and Ng [2000]. The estimate of the probability of detection is biased upwards by 2%; the loss in wealth is biased downwards by 1%; and the sensitivity in the loss in wealth to manipulation is biased downwards by 0.08. Second, the second-stage SMM estimates have a larger bias and worse asymptotic properties than the first-stage estimates. This finding is consistent with the extant literature on the finite sample bias of the two-step GMM estimator [e.g., Altonji and Segal, 1996]. Third, the asymptotic confidence intervals are more likely to include the true parameter as the number of simulations increases, but this improvement is not monotonic in the number of simulations. For instance, statistics for the estimates obtained using 3,000 simulations are not strictly better than the statistics for the estimates obtained using 1,000 simulations. At the same time, there is a significant increase in the computational time in going from 1,000 to 3,000 simulations for each executive. Based on these findings, I use 1,000 simulations per executive when I estimate the model.

B.2 Simulation details

To simulate the model, I first fix the set of independent random shocks for the intrinsic value process, turnover decision, termination decision, and detection of manipulation. The random draws must be fixed to avoid "chatter" (the noise introduced by using different random draws) when optimizing the SMM objective function [McFadden, 1989]. Next, for each 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 each executive, I simulate the data according to the model. First, I simulate the intrinsic value paths.[41] Second, for each 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, 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 calculate a path for whether the executive manipulates and by how much. If he manipulates, I also observe the manipulation in each period and whether the manipulation is detected. Finally, once manipulation is detected, I observe whether the manager is terminated.

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

[41] 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; thus, there is no need to employ a burn-in period to dissipate the effect of an arbitrary choice of a starting point.

is observed 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 the manipulation being detected before the manager leaves the firm 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 that they are observed in the data. Finally, I use the restatement events and the biases in the first two periods from the simulated sample to compute the moments.

B.3 Optimization details

The structural estimation involves optimizing the SMM objective function. For every guess of parameters (g, κ_1, κ_2), it is necessary to solve the optimization problem for each executive, simulate the data, and compute moments based on the simulated data. I constrain the parameters to be in the following intervals: $g \in [0.0001, 1], \kappa_1 \in [0.0001, 0.5], \kappa_2 \in [0.0001, 3]$.[42] Solving the optimization problem for each executive is computationally intensive. For example, it takes about 110 seconds on a 32-processor cluster to evaluate the SMM objective function once.[43] It is common to restart optimization from the first value to which the optimization converges in order to increase the likelihood of finding a global optimum. I also re-start the optimization function once and find that the new optimum value is very close to the first value, and the objective function improves by at most 10^{-4}.

I use a genetic algorithm [Holland, 1992] to select the starting values for the deterministic directional search. The genetic algorithm incorporates the principles of biological evolution

[42]The interval for the probability of manipulation being detected, g, is straightforward. The wealth loss, 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. This parameter is expected to be low and I constrain it to $\kappa_1 \in [0.0001, 0.5]$. The sensitivity of the loss in wealth to the magnitude of manipulation, κ_2, is constrained to $\kappa_2 \in [0, 3]$.

[43]Simulated annealing is commonly used to optimize a non-smooth objective function and to avoid local minima [e.g., Rust, 1994, Taylor, 2010]. 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.

and selects the candidate points by keeping the best ones without any change and replacing the rest of the population by combining the best points (i.e., performing crossover) and adding random mutations. At each restart of the SMM optimization, I run the genetic algorithm for two generations with the number of points in each generation being 20 (this implies 60 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 within which it is not optimal to manipulate).[44] After the genetic algorithm locates a region that potentially contains the global minimum, I refine the point using another global optimization algorithm – the patternsearch,[45] which searches the points around the current point in pre-specified directions. I run the pattern search until it reaches convergence.

[44]The specific settings for the genetic algorithm that I use in Matlab are: gaoptions = gaoptimset(@ga); gaoptions.PopulationSize = 20; gaoptions.Vectorized = 'off'; gaoptions.UseParallel = 'never'; gaoptions.Display = 'diagnose'; gaoptions.EliteCount = 3; gaoptions.CreationFcn = @gacreationlinearfeasible; gaoptions.CrossoverFraction = .7; gaoptions.CrossoverFcn = @crossoverheuristic; gaoptions.MutationFcn1 = @mutationadaptfeasible; gaoptions.MutationFcn2 = 0.75; gaoptions.MutationFcn3 = 0.25; gaoptions.Generations = 2.

[45]The specific setting for the patternsearch that I use in Matlab are: psoptions = psoptimset; psoptions.UseParallel = 'never'; psoptions.Display = 'diagnose'; psoptions.Cache = 'on'; psoptions.CacheTol = 1e-4; psoptions.ScaleMesh = 'off'; psoptions.InitialMeshSize = 0.05; psoptions.MaxMeshSize = 1.5; psoptions.MeshContraction = 0.5; psoptions.MeshExpansion = 2; psoptions.MeshAccelerator = 'on'; psoptions.PollMethod = 'GSSPositiveBasis2N'; psoptions.CompletePoll = 'on'; psoptions.SearchMethod = 'MADSPositiveBasis2N'; psoptions.CompleteSearch = 'on'; psoptions.TolMesh = 1e-4; psoptions.TolX = 1e-4; psoptions.TolFun = 1e-6.

