Information versus Investment

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Abstract

Firms' efficient long-term investment and accurate reporting of information about performance both serve crucial roles in the economy and capital markets. We argue quantitatively that the two goals are in direct conflict in the presence of realistic manager compensation contracts, which provide managers with incentives both to misreport financial statements and to distort their real investment choices. We build a dynamic structural model rich enough to capture a natural tradeoff between investment and information. The model matches a range of observable moments constructed from data on firm investment and periods of detected misreporting by firms. Counterfactuals show that regulations preventing misreporting do in fact incentivize managers to distort real investment, whose volatility rises. This excess volatility lowers firm value, suggesting a quantitatively meaningfully tradeoff.

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1. Introduction

Shareholders rely on firm managers to carry out two distinct tasks: making long-term investment choices and disclosing information about firm performance. Both tasks matter. Firm investment ensures the long-term growth of the firm, while accurate disclosure of financial information allows for the efficient pricing of assets, which is essential for the health and transparency of capital markets overall. Unfortunately, in an incomplete contracting environment, managers' incentives need not be set to perform these two tasks optimally, so it is possible to observe a trade-off between the accurate disclosure of information and the efficiency of investment choices. A large literature on capital misallocation in economics examines the negative impact of distortions or frictions that reduce the efficiency of investment. We contribute to this literature by quantifying the real effects of frictions that induce firms to substitute between making efficient investment choices and revealing accurate information. In other words, we examine whether there is in fact a meaningful tradeoff between the efficiency of firm investment and the quality of information disclosure.

This question is difficult because information frictions are notoriously hard to measure, as we almost never observe the information that has been concealed, only the ongoing equilibrium with information barriers. To overcome this hurdle, we examine the arena of earnings misreporting, which is a natural laboratory to examine a question involving information. Data on earnings announcements, realizations, and restatements are widely available. Moreover, while instances of fraudulent disclosure are infrequent, they exist, so we can observe a snapshot of investment decisions surrounding deliberate information manipulation. Of course, not all fraudulent disclosure is detected, with the result that quantifying the economic magnitude of the relevant information frictions requires imposing some structure on the data.

Therefore, we use these data to estimate a dynamic model of earnings reporting and real intangible investment, where we focus on intangible instead of fixed investment because accounting rules imply expenditures on intangibles have a direct impact on earnings, while fixed investment expenditures do not. The basic idea is simple: managers facing short-term incentives to distort the information available to investors can do so either through misreporting their financial statements, through distortions of their investment choices, or through both actions at once. The implication is that if disclosure regulation causes the cost of one tool for manipulation to change, then in equilibrium use of the other tool will be affected. To reflect this notion, in the model, managers have incentives to manipulate both information about earnings and intangible investment, but they also face costs if they are caught manipulating.

The model matches a wide array of data moments related to both real investment outcomes and accounting restatements. Moreover, in the estimated model, managers choose reporting bias equal to around 2% of sales, conditional upon restatement. When we counterfactually make information manipulation prohibitively costly, managers optimally manipulate earnings more via adjustments to intangible investment. Growth in intangible investment becomes approximately 10% more volatile, and firm value drops by approximately half a percent. We also quantify the slope of this trade-off between earnings manipulation and investment volatility. We find that a one percentage point reduction in bias can be achieved only through an increase in the volatility of investment of approximately half a percentage point.

The intuition behind these results requires a more complete description of the model, which features conflicting managerial compensation incentives. On the one hand, managers have long-term incentives that are aligned with shareholder incentives and that are delivered by stock compensation. This part of managers' compensation package implies that they benefit when they make efficient investment choices and are hurt when they do not. On the other hand, incentive alignment between managers and shareholders is incomplete, as options compensation gives managers short-term incentives to manipulate information to boost the firm's stock price. However, these short-term incentives are tempered by a probability that the manager gets caught manipulating and receives punishment.

With this compensation structure in place, managers then choose both long-term investment and short-term earnings manipulation to maximize their utility over an infinite horizon. They face a stochastic, decreasing returns production function that transforms intangible investment into sales, with the stochastic portion of this technology exhibiting persistence. They also face an exogenous, privately observed, transitory shock to earnings, which is non-fundamental in the sense that it has no effect on actual cash flows, while at the same time affecting observable earnings. Earnings manipulation feeds into stock prices because investors rationally price the firm using an information set that is more restricted than the managers'. Therefore, managers manipulate reported earnings and also opportunistically either cut or overinvest in intangible at suboptimal times. The result is less accurate information provision to the public and intertemporal capital misallocation that produces an efficiency loss in real terms.

The optimal response of a manager to incentives depends crucially on the joint outcome of the fundamental and nonfundamental shock. First, suppose the manager is unlucky today with a negative transitory earnings shock. In this case, if fundamentals are also bad, his options compensation is with high probability out of the money, so neither severe cuts to investment nor upward bias in earnings would lead to a positive options payout. Thus, his utility maximizing choice is to bias earnings downward, while at the same time increasing R&D spending. The first action lowers the strike price for future options compensation, and the second raises the likelihood that the future stock price will be high. In contrast, when faced with positive fundamental and nonfundamental shocks, the manager's options compensation is very likely in the money. Therefore, relative to the case of low shocks, he reverses these two forms of manipulation to boost the current stock price, which results in a payoff from his options. Of course, in the absence of options compensation, the manager would ignore any transitory earnings volatility and simply respond to the persistent fundamental shock.

These results would have been hard to obtain in a reduced form setting. Although managers can be caught misstating earnings, and although these episodes result earnings restatements, manipulation or biases in reported earnings likely go unobserved most of the time. Moreover, the mechanisms whereby earnings manipulation spills over into real outcomes are also unobservable. Questions that are couched in terms of unobservables are prime candidates for structural estimation. For example, Zakolyukina (forthcoming) also takes a structural approach to the estimation of the likelihood of manipulation. We build upon this work by examining not only the probability of manipulation, but also the spillover onto real firm decisions.

The general notion that there is a tradeoff between information and investment is grounded in the survey evidence in Graham, Harvey, and Rajgopal (2005) that managers rely on both misreporting and investment distortions to manipulate earnings, with many expressing a willingness to cut intangible investment (R&D) expenditures in order to hit an earnings target. Even a cursory pass at the data provides evidence consistent with the survey's suggestions. Figure 1 plots the dynamics of intangible investment and earnings reporting bias around periods in which firms are publicly forced to revise their earnings downward, based on a sample of data that we discuss further below. Investment is around 2.5% lower in periods in which firms misreport their earnings, while earnings are biased upward at the same time. The concurrence of a dip in investment with a misreporting event is consistent with the idea that firms do indeed rely jointly on both investment and reporting tools for manipulation. The natural implication is that reduced flexibility in misreporting can in theory result in managers' reliance on value destroying investment distortions, which we term real manipulation.

This trade-off matters because it imposes an equilibrium constraint on policy. For example, disclosure regulation, such as the Sarbanes-Oxley Act (SOX), has been criticized for forcing firms to substitute real earnings manipulation for manipulation based on the misreporting of accounting accruals (Cohen, Dey, and Lys 2008). More generally, because compensation packages with short-term incentives prompt managers to manipulate, and because these packages are pervasive (Edmans, Gabaix, and Jenter 2017), increasing information accuracy can lower real efficiency. Thus, quantifying the extent of this substitution is clearly of interest to policymakers and corporate boards.

These results are also of interest to macroeconomists, given the large literature linking endogenous growth of the economy as a whole to sustained intangible investments at the firm level. As such, distortions to long-term or intangible investments through earnings pressure may have important macroeconomic consequences, as emphasized recently by Terry (2015). Moreover, the link between intangible investment and earnings manipulation seems intuitive, as intangible investments like R&D and advertising are expensed rather than capitalized and subsequently depreciated. Therefore, these investments provide an immediate impact on current-period earnings figures, so they are a natural tool for manipulation.

Our project links to two distinct literatures. The first is the accounting literature that examines earnings management, as managers in our model engage in two types of management: accruals manipulation, which occurs through earnings misreporting, and real manipulation, which occurs through opportunistic changes to long-term investment. As such, this paper contributes to the empirical literatures on both accrual-based and real earnings management.

Empirical patterns consistent with accruals and real manipulation have been documented in reduced-form studies in accounting for decades. This literature traditionally measures both accrual-based and real earnings management using residuals from linear regressions. For example, Jones (1991), Dechow, Sloan, and Sweeney (1995), and Kothari, Leone, and Wasley (2005) measure accrual-based earnings management via discretionary accruals models, which are regressions of total accruals on variables correlated with theoretical normal accruals. Similarly, discretionary R&D expenditures are residuals of regressions with R&D as a dependent variable (e.g., Roychowdhury 2006; Cohen et al. 2008; Zang 2011). Using these measures, the literature has documented substitution between accrual-based and real earnings management (e.g., Cohen et al. 2008; Cohen and Zarowin 2010; Zang 2011).

We advance this literature by substituting an economic model for statistical models of manipulation and R&D. The advantage of this approach is twofold. First, we can quantify the real-accruals manipulation substitution slope. This step is both a quantitative and qualitative advance beyond the reduced-form evidence that predates ours, as the notion of the slope of a trade-off is difficult to formulate in a regression framework. Moreover, we address the call in Leuz and Wysocki (2016) for more research on the real effects of disclosure regulation and its aggregate impact on the economy.[1]

Second, we contribute to the large literature in finance and macroeconomics that studies distortions to real investment decisions. Here, our contribution is a demonstration that distortions caused by earnings pressures and information manipulation constitute a distinct and quantitatively important friction alongside long-studied forces such as financial frictions, adjustment costs, or agency frictions, as in Cooper and Haltiwanger (2006), Hennessy and Whited (2007), and Nikolov and Whited (2014). We enter this picture by using transparent structural estimation to determine the quantitative relevance of the trade-off between information revelation and investment efficiency.

Our model builds on several features of models in this literature. For example, firms in the model are subject to *exogenous* shocks to their productivity or profitability as in Hopenhayn (1992). Simultaneously, managers choose intangible investment that leads to innovation and *endogenous* growth from new ideas. At its core, the model features growth at the micro level that shares the same source—innovation—as models of macro-level endogenous growth (Romer 1990; Aghion and Howitt 1992). Because idiosyncratic shocks differentiate firms and drive their innovation decisions, the firm-level environment bears some similarity to the Schumpeterian model of Klette and Kortum (2004), although lumpy innovation arrivals and entry/exit dynamics are absent.

Two papers are particularly closely related to ours. The first is Terry (2015), which, like our work, examine the effects of information manipulation on R&D. However, our work is distinct in several ways. While Terry (2015) uses a general equilibrium framework and can thus make welfare statements, we use a more flexible partial equilibrium framework that allows us to make value statements. More importantly, this flexibility allows us to examine cross-sectional heterogeneity in the effects of manipulation, as well as the large structural breaks in information disclosure rules stemming from the Sarbanes-Oxley and Dodd-Frank Acts. In addition, our

[1] As we model explicit incentives for manipulation, our paper also touches on the theoretical and empirical literature on moral hazard problems that can arise from performance measure manipulation. See, for example, Lambert (2001), Margiotta and Miller (2000), Armstrong, Jagolinzer, and Larcker (2010), Gayle and Miller (2015), Li (2016), Gayle, Li, and Miller (2016), and Glover and Levine (2017).

model contains a distinct motive for manipulation because we model manipulation incentives as the outcome of observed compensation schemes. Because of this model feature and because we employ micro data on earnings restatements to identify the model parameters related to manipulation, our work has important quantitative implications for executive compensation policy. In contrast, manipulation incentives are modeled exogenously in Terry (2015), which focuses on macroeconomic effects instead of microeconomic policy implications.

The second closely related paper is Benmelech, Kandel, and Veronesi (2010), which explores how stock-based compensation induces mangers to conceal information and choose suboptimal investment policies. While their model shares several important tradeoffs with ours, their analysis is theoretical. We extend this line of research by attempting to quantify the empirical relevance of the frictions that force important interactions between investment efficiency and information disclosure.

The remainder of the paper is organized as follows. Section 2 develops our model and analyzes optimal policies. Section 3 describes our data and provides summary statistics. Section 4 outlines our estimation strategy. Section 5 presents estimation results and our counterfactuals. Section 6 concludes.

2. Model

Time is discrete and the horizon is infinite. There is a unit mass of infinitely lived firms, each of which is run by a manager who receives both equity and options compensation. He chooses intangible investment, as well as potential earnings misreporting to maximize his own utility.

