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Abstract

We quantify the real implications of trade-offs between firm information disclosure and long-term investment efficiency. We estimate a dynamic equilibrium model in which firm managers confront realistic incentives to misreport earnings and distort their real investment choices. The model implies a socially optimal level of disclosure regulation that exceeds the estimated value. Counterfactual analysis reveals that eliminating earnings misreporting completely through disclosure regulation incentivizes managers to distort real investment. Lower earnings informativeness raises the cost of capital, which results in a 5.7% drop in average firm value, but more modest effects on social welfare and aggregate growth.

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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 and the economy, while accurate disclosure of financial information allows for the efficient pricing of assets, which is essential for the health and transparency of capital markets. 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. We aim to understand whether this trade-off is empirically important and to quantify the real effects of frictions that induce firms to substitute between making efficient investment choices and revealing accurate information.

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 turn to the arena of earnings misreporting, which is a natural laboratory to examine a question involving information. Data on earnings announcements, realizations, and, critically, 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, and not all earnings restatements reveal fraud, with the result that quantifying the economic magnitude of the relevant information frictions requires imposing some structure on the data.

To this end, we use these data to estimate a dynamic equilibrium model of earnings reporting and real intangible investment, where we focus on intangibles because accounting rules imply that the immediate impact of intangible-asset spending on earnings exceeds that of spending on fixed assets. We find that the model matches a wide array of data moments related to both real investment and accounting restatements. We use this estimated model to understand the counterfactual effects of disclosure regulation on firm value, growth, and social welfare.

To describe these results, we first elaborate on the model. The backbone is an infinite horizon, general equilibrium framework with a household, a financial intermediary, a final goods producer, and many heterogeneous intermediate goods firms. These firms invest in a decreasing-returns technology that allows them to innovate new varieties of goods, which drive aggregate growth and welfare as in Romer (1990).

The tension in the model lies in the intermediate goods sector, which has three features that provide a meaningful trade-off between earnings manipulation and investment distortion. First, managers face conflicting incentives. On the one hand, stock compensation aligns their long-term incentives with those of shareholders, so managers benefit when they make efficient investment choices and suffer when they do not. On the other hand, manager–shareholder incentive alignment is incomplete, as managers' compensation contracts also give them short-term incentives to both beat average earnings and smooth current earnings. They respond by manipulating information either by lying about earnings or by altering investment expenditures. Second, incentives to manipulate earnings are tempered because the model contains a notion of disclosure regulation, so the manager can with some probability get caught and face punishment. Third, managers face transitory shocks to earnings that do not affect fundamental cash flows and that cannot be observed by the household.

With this incentive structure in place, managers choose both long-term investment and short-term earnings manipulation to maximize their utility over an infinite horizon. Facing the incentives described above, managers choose policies that deviate from a value-maximizing benchmark. In particular, after a negative transitory shock, they often choose lower levels of intangible investment to boost earnings. In contrast, managers facing high or positive transitory shocks usually boost their investment, thus smoothing earnings today. The result is high sensitivity of investment to a transitory, non-fundamental shock that a forward-looking, value-maximizing firm would ignore. Moreover, because managers can manipulate information both by misreporting and by investing suboptimally, and because increasing the cost of one tool for manipulation affects the use of the other, investment policies depend crucially upon disclosure regulation. Thus, one important result is that disclosure regulation can sometimes depress firm value by encouraging inefficient investment.

Because both real investment distortions and earnings manipulation make observed earnings less informative, they have a further, quantitatively strong effect on growth, welfare, and firm value. We assume that while the household can only observe reported, and possibly manipulated earnings, the financial intermediary knows all information about the firms. This advantage allows the intermediary to extract information rents when it mediates the household's equity ownership in the firms. In equilibrium, this rent extraction raises the firms' cost of capital, with less informative earnings implying a higher cost of capital.

This description of the key features of the model allows us to discuss the intuition behind the core results from our model. The main result is a socially optimal level of disclosure regulation, which arises because regulation exerts two opposing forces on earnings informativeness. First, as regulation initially rises from zero, earnings manipulation falls, so earnings informativeness rises, and the cost of capital falls. Firm value, growth, and social welfare rise. Second, and in contrast, as regulation continues to increase, although earnings manipulation continues to fall, managers intensify their real investment manipulation. Earnings informativeness falls, leading to a rise in the cost of capital, a mechanical drop in firm value, and a smaller drop in welfare. We find that the socially-optimal level of regulation exceeds our estimated level. Interestingly, the optimal level of regulation for the maximization of firm value is lower. The structure of the manager's compensation contract means that more manipulation is typically associated with higher investment. This extra investment is less valuable to the firm than for welfare more generally, as investment adds to the number of available goods, thus raising productivity, growth, and household utility, that is, welfare.

We also examine the effects of shutting down earnings manipulation completely by making regulation extreme. For the model as parameterized in our baseline estimation, earnings informativeness falls, as firms substitute strongly toward real investment manipulation. The cost of capital rises by 0.3 percentage points, leading to a fall in firm value of 5.7%, but a tiny rise in welfare of 0.1%, again because social welfare and firm value diverge. We also examine an equally extreme environment with no incentives for either investment or earnings manipulation. While this case is unlikely to occur in practice because of real-world agency conflicts that give rise to these incentives in the first place, it is nonetheless instructive. We find that earnings informativeness rises, the cost of capital falls by 0.14 percentage points, and firm value rises by 2.4%. As before, we only find modest shifts in welfare.

These quantitative results and trade-offs are likely to be of interest to policymakers and corporate boards. For example, 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). We enrich this discussion by providing new information based on our result that estimated regulation falls short of socially optimal regulation. In addition, because we show that short-term incentives sometimes can have strong, counterintuitive effects on firm value, corporate boards that set incentive packages might find the magnitude of these effects useful.

The general notion of a trade-off 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 such as R&D and advertising expenditures to hit an earnings target. In addition, 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 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 result in managers' reliance on value-destroying investment distortions.

Our project links two distinct literatures. The first consists of empirical studies that investigate the relationship between accruals manipulation, which occurs through earnings misreporting, and real manipulation, which occurs through opportunistic changes to long-term investment. Empirical patterns consistent with accruals and real manipulation have been found in reduced-form studies in accounting for decades. These studies usually measure both accrual-based and real earnings management using regression residuals. For example, accrual-based earnings management is measured via discretionary accruals models, which are regressions of total accruals on variables correlated with theoretical normal accruals (e.g., Jones 1991; Dechow, Sloan, and Sweeney 1995; Kothari, Leone, and Wasley 2005). Similarly, discretionary R&D expenditures are residuals of regressions with R&D as a dependent variable (e.g., Roychowdhury 2006; Cohen, Dey, and Lys 2008; Zang 2011). Using these methods, the literature has found substitution between measures of accrual-based and real earnings management (e.g., Cohen, Dey, and Lys 2008; Cohen and Zarowin 2010; Zang 2011). Interestingly, Terry (2017) finds no evidence consistent with tangible investment distortions around earnings thresholds, consistent with accounting rules that do not require tangible investment to be expensed immediately.

We advance this literature by substituting an economic model for statistical models of manipulation and investment in intangibles. The advantage of this approach is twofold. First, we can quantify the slope of the substitution between real and accruals manipulation. 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

[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 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).

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).

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. This growth that stems from innovation is shared by macro-level models of endogenous growth (Romer 1990; Aghion and Howitt 1992). Because idiosyncratic shocks differentiate firms and drive their innovation decisions, the firm-level environment or heterogeneity is richer than in many baseline models of endogenous growth, although lumpy innovation arrivals and entry/exit dynamics are absent.

Three papers are particularly close to ours. The first is Terry (2017), which, like our work, examines the effects of information manipulation on intangible investment. Both our work and Terry (2017) use general equilibrium settings, and in both models, the incentives of firms to meet earnings targets distort their investment policies. However, in our model, misreporting also affects real outcomes via its effect on the cost of capital, whereas this mechanism is absent in Terry (2017). In addition, while misreporting in Terry (2017) is highly stylized, our model incorporates realistic features of the institutional information disclosure environment, such as detection and punishment. This realism 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 Act (SOX). Interestingly, with regard to SOX, by estimating our model both pre- and post-SOX, we find that the small change in the number of detected incidents of manipulation is largely the product of a perceived ex-ante cost of detection. Finally, because we also employ a richer misreporting environment, we can target micro data on earnings restatements to identify the model parameters related to manipulation.