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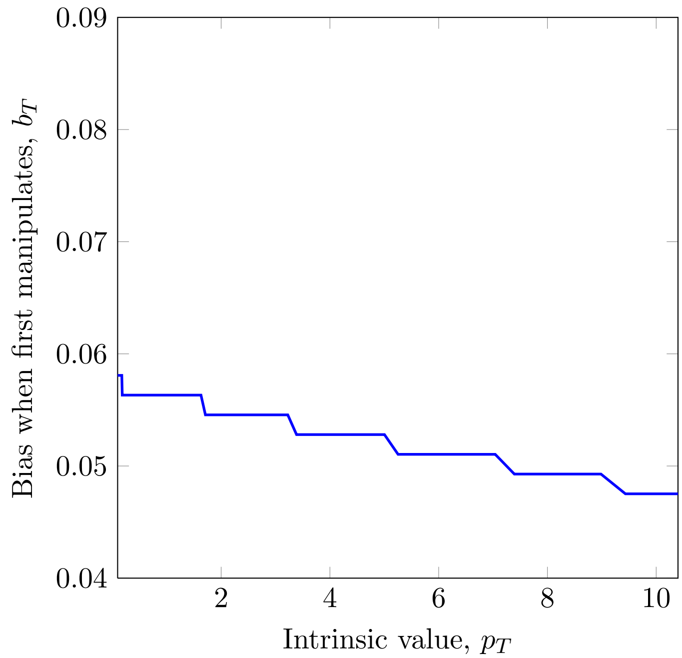
Fig. 1. Optimal magnitude of bias in net assets in the final period

This figure depicts the optimal magnitude of manipulation in the final period T if the manager has not manipulated before $b_T(p_T)$ and the optimal magnitude of manipulation if the manager has manipulated before $b_T(p_T, b_{T-1})$ for the model described in Section 3. I set the cost of manipulation parameters to their estimated values (Table 5, Panel A) and the executive-specific parameters to their median values (Table 4).