2.1 Firms and Fundamentals

The firm's revenue net of flexible inputs, Y, is the product of endogenous quality, Q, and exogenous productivity, ν_y, which follows an $AR(1)$ process in logs:

$$\log \nu_y' = \rho_y \log \nu_y + \eta_y', \quad \eta_y' \sim N(0, \sigma_y^2). \tag{1}$$

Here, a prime indicates a variable in the subsequent period, and $|\rho_y| < 1$. Consistent with much of the endogenous growth literature (Romer 1990), the production function $Y = \nu_y Q$ exhibits increasing returns in the sum of endogenous quality, Q, and exogenous quality, ν_y. The manager can choose expenditures in intangible capital or R&D, denoted as W, which drives growth in endogenous productivity Q according to:

$$Q' - Q = \Delta Q' = \xi W^{\gamma} Q^{1-\gamma}, \quad 0 < \gamma < 1. \tag{2}$$

The parameter ξ represents a multiplicative productivity shifting parameter. For simplicity, we assume that Q does not depreciate and there are no adjustment costs for intangible investment. These assumptions are innocuous, as none of our eventual model predictions depend on the variable Q.

This production technology exhibits decreasing returns, given by γ, and it implies that the growth rate in endogenous productivity is identically given by:

$$g \equiv \frac{\Delta Q'}{Q} = \xi \left(\frac{W}{Q} \right)^{\gamma}.$$

Distributions to shareholders, D, are given by output minus R&D:

$$D \equiv Y - p_w W, \tag{3}$$

in which p_w is the price of R&D relative to output. Because we have no depreciated capital expenditures in the model, from an accounting perspective, $Y - p_w W$ can be thought of as intrinsic earnings that ultimately convert to shareholder cash flows. We abstract from physical capital accumulation for two reasons. First, because investment in property, plant, and equipment is not immediately expensed, this type of investment only has an impact on earnings when it is depreciated, so the ex ante likelihood of a large impact on earnings management is small. Second, we want to maintain model simplicity and tractability.

2.2 Reporting and Manipulation

In each period, the firm must report its earnings, Π, to investors. We allow for observed earnings to deviate from intrinsic earnings, $Y - p_w W$, in two ways. First, we specify an accounting shock, ν_π that drives non-fundamental exogenous variation in earnings Π, with

$$\nu_\pi \sim N(0, \sigma_\pi^2). \tag{4}$$

This shock has no actual cash flow consequences and simply reflects deficiencies in accounting standards related to accurate estimation of intrinsic cash flows. Below, we refer to the shock, ν_π, as a non-fundamental shock or profit shock.

Next, the manager can manipulate earnings by introducing bias into the book value of the firm. In particular, the manager enters the current period with an inherited bias in book value given by B_{-1}. He then chooses a new level of bias, B, to obtain a net distortion, $B - B_{-1}$, to reported earnings. These two extra components of earnings imply that

$$\Pi \equiv Y - p_w W + \nu_\pi Q + B - B_{-1}. \tag{5}$$

This specification allows for the mechanical partial reversal of accruals-based manipulation because the manager can always compensate for any reversal of bad accruals by manipulating even more with an appropriate choice of B.

If the new choice of bias, B, is nonzero, then the manager faces a constant probability, λ, of discovery. [2] This model feature realistically implies that a manager can go for some time without getting caught. In addition, he can also reverse the manipulation in those periods in which he does not get caught and thus remain forever undetected for that specific episode of manipulation. If he is discovered, he must pay a private cost of

$$MC(B, Q) = \left[\kappa_f + \kappa_q \left(\frac{B}{Q}\right)^2\right] Q, \quad \kappa_f, \kappa_q \geq 0. \tag{6}$$

In principle, such costs could arise either outside the firm from investor pressures or litigation risk. Alternatively, they could arise inside the firm as a part of a sophisticated manager compensation contract. In addition, such costs could represent real disruptions and resource losses for the firm itself (e.g., litigation risk) or purely non-pecuniary internal costs for the manager (e.g., career or reputational concerns). In our counterfactuals below, we want to isolate the effects of these costs on managerial actions, and we want to avoid a purely mechanical impact of the costs themselves on the implied changes in firm value. Therefore, we conservatively assume that all of the smoothing and misreporting incentives reflected in (6) are purely non-pecuniary and internal to the manager. Finally, we assume that upon discovery and after payment of the private cost, $MC(B, Q)$, bias is unwound and reflected in the current value of the firm.

2.3 Managers' Incentives

Managers are risk neutral, and their compensation contracts have two components. The first is a fixed fraction, $\theta_d > 0$, of the outstanding equity of the firm. As such, the manager receives the same fraction, θ_d, of the distributions to shareholders. The second component is option compensation, where the manager is granted θ_o options, where $\theta_o > 0$ and also expressed as a fraction of total equity. We assume that each period the option grant is refreshed so that the strike price is always last period's stock price, denoted as P_{-1}. Thus, each period the manager

[2] While intuition would suggest that the probability of detection ought to depend on the size of the bias, the rarity of restatements does not allow us to identify the relation between bias size and detection probability.

receives a cash flow of D_M, which is given by:

$$D_M \equiv \theta_d D + \theta_o \max\{P - P_{-1}, 0\}, \tag{7}$$

where P is the current ex-dividend stock price. The stock price is rationally determined based on an information set discussed below. This compensation framework directly follows the structure of Glover and Levine (2017), although we omit fixed compensation because the manager's risk neutrality renders such compensation irrelevant for the manager's choice of policies. In contrast, the two components of compensation that we model have important implications for the manager's actions. The stock component aligns the managers' incentives with those of long-term shareholders, while the options component gives the manager an incentive to boost the current period share price above last period's price. While we model options for simplicity, any compensation scheme that is convex in measures of firm performance, such as the the stock price or earnings, would provide similar incentives. Performance-based equity vesting is one such example (Edmans et al. 2017).

We motivate this compensation scheme in large part by the survey of CEO compensation by Frydman and Jenter (2010), which documents that most CEO compensation packages contain salary, bonuses, payouts from long-term incentives plans, and restricted option and stock grants. Because the manager is risk-neutral, the fixed cash component is irrelevant for manipulation and investment decisions, so we omit the salary components.

As in Nikolov and Whited (2014) and Glover and Levine (2017), we remain silent on the optimality of this compensation structure. Instead, we model actual contracts, as our goal is to quantify empirically the trade-off between information and investment in the face of incentives that are widely observed but that do not necessarily induce behavior that maximizes shareholder value. This strategy is sensible given the evidence in Dittmann and Maug (2007) that standard principal-agent models cannot rationalize observed executive compensation contracts. Alternatively, another reasonable view of this compensation policy is that it is a reduced-form description of a contracting outcome that allows for equilibrium self-interested behavior on the part of the agent, as in Zhu (2013). One final alternative interpretation of our contracting specification is that the contracting environment is incomplete and that the contract we specify is optimal, given an agency issue that is both outside the model and that we do not observe. The incompleteness of the contracting environment implies that the misbehavior that we model cannot be contained via contracts.

2.4 Investor Pricing

If investors and managers have identical information sets, then manipulation is of no value to the manager because investors can see through this behavior. One of our central goals is to examine a trade-off between R&D efficiency and the accuracy of investor pricing of a firm relative to underlying true firm value. To this end, we assume that the price $P(\mathcal{I})$ of the firm in the market is a rational pricing function based on some information set, $\mathcal{I}$ for risk-neutral investors, which at a minimum includes observable firm earnings, Π. Because outsider investors make a rational inference based on their information set, to prevent full unravelling of manipulation we assume the investor information set does not include the full state vector. More specifically, while we assume that investors know that the manager has an incentive to misreport, at a minimum, we have to exclude the nonfundamental shock, ν_π from the investors' information set. As long as we exclude ν_π, we can include other variables such as R&D expenditure or dividends. Given the investors' information set, the pricing function represents investors' conditional expectation of the discounted stream of distributions to investors. It is given by:

$$P(\mathcal{I}) \equiv \mathbb{E}\left(\frac{1}{1+r} V_F' \mid \mathcal{I}\right), \tag{8}$$

where V_F is fundamental value of the firm, which we define next.

2.5 Managers' Dynamic Optimization Problem

We now describe the manager's dynamic optimization problem. He faces a state vector at any time of $(\nu_y, \nu_\pi, P_{-1}, B_{-1}, Q)$, and he discounts cash flows at a rate r. He optimally chooses R&D, W, and new gross bias, B. Given that the manager wants to maximize the expected discounted value of his compensation, the manager's private value function is given by V_M, as follows:

$$V_M(\nu_y, \nu_\pi, P_{-1}, B_{-1}, Q) = \max_{W,B} \left\{ \begin{array}{c} \mathbb{I}(B=0)\left(D_M + \dfrac{1}{1+r}\mathbb{E}V_M(\nu_y', \nu_\pi', P, 0, Q')\right) \\ + \\ \mathbb{I}(B \neq 0)(1-\lambda)\left(D_M + \dfrac{1}{1+r}\mathbb{E}V_M(\nu_y', \nu_\pi', P, B, Q')\right) \\ + \\ \mathbb{I}(B \neq 0)\lambda\left(D_M|_{B=0} - MC(B,Q) + \dfrac{1}{1+r}\mathbb{E}V_M(\nu_y', \nu_\pi', P|_{B=0}, 0, Q')\right), \end{array} \right\} \tag{9}$$

subject to the constraints and definitions given in (1)–(7). The first line in curly brackets in (9) is the value to the manager if he chooses not to engage in book-value manipulation. The second line represents the case in which he chooses to manipulate but does not get caught. The third line represents the case in which he does get caught.

While (9) gives lifetime managerial utility, it does not represent the fundamental value of the firm, which we denote as V_F, and which is simply the expected present value of distributions to shareholders. On the basis of the manager's privately optimal policies B^* and

W^*, the fundamental value of the firm V_F is thus given by

$$V_F(\nu_y, \nu_\pi, P_{-1}, B_{-1}, Q) = \left\{ \begin{array}{c} \mathbb{I}(B^* = 0)\left(D^* + \dfrac{1}{1+r}\mathbb{E}V_F(\nu_y', \nu_\pi', P, 0, Q')\right) \\ + \\ \mathbb{I}(B^* \neq 0)(1-\lambda)\left(D^* + \dfrac{1}{1+r}\mathbb{E}V_F(\nu_y', \nu_\pi', P, B^*, Q')\right) \\ + \\ \mathbb{I}(B^* \neq 0)\lambda\left(D^* + \dfrac{1}{1+r}\mathbb{E}V_F(\nu_y', \nu_\pi', P|_{B=0}, 0, Q')\right), \end{array} \right\}, \quad (10)$$

in which D^* is given by (3), evaluated at the policies B^* and W^*. We note that in the absence of options compensation, the manager has no incentive to manipulate, so managerial utility, (9), equals fundamental firm value (10).

Next, to reduce the state space of the model, we normalize output, R&D, and distributions by endogenous productivity, Q, as follows:

$$y \equiv \frac{Y}{Q} = \nu_y, \quad d \equiv \frac{D}{Q} = y - p_w w, \quad w \equiv \frac{W}{Q}, \quad g = \xi w^\gamma.$$

Earnings also naturally scale linearly with Q, so scaled earnings are given by:

$$\pi \equiv \frac{\Pi}{Q} = y - p_w w + \nu_\pi + b - b_{-1}, \quad b \equiv \frac{B}{Q}, \quad b_{-1} \equiv \frac{B_{-1}}{Q}.$$

Similarly, normalized by endogenous productivity, Q, manager incentives are given by

$$d_m \equiv \frac{D_M}{Q} = \theta_d d + \theta_o \max\left\{p - p_{-1}, 0\right\}, \quad p \equiv \frac{P}{Q}, \quad p_{-1} \equiv \frac{P_{-1}}{Q}.$$

The manager's value function (9) is homogenous in Q, so we can write

$$V_M(\nu_y, \nu_\pi, P_{-1}, B_{-1}, Q) = Q v_m(\nu_y, \nu_\pi, p_{-1}, b_{-1}),$$

where the normalized manager value function is given by

$$v_m(\nu_y, \nu_\pi, p_{-1}, b_{-1}) = \max_{w,b} \left\{ \begin{array}{c} \mathbb{I}(b=0)\left(d_m + \dfrac{1+g(w)}{1+r}\mathbb{E}v_m(\nu_y', \nu_\pi', \frac{p}{1+g(w)}, 0)\right) \\ + \\ \mathbb{I}(b \neq 0)(1-\lambda)\left(d_m + \dfrac{1+g(w)}{1+r}\mathbb{E}v_m(\nu_y', \nu_\pi', \frac{p}{1+g(w)}, \frac{b}{1+g(w)})\right) \\ + \\ \mathbb{I}(b \neq 0)\lambda\left(d_m|_{b=0} - mc(b) + \dfrac{1+g(w)}{1+r}\mathbb{E}v_m(\nu_y', \nu_\pi', \frac{p}{1+g(w)}|_{b=0}, 0)\right) \end{array} \right\} \tag{11}$$

subject to the following constraints and processes:

$$\begin{aligned}
y &= \nu_y, \quad \log \nu_y = \rho_y \log \nu_{y,-1} + \eta_y, \quad \eta_y \sim N(0, \sigma_y^2) \\
d &= y - p_w w \\
\nu_\pi &\sim N(0, \sigma_\pi^2) \\
\pi &= y - p_w w + \nu_\pi + b - b_{-1} \\
d_m &= \theta_d d + \theta_o \max\{p - p_{-1}, 0\} \\
mc(b) &= MC(B/Q, 1) \\
g(w) &= \xi w^\gamma \\
p &= \mathbb{E}\left(v_f|\mathcal{I}\right).
\end{aligned}$$