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

The third paper is Zakolyukina (2018), who also structurally estimates the likelihood of misreporting. While our model incorporates similar notions of detection, punishment, and balance sheet dynamics, the model in Zakolyukina (2018) does not link earnings manipulation to the cost of capital or to real outcomes such as investment, growth, or welfare.

2. Model

We develop a general equilibrium model of aggregate endogenous growth based on firm-level innovation. The model features pressure on firm managers to manipulate earnings, either by distorting intangible investment or misreporting earnings. In equilibrium, both types of manipulation are endogenously linked to earnings informativeness, which in turn affects the cost of capital, and hence underlying firm value. In this framework, disclosure regulation has a direct, potentially negative impact on the efficiency of firm investment because it influences managers' intangible investment choices. Regulation also has an indirect, potentially positive impact on innovation through higher information quality and a lower cost of capital.

2.1 Environment

Time is discrete, and there is no aggregate uncertainty. A representative final goods firm produces output that serves two purposes. It can be consumed by a representative household or be used by heterogeneous intermediate goods firms as an input to produce different varieties of intermediate goods. These firms can also expand the set of varieties by investing in their innovation, which is the source of aggregate growth in the model. Each intermediate goods firm is run by a manager facing incentives to manipulate profits. A financial intermediary channels equity financing from households to firms, where this intermediation is subject to frictions linked to the informativeness of earnings for fundamental firm value.

2.2 Final goods firm

At time t, a representative final goods firm produces output, Y_t, using a constant returns to scale technology:

$$Y_t = L_t^{1-\alpha} \int_0^{Q_t} z_{jt}^{1-\alpha} x_{jt}^{\alpha} dj. \tag{1}$$

Above, L_t is the quantity of land used in production, and x_{jt} is the quantity of intermediate variety j, where $j \in [0, Q_t]$ indexes the varieties of intermediate goods in existence. Hence, the current mass of varieties is Q_t. Each variety's usefulness in production is shifted by an exogenous marginal product level, z_{jt}. The land share in production is $1-\alpha$, where $\alpha \in (0,1)$.

Note that if land and all intermediate varieties were used in equilibrium at fixed levels L^* and x^* with values of $z_{jt} = z^* = 1$, then output would be given by $Y_t = Q_t {L^*}^{1-\alpha} {x^*}^{\alpha}$. It is immediate that growth of the aggregate economy in this simple case is equal to growth of the mass of varieties, Q_t. This result places our model in the class of general equilibrium, expanding variety endogenous growth models in the spirit of Romer (1990). Intuitively, aggregate productivity is directly proportional to the mass of varieties because only through the creation of more varieties is this economy able to overcome diminishing returns to land and individual intermediate inputs. Although the equilibrium fleshed out below features more richness at the micro level than this simple illustrative case, the equilibrium preserves the key underlying logic of endogenous aggregate growth that is due solely to the innovation of new varieties, which increases Q_t over time.

The final goods firm solves a static profit maximization problem:

$$\max_{L_t, \{x_{jt}\}} Y_t - P_t^L L_t - \int_0^{Q_t} p_{jt} x_{jt} dj,$$

taking as given the price of its output (normalized to 1), the rental price of land, P_t^L, and the price, p_{jt}, of variety j. The optimality condition for the final goods firm's demand, x_{jt}, for variety j is given by

$$x_{jt} = z_{jt} \left(\frac{\alpha}{p_{jt}} \right)^{\frac{1}{1-\alpha}} L_t. \tag{2}$$

2.3 Intermediate goods firms

A fixed mass of intermediate goods firms indexed by $k \in [0, 1]$ produces intermediate varieties and invests in the innovation of new varieties. We first describe the static optimization problem of a firm selling an existing intermediate variety to the final goods firm. Then we describe a firm's dynamic innovation decision that drives the creation of new varieties. Finally, we lay out the accounting definition of earnings in the model, the potential for earnings misreporting, and a manager's dynamic incentives.

2.3.1. Static optimization for existing varieties

Any existing variety, j, can be produced using a linear technology that transforms final output into intermediate goods with a constant marginal cost, $\psi > 0$. We assume that a patent gives firm k that innovated variety j the right to produce this good monopolistically for one period, which can be interpreted as the statutory patent length or, more reasonably, as the shorter length of effective monopoly protection given churn in product markets or new competitor goods. After this protection expires, the variety goes off-patent and can be produced by any firm. During the monopoly protection period, the innovator firm sets the price, p_{jt}, for good j optimally, taking as given the final goods firm's demand $x_{jt}(p_{jt}, z_{jt}, L_t)$ from equation (2). The resulting static profit maximization problem is:

$$\max_{p_{jt}} p_{jt} x_{jt}(p_{jt}, z_{jt}, L_t) - \psi x_{jt}(p_{jt}, z_{jt}, L_t). \tag{3}$$

The constant elasticity of demand in equation (2) implies that the solution to this problem is an optimal monopoly price, p_m, given by a markup over marginal cost:

$$p_{jt}^m = p_m = \frac{\psi}{\alpha} > \psi, \tag{4}$$

with implied monopoly output given by

$$x^m_{jt} = x_{jt}(p_{jt}, z_{jt}, L_t) = z_{jt}\alpha^{\frac{2}{1-\alpha}}\psi^{-\frac{\alpha}{1-\alpha}}L_t. \tag{5}$$

In turn, these prices and quantities imply optimal monopoly revenues for variety j, r^m_{jt}, as:

$$r^m_{jt} = p^m_{jt}x_{jt}(p^m_{jt}, z_{jt}, L_t) = z_{jt}\alpha^{\frac{1+\alpha}{1-\alpha}}\psi^{-\frac{\alpha}{1-\alpha}}L_t, \tag{6}$$

and monopoly profits, π^m_{jt}, as:

$$\pi^m_{jt} = p^m_{jt}x_{jt}(p^m_{jt}, z_{jt}, L_t) - \psi x_{jt}(p^m_{jt}, z_{jt}, L_t) = (1-\alpha)r^m_{jt} = (1-\alpha)z_{jt}\alpha^{\frac{1+\alpha}{1-\alpha}}L_t. \tag{7}$$

Given the constant markup pricing rule in equation (4), profits, π^m_{jt}, for variety j are proportional to both revenues, r^m_{jt}, and the exogenous demand shifter, z_{jt}.

We make three further assumptions about the production of existing intermediate varieties. First, to reduce the number of state variables, we assume the demand shifter, z_{jt}, for newly innovated good j varies only at the level of the firm k producing the good. Second, for each firm k, we assume the demand shifter follows an exogenous persistent process:

$$\log z_{kt+1} = \rho \log z_{kt} + \zeta_{kt+1}, \quad \zeta_{kt+1} \sim N(0, \sigma^2_z) \tag{8}$$

with autocorrelation $\rho \in (0,1)$ and conditional variance $\sigma^2_z > 0$. Third, we assume that for any competitively produced off-patent good j, the demand shifters are uniformly given by $z_{jt} = 1$. Given the constant marginal cost of production, ψ, the competitive price, $p^c_{jt} = p_c = \psi$, prevails for all off-patent varieties, implying a competitive level of production $x_{cjt} = \left(\frac{\alpha}{\psi}\right)^{\frac{1}{1-\alpha}} L_t$ and zero profits $\pi^c_{jt} = 0$. Because off-patent varieties yield zero profits, we can ignore them in our description of an intermediate firm's dynamic optimization.

2.3.2. Dynamic firm innovation of new varieties

An intermediate goods firm k that spends W_{kt} units of final goods on intangible investment innovates a mass M_{kt+1} of new patent-protected varieties that are available for production in period $t+1$. The innovation function is given by:

$$M_{kt+1} = \bar{\xi} W_{kt}^{\gamma} Q_t^{1-\gamma}, \tag{9}$$

where $\bar{\xi} > 0$ is a fixed innovation productivity level, and $\gamma \in (0,1)$ is the elasticity of innovation to investment. Equation (9) implies that intangible investment becomes more productive when there are more pre-existing ideas embodied in the economy-wide mass of varieties Q_t. These idea externalities play an important role in the quantification of welfare below in our counterfactuals. Finally, as in Romer (1990), the form of equation (9) ensures homogeneity of firm innovation incentives and hence balanced growth over time.