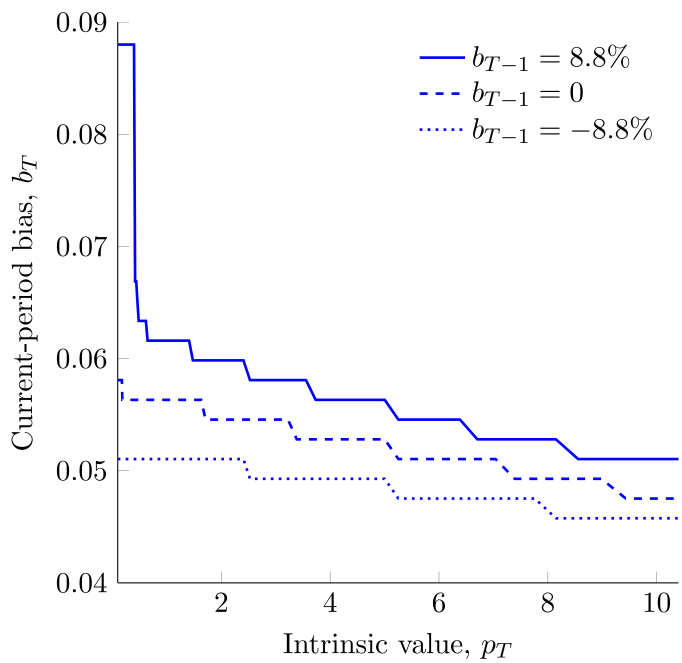


Table 1. Variable definitions

	Definition	Source
	Executive-specific parameters	
P_0	Stock price at the end of the third month following the fiscal year end before the CEO joins the firm.	CRSP
$\widehat{P}_t$	Stock price at the end of the third month following the fiscal year end in year t.	CRSP
$\widehat{p}_t$	Scaled stock price $\widehat{P}_t/P_0$ at the end of the third month following the fiscal year end in year t.	CRSP
N_t^{EPS}	Total number of shares used in calculation of earnings per share (basic) in year t.	Compustat
n_t^v, n_t^{nv}	Scaled vested and non-vested equity holdings set equal to N_t/N_1, where N_t is defined as $N_t^{stock} + N_t^{options} \times d$ in respective groups; where N_t^{stock} is the number of stocks the CEO owns at time t, $N_t^{options}$ is the number of options the CEO owns at time t, and d is the mean stock option delta computed under the assumptions of Core and Guay [2002] for all firms in the same industry. This variable is winsorized at the 5th and 95th percentiles.	Equilar, CRSP
w_t	Scaled estimate of a CEO's cash wealth set equal to $W_t/(n_1P_0)$, where W_1 equals the CEO's firm-specific wealth in the first period (when $\eta = 1$); W_t is the sum of his cash compensation and cash wealth in the prior period. I assume that the CEO earns a risk-free rate of 2% on his cash wealth every year. This variable is winsorized, such that the resulting c_t is within its 5th to 95th percentiles.	Equilar
c_t	The ratio of the scaled cash wealth to the value of one dollar inflation in reported earnings $\overline{c} = w_t/(n_t\beta)$. This variable is winsorized at the 5th and 95th percentiles.	Equilar
	Industry-specific parameters based on Standard & Poor's Global Industry classification groups	
μ	Median 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 (the 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	Median standard deviation 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	Median 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 a positive net income.	Compustat
	Variables observed in the case of restatements	
$B^{(1)}$	Correction of earnings per share in the first restated period.	AuditAnalytics
$B^{(1)} - B^{(2)}$	Correction of earnings per share in the second restated period.	AuditAnalytics
$b^{(1)}, b^{(2)}$	Scaled per share bias in net assets: $b^{(t)} = B^{(t)}/P_0$. This variable is winsorized at the 5th and 95th percentiles of restatements in the non-technical sample.	

	Fixed parameters	
$\gamma = 2$	Relative risk aversion parameter.	
$T = 85$	CEOs' retirement age.	
$\eta = 1$	Multiplier for estimating CEOs' total cash wealth in the first period, in which the total wealth is the sum of outside and firm-specific wealth. CEOs' outside cash wealth is assumed to be equal to η multiplied by their firm-specific wealth as in Conyon et al. [2011].	
$r = 2\%$	Risk-free rate for cash wealth accumulation. In addition, $1/(1 + r_f)$ serves as a time-discount factor in the manager's optimization problem.	
ϕ	Probability of a restatement-related termination, which is computed as a fraction of CEOs who leave the firm between the end of a restated period and 12 months after a restatement filing date: $\phi = 0.12$ in the non-technical sample, $\phi = 0.14$ in the nontrivial sample.	
f	Probability of a CEO leaving a firm, which is defined as the annual turnover rate across CEOs with the same tenure. It is assumed to equal 0.1 if the CEO's tenure is longer than 10 years.	Equilar, Boardex
	Estimated parameters	
g	Probability of manipulation being detected in each period.	
κ_1	Loss in the manager's wealth if manipulation is detected.	
κ_2	Sensitivity of the loss in the manager's wealth to the magnitude of manipulation if manipulation is detected.	

Table 2. Descriptive statistics: comparison with Compustat universe

This table presents p-values for the two sample tests when one sample is Compustat firms listed on the NYSE and NASDAQ and another sample consists of distinct firms from the sample of non-technical restatements in 2006. The t-test is the test for the difference in means. The WMW test is the Mann-Whitney two-sample rank-sum test where the null hypothesis states that the two samples of variables are drawn from the same population. The variables are computed using annual Compustat data. Market value is defined as $(CSHO \cdot PRCC\_F)$; Total assets as AT; Sales as SALE; ROA as operating income after depreciation, scaled by assets (OIADP/AT); Profit margin as operating income after depreciation scaled by sales (OIADP/SALE); Sales growth as percentage change in sales; Book-to-market as shareholders' equity scaled by market capitalization (SEQ/MV); Leverage as the sum of long term debt and debt in current liabilities divided by assets ((DLTT+DLC)/AT); Free Cash Flow as the difference between operating cash flows and average capital expenditures over the previous three years (OANCF - CAPX_Mean). Variables are winsorized at 1- and 99- percentile.

	Compustat sample	Non-technical restatements		Compustat sample	Non-technical restatements	
	Mean	Mean	t-test p-value	Median	Median	WMW p-value
			Size			
Market value	4040.58	5864.42	0.01	573.57	967.19	0.00
Total assets	7382.12	11 835.24	0.09	668.20	999.71	0.00
Sales	2808.53	4545.52	0.00	324.64	596.57	0.00
			Profitability			
ROA	0.04	0.04	0.15	0.06	0.06	0.33
Profit margin	−1.30	−0.93	0.52	0.11	0.10	0.24
			Growth			
Sales growth	67.26	20.29	0.18	12.75	9.90	0.00
			Capital structure			
Book-to-market	0.42	0.43	0.94	0.44	0.43	0.80
Leverage	0.20	0.21	0.48	0.14	0.16	0.04
Free cash flows	170.21	246.40	0.35	14.21	27.97	0.00
Number of obs.	4,041	1,204		4,041	1,204	

Table 3. Restatement characteristics

This table contains descriptive statistics for the restatements from the non-technical and nontrivial restatements samples. Revenue recognition, core expenses, and non-core expenses issues are defined as in Scholz [2008]. Fraud category, identified by Audit Analytics, includes restatements in which the disclosure text indicates that errors were the result of improper, illegal, or falsified reporting, often for personal gain. SEC investigation category, as identified by Audit Analytics, includes both formal and informal investigations. Class-action lawsuits includes lawsuits in which class action period overlaps with the restated period and excludes lawsuits that were dismissed before trial or withdrawn. Security class action settlement is in millions and originates from the Woodruff-Sawyer & Co database.