The definition of scaled manager value v_m given by (11) implicitly contains, through the pricing function, an equivalent scaled concept for fundamental firm value $v_f \equiv \frac{V_F}{Q}$, which is given by

$$v_f(\nu_y, \nu_\pi, p_{-1}, b_{-1}) = \left\{ \begin{array}{c} \mathbb{I}(b=0)\left(d + \dfrac{1+g(w)}{1+r}\mathbb{E}v_f(\nu'_y, \nu'_\pi, \frac{p}{1+g(w)}, 0)\right) \\ + \\ \mathbb{I}(b \neq 0)(1-\lambda)\left(d + \dfrac{1+g(w)}{1+r}\mathbb{E}v_f(\nu'_y, \nu'_\pi, \frac{p}{1+g(w)}, \frac{b}{1+g(w)})\right) \\ + \\ \mathbb{I}(b \neq 0)\lambda\left(d + \dfrac{1+g(w)}{1+r}\mathbb{E}v_f(\nu'_y, \nu'_\pi, \frac{p}{1+g(w)}|_{b=0}, 0)\right) \end{array} \right\}. \quad (12)$$

Here, the fundamental firm value function is evaluated at the optimal policies b, w derived from the manager dynamic optimization, and the transitions and constraints are identical to the v_m definition.

Scaling implies that all of our lower case variables are measured in terms of dollars per quality unit. Because quality units are unobservable, scaling implies that our model has empirical predictions for the growth rates of observable variables such as R&D expenditure, but not for the levels.

2.6 Model Solution Algorithm

To solve the model, which does not have a closed-form solution, we rely on numerical dynamic programming techniques applied to the stationary recursive formulation in (11). We face two challenges. First, the value of the firm, given by (12), requires a rational pricing function, given by (8), and vice versa. Second, the model's solution is sensitive to the discounting implied by the quality growth rate, $g(w)$, which appears both in the continuation values of (11) as well as in the endogenous state transitions. Because a firm's desired R&D level, w, and hence its growth rate, $g(w)$, depend crucially upon the efficiency of R&D, as embodied in the parameter ξ, the model's solution and scaling is quite sensitive to this parameter.

For a given model parameterization, we jointly handle both problems by an alternating procedure. First, given a value for the parameter ξ, we use fixed point iteration to converge on a rational pricing function. Second, given the pricing function, we iterate on the value of ξ until the observed growth rate in the model matches its empirical counterpart, implementing a simple bisection solution. When both conditions are satisfied, i.e., when the assumed pricing function is rational and when the model's growth rates match their empirical counterparts, we have achieved an internally consistent model solution.

We first describe the solution for the rational pricing function, taking as given a value for ξ. We begin by assuming that the investors' information set $\mathcal{I}$ contains observable earnings, π. Then, we guess a linear rational pricing function of earnings, which we denote as $p^{(i)}(\pi)$. Given this guess, we use policy function iteration to solve (12), obtaining optimal R&D and manipulation policies, denoted as $b^{(i)}$ and $w^{(i)}$. We construct the implied firm value function $v_f^{(i)}$ by forward iteration on equation (12) using $b^{(i)}$ and $w^{(i)}$. We construct the implied stationary distribution $\mu^{(i)}$ induced by $b(\cdot)$, $w(\cdot)$, and the exogenous transitions in (1) and (4). Then, we update the pricing function, using

$$p^{(i+1)}(\pi) = \mathbb{E}_{\mu^{(i)}}\left(\frac{1+g(w^{(i)})}{1+r} v_f^{(i)\prime} \middle| \pi \right).$$

We then return to the policy function iteration step and repeat until $\|p^{(i+1)} - p^{(i)}\| < \varepsilon_P$, in ε_P is a preset tolerance.

We now describe the second block of our solution procedure, which involves iteration on ξ given a pricing function. The value of ξ determines the average payoff to R&D and hence average growth rates, because ξ shifts the level of the innovation function (2). To provide empirical discipline for this parameter and ensure that the model scaling of the innovation function matches that seen in the data, we first extract the average sales growth rate from the data, $\hat{g}_y^{data}$. Then, we choose the value of ξ in the model to satisfy the following equation:

$$g_y^{sim}(\xi) = \hat{g}_y^{data}. \tag{13}$$

We solve (13) via bisection, re-solving the model at different candidate values of ξ until the equation above holds to a preset tolerance.

We alternate between the first block, obtaining a rational pricing function, and the second block, scaling the innovation function, until both are simultaneously satisfied, a procedure that works efficiently in the model in practice.

2.7 Revenue Recognition

The model contains one further parameter that does not enter into the managerial optimization problem but that does enter into the simulation of data from the model and is important for matching simulated with actual data moments. This parameter reflects accrual accounting, which is an important feature of earnings measurement and which is designed to provide a better indication of company's performance or economic earnings than operating cash flows (FASB 1978).[3]

Accrual accounting induces a wedge between the measurements of earnings and operating cash flows, so accounting earnings do not generally correspond to cash inflows and outflows for the period. Moreover, because accruals are managers' forecasts of future cash flows, these forecasts must reconcile with realized cash flows in the future (e.g., Allen, Larson, and Sloan 2013; Nikolaev 2016). This reconciliation property implies that we can view operating cash flows as a reshuffling of accounting earnings across adjacent periods. As such, we allow for a random portion of accounting earnings to be realized as cash flows in the periods immediately before or immediately after the current period. Although we allow for reshuffling in only one adjacent period, this idea is similar to the mechanism underlying the accrual quality measure in Dechow and Dichev (2002), who represent accounting earnings as the sum of past, present, and future cash flows that are recognized in the current period earnings, with an allowance for estimation errors.

To implement this principle, we first define a parameter $\hat{p}_s \in (0, 1)$, which represents the

[3] According to Statement of Financial Accounting Concepts No. 1, "Information about enterprise earnings based on accrual accounting generally provides a better indication of an enterprise's present and continuing ability to generate favorable cash flows than information limited to the financial effects of cash receipts and payments."

probability of intertemporal cash flow reshuffling. Next, we draw a set of uniform shocks, $\zeta^s_{it}, \quad \forall i, t$, where i indexes firms and t indexes time. We then initialize observed cash flows at time 1, which we denote $\tilde{d}_{i,1}$, equal to the actual cash flow simulated directly from the model, that is, $\tilde{d}_{i,1} \equiv y_{i,1} - p_w w_{i,1}$. Finally, iteratively progressing from $t = 2, ..., T-1$ for each firm i, we update the observed cash-flow series by the following rules:

$$\begin{aligned}
&\text{If } \zeta^s_{it} < 0.5, \quad \text{set} \quad \tilde{d}_{it-1} = \tilde{d}_{it-1} + 2\hat{p}_s(0.5 - \zeta^s_{it}) \text{ and } \tilde{d}_{it} = \tilde{d}_{it} - 2\hat{p}_s(0.5 - \zeta^s_{it}) \\
&\text{If } \zeta^s_{it} > 0.5, \quad \text{set} \quad \tilde{d}_{it+1} = \tilde{d}_{it+1} + 2\hat{p}_s(\zeta^s_{it} - 0.5) \text{ and } \tilde{d}_{it} = \tilde{d}_{it} - 2\hat{p}_s(\zeta^s_{it} - 0.5).
\end{aligned}$$

In words, this procedure randomly pushes forward some portion of today's cash flows into tomorrow and yesterday, given the random mistiming or reshuffling shock, ζ^s_{it}, keeping the sum of cash flows over any medium-term horizon unchanged, where here the horizon is three years.

2.8 Optimal Policies

Each period, the manager chooses how much to invest and whether to bias her earnings report. Figure 2 plots her choices as a function of the persistent fundamental shock, ν_y. The manager's decision depends upon two sometimes conflicting incentives embedded in her compensation. On the one hand, because of her equity ownership in the firm, the manager wishes to choose higher investment when the firm's fundamental conditions are more favorable, as value maximization dictates. On the other hand, because she also receives options compensation, the manager internalizes the impact of her reported profits on the value of the firm relative to the strike price embedded in her compensation. The nonlinearity of the options compensation leads the manager to choose different paths for investment and bias, depending upon whether she faces high or low short-term non-fundamental shocks, ν_π, to profits, even though a value-maximizing manager would ignore all short-term non-fundamental shocks.

The left column of Figure 2 plots investment and bias during bad times, i.e., in the face of an adverse non-fundamental shock to profits. In this case, if fundamental business conditions, ν_y, are also unfavorable, then neither severe cuts to investment nor reasonable upward bias in earnings would lead to a market price above the manager's current option strike price. Therefore, the manager chooses a high level of investment (top left panel, left side) and a negative bias (bottom left panel, left side) in her current earnings in order to reduce her reported profits. The result is a lower strike price and higher future expected value of her new options grants as a result of an "earnings bath" in the present period. This feature of the model appears to born out in the data. For example, Yermack (1997) finds a V-shaped pattern in returns around stock option grant dates, which can be attributed to the opportunistic release of information or the timing of grants. In addition, Aboody and Kasznik (2000) examine stock price behavior around *scheduled* option grants, concluding that executives opportunistically time the release of information around grant dates.

In contrast, a manager facing more favorable fundamental conditions finds manipulating her earnings downwards through bias too costly to justify and chooses zero manipulation (bottom left panel, right side). No longer seeking to artificially depress her profits today, the manager then chooses a smaller investment policy (top left panel, right side). Within each of these regions, the manager's investment policy is upward-sloped with respect to the fundamental shock, reflecting the value-maximization incentives to invest more during persistently good times.

The right column of Figure 2 plots investment and bias during good times, i.e., in the face of a positive non-fundamental shock to profits. If fundamental business conditions, ν_y, are also highly favorable, then with high likelihood the manager's options compensation will be in the money. Therefore, the manager places a high value on profits today relative to future profits. The result is upward bias of reported income (bottom right panel, right side) and opportunistic cuts to investment (top right panel, right side). For firms with less favorable fundamental conditions, the upward bias in profits required to inflate their options compensation is too large to justify given the fixed cost of manipulation. Therefore, the manager chooses zero bias (bottom right panel, left side) and no longer opportunistically cuts her investment (top right panel, left side). Within each of these regions, the manager's equity compensation causes her to choose investment that increases with the fundamental shock, but once again the options compensation and non-fundamental shocks induce substantial variation in the level of investment and bias.

Another interesting feature of the model is path dependence whereby a manager's past choices affect her current behavior. This path dependence is embedded in the strike price of her options compensation and the lagged or accumulated bias in earnings on the balance sheet. To illustrate this feature of the model, in Figure 3, we plot average investment and current bias as a function of the strike price and lagged bias. The left two panels plot optimal policies as a function of the strike price. Here, we see that for a manager with higher past earnings performance and hence with a higher strike price, her options lie out of the money with higher probability. Therefore, she prefers to manipulate reported earnings downward to increase the expected value of her newly granted options. The result is a choice of higher investment (top left panel) and downward reporting bias (bottom left panel).

The right two panels plot optimal policies as a function of bias. Here, we find a similarly intuitive result, as a manager with more accumulated bias on her balance sheet faces higher punishment if discovered for any current bias she chooses to introduce. A high-bias manager has less flexibility to manipulate her earnings or the value of their options compensation upwards today. Naturally, a manager with less flexibility today chooses to maximize future options compensation instead by unravelling bias and increasing investment today (right column). The result is lower profits today, a lower strike price on current options grants, and a favorable shift in the value of the manager's future compensation. Because neither the lagged performance of the firm nor the accumulated bias on a firm's balance sheet reflects fundamental conditions at the firm, the reaction of investment to these factors drives a further wedge between a manager's investment choices and the choices that maximize value.

3. Data

3.1 Sources

The data come from several sources. The financial data are from Compustat, and the data on executive compensation are from Equilar, which collects these data from annual proxy filings (DEF 14A). Its coverage is more than double the coverage of Compustat ExecuComp, whose universe is the S&P 1500. In contrast, Equilar covers virtually all public companies. The data on restatements are from Audit Analytics, where we use restatements that correct accounting errors as a measure of detected misstatements.