2.3.3. Firm profits, misreporting, and detection

Cash flows to shareholders, D_{kt}^f, are given by output minus intangible investment expenditure:

$$D_{kt}^f = \pi_{kt}^m M_{kt} - W_{kt}, \tag{10}$$

where $Y_{kt} \equiv \pi_{kt}^m M_{kt}$ is output, and π_{kt}^m is given by equation (7). This expression represents operating profits from each of the firm's preexisting mass M_{kt} of on-patent monopoly varieties, net of intangible investment costs, which are fully expensed. From an accounting perspective, D_{kt}^f can be thought of as intrinsic earnings that ultimately convert to shareholder cash flows.

We allow reported earnings to deviate from D_{kt}^f in two ways. First, we allow for an i.i.d. accounting shock, ν_{kt}, that drives non-fundamental exogenous variation in earnings, with $\nu_{kt} \sim N(0, \sigma_\nu^2)$. This shock has no actual cash flow consequences and simply reflects deficiencies in accounting standards related to the accurate estimation of intrinsic cash flows. Below, we refer to the shock, ν_{kt}, as a non-fundamental shock or profit shock.

Second, the manager can manipulate earnings by introducing bias into the book value of the firm because earnings are the first difference of book value. As such, the manager enters the current period with an inherited bias in book value given by B_{kt-1}. He then chooses a new level of bias, B_{kt}, to obtain a net distortion in reported earnings equal to $B_{kt} - B_{kt-1}$, which can be either positive or negative. These two extra components of earnings imply that total earnings, Π_{kt}, are given by:

$$\Pi_{kt} = \pi^m_{kt} M_{kt} - W_{kt} + \nu_{kt} Q_t + B_{kt} - B_{kt-1}. \tag{11}$$

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_{kt}. These sorts of balance sheet dynamics capture the intertemporal nature of accruals manipulation and distinguish our model from the one in Terry (2017), in which misreporting is static.

Embedded in the formula for earnings (11) above are two potential avenues for the manager of firm k to manipulate profits: real manipulation through changes in the level of intangible investment W_{kt} and misreporting through choices of bias B_{kt}. We assume that any misreporting by the manager, $B_{kt} \neq 0$, is detected with a constant exogenous probability $\lambda \in (0, 1)$, as in Zakolyukina (2018). This feature of the model realistically implies that managers can go for some time without getting caught. In addition, they can also reverse the manipulation in those periods in which they do not get caught and thus remain forever undetected for that specific episode of manipulation. If they are discovered, they must restate their financials with $B_{kt} = 0$ and suffer a private cost of

$$MC(B_{kt}, Q_t) = \left[\kappa_f + \kappa_q \left(\frac{B_{kt}}{Q_t}\right)^2\right] Q_t. \tag{12}$$

The manager's punishment, $MC(B_{kt}, Q_t)$, scales homogeneously with Q_t and contains two components: a fixed term, $\kappa_f \geq 0$, which is independent of the degree of manipulation and a term governed by $\kappa_q \geq 0$, which scales quadratically in the magnitude of misreporting.

In principle, these costs could arise either outside the firm from litigation risk or pressure from investors or regulators. Alternatively, they could arise inside the firm as a part of a sophisticated manager compensation contract. In addition, these 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 (12) are purely non-pecuniary and internal to the manager.

2.3.4. Manager dynamic optimization

Firm decisions over intangible investment, W_{kt}, and bias, B_{kt}, are made by a risk-neutral manager with flow compensation given by

$$D^m_{kt} = \theta_d D^f_{kt} + \theta_f \mathbb{I}\left(\frac{\Pi_{kt}}{Q_t} \geq \bar{\pi}\right) Q_t - \frac{\theta_q}{2}\left(\frac{\Pi_{kt}}{Q_t} - \bar{\pi}\right)^2 Q_t. \tag{13}$$

The first term comes from managerial ownership of a fixed share, θ_d, of the outstanding equity, so the manager receives the same fraction, θ_d, of the distributions to shareholders. The second two terms represent an exogenous contract featuring short-term incentives for managers to deliver smooth earnings above a fixed endogenous threshold $\bar{\pi}$ given by:

$$\bar{\pi} = \mathbb{E}\frac{\Pi_{kt}}{Q_t}. \tag{14}$$

The payoff, D^m_{kt}, omits fixed compensation because manager risk neutrality renders such compensation irrelevant for the choice of policies. The three components of compensation in the model have important implications for the manager's actions. The stock component aligns the managers' incentives with those of long-term shareholders. The short-term earnings threshold component gives the manager an incentive to report current-period earnings at least as high as average earnings.[2] While we model the incentive to beat average earnings for simplicity, any compensation scheme with jumps in the measures of firm performance, such as the stock price or earnings, would provide similar incentives. Performance-based equity grants, options-based compensation, and bonus plans serve as examples. The quadratic short-term

[2]This benchmark plays a role similar to the analyst expectations benchmark in Terry (2017). Both models produce substantial manipulation because many earnings realizations endogenously occur near the threshold.

earnings term gives the manager an incentive to avoid high volatility in reported profits.[3]

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. Performance-based equity grants have been increasing since the mid-1990s (Bettis, Bizjak, Coles, and Kalpathy 2010) and have outpaced options as the most popular form of equity compensation after 2004 (Edmans, Gabaix, and Jenter 2017). Similar to bonus plans, these performance-based equity grants often have a discrete jump at a lower performance threshold and an incentive zone (Bettis, Bizjak, Coles, and Kalpathy 2018). These plans are often complex and, for performance shares, can have linear or non-linear mappings from performance to the number of securities granted in the incentive zone.

Our contract emphasizes the discrete jump in compensation and for simplicity abstracts away from the complexities of the performance–payoff mapping in the incentive zone. We also focus on discrete jumps because of the large literature on meeting or beating earnings targets. This literature shows that reported earnings tend to exceed three thresholds based on avoiding losses, sustaining recent earnings, and meeting analysts' expectations (e.g., Burgstahler and Dichev 1997; DeGeorge, Patel, and Zeckhauser 1999). Our average earnings threshold can be taken as representing analysts' earnings expectations. In addition, Terry (2017) demonstrates how earnings targets can arise naturally as a feasible, implementable tool to alleviate agency conflicts such as empire building or shirking. We include the smoothing motive in the contract, θ_q, in light of pervasive evidence of income smoothing (e.g., Subramanyam 1996; Tucker and Zarowin 2006; Wu 2018), with firms making accounting choices to report a smooth stream of earnings (e.g., Moses 1987; Kanagaretnam, Lobo, and Yang 2004).

In summary, as in Nikolov and Whited (2014) and Glover and Levine (2017), our aim is

[3]Note that we omit the direct impact of manager compensation from cash flows in equation (10). This choice is without loss of generality if we allow for a fixed component of manager compensation that leads to zero net pay in expected present discounted value. Such a change to the contract does not impact policies but does neutralize the direct effect of manager compensation on the average firm value levels, and we consider this possibility later in our counterfactual analysis. We also omit manager compensation below from the goods market-clearing conditions, a choice that leaves manager policies undistorted and is also innocuous if we allow for lump-sum taxes on managers rebated to the aggregate household.

to model observed contracts, so we remain silent on the optimality of these incentives. One interpretation of our contract is that it summarizes the outcome of an incomplete contracting environment in which boards use compensation contracts to incentivize good managerial behavior, but the incompleteness of the contracting environment implies that the misbehavior that we model cannot be contained via contracts. This interpretation is backed by the evidence in Dittmann and Maug (2007) that standard principal-agent models cannot rationalize observed executive compensation contracts.