	Non-technical restatements	Nontrivial restatements
Revenue recognition (%)	21.82	37.37
Core expenses (%)	47.27	54.55
Non-core expenses (%)	62.42	48.48
Number of issues restated	2.37	2.61
Number of years restated	2.18	2.11
Fraud disclosed (%)	3.64	5.05
SEC investigation (%)	6.06	7.07
Security class action (%)	8.48	8.08
Security class action settlement	25.39	8.47
Annual return in the year of a restatement (%)	−25.01	−26.23
Number of obs.	165	99

Table 4. Descriptive statistics

This table contains summary statistics for the sample of 1,513 CEOs, in which an intentional misstatement is defined as a non-technical restatement and the sample of 1,462 CEOs, in which an intentional misstatement is defined as a nontrivial restatement. The descriptive statistics represent the within-CEO means. Additional details on the variable measurement can be found in Table 1.

Non-technical restatements (N = 1,513)					
	Mean	Std dev	25th	50th	75th
Cash wealth, $\overline{w}_t$ (%)	191.19	141.32	126.11	151.00	199.23
Vested equity, $\overline{n^v}_t$ (%)	99.04	57.09	71.14	92.03	108.86
Non-vested equity, $\overline{n_t^{nv}}$(%)	35.06	28.87	8.18	31.80	55.78
Cost ratio, $\overline{c_t} = \overline{w_t/n_t\beta}$ (%)	8.38	7.88	4.94	6.52	9.07
CEO age	52.84	7.16	48.00	53.00	57.50
Number of years a CEO in the sample	3.93	1.73	3.00	4.00	5.00
Probability of leaving the firm, $\overline{f_t}$ (%)	7.40	4.07	3.88	7.14	10.16
Expected return, μ (%)	8.33	1.38	7.85	8.26	8.98
Return volatility, σ (%)	39.41	9.83	34.64	38.89	43.34
Price-to-earnings multiple, β	20.80	4.70	16.23	19.33	23.89
Price, $\overline{\widehat{P}_t/P_0}$	1.11	0.71	0.66	0.95	1.31
Bias in net assets for non-technical restatements (N = 165)					
	Mean	Std dev	25th	50th	75th
Bias in net assets, $b^{(1)}$ (0.01%)	108.32	219.02	0.00	27.72	125.81
Bias in net assets, $b^{(2)}$ (0.01%)	65.88	169.70	0.00	0.00	54.44
Bias in net assets for nontrivial restatements (N = 99)					
	Mean	Std dev	25th	50th	75th
Bias in net assets, $b^{(1)}$ (0.01%)	105.38	210.74	0.00	30.55	95.77
Bias in net assets, $b^{(2)}$ (0.01%)	76.95	173.96	0.00	0.00	80.31

Table 5. 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, and the fixed parameters are the following: $\gamma = 2$, $T = 85$, $\eta = 1$. Panel A contains estimates based on the sample of 1,361 CEOs, in which an intentional misstatement is defined as a non-technical restatement. Panel B contains estimates based on the sample of 1,315 CEOs, in which an intentional misstatement is defined as a nontrivial restatement. 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 listed in parentheses.

Panel A: Non-technical restatements				
Prob. of detection g (%)	Loss in wealth κ_1 (%)	Sensitivity of loss to bias κ_2	J-test	p-value
8.74***	0.03	1.17***	0.03	0.85
(0.47)	(4.65)	(0.37)		
Panel B: Nontrivial restatements				
Prob. of detection g (%)	Loss in wealth κ_1 (%)	Sensitivity of loss to bias κ_2	J-test	p-value
6.96***	7.88	0.96***	1.67	0.20
(0.35)	(5.38)	(0.33)		

Table 6. 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, and the fixed parameters are the following: $\gamma = 2$, $T = 85$, $\eta = 1$. The choice of moments is discussed in Section 4. Panel A contains estimates based on the sample of 1,361 CEOs, in which an intentional misstatement is defined as a non-technical restatement. Panel B contains estimates based on the sample of of 1,315 CEOs, in which an intentional misstatement is defined as a nontrivial restatement. For each definition of an intentional misstatement, I simulate 10,000 samples of manipulation decisions for the sample CEOs under the estimated parameters reported in Table 5 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: Non-technical restatements				
	Empirical value	Simulated value	Standard error	p-value
Restatement rate (1%)	10.87	10.76	0.08	0.07
Mean $b^{(1)}$ (0.01%)	240.60	240.31	3.43	0.46
Mean $b^{(2)}b^{(1)}$ (0.01%)	123.53	123.77	1.43	0.44
Mean cost for restating firms (1%)	1.16	1.15	0.01	0.41
Panel B: Nontrivial restatements				
	Empirical value	Simulated value	Standard error	p-value
Restatement rate (1%)	6.77	6.83	0.07	0.16
Mean $b^{(2)}$ (0.01%)	144.30	144.61	3.22	0.46
Mean $b^{(2)}b^{(1)}$ (0.01%)	97.74	93.65	1.41	0.00
Mean cost for restating firms (1%)	0.76	0.67	0.01	0.00