Data availability from the intersection of these three sources means that our sample spans sixteen years from 2000 to 2015 and includes firms incorporated in the United States and listed on the NYSE, Amex, or NASDAQ. For firms included in the sample, we require all variables used in the estimation to be non-missing. Because we need sufficient time-series variation in our data to identify some of our model parameters, we also require seven years of sales revenue data, where three years of these data must be consecutive. We further consider two samples of firms. The first sample excludes firms for which all SG&A expenses are missing or zero (SG&A sample), and the second sample excludes firms for which all R&D expenses are missing or zero (R&D sample). These restrictions retain firms for which the discretionary investment into SG&A or R&D decisions are relevant. For both samples, we further exclude firms in the financial and utilities sectors, which we define as Global Industry Classification Standard (GICS) sectors 40, 55, and 60. For the R&D sample, we also exclude transportation (GICS sector 2030) and food and staples retailing (GICS sector 3010). Table 1 provides the variable definitions.

Although manipulation is chosen optimally by the manager in the model, not all restatements observed in the data correct intentional manipulation. As such, classifying restatements as intentional incurs some unavoidable discretion, and the choice of any particular definition of an intentional restatement reflects a trade-off between the number of restatements and the likelihood that these restatements correct intentional misstatements. We therefore adopt two definitions of an intentional misstatement.

The first group includes restatements of revenue recognition errors, where we identify revenue recognition restatements with Audit Analtytics data. Because all considered restatements are related to errors, our sample excludes retrospective revisions related to the application of SEC Staff Accounting Bulletin (SAB) No. 101 restatements. As such, our sample includes only errors in SAB 101 implementation. Revenue recognition restatements elicit the largest negative market reaction relative to other types of errors (e.g., Palmrose, Richardson, and Scholz 2004; Scholz 2008). Moreover, the closely related model of intentional manipulation in Zakolyukina (forthcoming) has more power to explain these types of errors relative to other types of errors such as expense recognition errors.

The second group includes restatements classified as irregularities under three criteria. The first criterion is irregularity restatements as classified in Hennes, Leone, and Miller (2008). To create this group, we search all of Audit Analytics' restatement disclosure narratives for the three criteria definted in this paper. The first is the presence of the derivative forms of the words "fraud" or "irregularity." The second is SEC or Department of Justice formal or informal investigations. The third is discussion of independent investigations by an audit committee or a special committee. After automatic pre-screening for search terms, we read each relevant disclosure to make a final judgment about whether the particular disclosure satisfies the irregularity criteria.

The second criterion is restatements surrounded by events pointing to potential irregularities as specified in Appendix 2 in Cheffers, Usvyatsky, and Pakaluk (2014). For instance, these events include CEO or CFO dismissals due to internal investigations or suspected wrongdoing, auditor changes related to SEC inquiry or management unreliability, or the restated period overlapping with the violation period alleged by the Accounting and Auditing Enforcement Releases (AAERs) from Dechow, Ge, Larson, and Sloan (2011). We require these events to happen within one year before or after the restatement.

The third criterion is restatements that involve Rule 10b-5 allegations of fraud, both in cases brought by the SEC and in security class action lawsuits. A Rule 10b-5 allegation requires scienter (Choi and Pritchard 2016) and thus represents a category of misstatements with allegations of intentional fraud. For class action lawsuits, we require that the case not be dismissed or terminated. We also require a related AAER period to overlap with the periods restated for the SEC cases. For the security class action lawsuits, we require the class period to overlap with the periods restated. In each case, we read legal summaries to confirm that allegations involve earnings misstatements. We exclude two categories of restatements from the irregularity group, lease restatements and option backdating restatements, as both are less likely to be intentional.[4]

In the main specification, we combine revenue recognition and irregularity restatements. Finally, for all restatements, we require that misstatements have a nonzero net income effect over restated period. This requirement is important because in the estimation, we set the bias in book value equal to the cumulative impact of a restatement on net income. Finally, we only keep restatements that correct annual financial statements.

3.2 Subsample construction

Our sample period covers two significant changes in disclosure regulation: the Sarbanes-Oxley Act (SOX) and the Dodd-Frank Act (DFA). SOX constituted major disclosure regulation. Section 302 requires CEOs and CFOs to certify financial statements and establishes CEOs and CFOs as having direct responsibility for the accuracy of financial reports and internal controls over financial reporting. Section 404[a] requires management certification of internal controls over financial reporting. The first year of Section 404[a] compliance for smaller companies was 2007. Section 404[b] requires auditors to attest to the management's assessment of internal controls. U.S. accelerated filers had to implement Section 404[b] after November 15, 2004.

[4]In the Audit Analytics taxonomy, lease restatements correspond to the categories 21 (Lease SFAS 5 legal contingency and commitment issues) and 42 (Lease leasehold and FAS 13 98 only subcategory). Option backdating corresponds to categories 17 (Deferred stock-based and/or executive compensation issues) and 48 (Deferred stock-based options backdating only subcategory).

DFA exempted U.S. non-accelerated filers from Section 404[b] compliance entirely.

While DFA has fewer direct implications for disclosure than SOX, it nonetheless includes significant whistleblower protection. This program requires the SEC to pay an award to eligible whistleblowers, strengthens anti-retaliation protection, and allows a whistleblower to report misconduct directly to the SEC without first reporting through internal compliance.

This legislation and concurrent events have changed the expected cost of manipulation, both in terms of detection probability and penalty. Accordingly, there are three distinct regimes that can affect the misstatement cost parameters: the pre-SOX period ending in August 2002, the post-DFA period starting in July 2010, and the period between SOX and DFA (SOX–DFA).

We use this subsample heterogeneity as follows. First, we estimate our model on the subsample with the longest time span, the SOX-DFA period. Next, to understand whether this disclosure regulation affected manipulation, we assume that we obtain consistent estimates of the innovation production parameters and then use data from the other subsamples to reestimate the parameters related to manipulation.

3.3 Summary statistics

Because the patterns in descriptive statistics are similar for the SG&A and R&D samples, the discussion below focuses on the SG&A sample. Figure 4 plots the incidence of restatements and the corresponding rate of restated annual periods by year. These two quantities are not identical because when a restatement occurs, financial statements from several previous years are often corrected at the same time. The incidence of restatements increases dramatically right after the passage of SOX and peaks after the SOX Section 404 implementation of internal control disclosures in 2004 (Whalen, Usvyatsky, and Tanona 2016). Incidence steadily declines thereafter. This pattern is consistent with detection probability increasing in the post-SOX period. Because of the backward-looking nature of restatements, the rate of restated annual periods also declines over time.

Figure 5 plots the ratio of the bias in earnings to sales as a function of time. Because the cost of manipulation increases over this time period, the magnitude of earnings misstatements naturally declines over time.

Table 2 (panel A) provides descriptive statistics for restatements, CEO compensation, and firm characteristics for the SG&A sample. For the combined sample of restatements, the mean (median) bias in book value is \$50.1 (\$3.6) million or 4.7% (0.7%) of sales. The corresponding bias in earnings is \$13.7 (\$1.2) million or 1.5% (0.2%) of sales. For the irregularity restatements, the mean (median) bias in book value is \$71.9 (\$5.9) million or 5.6% (0.9%) of sales. The corresponding bias in earnings is \$19.5 (\$1.7) million or 1.7% (0.3%) of sales.

This table also provides descriptive statistics for the two forms of compensation that we model. In line with the evidence in Frydman and Jenter (2010), the mean (median) CEO holds 5.3% (0.8%), and his options compensation constitutes 1.0% (0.5%) of all outstanding stock.

Finally, table 2 provides descriptive statistics for the variables used in estimation, as well as other firm characteristics. Recall that many of our moments are growth rates, which we compute as differences relative to the absolute value of an average following Davis and Haltiwanger (1992) and Terry (2015). For instance, the one-year growth in x_t is computed as

$$\Delta x = \begin{cases} 0, x_t = 0 \text{ and } x_{t-1} = 0, \\ 2\frac{x_t - x_{t-1}}{|x_t| + |x_{t-1}|}, \text{ otherwise.} \end{cases} \tag{14}$$

These growth rates have the advantage of being bounded within $[-2; 2]$. This restriction is important because often variables shift from zero to nonzero values, so, for example, the shift from zero to positive R&D investment results in a finite rather than a missing value.

The mean one-year growth in cash flows is 4.4%, the one-year growth in earnings is 4.8%, the one-year growth in SG&A is 7.0%, the one-year growth in R&D is 6.6% and the three-year growth in sales is 24.0%. Because this last figure is quite large, and because it likely reflects not only greenfield growth but also mergers, entry, and exit, we use a sales weighted growth rate in our estimation. Finally, the firms in our sample are identical in size to a generic Compustat sample. The mean firm assets are \$2.93 billion in our sample, while the mean assets of all firms in Compustat over the same period is \$2.52 billion.

4. Estimation

Two of the model parameters, θ_d and θ_o, can be estimated directly from our Equilar data. Following Nikolov and Whited (2014) and Glover and Levine (2017), we set the equity share, θ_d, equal to the fraction of manager-owned shares to total shares outstanding. Similarly, we set the managers' option share, θ_o, equal to the fraction of manager-owned unexercised options to total shares outstanding. Another of the model parameters, the discount rate, r, we set to 6%. This figure represents a premium over the 3.84% average ten-year Treasury bond over our sample period, and it is generally consistent with evidence that managers set discount rates higher than one would predict using a standard model (Graham and Harvey 2001).

We also estimate two parameters—the innovation productivity shifter, ξ, and the rate of earnings conversion to cash flows, $\hat{p}_s$,—separately. The parameter ξ shifts the innovation production function and thus maps strongly and positively into the mean growth rate, $\mathbb{E}_y\Delta_3 y$. This growth rate is computed as the sales-weighted three-year growth rate of sales, given by $\mathbb{E}_y\left(y_{i,t-3}\Delta_3 y_{i,t}\right)/\mathbb{E}_y\left(y_{i,t-3}\right)$ with $\Delta_3 y_{i,t} = 2(y_{i,t} - y_{i,t-3})/(y_{i,t} + y_{i,t-3})$. An estimate of the parameter ξ directly affects the estimates of the growth implications of our model. Because having an accurate estimate of ξ is important for our main results, we target the moment $\mathbb{E}_y\Delta_3 y$ exactly in the bisection procedure for ξ described above in our discussion of the model solution.

To estimate the rate of earnings conversion to cash flows, we follow accounting literature and estimate $\hat{p}_s$ from a regression of earnings, π_t, on past, future, and current cash flows, d_t, with all variables scaled by average total assets. Specifically, we estimate $\hat{p}_s$ as the average of

β_{t-1} and β_{t+1} from the following regression

$$\pi_t = \alpha + \beta_{t-1} d_{t-1} + \beta_t d_t + \beta_{t+1} d_{t+1} + \upsilon_t, \tag{15}$$

which is similar but not identical to Dechow and Dichev (2002). Because cash collection and disbursement policies can be firm- and year-specific, we include firm and year fixed effects in this regression. For the SOX–DF period in SG&A sample, $\hat{p}_s$ equals 17.34% that is 17.34% of earnings get collected in cash in the preceding or following years.

We estimate the model's remaining parameters using a simulated minimum distance estimator, where we need to simulate because of the presence of the earnings reshuffling shock, ζ_{it}^s. The mechanics of the estimation are straightforward and by now familiar (Bazdresch, Kahn, and Whited 2018). For a given set of parameters, we solve the model and use the solution to generate simulated data, which is ten times the size of our data set (Michaelides and Ng 2000). Next, we calculate a set of statistics, which are either moments or functions of moments. Based on the distance between model-generated statistics and their empirical counterparts, the values of the structural parameters are updated. To gauge this distance, we use the inverse covariance matrix of the empirical moments. To minimize the econometric objective function, we use a particle swarm algorithm as in Terry (2015).

4.1 Identification

We have eight remaining model parameters to estimate: p_w, the relative price of intangible investment; γ, the elasticity of innovation to investment; ρ_y and σ_y, the persistence and volatility of the fundamental shock; σ_π, the volatility of the non-fundamental shock to profits; κ_f and κ_q, the fixed and quadratic costs of manipulation, conditional upon discovery; and λ, the probability of manipulation discovery.

To identify these parameters, we use 17 moment conditions. The first set of seven moments does not rely on manipulation data. It includes the mean ratio of intangible investment to sales, given by $\mathbb{E}(w/y)$. The next three moments are variances. The first of these is the variance of observed dividend growth, Δd, defined as $\Delta d = 2(d - d_{-1})/(d + d_{-1})$. The next two variances are those of the growth rates of reported earnings, $\Delta \pi$, and intangible investment, Δw, which are defined similarly. The next three moments are covariances, in particular, the three possible covariances between Δd, $\Delta \pi$, and Δw.