We normalize the manager cash flow share θ_d to one without loss of generality. Given a firm's required rate of return $R^f > 1$, which we characterize and endogenize below, the manager solves a problem by optimizing the expected present discounted value of their compensation net of private costs of manipulation. The manager's dynamic problem is characterized by a Bellman equation V^m:

$$V^m(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t) = \max_{W_{kt}, B_{kt}} \left[\begin{array}{c} \mathbb{I}(B_{kt} = 0) \left(D^m_{kt} + \frac{1}{R^f} \mathbb{E} \left[V^m(z_{kt+1}, \nu_{kt+1}, 0, M_{kt+1}, Q_{t+1}) | z_{kt} \right] \right) \\ \mathbb{I}(B_{kt} \neq 0)(1-\lambda) \left(D^m_{kt} + \frac{1}{R^f} \mathbb{E} \left[V^m(z_{kt+1}, \nu_{kt+1}, B_{kt}, M_{kt+1}, Q_{t+1}) | z_{kt} \right] \right) \\ \mathbb{I}(B_{kt} \neq 0)\lambda \left(D^m_{kt}|_{B_{kt}=0} - MC(B_{kt}, Q_t) + \frac{1}{R^f} \mathbb{E} \left[V^m(z_{kt+1}, \nu_{kt+1}, 0, M_{kt+1}, Q_{t+1}) | z_{kt} \right] \right) \end{array} \right]. \quad (15)$$

A manager chooses investment, W_{kt}, and bias, B_{kt}, given an exogenous persistent demand shifter, z_{kt}, exogenous i.i.d. noise in profits ν_{kt}, bias from the previous period, B_{kt-1}, a mass of on-patent varieties newly innovated for production, M_{kt}, and an economy-wide variety mass, Q_t. These choices imply one of three outcomes in the Bellman equation (15). First, if the manager chooses not to misreport, with $B_{kt} = 0$, then the manager receives payoffs given by their flow compensation, D^m_{kt}, and continues to the next period with zero bias on their books. Second, if the manager chooses to misreport with $B_{kt} \neq 0$, with probability $1 - \lambda$, the misreporting goes undetected and the manager continues to the next period with bias, B_{kt}, after receiving flow compensation, D^m_{kt}. Third, with probability λ, a misreported statement is detected, in which case the manager is forced to restate their profits, receiving their compensation, $D^m_{kt}|_{B_{kt}=0}$, net of the private costs of punishment for misreporting, $MC(B_{kt}, Q_t)$. In all cases, investment determines the mass of varieties available for production in the next period, M_{kt+1}.

While (15) gives lifetime managerial utility, it does not represent the fundamental value of the firm, which is simply the expected present value of distributions to shareholders. On the basis of the manager's privately optimal policies, W^*_{kt} and B^*_{kt} from equation (15), the fundamental value of the firm is:

$$V^f(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t) =$$
$$\begin{bmatrix} \mathbb{I}(B^*_{kt} = 0)\left(D^{f*}_{kt} + \frac{1}{R^f}\mathbb{E}\left[V^f(z_{kt+1}, \nu_{kt+1}, 0, M^*_{kt+1}, Q_{t+1})|z_{kt}\right]\right) \\ \mathbb{I}(B^*_{kt} \neq 0)(1-\lambda)\left(D^{f*}_{kt} + \frac{1}{R^f}\mathbb{E}\left[V^f(z_{kt+1}, \nu_{kt+1}, B^*_{kt}, M^*_{kt+1}, Q_{t+1})|z_{kt}\right]\right) \\ \mathbb{I}(B^*_{kt} \neq 0)\lambda\left(D^{f*}_{kt} + \frac{1}{R^f}\mathbb{E}\left[V^f(z_{kt+1}, \nu_{kt+1}, 0, M^*_{kt+1}, Q_{t+1})|z_{kt}\right]\right) \end{bmatrix}, \quad (16)$$

where values with a * superscript are implied by the optimal manager-chosen policies. We note that in the absence of the incentives to manipulate earnings ($\theta_f = \theta_q = 0$), managerial utility, (15), equals fundamental firm value (16).

2.4 Representative household

A representative household has constant relative risk aversion $\eta > 0$ over consumption and discounts the future at a rate $\beta \in (0, 1)$. Given the lack of aggregate uncertainty in the model, the household's lifetime welfare maximization problem starting from period 0 is:

$$\max_{\{S_{t+1}, E_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \frac{C_t^{1-\eta}}{1-\eta}. \quad (17)$$

At period t, the household chooses savings, S_{t+1}, in a one-period bond with known gross real return R^h_{t+1} paid in period $t+1$. The household also chooses investment in pooled intermediate goods firm equity, E_{t+1}, through an intermediary described below offering the known aggregate return $\tilde{R}^h_{t+1}$ in period $t+1$. The household owns land in the economy in the fixed amount $L_t = 1$ and rents this factor to the final goods sector at the price P^L_t, a sector which it also owns.[4] The household's budget constraint is period t is given by:

$$C_t + S_{t+1} + E_{t+1} = S_t R_t^h + E_t \tilde{R}_t^h + P_t^L L_t. \tag{18}$$

2.5 Investment intermediary

A risk-neutral investment intermediary collects the equity investment, E_{t+1}, from the household each period to provide equity finance to a diversified portfolio consisting of all active intermediate goods producers. The intermediary observes the firm's full state vector and therefore knows the firm's fundamental ex-dividend value, $\tilde{V}_{kt}^f = V^f(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t) - D_{kt}^f$. The household, by contrast, not only is unable to invest directly in firm equity but also has less precise information about idiosyncratic firm states, observing only firm reported earnings, Π_{kt}, and forming expectations given by $\mathbb{E}\left(\tilde{V}_{kt+1}^f | \Pi_{kt}\right)$.

The investment intermediary offers the household a claim to the return $\tilde{R}_{kt+1}^h$ on an individual firm k, where

$$\tilde{R}_{kt+1}^h = \frac{D_{kt+1}^f + \tilde{V}_{kt+1}^f - \tau\left[\tilde{V}_{kt+1}^f - \mathbb{E}\left(\tilde{V}_{kt+1}^f | \Pi_{kt+1}\right)\right]^+}{\tilde{V}_{kt}^f + \tau\left[\mathbb{E}\left(\tilde{V}_{kt}^f | \Pi_{kt}\right) - \tilde{V}_{kt}^f\right]^+}. \tag{19}$$

This expression reflects payment at time t for equity in firm k at a price of:

$$\tilde{V}_{kt}^f + \tau\left[\mathbb{E}\left(\tilde{V}_{kt}^f | \Pi_{kt}\right) - \tilde{V}_{kt}^f\right]^+ \geq \tilde{V}_{kt}^f, \tag{20}$$

which is higher than the fundamental value, $\tilde{V}_{kt}^f$, when the household's valuation is more optimistic than the intermediary's. Equation (19) also reflects the household's realized resale price at time $t+1$, which is given by:

$$\tilde{V}_{kt+1}^f - \tau\left[\tilde{V}_{kt+1}^f - \mathbb{E}\left(\tilde{V}_{kt+1}^f | \Pi_{kt+1}\right)\right]^+ \leq \tilde{V}_{kt+1}^f. \tag{21}$$

This resale price is less than fundamental value when the household's valuations are less

[4] As usual, the constant returns to scale final goods technology yields zero profits in equilibrium, so we omit payouts from this sector to the household in their budget constraint without loss of generality.

optimistic than the intermediary's. The exogenous parameter $\tau \in [0, 1]$ is the fraction of the intermediary's superior information that it is able to claim, with τ reflecting unmodeled details of bargaining between the intermediary and household. Because the intermediary is extracting information rents based on τ, the inequalities (20) and (21) imply that the return for firm k realized by the household, $\tilde{R}^h_{kt+1}$, is less than or equal to the fundamental return, $R^f_{kt+1} = (D^f_{kt+1} + \tilde{V}^f_{kt+1})/\tilde{V}^f_{kt}$, that is:

$$\tilde{R}^h_{kt+1} \leq R^f_{kt+1}. \tag{22}$$

Aggregating the return inequality (22) across all firms in the economy $k \in [0, 1]$, we see that the total return on equity holdings, E_t, for the household, $\tilde{R}^h_{t+1}$, is less than or equal to the average fundamental return R^f_{t+1} required by intermediaries from firms, given by:

$$\tilde{R}^h_{t+1} = \int \tilde{R}^h_{kt+1} dk \leq \int R^f_{kt+1} dk = R^f_{t+1}. \tag{23}$$

Next, to guarantee household participation in equilibrium, the intermediary must offer the household a return, $\tilde{R}^h_{t+1}$, on equity investments equal to the return, R^h_{t+1}, on risk-free bonds. Note that the required fundamental return or cost of capital, R^f_{t+1}, for firms is in general higher than the return received by households, an accounting information premium that rises when earnings become less informative for fundamental firm valuation or when the fraction of information rents captured by intermediaries, τ, rises. Put differently, when earnings are less informative, the household's return is lower, so, in equilibrium, a higher underlying firm return or cost of capital, R^f_{t+1}, is needed to induce the household to invest. Note that only in the special case of $\tau = 0$ does the quality of the informativeness of earnings for firm value become irrelevant, in which case the firm's cost of capital equals the risk-free rate.