Table 7. Unconditional 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 1,361 CEOs, in which an intentional misstatement is defined as a non-technical restatement. Panel B contains summary statistics for the model-implied bias computed under the cost parameter estimates obtained for the sample of 1,315 CEOs, in which an intentional misstatement is defined as a nontrivial restatement. The variables are defined in Table 1, and the fixed parameters are the following: $\gamma = 2$, $T = 85$, $\eta = 1$. The details on bias estimation are described in Section 5.3. I compute the fraction of CEO-years when the CEO manipulates, the equally weighted and value-weighted biases in the stock price (defined as the difference between the stock price and the firm's intrinsic value as a percentage of the stock price) over all CEO-years. *Bias in net assets* is the bias in net assets scaled by the lag of total assets, i.e., $\widehat{b}_t P_0 N_t^{EPS}/AT_{t-1}$, where $\widehat{b}_t$ is the model-implied bias in net assets. *Bias in earnings* is the bias in earnings scaled by the lag of total assets, i.e., $(\widehat{b}_t - \widehat{b}_{t-1}) P_0 N_t^{EPS}/AT_{t-1}$. *Bias in price* is the difference between the stock price and the firm's 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 $\beta\widehat{b}_t$. *Bias in net assets*, *Bias in earnings*, and *Bias in price* are winsorized at the 5th and 95th percentiles.

Panel A: Non-technical restatements (N = 5,375)					
Fraction of CEO-years when CEO manipulates (%)		Equally weighted bias in price (%)		Value-weighted bias in price (%)	
45.17		10.78		5.68	
	Mean	Std dev	25th	50th	75th
Bias in net assets (%)	0.86	1.42	0.00	0.00	1.28
Bias in earnings (%)	0.43	0.82	0.00	0.00	0.49
Bias in price (%)	10.78	19.75	0.00	0.00	16.05
Cost impact of bias (%)	19.55	29.68	0.00	0.00	42.46
Panel B: Nontrivial restatements (N = 5,005)					
Fraction of CEO-years when CEO manipulates (%)		Equally weighted bias in price (%)		Value-weighted bias in price (%)	
36.64		10.58		5.12	
	Mean	Std dev	25th	50th	75th
Bias in net assets (%)	0.69	1.29	0.00	0.00	0.87
Bias in earnings (%)	0.41	0.81	0.00	0.00	0.34
Bias in price (%)	10.58	20.50	0.00	0.00	12.46
Cost impact of bias (%)	16.14	30.22	0.00	0.00	38.89

Table 8. Model-implied measure of manipulation conditional on CEO manipulating

Panel A contains summary statistics for the model-implied bias computed under the cost parameter estimates obtained for the sample of 1,361 CEOs, in which an intentional misstatement is defined as a non-technical restatement. Panel B contains summary statistics for the model-implied bias computed under the cost parameter estimates obtained for the sample of 1,315 CEOs, in which an intentional misstatement is defined as a nontrivial restatement. The variables are defined in Table 1, and the fixed parameters are the following: $\gamma = 2$, $T = 85$, $\eta = 1$. The details on bias estimation are provided in Section 5.3. I compute the fraction of manipulating CEOs in the full sample and the equally weighted and value-weighted biases in the stock price (defined as the difference between the stock price and the firm's intrinsic value as a percentage of the stock price) over CEO-years in which CEOs manipulate according to the model. *Bias in net assets* is the bias in net assets scaled by the lag of total assets, i.e., $\widehat{b}_t P_0 N_t^{EPS}/AT_{t-1}$, where $\widehat{b}_t$ is the model-implied bias in net assets. *Bias in earnings* is the bias in earnings scaled by the lag of total assets, i.e., $(\widehat{b}_t - \widehat{b}_{t-1})P_0 N_t^{EPS}/AT_{t-1}$. *Bias in price* is the difference between the stock price and the firm's 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 $\beta\widehat{b}_t$. *Bias in net assets*, *Bias in earnings*, and *Bias in price* are winsorized at the 5th and 95th percentiles.