The second set of ten moments is directly related to manipulation and detection. The first is the probability of detection, $\mathbb{E}(I_D)$, in which the dummy variable, I_D, indicates the actual discovery of manipulation in a period. The second is the mean absolute ratio of manipulation to sales, conditional upon detection, $\mathbb{E}\left(|b/y| \mid I_D\right)$. The third is the variance of the absolute ratio of manipulation to sales, conditional upon detection, $\mathbb{C}ov\left(|b/y|, |b/y| \mid I_D\right)$. The forth is the skewness of the absolute ratio of manipulation to sales, conditional upon detection, $\mathbb{S}kew\left(|b/y| \mid I_D\right)$. The remaining six moments are covariances between dividend growth, Δd, earnings growth, $\Delta \pi$, and intangible investment growth, Δw, conditional upon detection.

While each of these moments is related to nearly all of the parameters in the model, some moments have strong monotonic relationships to certain parameters and are thus particularly useful for identifying those parameters. To ascertain the strength of these relationships, we perform a battery of comparative statics exercises, which we then use to justify our moment choices.

We start with technological parameters. The first technological parameter is the price of intangible investment, p_w. This parameter determines the costliness of intangible investment in terms of the numeraire output and maps positively into the size of intangible investment $\mathbb{E}(w/y)$. The second technological parameter is γ, which governs the returns to intangible investment in the innovation equation. Intuitively, when this parameter is higher, intangible investment responds more strongly to shocks, so a high level for γ results in high covariances between intangible investment and indicators of fundamentals, in particular, dividends and earnings, both unconditionally and conditional upon detection. Naturally, if investment is more responsive, it also has a higher variance, so γ also affects this latter moment.

Next, we consider the persistence of the fundamental shock, ρ_y. This parameter affects many different moments. Specifically, ρ_y maps negatively into the volatility of all growth rates in the model because higher persistence drives lower volatility in the growth rate of fundamentals. This negative relation holds for all of the growth rate volatility moments conditional upon detection as well. A separate, less mechanical effect is also at work. Because higher fundamental persistence makes today's fundamental shock more informative for tomorrow, the covariance of the output shock and investment increases. This effect leads to a higher covariance between dividend and investment growth. Because accruals manipulation allows the manager to choose a more fundamentals-aligned investment level without sacrificing earnings, this last effect is more pronounced when manipulation is discovered. Unlike the persistence parameter, ρ_y, the volatility of the fundamental shock, σ_y, is a neutral volatility shifter that primarily affects observable growth rate variances. Although σ_y mechanically affects covariances, these effects are small relative to the effects on volatilities.

The identification of the volatility of our nonfundamental earnings shock, σ_π, operates somewhat differently. First, mechanically, we have a strong positive link between this parameter and the variance of earnings, both unconditionally and conditional upon detection. However, the volatility of non-fundamental shocks also maps into the volatility of investment, conditional upon there being a motive for real manipulation, which in our model takes the form of high accruals-based manipulation costs. Naturally, this mapping is weaker when accruals-based manipulation is present. Next, because dividends include investment, because positive profit shocks force options to be in the money, and because there is less investment when options are in the money, higher nonfundamental shock volatility leads to lower comovement between dividends and profits. This effect is stronger when more real manipulation occurs.

Next, we consider the manipulation cost parameters, starting with the quadratic cost parameter, κ_q. This parameter determines the costliness of accruals manipulation on the intensive margin. The mean absolute ratio of manipulation to sales, conditional upon detection, decrease in κ_q, as does the variance of bias upon detection. When accruals manipulation is more costly, more manipulation occurs through investment, so the variance of investment growth increases. In addition, a higher cost reduces the covariance between investment and dividend growth, as investment becomes a tool with which to respond to non-fundamental shocks. Because non-fundamental shocks (when positive) tend to push options into the money, if κ_q is large, the model produces cuts in investment, with the result that the covariance between earnings and profits growth is negative.

Our second manipulation cost parameter, κ_f, quantifies the fixed costs of manipulation, conditional upon detection of manipulation. As such, this parameter determines the cost of accruals manipulation at the extensive margin. Mechanically, a higher fixed cost of discovery of manipulation leads to a lower probability of manipulation and hence detection, so the probability of detection is lower. Note, however, that the detection probability is also driven in large part by the random detection likelihood parameter λ, which maps more strongly into detection, $\mathbb{E}(I_D)$, relative to the κ_f parameter. A second effect operates through increasing returns to manipulation, which naturally arises in the presence of a fixed cost. In this case, manipulation does not occur unless it is highly worth it, so a high fixed cost implies a higher average bias, $\mathbb{E}\left(|b/y| \mid I_D\right)$ as well as a larger magnitude of the skewness of bias given detection.

Both parameters, κ_f and κ_q, affect the magnitude of detected manipulation. However, they have different effects on the variance and skewness of the absolute ratio of manipulation to sales, conditional upon detection moments. If κ_q were near zero and κ_f were high, then the magnitude of the manipulation would have higher skewness, as the firm would optimally not manipulate very often, but when it did, it would manipulate a lot. Conversely, if κ_q were high and κ_f were zero, the distribution of manipulation would be much more symmetric. So skewness should depend on the relative magnitudes of κ_q and κ_f. A similar argument applies to the variance of manipulation.

Finally, the probability of detection, λ, governs the likelihood of the discovery of manipulation, which is a Poisson-style shock in the model. Mechanically, the likelihood of detection goes up, but because firms internalize the likelihood of discovery in their manipulation choices, the amount of manipulation increases less. The slope of each of these mappings increases with κ_f.

5. Estimation results and counterfactuals

The results from our estimation using the SG&A sample are in Table 3. In Panel A, we report the actual data moments, the model-simulated moments, and t-statistics for the null of the equality of each pair of moments. While all but three of the moment pairs are insignificantly different from each other, few are economically different, and several of these pairs match up nicely. Overall, however, we believe the fit of the model is remarkably good, given that we have a high degree of overidentification. Accordingly, it is a useful laboratory for counterfactual policy experiments.

Next, we turn to the parameter estimates, which are reported in Panel B. These parameters divide naturally into two groups, reflecting firm fundamentals on the one hand and income reporting or manager incentives on the other hand. Turning to the first group of parameter estimates, the implied fundamentals for firms are in line with many of the extant estimates in the literature. Intangible investment has a relative price of just less than 1 with $\hat{p}_w \approx 0.77$. The persistence of productivity or profitability of $\hat{\rho} \approx 0.50$ lies below the level of the estimated persistence of productivity in all U.S. firms estimated by Winberry (2016) (≈ 0.78) or in U.S. manufacturing estimated by Castro, Clementi, and Lee (2015) (≈ 0.45). This result is to be expected because these two papers estimate the combined endogenous and exogenous persistence of productivity while our estimates isolate the exogenous component of productivity. The total conditional volatility of shocks to firm profitability each year is $\sqrt{\hat{\sigma}_y^2 + \hat{\sigma}_\pi^2} \approx 0.36$, which is slightly higher than the total volatility of shocks to U.S. public firms estimated by studies that omit a role for non-fundamental shocks such as Gourio and Rudanko (2014). Finally, the estimated elasticity of innovation to intangible investments $\hat{\gamma} \approx 0.46$ lies well below one, consistent with the evidence from patenting, firm growth, and R&D in papers including Acemoglu, Akcigit, Bloom, and Kerr (2013). The parameters governing reporting incentives for the manager mostly relate to manager preferences and lack a direct empirical equivalent. One exception is the probability of detection $\hat{\lambda} \approx 0.055$, which compares well to the estimates from a similar dynamic model in Zakolyukina (forthcoming). Overall, the parameters in Table 3 appear reasonable.

Table 4 reports use the results from using R&D as a measure of investment. While most of these estimation results are quite similar to those in Table 3, two differences are worth emphasis. First, the mean ratio of investment to sales in this sample is higher than in the SG&A sample by approximately a factor of two, even though R&D is but one component of SG&D. This result stems from some firms in this sample with very few sales. Second, the estimated relative price of investment is much larger. This result is also to be expected, given that we are using a different concept of investment. Finally, the three parameters governing manipulation are remarkably similar in Tables 3 and 4. This result is not necessarily to be expected, given that the samples used in the estimation are different. It thus indicates that at least along the dimensions of misreporting and detection, the two samples of firms appear to behave similarly.

5.1 The dynamics of restatement and intangible investment

The model provides high-powered incentives to managers to shift reported profits upwards in periods when their options compensation is in the money. Managers have two tools with which they can achieve this upward manipulation, biased reporting or real investment shifts, and each tool is costly at the margin. The direct implication within the model is that managers will use both levers to manipulate their earnings upward in such periods, leading to a positive shift in bias as well as a lower level of intangible investment. Empirically, Figure 1 displayed exactly this pattern. But does the empirical result hold up when estimated off of simulated model data? We then run the panel regressions in simulated data:

$$X_{jt} = \sum_{k=-K}^{K} \beta_k \mathbb{I}(\text{Upward Bias Restated})_{jt+k} + \varepsilon_{jt}.$$

To match our empirical approach in the construction of Figure 1, X_{jt} is either the R&D to sales ratio in the model (left panel) or the bias to sales ration (right panel). In Figure 6, we plot the coefficients β_k, which trace out the within-firm idiosyncratic variation in intangible investment at horizons k periods away from the restatement event. The red line on the left hand side plots the resulting dynamics of R&D in the data, and we see a quick drop in R&D of around 20% for the firm in periods in which upward bias is restated, labelled "0." On the right hand side, we see upward manipulation of reported earnings by around 2.4% on average.

The model doesn't exactly match the untargeted quantitative size of the contemporaneous drop in investment in periods with upwards bias in the data, but the qualitative message in both cases is clear. Managers cut their investment in periods in which they have upwardly misreported profits. Examination of each plot in Figure 1 and Figure 6 also reveals that the model and data dynamics match along another untargeted dimension, the transitory nature of the associated R&D declines. In the model, R&D rebounds quickly because of the short-lived nature of opportunities for manipulation of options compensation. The transitory observed fluctuation in R&D is not an extraneous feature of the model. Instead, mismatch between the short-term variation in incentives to manipulate long-term investment, on the one hand, and more persistent variation in incentives to invest, on the other hand, drive the efficiency loss for firms in a context with real investment manipulation.

5.2 Counterfactuals

In the presence of options compensation, managers face incentives to manipulate their reported earnings using one of two available tools: real investment choices or bias in reporting. Reporting is subject to convex costs upon discovery, and large manipulation of investment leads to more costly deviations from a value maximizing benchmark. Therefore, managers in general will substitute across the two different forms of manipulation, shifting their investment only moderately while simultaneously introducing some bias in their reporting. The result, of course, is a classic trade-off. Managers facing higher cost of biased reporting will release more accurate income statements but choose less efficient, and more volatile, investment paths.

In Table 5, we quantify these trade-offs based on a series of counterfactual calculations, reporting a set of results based on the baseline estimated model and a model with no reporting bias, and a value-maximizing firm for comparison. We compute these counterfactuals based on the sets of parameter estimates from Table 3. The first column of the table reports that managers in the baseline estimated model in equilibrium choose reporting bias equal to around 4% of sales, conditional upon restatement. A manager facing infinite costs of misreporting in the second column, and choosing no bias, clearly releases more accurate income statements. However, the second row emphasizes the trade-off discussed above. Because managers without the ability to misreport their profits choose to manipulate through their investment alone, the volatility of investment growth increases by around a tenth relative to the baseline model. Distortions to the path of investment lead to a loss in the underlying or fundamental firm value, and the third row reports that eliminating bias in income statements from the estimated equilibrium would cost around half a percent of firm value on average. Of course, in an environment with no options compensation and hence value-maximizing managers, no trade-off between accuracy and firm value exists.

The counterfactual cases considered in Table 5 are informative but extreme. Figure 7 plots the equilibrium trade-off between investment efficiency and bias in reporting as the cost of bias κ_q varies more moderately. As the costs of manipulation decline, average bias increases on the horizontal axis, but investment efficiency improves, as reflected in lower investment volatility on the vertical axis. Starting from the estimated model, indicated with the circular marker on the figure, a one percent reduction in bias can be achieved only through around half a percent increase in the volatility of investment. Policymakers concerned with both the accuracy of income reporting and the real efficiency of firms must take the quantitative magnitude of this trade-off, which constrains their choices, into account when designing reporting regulation.