2.6 Stationary general equilibrium on a balanced growth path

In Internet Appendix A, we provide a full definition and characterization of general equilibrium with a stationary cross-sectional distribution of intermediary goods firms at the micro level and balanced growth at the aggregate level. The distribution involves a set of prices, returns, quantities, value functions, and policies such that i) the competitive final goods firm optimally demands land and intermediate goods output, ii) managers of intermediate goods firms choose investment and misreporting to solve their dynamic optimization problem, iii) the household optimally chooses savings in the risk-free bond and the equity intermediary, iv) the goods market clears, or equivalently, a resource constraint linking aggregate output to total consumption, investment, and intermediate goods production is satisfied, v) the bond market clears with the risk-free bond in zero net supply, vi) the land market clears with a total fixed supply of 1, vii) the growth rate of all aggregate real quantities is constant at the growth rate $1 + g$ of the mass of varieties each period, viii) all returns are constant across periods, ix) the target average earnings level for manager compensation is equal to average realized earnings across firms, and ix) the cross-sectional distribution of intermediate goods firms is constant and replicates itself from period to period. We briefly note a few key insights and useful results from the characterization of our balanced growth path equilibrium.

First, given that the mass of varieties, Q_t, grows at the constant rate $1 + g$, we can exploit the fact that the manager value function is homogeneous of degree one in the nonstationary state variable Q_t to write it in a simplified stationary rescaled form. In particular, dropping firm k and time t subscripts, and using $_{-1}$ and $'$ to refer to lagged and future values respectively, the manager value function can be written

$$V^m(z, \nu, B_{-1}, M, Q) = Qv^m(z, \nu, b_{-1}, m). \tag{24}$$

We use lowercase variables to refer to their uppercase counterparts scaled by the aggregate mass of varieties Q. The manager value function, v^m, satisfies a rescaled Bellman equation that is linked to (15) but that can be solved numerically using standard dynamic programming techniques given its stationary nature. Similarly, the fundamental value function, V^f, can be rewritten in stationary rescaled form, v^f, and computed numerically.

Second, given this rescaling, the net growth rate $g = (Q' - Q)/Q$ of the economy can be written as a function of individual firm innovation decisions through

$$g = \int m'(z,\nu,b_{-1},m)dF(z,\nu,b_{-1},m) = \int \bar{\xi}w(z,\nu,b_{-1},m)^{\gamma}dF(z,\nu,b_{-1},m), \qquad (25)$$

where $F(z,\nu,b_{-1},m)$ is the equilibrium stationary distribution of normalized firm states, and $m' = \bar{\xi}w^{\gamma}$ is an individual firm's chosen mass of newly innovated varieties for production in the next period, normalized by Q according to (9). Because the elasticity, γ, of innovation, m', to intangible investment, w, lies between 0 and 1, Jensen's inequality applied to equation (25) reveals that aggregate growth can decline if individual firm investment decisions, w, are distorted or noisier because of short-term earnings manipulation. In other words, real manipulation of earnings through channels such as investment cuts can cause misallocation and changes in aggregate growth in this economy.

Third, the household optimality conditions for savings in the risk-free bond and the equity intermediary imply that in the stationary balanced growth path with constant growth of consumption at rate $1+g$, these two securities have an identical return:

$$\tilde{R}^h = R^h = \frac{1}{\beta}(1+g)^{\eta}. \qquad (26)$$

The household's risk-free return, R^h, of course, is less than an intermediate goods firm's cost of capital R^f because of the endogenous information premium linked to the quality or informativeness of earnings as outlined above.

2.7 Solution

Given a parameterization of the model, we numerically solve the model with an outer loop/inner loop approach. We repeatedly guess values triplets of innovation productivity, $\bar{\xi}$, information rents, τ, and target earnings, $\bar{\pi}$. Given these guesses, we solve the manager's dynamic problem numerically and check three crucial fixed points linked to i) whether realized growth implied by (25), given innovation productivity $\bar{\xi}$ and manager policies, equals aggregate per-capita GDP growth, $\hat{g}$, which is targeted from empirical data, ii) whether realized household equity returns given τ and average firm returns targeted from empirical data $\hat{R}^f$ are equal to the household's equilibrium required return from (26), and iii) whether realized average earnings are equal to the managers' target level $\bar{\pi}$ according to (14). We update our guesses if the conditions are not met, iterating to convergence. Internet Appendix A provides more details on the implementation of our numerical solution techniques.

2.8 Revenue recognition

The model contains one more parameter that does not affect the managerial optimization problem but that does affect the simulation of data from the model and thus matters for matching simulated and data moments. This parameter reflects accrual accounting, which is an important feature of earnings measurement that is designed to provide a better indication of a company's performance or economic earnings than operating cash flows (FASB 1978).[5]

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 within a period. Moreover, because accruals are managers' forecasts of future cash flows, accruals must be reconciled with realized cash flows in the future (e.g., Allen, Larson, and Sloan 2013; Nikolaev 2016). As such, operating cash flows can be viewed as a reshuffling of accounting earnings across adjacent periods. To reflect this reshuffling, we allow for a random portion of accounting earnings to be realized as cash flows in the periods immediately before or 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 in simulated data from a panel of firms, we define a parameter $\hat{p}_s \in (0, 1)$, which is the probability of intertemporal cash flow reshuffling. Next, we draw a

[5]Statement of Financial Accounting Concepts No. 1 states, "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."

set of uniform shocks, $\zeta^s_{kt}, \quad \forall k, t$. We then initialize observed cash flows at time 1, which we denote $\tilde{d}_{k,1}$, equal to the actual cash flow simulated directly from the model, that is, $\tilde{d}_{k,1} \equiv d_{k,1}$. Finally, iteratively progressing from $t = 2, ..., T-1$ for each firm k and a total number of periods T, we update the observed cash-flow series by the following rules:

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

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_{kt}, keeping the sum of cash flows over any medium-term horizon unchanged, where the horizon is three years.

2.9 Optimal policies

Each period, managers choose investment and the amount of bias in their earnings reports. Figure 2 plots these choices as a function of the persistent fundamental shock, z (left column) and the transitory profit shock ν (right column). We compute these policies at our set of baseline estimated parameters described below. The top row plots mean investment, w, as a function of each shock, and the bottom row plots mean bias, b.

In the top left panel, we see an intuitive positive response of investment to the fundamental shock z. As z rises, so does the average marginal product of investment, because the persistence in z implies higher demand from the final goods sector both now and in the future. Such a pattern and mechanism would also be present in a fully value-maximizing model.

However, the estimated model embodies managerial manipulation incentives via the contract parameters in equation (13), so the top right panel shows that managers also adjust investment, w, in response to the transitory profit shock, ν. This profit shock contains no information about the payoff to investment, so a value maximizing manager would ignore it. However, our estimated smoothing incentives in the parameter $\theta_q > 0$ imply that managers choose low investment when this shock is high and high investment when this shock is low. In addition, given the estimated value of $\theta_f > 0$, for intermediate levels of the profit shock, the manager can cut intangible investment to boost earnings above the nearby average target level, $\bar{\pi}$.

The manager's choice of bias, b, also responds to the fundamental and profit shocks. Because bias does not affect the fundamentals of innovation or production, the desire to manipulate earnings drives all of the observed bias choices of the manager. As seen in the bottom left panel, in response to high z shocks, the manager smooths earnings by choosing negative bias levels, and positive bias in response to low shocks. Earnings smoothing incentives also drive the overall negative slope of the manager's chosen bias with respect to the transitory profit shock, ν, in the bottom right panel. However, for intermediate values of ν, firms boost bias to high levels to meet their nearby earnings threshold levels, $\bar{\pi}$.

The main message from Figure 2 is that managers use both investment and bias to manipulate profits, allowing for substitution between the two. Moreover, the responsiveness of investment to non-fundamental transitory profit shocks implies substantial scope for misallocation and lost firm value to affect both individual firm and economy-wide outcomes.

3. Data

3.1 Sources

The data come from two sources. Compustat provides financial data, and Audit Analytics provides the data on restatements, where we use restatements that correct accounting errors as a measure of detected misstatements. Data availability from the intersection of these sources restricts our sample to the years from 1999 to 2015. The sample 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 consider two subsamples of firms, which correspond to two definitions of intangible investment. The first definition is SG&A, which is a broad measure that includes expenditure on strict R&D, as well as on organizational capital (Eisfeldt and Papanikolaou 2013). The second definition is strict R&D. Given these definitions, 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 definitions of all of our variables.