Panel A: Non-technical restatements (N = 2,428)					
Fraction of CEOs who manipulate (%)		Equally weighted bias in price (%)		Value-weighted bias in price (%)	
66.42		23.96		15.54	
	Mean	Std dev	25th	50th	75th
Bias in net assets (%)	2.08	2.14	0.64	1.48	2.76
Bias in earnings (%)	1.03	1.37	0.12	0.65	1.59
Bias in price (%)	23.96	23.37	2.66	19.94	42.51
Cost impact of bias (%)	43.29	30.38	33.64	46.05	62.72
Panel B: Nontrivial restatements (N = 1,834)					
Fraction of CEOs who manipulate (%)		Equally weighted bias in price (%)		Value-weighted bias in price (%)	
58.86		28.98		18.96	
	Mean	Std dev	25th	50th	75th
Bias in net assets (%)	2.08	2.43	0.62	1.52	2.91
Bias in earnings (%)	1.20	1.57	0.22	0.84	1.87
Bias in price (%)	28.98	24.73	6.58	27.46	51.78
Cost impact of bias (%)	44.05	35.55	36.08	47.96	67.22

Table 9. 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.

	Definition
Total accruals	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 the lag of total assets.
Accruals as in Richardson et al. [2005]	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 is simplified 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 the lag of total assets.
Jones model discretionary accruals	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 the lag of total assets, AT_{t-1}. Estimation requires at least ten observations per group.
Modified Jones model discretionary accruals	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	The difference between Jones model discretionary accruals for firm i and the mean Jones model discretionary accruals for the matched firms, where the matching is performed based on the two-digit SIC code (or on the one-digit SIC code if the match on the two-digit SIC code is empty), fiscal year, and ROA_t for a matched firm within a 1.5% 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 10. Out-of-sample performance

This table reports out-of-sample performance statistics for the model-implied measure of manipulation and measures of discretionary accruals. Additional details can be found in Section 5.4. The variables are defined in Table 1, and the fixed parameters are the following: $\gamma = 2$, $T = 85$, $\eta = 1$. The performance statistics include the bias (Bias), the mean absolute deviation (Mean Abs Dev), the median absolute deviation (Med Abs Dev) and the root mean squared error (RMSE). I compute these statistics by calculating the difference between the true value observed in the holdout sample and the estimate (i.e., deviation). The statistics for the probability of manipulation are computed using all CEO-years for executives who restate in the holdout sample, whereas the statistics for the magnitude of misreporting are computed using only CEO-years in which an executive actually misreports in the holdout sample. The model-implied bias in earnings is computed as the bias in earnings scaled by the lag of total assets, i.e., $(\widehat{b}_t - \widehat{b}_{t-1})P_0 N_t^{EPS}/AT_{t-1}$, where $\widehat{b}_t$ is the model-implied manipulation. Discretionary accruals are defined in Table 9.

Panel A: Non-technical restatements				
Probability of manipulation (number of CEOs = 16, number of obs. = 77)				
	Bias	Mean Abs Dev	Med Abs Dev	RMSE
Model-implied probability(%)	−30.34	58.49	100.00	76.12
Discretionary accruals-implied prob.(%)	−59.74	59.74	100.00	77.29
Magnitude of manipulation in earnings (number of CEOs = 16, number of obs. = 31)				
	Bias	Mean Abs Dev	Med Abs Dev	RMSE
Model-implied bias in earnings (%)	−0.21	0.60	0.16	1.03
Total accruals (%)	7.07	10.58	7.08	14.74
Accruals as in Richardson et al. [2005] (%)	−2.66	9.02	7.14	12.42
Jones model discr. accruals (%)	−0.36	7.12	4.02	11.82
Modified Jones model discr. accruals (%)	−0.35	6.93	4.08	11.81
Performance-matched discr. accruals (%)	0.38	6.34	4.65	8.35
Panel A: Nontrivial restatements				
Probability of manipulation (number of CEOs = 10, number of obs. = 51)				
	Bias	Mean Abs Dev	Med Abs Dev	RMSE
Model-implied probability (%)	−28.14	62.61	95.00	76.03
Discretionary accruals-implied prob.(%)	−66.67	66.67	100.00	81.65
Magnitude of manipulation in earnings (number of CEOs = 10, number of obs. = 17)				
	Bias	Mean Abs Dev	Med Abs Dev	RMSE
Model-implied bias in earnings (%)	0.32	1.41	1.26	1.85
Total accruals (%)	7.41	12.08	12.07	13.77
Accruals as in Richardson et al. [2005] (%)	−6.72	13.09	12.13	15.71
Jones model discr. accruals (%)	−1.56	8.20	5.31	11.52
Modified Jones model discr. accruals (%)	−1.54	8.12	5.18	11.35
Performance-matched discr. accruals (%)	1.46	9.26	6.73	11.97

Table 11. Alternative specifications: parameter estimates

This table contains estimates of the cost of manipulation parameters for the model described in Section 3 under different choices of the risk aversion parameter, γ, the retirement age, T, and the multiplier for estimating CEOs' total cash wealth, η. The parameters are defined in Table 1. Panel A contains estimates based on the sample of 1,361 CEOs, in which an intentional misstatement is defined as a non-technical restatement. Panel B contains estimates based on the sample of 1,315 CEOs, in which an intentional misstatement is defined as a nontrivial restatement. 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 listed in parentheses.