6. Conclusion

We quantify the importance of managers' opportunistic distortion of information to the public as a force that improves the efficiency of their investment choices. While it is counterintuitive to imagine that less information could lead to better real outcomes, this seemingly counterintuitive connection makes sense in the context of widespread observed compensation structures. On the one hand, many features of compensation contracts, such as options compensation, give managers the incentive to manipulate stock prices through earnings disclosures. On the other hand, disclosure regulation does not erase these incentives, so when managers find it costly to manipulate earnings, they substitute opportunistic cuts to investment, which can have adverse effects on shareholder value. Indeed, survey evidence suggests that managers facing pressures to report high earnings numbers appear to both misreport their earnings and distort long-term investments (Graham et al. 2005). If managers are willing to substitute between these two forms of manipulation, then reforms either to reporting regulations or executive compensation may face a crucial trade-off between the accuracy of information reported by firms and the efficiency of long-term investment (Cohen et al. 2008).

However, given the scale of recent reforms to firm disclosure regulations, e.g. the Sarbanes-Oxley and Dodd-Frank Acts in the United States, quantifying the extent of this trade-off seems crucial. Our vehicle for addressing this question is estimation of a dynamic model that incorporates all four ingredients necessary to generate the trade-off between misreporting and investment efficiency: a compensation structure with both short-term and long-term incentives, asymmetric information between managers and investors that allows information manipulation to work, persistent investment opportunities that enhance firm growth, and punishment for misreporting. Because the extent of misreporting, the payoffs to long-term investments, and the counterfactual response of firms to various policy and compensation regimes are difficult to measure with reduced-form exercises, our question requires estimating a dynamic model.

Our results are interesting and potentially useful for informing the debate over information disclosure regulation. Our model estimates imply that when managers are caught misreporting and forced to restate, their reporting bias equals 2% of sales. In the model, if we make the cost of misreporting high, it disappears, but then managers mistime investment so that it does not occur when investment opportunities are best. This suboptimal behavior cuts shareholder value by half a percent. Interestingly, the value loss from the existence of short-term incentives is much larger, at about 13%.

One ubiquitous drawback of our approach is the necessity of making model simplifications. For example, we only allow for one input into the production process, the firm faces no financial frictions, and the only short-term incentive comes from options compensation. We conjecture that advances in computing power will allow the specification of richer models to further our understanding of the little explored trade-offs between information manipulation, career concerns, and the efficiency of the real economy.

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Table 1: Data definitions

This table presents definitions and data sources for variables used in estimation. Compustat data codes are in parentheses.

A. Firm-specific variables	
θ_d	CEOs' stock holdings (excluding options exercisable within 60 days) as a fraction of total shares outstanding. Equilar.
θ_o	CEOs' *exercisable* option holdings as a fraction of total shares outstanding. Equilar.
y	Sale revenues (SALE). Compustat.
$p_w w$	Investment. For SG&A sample, investment is XSGA; for R&D sample, investment is XRD. Compustat.
d	Free cash flow is cash from operations (OANCF) minus net capital expenditures (CAPX - SPPE). Compustat.
π	Earnings is income before extraordinary items (IB). Compustat.
B. Restatement-specific variables	
I_D	The indicator variable for detection that equals 1, when manipulation is detected and a firm restates its earnings. We use I_{D_1} to denote detection after the first misstated year; and I_{D_2} to denote detection after the second misstated year. Audit Analytics advanced restatement feed.
I_R	The indicator variable that equals 1 in the years in which retained earnings were corrected by a restatement. Audit Analytics advanced restatement feed.
b_t	The bias in book value that equals the cumulative correction of net income. Audit Analytics advanced restatement feed.

Table 2:
Descriptive statistics

This table presents descriptive statistics for the variables used in estimation. The sample is based on Equilar, Audit Analytics advanced restatements, and Compustat. The sample covers the period from 2000 to 2014 at an annual frequency. Compustat data codes are in parentheses. *Earnings* is income before extraordinary items (IB). *Free cash flow* is cash from operations (OANCF) minus capital expenditures (CAPX - SPPE). *R&D* is R&D expense (XRD) with missing values set to 0. *SG&A* is SG&A expense (XSGA) with missing values set to 0. *Market value* is the product of common shares outstanding (CSHO) and fiscal-year closing price (PRCC_F). *Total assets* is assets total (AT). *Sales* is sales revenue (SALE). *Market-to-book* is the sum of market value and total assets minus book value of equity divided by total assets. *Fiscal-year return* computed using fiscal-year closing stock prices. *Ownership* is the difference between shares owned (OWN_HOLDINGS) and options exercisable within 60 days (OWN_OPT_EX_60) divided by shares outstanding at fiscal-year end (SHARES_OUT_FY). *Unexercised options, Exercisable* is vested option holdings (OPT_UNEX_EX) with missing values set to 0 divided by shares outstanding at fiscal-year end (SHARES_OUT_FY). *Bias in book value* is the cumulative change in restated net income. *Bias in earnings* is the change in restated net income. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles.

A. SG&A sample

	Obs.	Mean	Std.Dev	p25	p50	p75
Revenue recognition errors and irregularities (N = 415)						
Bias in book value ($mn)	1,267	50.055	288.290	0.506	3.624	22.184
Bias in book value to sales	1,267	0.047	0.132	0.001	0.007	0.031
Bias in earnings ($mn)	1,267	13.664	179.719	0.000	1.153	6.490
Bias in earnings to sales	1,267	0.015	0.053	0.000	0.002	0.011
Annual bias in earnings growth	865	-0.046	1.388	-1.334	0.000	1.110
Irregularities (N = 259)						
Bias in book value ($mn)	830	71.924	353.260	0.748	5.867	33.775
Bias in book value to sales	830	0.056	0.154	0.001	0.009	0.041
Bias in earnings ($mn)	830	19.517	220.758	0.076	1.680	10.378
Bias in earnings to sales	830	0.017	0.059	0.000	0.003	0.013
Annual bias in earnings growth	580	-0.061	1.374	-1.303	-0.018	1.103
CEO equity holdings (N = 3,604)						
Ownership (%)	33,507	5.272	10.891	0.197	0.798	3.949
Unexercised options, Exercisable (%)	33,507	1.032	1.436	0.084	0.532	1.367
Firm characteristics (N = 3,604)						
Obs.	33,507	11.813	4.244	8.000	13.000	16.000
Market value ($bn)	33,497	2.895	7.443	0.137	0.515	1.913
Total assets ($bn)	33,507	2.930	9.064	0.132	0.503	1.930
Sales ($bn)	33,507	2.382	5.826	0.117	0.475	1.743
Market-to-book	33,497	1.992	1.851	1.133	1.513	2.228
Fiscal-year return	33,461	0.167	0.719	-0.223	0.053	0.365
Return on assets	33,507	-0.018	0.288	-0.021	0.037	0.077
SG&A to sales	33,507	0.313	0.349	0.115	0.225	0.387
Annual free cash flow growth	33,507	0.044	1.182	-0.643	0.061	0.761
Annual earnings growth	33,507	0.048	1.089	-0.459	0.105	0.577
Annual SG&A growth	33,507	0.070	0.217	-0.021	0.056	0.152
3-year sales growth	33,507	0.240	0.481	-0.011	0.214	0.485

Table 2: —*Continued*

B. R&D sample

	Obs.	Mean	Std.Dev	p25	p50	p75
Revenue recognition errors and irregularities (N = 238)						
Bias in book value ($mn)	716	54.963	264.926	0.413	3.071	23.999
Bias in book value to sales	716	0.068	0.179	0.001	0.008	0.054
Bias in earnings ($mn)	716	15.766	118.835	-0.008	1.042	6.875
Bias in earnings to sales	716	0.023	0.079	-0.000	0.002	0.016
Annual bias in earnings growth	485	-0.021	1.400	-1.280	-0.022	1.166
Irregularities (N = 154)						
Bias in book value ($mn)	501	74.236	313.979	0.452	5.113	41.597
Bias in book value to sales	501	0.077	0.205	0.001	0.009	0.059
Bias in earnings ($mn)	501	21.221	141.314	-0.012	1.666	10.903
Bias in earnings to sales	501	0.025	0.092	-0.000	0.003	0.018
Annual bias in earnings growth	352	-0.007	1.393	-1.238	-0.023	1.180
CEO equity holdings (N = 2,152)						
Ownership (%)	19,948	4.067	8.906	0.155	0.641	2.796
Unexercised options, Exercisable (%)	19,948	1.130	1.472	0.162	0.652	1.499
Firm characteristics (N = 2,152)						
Obs.	19,948	11.787	4.250	8.000	13.000	16.000
Market value ($bn)	19,948	3.160	8.295	0.124	0.467	1.846
Total assets ($bn)	19,948	2.886	10.125	0.090	0.353	1.548
Sales ($bn)	19,948	2.142	5.926	0.064	0.285	1.299
Market-to-book	19,948	2.320	2.313	1.239	1.712	2.622
Fiscal-year return	19,928	0.167	0.749	-0.244	0.045	0.364
Return on assets	19,948	-0.064	0.376	-0.069	0.030	0.076
R&D to sales	19,948	0.620	2.988	0.014	0.057	0.172
Annual free cash flow growth	19,948	0.058	1.137	-0.556	0.065	0.713
Annual earnings growth	19,948	0.053	1.089	-0.475	0.098	0.602
Annual R&D growth	19,948	0.066	0.391	-0.060	0.044	0.188
3-year sales growth	19,948	0.231	0.541	-0.033	0.210	0.500

Table 3: Baseline estimation results: SG&A

A. Moments

	Data moments	Simulated moments	t-statistics
Mean ratio of SG&A to sales	0.3211	0.3349	-8.1851
Incidence of detection	0.0143	0.0041	12.8989
Mean absolute bias relative to sales, given detection	0.0617	0.0407	2.3691
Variance of dividend growth	1.2953	0.2594	8.0644
Covariance of dividend and earnings growth	0.2728	0.2683	0.4062
Covariance of dividend and R&D growth	-0.0157	-0.0189	1.8634
Variance of earnings growth	1.0901	0.7776	5.8829
Covariance of earnings and R&D growth	-0.0132	-0.0567	11.2074
Variance of R&D growth	0.0388	0.0199	4.6298
Variance of dividend growth, given detection	1.6449	0.3111	11.3861
Covariance of dividend and earnings growth, given detection	0.3977	0.3457	0.5543
Covariance of dividend and R&D growth, given detection	-0.0199	-0.0569	2.2140
Variance of earnings growth,given detection	1.3063	0.6917	7.7880
Covariance of earnings and R&D growth, given detection	-0.0283	-0.1070	10.1401
Variance of R&D growth, given detection	0.0370	0.0502	-3.1581
Variance of absolute bias, given detection	0.0211	0.0003	3.5790
Skewness of absolute bias, given detection	3.9855	1.2699	6.8389

B. Parameter estimates

p_w	ρ_y	σ_y	σ_π	κ_q	κ_f	γ	λ
0.7674	0.5039	0.2783	0.2325	24.7035	0.0298	0.4555	0.0551
(0.0008)	(0.0045)	(0.0026)	(0.0242)	(5.5622)	(0.0043)	(0.0009)	(0.0029)

The estimation is done with simulated minimum distance, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. Panel A reports the simulated and actual moments. Panel B reports the estimated structural parameters. p_w is the price of R&D relative to output. ρ_y is the serial correlation of the persistent productivity shock. σ_y is the volatility of the persistent productivity shock. σ_π is the volatility of the i.i.d. shock to earnings. κ_q is the quadratic cost of manipulation. κ_f is the fixed cost of maniupulation. γ is the curvature of the innovation production function. λ is the probability of manipulation detection.

Table 4: Baseline estimation results: R&D

A. Moments

	Data moments	Simulated moments	t-statistics
Mean ratio of R&D to sales	0.6577	0.5369	2.0790
Incidence of detection	0.0143	0.0076	8.4114
Mean absolute bias relative to sales, given detection	0.0864	0.0546	2.4285
Variance of dividend growth	1.1911	0.8585	1.8906
Covariance of dividend and earnings growth	0.3234	0.7626	-8.7012
Covariance of dividend and R&D growth	-0.0387	-0.0635	10.5873
Variance of earnings growth	1.1030	1.3527	-3.0668
Covariance of earnings and R&D growth	-0.0568	-0.1038	6.4382
Variance of R&D growth	0.1305	0.0418	20.3383
Variance of dividend growth, given detection	1.4683	1.1137	3.8572
Covariance of dividend and earnings growth, given detection	0.5580	1.3140	-7.6673
Covariance of dividend and R&D growth, given detection	-0.0030	-0.3449	10.9711
Variance of earnings growth,given detection	1.6155	1.7411	-1.0274
Covariance of earnings and R&D growth, given detection	-0.0323	-0.4889	11.6218
Variance of R&D growth, given detection	0.1336	0.1825	-1.9256
Variance of absolute bias, given detection	0.0344	0.0013	2.9619
Skewness of absolute bias, given detection	3.6313	1.5619	4.3310

B. Parameter estimates

p_w	ρ_y	σ_y	σ_π	κ_q	κ_f	γ	λ
1.1659	0.4863	0.3334	0.1596	21.8241	0.0239	0.5003	0.0461
(0.0006)	(0.0029)	(0.0215)	(0.0219)	(3.8673)	(0.0192)	(0.0233)	(0.0079)

The estimation is done with simulated minimum distance, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. Panel A reports the simulated and actual moments. Panel B reports the estimated structural parameters. p_w is the price of R&D relative to output. ρ_y is the serial correlation of the persistent productivity shock. σ_y is the volatility of the persistent productivity shock. σ_π is the volatility of the i.i.d. shock to earnings. κ_q is the quadratic cost of manipulation. κ_f is the fixed cost of maniupulation. γ is the curvature of the innovation production function. λ is the probability of manipulation detection.