Next, we describe our use of the Audit Analytics data, where the main issue is the definition of intentional manipulation. Although in our model, manipulation is chosen intentionally and optimally by the manager, in the data, not all observed restatements correct intentional manipulation (Hennes, Leone, and Miller 2008; Karpoff, Koester, Lee, and Martin 2017). 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 definition includes restatements of revenue recognition errors, where we identify revenue recognition restatements with the Audit Analytics data.[6] We focus on revenue recognition restatements because they elicit the largest negative market reaction relative to other types of errors, such as expense recognition errors (e.g., Palmrose, Richardson, and Scholz 2004; Scholz 2008). Moreover, the closely related model of intentional manipulation in Zakolyukina (2018) has more power to explain revenue recognition errors.

The second definition includes three separate groups of restatements, each of which is classified as an irregularity under a separate criterion. We create the first group following the

[6] Because we want to isolate errors, as opposed to revisions, our sample excludes retrospective revisions related to the application of SEC Staff Accounting Bulletin (SAB) No. 101. Thus, our sample includes only errors in SAB 101 implementation.

classification scheme in Hennes, Leone, and Miller (2008), searching all of Audit Analytics' restatement disclosure textual narratives for three patterns. The first is the presence of derivative forms of the words "fraud" or "irregularity." The second is SEC or Department of Justice formal or informal investigations. The third is the 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 can be classified as an irregularity.

The second group 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 resulting from internal investigations or suspected wrongdoing, auditor changes related to SEC inquiry or management unreliability, or overlap between the restated period and 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 group is restatements involving Rule 10b-5 allegations of fraud, in both cases brought by the SEC and security class action lawsuits. A Rule 10b-5 allegation requires scienter (Choi and Pritchard 2016) and thus is a category of misstatements with allegations of intentional fraud. For class action lawsuits, we require that the case not be dismissed or terminated. For the SEC cases, we also require a related AAER period to overlap with the periods restated. For 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 lease restatements and option backdating restatements from the irregularity group, as both are less likely to be intentional.[7]

For our main specification, we combine revenue recognition and irregularity restatements, later examining the irregularity restatements separately. In all cases, we require misstatements

[7]In Audit Analytics, lease restatements correspond to 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).

to have a nonzero net-income effect over the restated period. This requirement is important because we calculate the bias in book value in the data as 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 one change in disclosure regulation—the Sarbanes-Oxley Act (SOX). SOX contains three sections that significantly changed financial disclosures (Coates and Srinivasan 2014). First, 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. Second, Section 404[a] requires management certification of internal controls over financial reporting. Third, Section 404[b] requires auditors to attest to the management's assessment of internal controls.

This legislation changed the expected cost of manipulation, in terms of both penalty and detection probability. The incidence of restatements increased dramatically right after the passage of SOX and peaked after the SOX Section 404 implementation of internal control disclosures in 2004 (Whalen, Usvyatsky, and Tanona 2016). These changes are inconsistent with the time-invariant misreporting costs in equation (12). Accordingly, we consider two regimes: the pre-SOX period ending in August 2002 and the post-SOX period, and we treat these two sub-periods differently in our estimation below.

3.3 Summary statistics

Table 2 (Panel A) provides descriptive statistics for restatements and firm characteristics for the SG&A sample. For the combined sample of restatements, the mean (median) bias in book value is \$57 (\$6.4) million or 6.7% (1.1%) of sales. The corresponding bias in earnings is \$15.2 (\$1.4) million or, highly skewed, 172.6% (0.2%) of sales. For the irregularity restatements, the mean (median) bias in book value is \$76.3 (\$10.6) million or 7.9% (1.5%) of sales. The corresponding bias in earnings is \$20.2 (\$1.9) million or, highly skewed, 240.4% (0.3%) of sales.

Table 2 also provides descriptive statistics for the variables used in our estimations, as well as other firm characteristics. Mean one-year growth in cash flows is 5.7%, mean one-year growth in earnings is 4.4%, mean one-year growth in SG&A is 5.7%, mean one-year growth in R&D is 3.3%, and mean three-year growth in sales is 19.3%. Finally, the firms in our sample are identical in size to a generic Compustat sample. Mean firm assets are $2.82 billion in our sample, while the mean of assets of all firms in Compustat over the same period is $2.52 billion. Panel B provides the same statistics for the R&D sample, showing similar patterns in this sample.

4. Estimation

We structurally estimate most of the parameters of our model via a simulated minimum distance estimator discussed below. Before estimating the model, without loss of generality, we normalize the marginal cost of producing the intermediate goods, ψ, to deliver average monopoly profits equal to one. We also set the value of the constant relative risk aversion parameter, η, to 1.5, in line with Hall (2009), and we set the household's annual time preference rate, β, to 1/1.02, in line with Terry (2017). We also estimate one parameter separately: the rate of earnings conversion to cash flows, $\hat{p}_s$. To estimate this parameter, we follow the accounting literature by regressing 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:

$$\pi_t = \alpha + \beta_{t-1} d_{t-1} + \beta_t d_t + \beta_{t+1} d_{t+1} + \upsilon_t, \tag{27}$$

which is similar to the specification in Dechow and Dichev (2002). Because cash collection and disbursement policies can be firm- and year-specific, we include firm and year fixed effects in (27). For the post-SOX SG&A sample, $\hat{p}_s$ is 18%, that is, 18% of earnings are collected in cash in the preceding or following years.

Given the quantitative centrality in our model of the growth rate, g, and a firm's cost of capital, R^f, we exactly match the values of these two objects in the model to their data counterparts. Average per capita U.S. real GDP growth in recent decades has been $\hat{g} \approx 2\%$ (Terry 2017). Also, for each subsample in our data, we compute the average stock return to extract $\hat{R}^f$, which, for example, equals 8.2% in our baseline post-SOX SG&A sample.[8] We adjust the values of two model parameters to match these two data targets exactly, regardless of the values of the other model parameters. We choose the productivity of investment, $\bar{\xi}$, in the innovation function (9) and the magnitude of information rents, τ, extracted by the intermediary in (19) to deliver within our numerical solution realized aggregate growth and a firm cost of capital exactly equal observed values, that is, $g = \hat{g}$ and $R^f = \hat{R}^f$. This procedure, described in more detail in Internet Appendix A, ensures that our estimated model always delivers empirically relevant growth and mean returns.

We estimate the remaining parameters, $(\rho, \sigma_z, \sigma_\nu, \kappa_q, \kappa_f, \gamma, \lambda, \theta_q, \theta_f, \alpha)$, using a simulated minimum distance estimator. The mechanics of the estimation are straightforward and by now familiar (Bazdresch, Kahn, and Whited 2018). Given a set of parameters, we solve the model and use the solution to generate a simulated panel of firms with a comparable number of time periods, but with many firms relative to our empirical sample (Michaelides and Ng 2000). Next, we calculate a set of statistics, which are either moments or functions of moments. We then choose parameter estimates to minimize the distance between the model-generated statistics and their empirical counterparts. To gauge this distance, we use the inverse covariance matrix of the empirical moments. To minimize the econometric objective function, we use a global stochastic optimization routine.

4.1 Identification

To identify these parameters, we use 21 moment conditions. Several moments do not rely on misreporting data. First, we include the mean ratio of intangible investment to sales,

[8] Although our model features no aggregate shocks and therefore no pricing kernel, we use the raw equity return instead of a risk-adjusted equity return because our real-world data are generated by agents facing high expected returns, so using a risk-adjusted return makes it difficult to match many of our moments.

$\mathbb{E}(w/y)$. The next three moments are the variances of observed cash flow growth, Δd, reported earnings growth, $\Delta\pi$, and intangible investment growth, Δw. We also include the three possible covariances between Δd, $\Delta\pi$, and Δw. Throughout, we compute grow rates as differences relative to the absolute value of an average, following Davis and Haltiwanger (1992) and Terry (2017). For any variable x, Δx is computed as:

$$\Delta x = \begin{cases} 0, x = 0 \text{ and } x_{-1} = 0, \\ 2\left(x - x_{-1}\right) \Big/ \left(|x| + |x_{-1}|\right), \text{ otherwise.} \end{cases} \tag{28}$$

These growth rates are bounded within $[-2; 2]$. This restriction is important because variables often shift from zero to nonzero values, so a standard definition would produce missing values.