Panel A: Non-technical restatements					
	Prob. of detection g (%)	Loss in wealth κ_1 (%)	Sensitivity of loss to bias κ_2	J-test	p-value
$\gamma = 2$, $T = 85$, $\eta = 1$	8.74***	0.03	1.17***	0.03	0.85
	(0.47)	(4.65)	(0.37)		
$\gamma = 3$, $T = 85$, $\eta = 1$	8.62***	1.16	0.98***	0.01	0.91
	(0.72)	(3.25)	(0.28)		
$\gamma = 2$, $T = 65$, $\eta = 1$	8.00***	0.01	0.60***	7.10	0.01
	(0.46)	(5.50)	(0.17)		
$\gamma = 2$, $T = 85$, $\eta = 0.5$	8.78***	0.26	1.29***	0.09	0.76
	(0.61)	(4.67)	(0.41)		
Panel B: Nontrivial restatements					
	Prob. of detection g (%)	Loss in wealth κ_1 (%)	Sensitivity of loss to bias κ_2	J-test	p-value
$\gamma = 2$, $T = 85$, $\eta = 1$	6.96***	7.88	0.96***	1.67	0.20
	(0.35)	(5.38)	(0.33)		
$\gamma = 3$, $T = 85$, $\eta = 1$	6.25***	9.90**	0.82**	1.91	0.17
	(0.53)	(4.69)	(0.35)		
$\gamma = 2$, $T = 65$, $\eta = 1$	7.22***	0.55	0.68***	0.08	0.77
	(0.98)	(7.23)	(0.22)		
$\gamma = 2$, $T = 85$, $\eta = 0.5$	6.93***	8.42*	1.26**	1.52	0.22
	(0.44)	(5.00)	(0.51)		

Table 12. Alternative specifications: unconditional model-implied measure of manipulation

This table contains statistics for the unconditional model-implied measure of manipulation for the model described in Section 3 under different choices of the risk aversion parameter, γ, the retirement age, T, and the multiplier for estimating CEOs' total cash wealth, η. Panel A contains summary statistics for the model-implied bias computed under the cost parameter estimates obtained for the sample of 1,361 CEOs, in which an intentional misstatement is defined as a non-technical restatement. Panel B contains summary statistics for the model-implied bias computed under the cost parameter estimates obtained for the sample of of 1,315 CEOs, in which an intentional misstatement is defined as a nontrivial restatement. The variables are defined in Table 1. The details of bias estimation are described in Section 5.3. I compute the fraction of CEO-years when CEO manipulates, the equally weighted and value-weighted biases in the stock price (defined as the difference between the stock price and the firm's intrinsic value as a percentage of the stock price) over all CEO-years.

Panel A: Non-technical restatements (N = 5,375)			
	Fraction of CEO-years when CEO manipulates (%)	Equally weighted bias in price (%)	Value-weighted bias in price (%)
$\gamma = 2$, $T = 85$, $\eta = 1$	45.17	10.78	5.68
$\gamma = 3$, $T = 85$, $\eta = 1$	46.62	10.95	5.97
$\gamma = 2$, $T = 65$, $\eta = 1$	33.95	11.24	4.57
$\gamma = 2$, $T = 85$, $\eta = 0.5$	45.54	10.86	5.89
Panel B: Nontrivial restatements (N = 5,005)			
	Fraction of CEO-years when CEO manipulates (%)	Equally weighted bias in price (%)	Value-weighted bias in price (%)
$\gamma = 2$, $T = 85$, $\eta = 1$	36.64	10.58	5.12
$\gamma = 3$, $T = 85$, $\eta = 1$	39.34	10.98	5.59
$\gamma = 2$, $T = 65$, $\eta = 1$	29.03	10.19	4.00
$\gamma = 2$, $T = 85$, $\eta = 0.5$	37.78	10.07	4.99

Table 13. Alternative specifications: model-implied measure of manipulation conditional on CEO manipulating

This table contains statistics for the model-implied measure of manipulation, conditional on the CEO manipulating, for the model described in Section 3 under different choices of the risk aversion parameter, γ, the retirement age, T, and the multiplier for estimating the CEOs' total cash wealth, η. Panel A contains summary statistics for the model-implied bias computed under the cost parameter estimates obtained for the sample of 1,361 CEOs, in which an intentional misstatement is defined as a non-technical restatement. Panel B contains summary statistics for the model-implied bias computed under the cost parameter estimates obtained for the sample of 1,315 CEOs, in which an intentional misstatement is defined as a nontrivial restatement. The variables are defined in Table 1. The details of bias estimation are described in Section 5.3. I compute the fraction of manipulating CEOs in the full sample as well as the equally weighted and value-weighted biases in the stock price (defined as the difference between the stock price and the firm's intrinsic value as a percentage of the stock price) over CEO-years in which CEOs manipulate according to the model.