Table 5: Bias vs. value: counterfactual experiments

Model	Baseline (Estimated)	No Bias ($\kappa_q = \kappa_f = \infty$)	Value Maximizing ($\theta_o = 0$)
Mean Bias	4.07	0.00	0.00
Investment Volatility	7.96	8.53	2.06
Firm Value Change from Baseline	0.00	-0.45	13.45

The table reports various outcomes computed under three alternative model parameterizations. The first column reports moments from the baseline model (with estimated parameters), the second column reports moments a model with no accounting bias (identical to baseline with bias costs κ_q, κ_f set to ∞), and the third column reports moments from a value maximizing model with no options compensation (identical to baseline with options weight $\theta_o = 0$). The first row reports the mean bias relative to sales conditional upon restatement. The second row reports the standard deviation of investment growth. The third row reports the average change in fundamental firm value relative to the baseline model. All counterfactual moments are computed using the ergodic distribution of the respective models, with all units in percent.

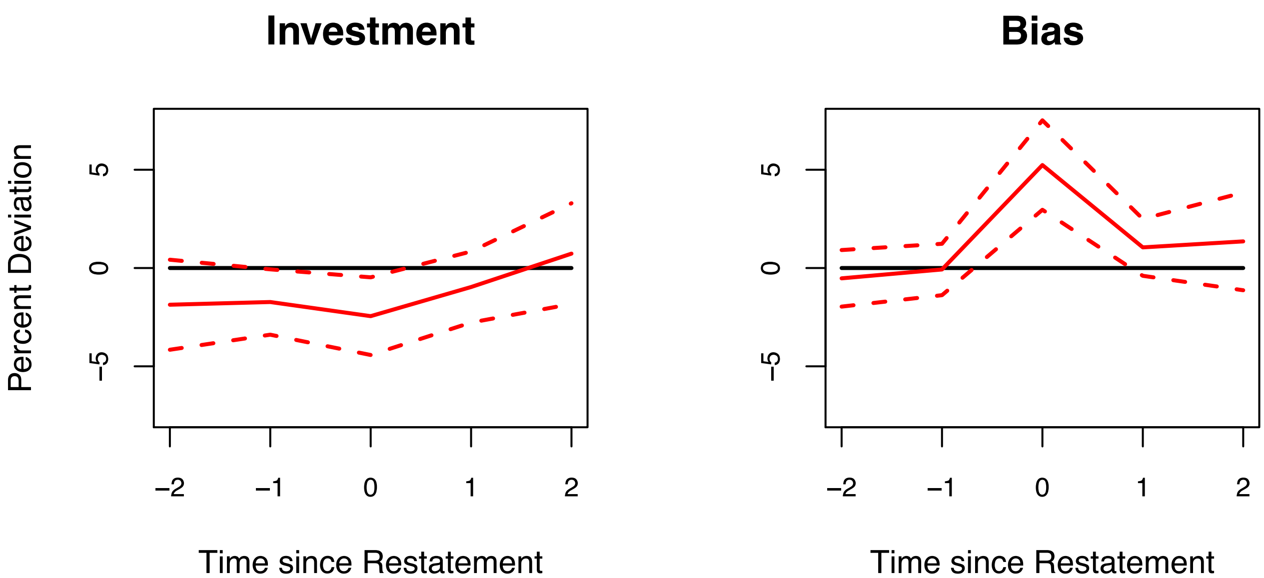


Figure 1: Dynamics around a restatement event

The figure plots the dynamics of intangible investment (left panel) and reporting bias (right panel) around firm restatement events in which earnings were biased upwards. In particular, each solid line in the figure plots estimated coefficients β_k, $k = -K, ..., K$ from the panel regression $X_{jt} = \sum_{k=-K}^{K} \beta_k \mathbb{I}(\text{Upward Bias Restated})_{jt+k} + f_s + g_t + \varepsilon_{jt}$. For firm j at time t in sector s, the variable X is selling, general, and administrative expenditures (left hand side) and reported bias in book value, both relative to sales. A full set of sector and time dummies together with indicators for public restatement of an upward bias in profits for firm j at the horizon k from year t is included. We use $K = 2$ for the figure estimates. The plotted error bands are 95% confidence intervals, clustered by firm.

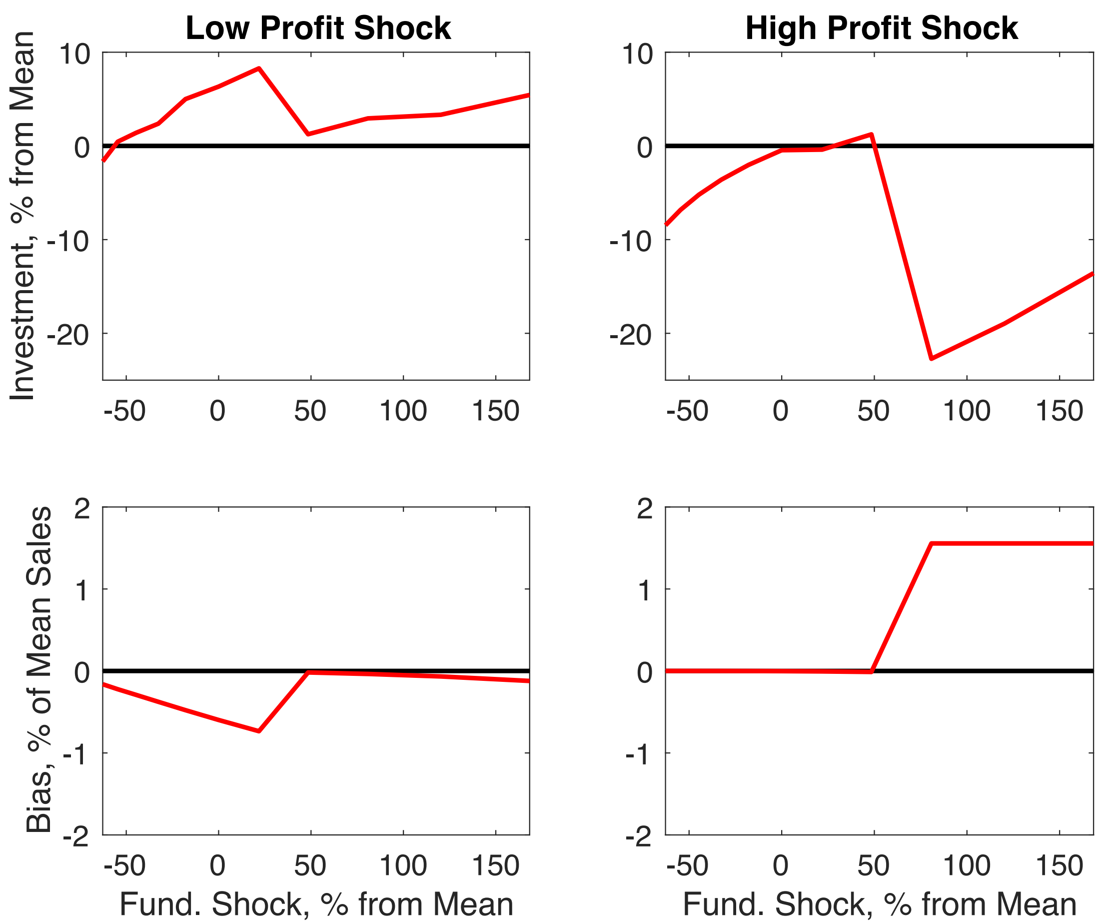


Figure 2: Investment and bias as a firm's profitability varies

Each panel of the figure plots a firm policy function - for their choice of investment or bias - in the estimated baseline model as a function of the fundamental shock v_y. The policy functions in the left column are conditioned on a low value of the profit shock $v_\pi = -0.54$, while the policy functions in the right column are conditioned on a high value of the profit shock $v_\pi = 0.54$. The top row plots a firm's investment policy in percent deviations from the mean investment policy in the model. The bottom row plots a firm's bias policy b as a percent of mean sales. The plotted policy functions are averages over the ergodic distribution of the model, conditioning upon the indicated values of the fundamental and profit shocks.

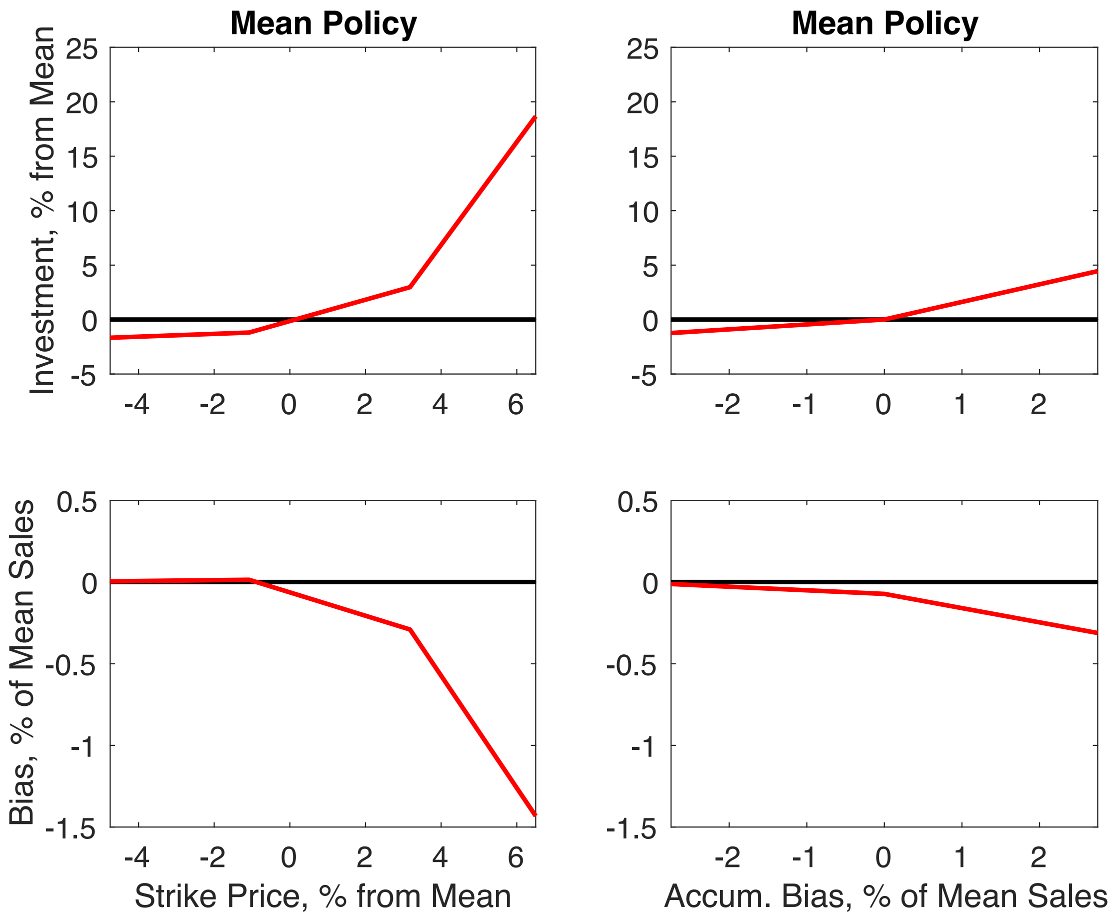


Figure 3: Investment and bias as a firm's history varies

Each panel of the figure plots a firm policy function - for their choice of investment or bias - in the estimated baseline model as a function of a state variable. The top row plots a firm's investment policy in percent deviations from the mean investment policy in the model. The bottom row plots a firm's bias policy b as a percent of mean sales. The left column plots policies as a function of the strike price of a manager's options compensation. The right column plots policies as a function of the accumulated bias on a firm's balance sheet. The plotted policy functions are averages over the ergodic distribution of the model.