The remaining 14 moments relate directly to misreporting and detection events. We include the probability of detection, $\mathbb{E}(I_D)$, in which the dummy variable, I_D, indicates the actual discovery of manipulation in a period. We also target the mean absolute ratio of manipulation to sales, conditional on detection, $\mathbb{E}\left(|b/y| \mid I_D\right)$, as well as the variance and skewness of the same manipulation ratio conditional on detection.

To allow for the possibility that misreporting firms behave differently from non-misreporting firms, we also duplicate the covariance matrix of cash flow growth, earnings growth, and intangible investment growth, except that we condition upon detection. Finally, recall that the change in bias, $b - b_{-1}$, directly shifts today's earnings. As such, this change is observable in detection events, so we also include in our list of moments are the covariance of the growth rate of today's earnings bias level, $\Delta(b - b_{-1})$, with earnings, cash flows, and investment growth, all conditional upon detection. For completeness, we also include the variance of $\Delta(b - b_{-1})$.

While each of these moments is related to nearly all model parameters, some moments have strong monotonic relationships with 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. The most relevant of these exercises are in Figure 3.

We start with the technological parameters. First, α governs the elasticity of demand and hence the size of markups in the intermediate goods sector. Because lower α implies higher markups, which then make sales of newly innovated goods more profitable, the mean ratio of investment to sales, $\mathbb{E}(w/y)$, declines strongly in α (Panel A of Figure 3). Second, γ governs the returns to intangible investment in the innovation equation (9). Intuitively, when this parameter is higher, investment, w, moves more strongly with the z shock, so cash flows, $d \approx z - w$, mechanically become more negatively correlated with w (Panel B). Naturally, if investment is more responsive, it also has a higher variance, so γ also affects this moment. Third, the fundamental shock persistence, ρ, induces a rise in the variance of investment, $\text{cov}(\Delta w, \Delta w)$ (Panel C). Because higher fundamental persistence makes today's fundamental shock more informative for tomorrow, investment responds more strongly to this shock, and its volatility rises. Finally, unlike the persistence parameter, ρ, the volatility of the fundamental shock, σ_z, is a neutral volatility shifter that primarily affects observable growth rate variances, in particular, the volatility of cash-flow growth, Δd (Panel D). Although σ_z mechanically affects covariances, these effects are small relative to the effects on volatilities.

Next, we consider the identification of parameters governing managerial incentives. First, as the incentive to beat the threshold, θ_f, increases, so does the incentive to cut investment to manipulate and push up profits. Thus, the covariance of profits and investment growth, conditional on detection, is driven down (Panel E). Second, as θ_q rises, the profit-smoothing motive intensifies, profits are manipulated more, and they become less correlated with cash flows, so the covariance between profits and cash flows declines (Panel F).

Next, we consider the identification of parameters governing the misreporting environment. First, the identification of the volatility of the non-fundamental earnings shock, σ_ν, is straightforward, as it produces a strong, positive effect on the variance of observable profits, both unconditionally (Panel G) and conditional upon detection. While the volatility of non-fundamental shocks also maps into the volatility of investment, if there is a motive for real manipulation, this mapping is weaker when punishment of accruals-based manipulation, embodied in κ_f and κ_q, is present.

Three moments identify the next three parameters that shape misreporting: the incidence of detection, and the mean and variance of the absolute bias. First, the probability of detection, λ, governs the likelihood of misreporting discovery and thus mechanically raises the observed likelihood of detection (Panel H). In addition, because firms internalize the likelihood of discovery in their manipulation choices, the amount and variance of manipulation also fall.

Next, we consider the punishment parameters. An increase in κ_q induces a fall in the variance of the ratio of bias to sales, conditional on detection (Panel I). Although κ_q also affects mean bias, the effect on the variance is more pronounced. Because the parameter, κ_f, quantifies the fixed costs of manipulation, conditional on detection of manipulation, κ_f determines the cost of accruals manipulation at the extensive margin and naturally affects the probability of detection. A stronger effect arises because this fixed cost implies increasing returns to manipulation, as manipulation does not occur unless it is highly worth it. Thus, a high fixed cost implies a higher average bias, $\mathbb{E}\left(|b/y| \mid I_D\right)$ (Panel J).

4.2 Estimation results

The results from our baseline estimation using the SG&A sample are in Table 3. For this estimation, we use data only from the post-SOX years so that we do not confront a model that contains one policy regime with data generated by two different policy regimes. 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 five moment pairs are significantly different from each other, few are economically different. This result stems from the high degree of overidentification in our model: 21 moments and 10 parameters. Nonetheless, the model does a good job of matching the volatilities of earnings, cash flows, investment, and bias growth, together with the broad magnitudes and most of the signs of covariances in the model. The moments that exhibit the greatest differences in the model versus the data are related to the magnitude of absolute bias in the model conditional upon detection. For these moments, the estimation faces a tension between matching the extreme skewness and variance of absolute bias during detected events, on the one hand, with the moderate average absolute bias levels seen in the data. Therefore, the estimation results in parameters that split the difference. Nonetheless, the fit of the highly overidentified model is remarkably good.

Next, we turn to the parameter estimates, which are in Panel B. These parameters divide naturally into two groups, one reflecting firm fundamentals and the other reflecting income reporting or manager incentives. In the first group of parameter estimates, the implied fundamentals for firms are in line with many of the extant estimates in the literature. The estimate $\hat{\alpha} \approx 0.5$ implies an elasticity of demand for newly innovated intermediate goods firms of around -2. The persistence of the fundamental shock, $\hat{\rho} \approx 0.16$, lies far below the level of the estimated persistence of profitability shocks in all U.S. firms in Winberry (2016) (≈ 0.78) or in U.S. manufacturing Castro, Clementi, and Lee (2015) (≈ 0.45). This result is to be expected. Our model with growth is difference-stationary and thus endogenizes a great deal of firm persistence via the accumulation of new innovations, instead of relying on an exogenous process with high persistence, which the commonly used levels-stationary frameworks require. The total conditional volatility of shocks to firm profitability each year is $\sqrt{\hat{\sigma}_z^2 + \hat{\sigma}_\nu^2} \approx 0.55$, which is comfortingly somewhat larger 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 investment, $\hat{\gamma} \approx 0.8$, lies well below one, consistent with the evidence in Acemoglu, Akcigit, Bloom, and Kerr (2013), and the papers cited therein.

The parameters governing managerial incentives, θ_f and θ_q, can be interpreted in terms of managerial utility. For example, $\theta_f = 0.037$ implies that missing the earnings target is equivalent in manager utility to a drop of 3.7% in mean earnings in the model. The estimated value of θ_q implies light smoothing incentives. For example, reporting a value of profits three times the size of the mean earnings target, $\bar{\pi}$, creates a cost equivalent in manager utility to about $(\theta_q/2)(2\bar{\pi})^2 = 0.1\%$ of operating profits, given that $\bar{\pi} = 0.246$ in our baseline estimate.

Similarly, our estimates of κ_f and κ_q imply that total cost of being detected at the mean level of bias is $\kappa_f + \kappa_q b^2 = 0.012 + 2.406(0.019^2) = 0.013$, or 1.3% of mean profits.

We estimate the probability of detection, $\hat{\lambda}$ to be 0.013, which is lower than the estimates from a similar dynamic model in Zakolyukina (2018). This difference arises because of two features of the model in Zakolyukina (2018) that are absent from ours. First, in Zakolyukina (2018) the probability of punishment is lower than the probability of detection. Also, in Zakolyukina (2018), managers can be punished for past manipulation even when current bias is zero. Both differences imply that a lower estimated detection probability is necessary to match observed and model-implied detection. Overall, the parameters in Table 3 are all precisely estimated and appear reasonable.

Table 4 contains the results from estimating the model using the R&D sample. While the results are similar, the model fit is worse. For example, only two of the moment pairs are insignificantly different from each other, despite the smaller sample size. Moreover, the model struggles to match the volatilities of cash flows, investment, and bias growth, while still displaying the challenges of the baseline model such as difficulty simultaneously matching the mean and higher moments of absolute bias. Accordingly, we focus during the rest of our analysis on results using as a baseline the SG&A post-SOX sample, although we compute various key counterfactuals for each alternative subsample as well.