Panel A: Non-technical restatements			
	Fraction of CEOs who manipulate (%)	Equally weighted bias in price (%)	Value-weighted bias in price (%)
$\gamma = 2$, $T = 85$, $\eta = 1$	66.42	23.96	15.54
$\gamma = 3$, $T = 85$, $\eta = 1$	67.01	23.56	15.51
$\gamma = 2$, $T = 65$, $\eta = 1$	54.05	33.36	19.62
$\gamma = 2$, $T = 85$, $\eta = 0.5$	66.42	23.93	15.94
Panel B: Nontrivial restatements			
	Fraction of CEOs who manipulate (%)	Equally weighted bias in price (%)	Value-weighted bias in price (%)
$\gamma = 2$, $T = 85$, $\eta = 1$	58.86	28.98	18.96
$\gamma = 3$, $T = 85$, $\eta = 1$	60.84	27.98	19.29
$\gamma = 2$, $T = 65$, $\eta = 1$	50.85	35.26	21.04
$\gamma = 2$, $T = 85$, $\eta = 0.5$	59.54	26.73	17.88

Table 14. Alternative specifications: out-of-sample performance

This table reports out-of-sample performance statistics for the model-implied measure of manipulation under different choices of the risk aversion parameter, γ, the retirement age, T, and the multiplier for estimating CEOs' total cash wealth, η. Additional details are presented in Section 5.4. The variables are defined in Table 1. These statistics include the bias (Bias), the mean absolute deviation (Mean Abs Dev), the median absolute deviation (Med Abs Dev) and the root mean squared error (RMSE). I compute these statistics by calculating the difference between the true value observed in the holdout sample and the estimate (i.e., deviation). The statistics for the probability of manipulation are computed using all CEO-years for executives who restate in the holdout sample, whereas the statistics for the magnitude of misreporting are computed using only CEO-years in which an executive actually misreports in the holdout sample. The model-implied bias in earnings is computed as the bias in earnings, scaled by the lag of total assets, i.e., $(\widehat{b}_t - \widehat{b}_{t-1})P_0 N_t^{EPS}/AT_{t-1}$, where $\widehat{b}_t$ is the model-implied manipulation.

Panel A: Non-technical restatements				
Probability of manipulation (number of CEOs = 16, number of obs. = 77)				
	Bias	Mean Abs Dev	Med Abs Dev	RMSE
$\gamma = 2$, $T = 85$, $\eta = 1$ (%)	−30.34	58.49	100.00	76.12
$\gamma = 3$, $T = 85$, $\eta = 1$ (%)	−26.78	57.14	97.00	74.10
$\gamma = 2$, $T = 65$, $\eta = 1$ (%)	−27.86	45.18	10.00	66.14
$\gamma = 2$, $T = 85$, $\eta = 0.5$ (%)	−29.71	58.13	100.00	75.95
Magnitude of manipulation in earnings (number of CEOs = 16, number of obs. = 31)				
	Bias	Mean Abs Dev	Med Abs Dev	RMSE
$\gamma = 2$, $T = 85$, $\eta = 1$ (%)	−0.21	0.60	0.16	1.03
$\gamma = 3$, $T = 85$, $\eta = 1$ (%)	−0.08	0.57	0.22	0.98
$\gamma = 2$, $T = 65$, $\eta = 1$ (%)	−1.72	2.40	0.68	5.72
$\gamma = 2$, $T = 85$, $\eta = 0.5$ (%)	−0.19	0.60	0.24	1.01
Panel B: Nontrivial restatements				
Probability of manipulation (number of CEOs = 10, number of obs. = 51)				
	Bias	Mean Abs Dev	Med Abs Dev	RMSE
$\gamma = 2$, $T = 85$, $\eta = 1$ (%)	−28.14	62.61	95.00	76.03
$\gamma = 3$, $T = 85$, $\eta = 1$ (%)	−29.86	63.27	87.00	76.27
$\gamma = 2$, $T = 65$, $\eta = 1$ (%)	−27.16	51.68	71.00	69.28
$\gamma = 2$, $T = 85$, $\eta = 0.5$ (%)	−24.65	61.12	95.00	75.24
Magnitude of manipulation in earnings (number of CEOs = 10, number of obs. = 17)				
	Bias	Mean Abs Dev	Med Abs Dev	RMSE
$\gamma = 2$, $T = 85$, $\eta = 1$ (%)	0.32	1.41	1.26	1.85
$\gamma = 3$, $T = 85$, $\eta = 1$ (%)	0.36	1.37	1.44	1.69
$\gamma = 2$, $T = 65$, $\eta = 1$ (%)	−1.21	2.77	2.35	3.62
$\gamma = 2$, $T = 85$, $\eta = 0.5$ (%)	0.37	1.27	1.13	1.60