Figure 4: Incidence of misreporting

This figure depicts restatement rate and restated annual financial statements by year for revenue recognition and irregularity restatements in SG&A sample.

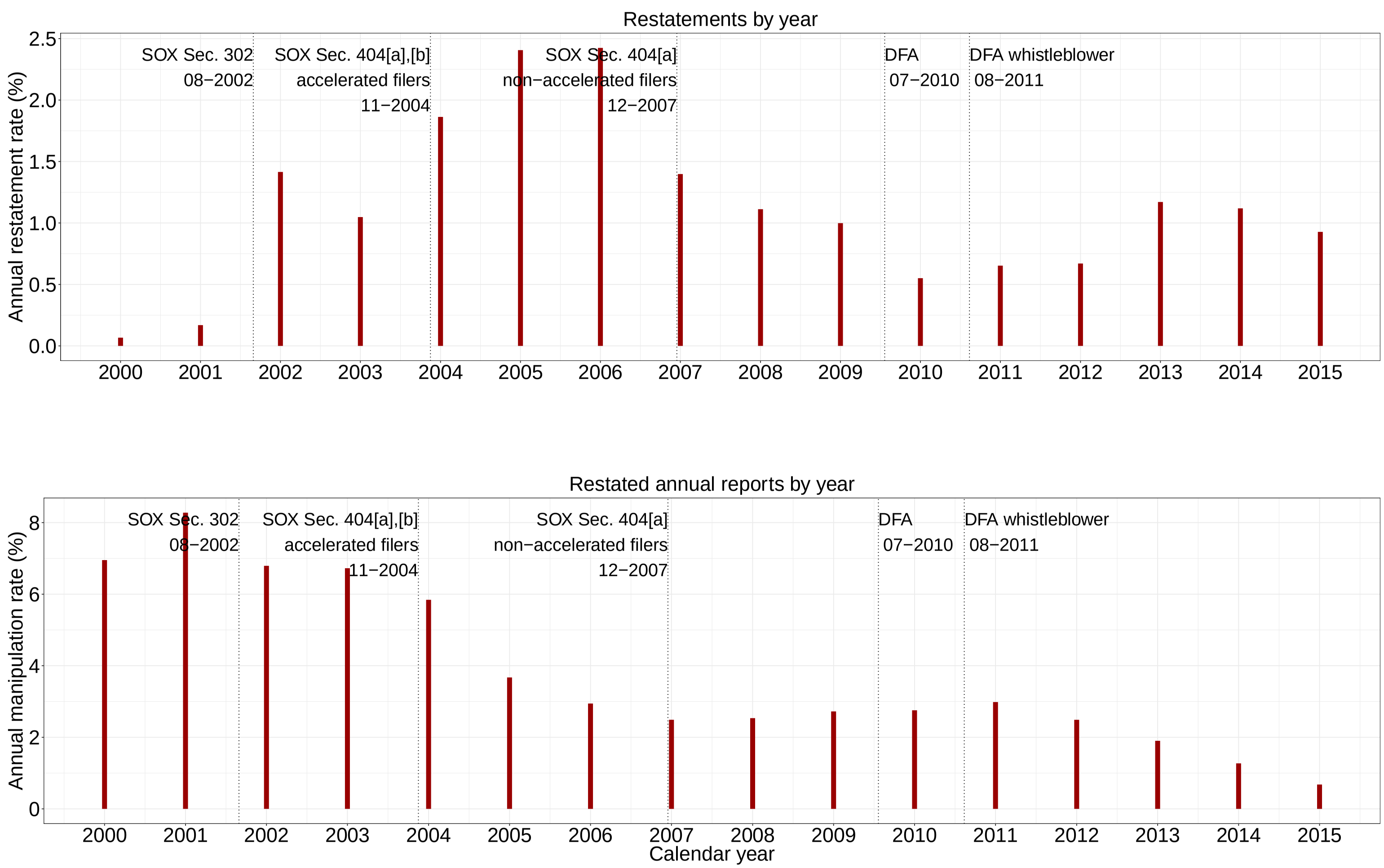
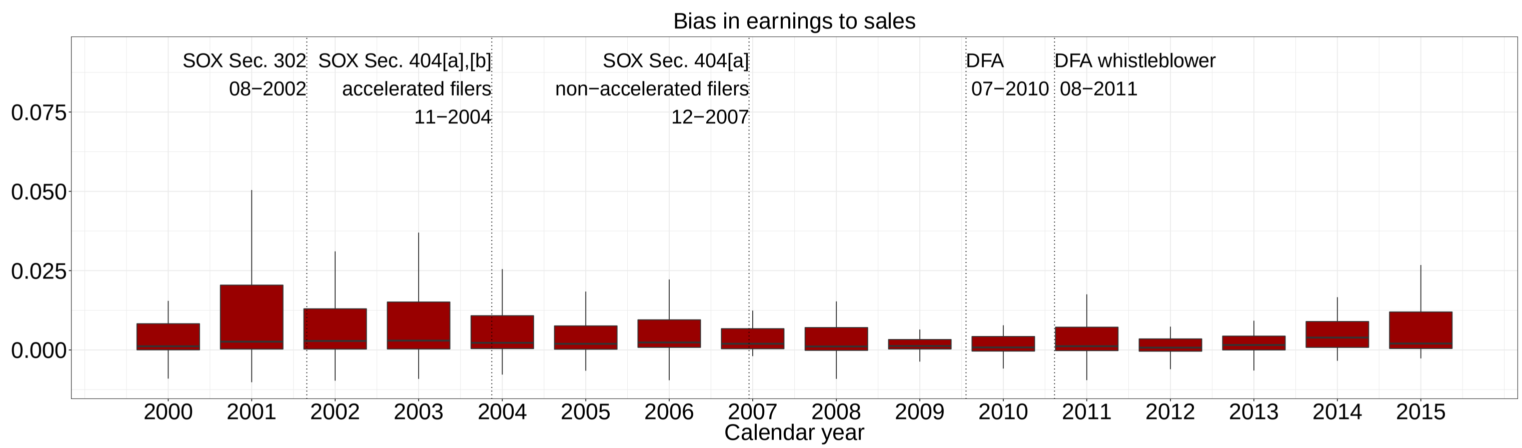


Figure 5: Magnitude of misreporting

This figure depicts the ratio of the bias in earnings to sales as a function of time for revenue recognition and irregularity restatements in SG&A sample.



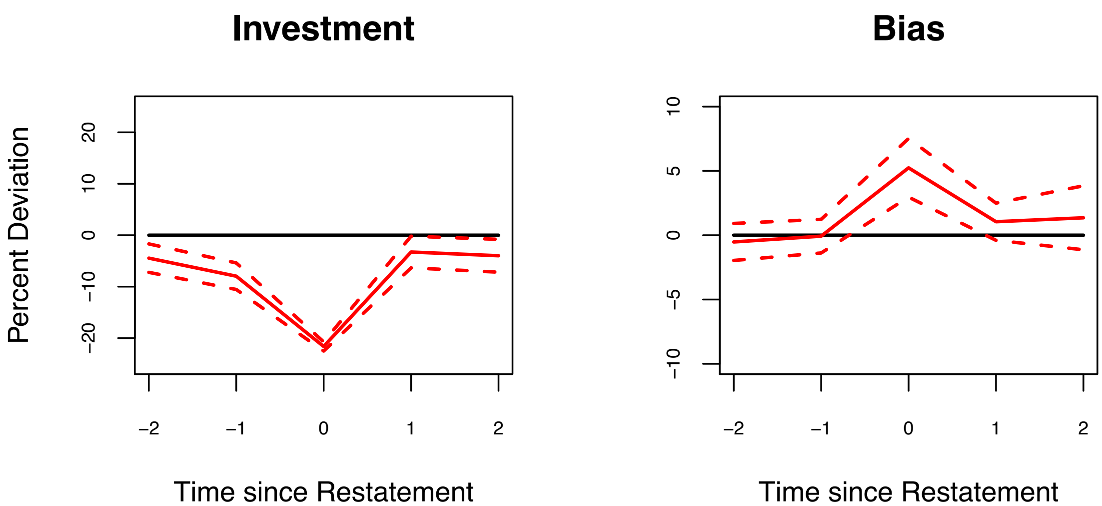


Figure 6: Dynamics around a restatement event - simulated data

The figure plots the dynamics of intangible investment (left panel) and reporting bias (right panel) around firm restatement events in which earnings were biased upwards. In particular, each solid line in the figure plots estimated coefficients $\beta_k,\ k = -K, ..., K$ from the panel regression $X_{jt} = \sum_{k=-K}^{K} \beta_k \mathbb{I}(\text{Upward Bias Restated})_{jt+k} + \varepsilon_{jt}$. For firm j at time t, the variable X is R&D expenditures (left hand side) and reported bias in book value, both relative to sales. We use $K = 2$ for the figure estimates. The plotted error bands are 95% confidence intervals, clustered by firm.

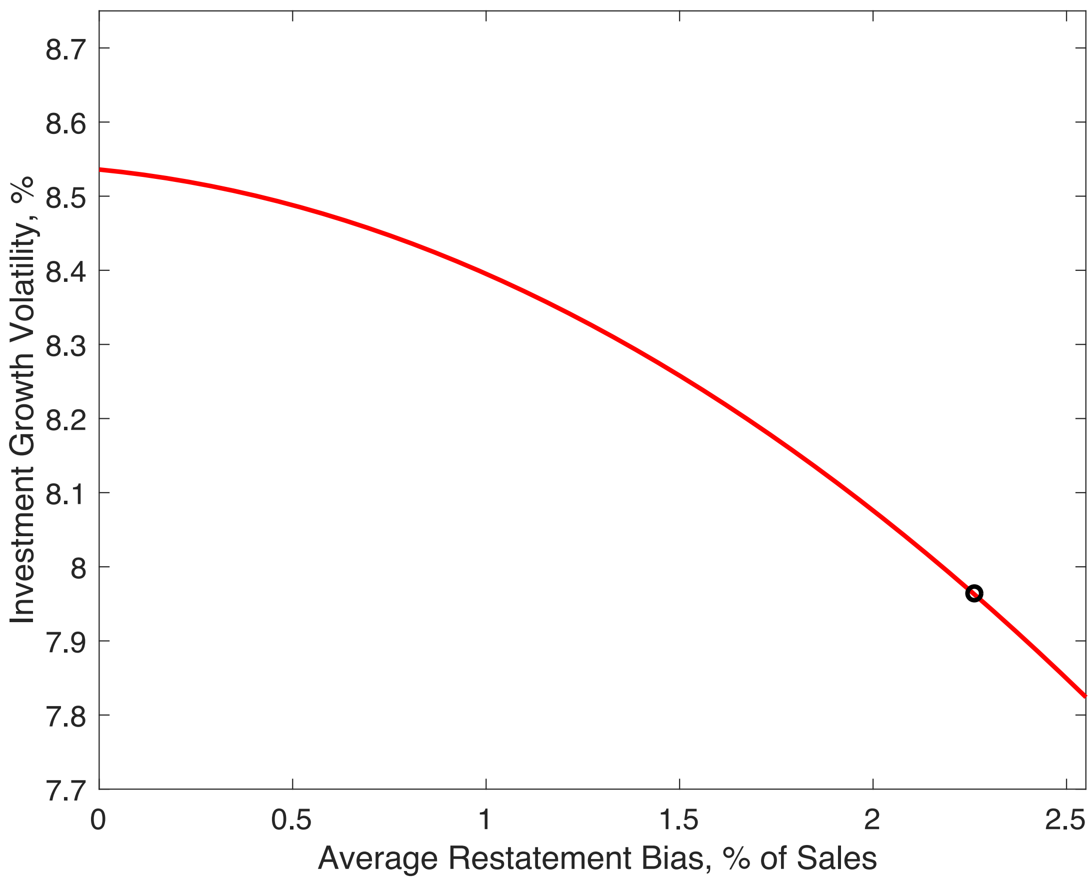


Figure 7: Tradeoffs

The figure plots the equilibrium volatility of investment growth (on the vertical axis) and average bias relative to sales in restatements (on the horizontal axis). Each point on the curve reports moments from a counterfactual experiment, starting from the baseline estimated parameterization of the model and changing only the manager's cost of bias κ_q either up or down. The curve is a polynomial interpolation of moments from a discrete set of counterfactual experiments. The infinite bias cost or no bias model lies at the intersection of the line with the vertical axis, and the baseline estimated model is represented by the circled point. At the baseline estimated model, the tangent slope or elasticity of investment volatility with respect to bias is equal to -0.45.