Next, in Table 5, we present a model estimation using a more stringent definition of restatements, which are the irregularity restatements described in Section 3, and which are more likely to be intentional. For ease of comparison, we also reproduce the results from Table 3. As seen in Panel A of Table 5, the fit of the models that use the two different restatement definitions is broadly similar, as are the parameter estimates in Panel B. We conclude that our baseline choice to focus on the broader definition of restatement events is robust to sharper alternative definitions.

In Table 6, we present the results from estimating the model using data from the pre-SOX period. For this estimation, we assume that all parameters that are unrelated to detection and punishment are as estimated for the post-SOX period. Our intent is to estimate deep technological and utility parameters with the larger post-SOX sample, and then assume that these parameters are the same in the pre-SOX sample. Again, for ease of comparison, we also reproduce the results from Table 3. For the pre-SOX estimation, we see that t-statistics on the moment conditions in Panel A, and the precision of our estimated parameters in Panel B are smaller, with the reason being the much smaller sample size. More important are the differences across the two subperiods in observable moments related to misreporting. We see a higher incidence of detection post-SOX, larger and more variable absolute bias, and more volatile bias growth, although these differences are quantitatively small.

To reconcile these results with the model, we note that a simpler model featuring only fixed costs of manipulation, κ_f, would face a tension between generating the higher frequency of misreporting post-SOX, which are linked to low fixed costs, and the simultaneous increase the magnitude of misreporting, which are linked to high fixed costs that generate more stringent selection. However, our model features additional flexibility because the detection probability λ can also shift and break the otherwise tight negative link between misreporting detection and magnitudes. Thus, while we estimate slightly larger consequences of misreporting post-SOX, with κ_f rising a bit and generating somewhat more serious misreporting magnitudes, we also estimate a lower ex-ante detection probability λ which softens the consequences of misreporting and results in a slight increase in the frequency of detection. In other words, although none of the changes we detect are quantitatively large across the pre- and post-SOX periods, our estimates are consistent with the view that SOX mostly increased the consequences of misreporting without meaningfully increasing the likelihood of detection.

One final issue we explore is our specification of a constant probability of detection, λ, that is independent of the size of the bias, B. Although the convexity of (12) implies that the expected cost of misreporting is increasing in bias, the probability of detection is not, so we approach this issue in two ways. First, as described in Internet Appendix B, we estimate logistic regressions for the probability of detection for both the pre-SOX and post-SOX periods, as well as for both the less and more serious restatements. Table IA.1 in Internet Appendix B shows insignificant coefficients of both signs on the magnitude of manipulation in either period or for either type of restatement.

Nonetheless, because of the small sample used for these regressions, we use our baseline sample (the less serious restatements for the pre-SOX period) to reestimate a version of the model in which the probability of detection is a logistic function of bias. We set the value of the slope coefficient in this function to 0.595, which is from Table IA.1. We then estimate the intercept, λ_0, as part of the simulated minimum distance estimation. For this estimation, we set all parameters except κ_q, κ_f, λ, and λ_0 to their values in Table 3. These results are reported in Table IA.2 in Internet Appendix B. Briefly, the average implied detection probabilities are similar in our baseline estimation and this expended estimation. The point estimate for the detection probability in our baseline pre-SOX estimation is 0.016, while in the estimation of this augmented model, for $\lambda_0 = -4.698$, $\lambda_1 = 0.595$, and $|b/y| = 0.172$, the average detection probability is $1/(1 + \exp(-\lambda_0 - \lambda_1 |b/y|)) = 0.010$.

4.3 The dynamics of restatement and intangible investment

As a final external validity check on the model, we see whether our model can reproduce the real-data patterns in Figure 1, which shows statistically significant cuts in investment and increases in bias around restatement events. To answer this question, we run in simulated data the same panel regressions used to generate Figure 1, which are given by:

$$X_{jt} = \sum_{k=-2}^{2} \beta_k \mathbb{I}(\text{Upward Bias Restated})_{jt+k} + \varepsilon_{jt}.$$

To match our empirical approach in the construction of Figure 1, X_{jt} is either the investment to sales ratio in the model (left panel) or the bias to sales ratio (right panel). In Figure 4, we plot the coefficients, β_k, that trace out the within-firm idiosyncratic variation in intangible investment at horizons k periods away from the restatement event. The solid line on the left-hand side plots the resulting dynamics of investment, and we see a quick drop of around

2.5% 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 a bit more than 22% on average. Intuitively, the model provides incentives for managers to shift reported profits upwards to beat earnings thresholds or smooth earnings. While managers can achieve this goal with either biased reporting or real investment cuts, each tool is costly on the margin. Therefore, managers use both levers to manipulate their earnings upward in during restatement periods.

We do not target the coefficients plotted in Figure 1, yet the model counterparts in Figure 4 display the same general patterns, although they are a bit sharper and more transitory than the patterns in Figure 1. In addition, the real-data patterns in Figure 1 are muted relative to the simulated-data patterns in Figure 4, as the model data are generated by the endogenous responses to only two shocks, while the real-world data reflect many more sources of uncertainty. Nonetheless, the qualitative message in both cases is identical: managers cut investment in periods in which they have upwardly misreported profits.

5. Counterfactuals

With our estimated model in hand, we explore the general equilibrium implications, at both the firm and aggregate levels, of changes in the consequences for financial misreporting. From a policy perspective, these consequences might arise from the litigation or regulatory environment surrounding listed firm financial disclosure.

In our first counterfactual experiment, we begin from our baseline post-SOX, SG&A sample estimates in Table 3 and vary the parameter κ_q, which governs the scale of misreporting punishment, from just above zero to a very high level. Figure 5 plots the probability of misreporting detection for each of these cases, with the baseline level $\widehat{\kappa_q}$ indicated with the circle. Intuitively, higher costs of misreporting cause firms to misreport less, eventually leading to zero misreporting in the model.

Figure 6 plots changes in several other outcomes over the same range of experiments. In Panel A, we see that increasing the cost of misreporting initially leads to a decline in the firm cost of capital, R^f, because less earnings bias leads to lower information rents earned by the financial intermediary, that is, more efficient financial markets. This salutary initial decline in the cost of capital spurs more investment and boosts growth (Panel B), firm value (Panel C), and aggregate welfare (Panel D). However, manager incentives for earnings manipulation remain even as the costs of misreporting or bias increase, so firms eventually substitute strongly towards real earnings manipulation through investment as κ_q rises. This increase in real earnings manipulation, even when paired with less bias in earnings, leads to a net decline in the informativeness of earnings. Intuitively, even though reported earnings are more accurate, they are generated through a process that often features investment cuts to boost profits and thus delinks today's earnings from long-run firm value. The result is an eventual sharp reversal and increase in the firm's cost of capital R^f. Unsurprisingly, a higher cost of capital eventually leads to lower firm value, growth rates, and welfare.

Next, we describe the socially optimal or welfare-maximizing level of misreporting costs. The bottom right panel reveals that a value of $\kappa_q \approx 6.3$, around $6.3/2.4 \approx 2.6$ times as high as the estimated level of costs $\hat{\kappa_q}$ in our model, would be optimal.

However, the interests of firms and society diverge because of subtle interactions between real investment manipulation and innovation externalities. Endogenous growth models such as ours feature suboptimally low firm innovation from a social perspective because investment creates positive externalities through higher variety levels, Q_t, in the innovation function (9). In our model, as κ_q increases and firms lose flexibility to manipulate earnings, they choose higher average investment to broaden the base of new varieties. More varieties boost operating profits and provide a higher base from which to manipulate reported profits. Innovation externalities then imply that this higher investment is more valuable for welfare than firm value. Thus, over an intermediate range of misreporting costs, tighter regulation can cause firms to suffer a loss in value even though social welfare still rises because of higher average investment and growth. The result is a lower level of privately optimal misreporting costs for firms, ($\kappa_q \approx 5.5$, maximizing firm value in the bottom left) than for society. This disconnect suggests potential difficulties in optimally tightening disclosure regulation beyond a point after which tightening becomes costly for firms.

In addition to the intermediate range of experiments considered in Figures 5 and 6, in Table 7, we report the results from a set of more extreme counterfactuals. In each panel, we present separate results based on each of our four sets of estimated model parameters. For each set, we consider three versions of the model: a model as estimated, a model with no reporting bias ($\kappa_f = \kappa_q = \infty$), and, for comparison, a value-maximizing model ($\theta_f = \theta_q = 0$).

The results are in line with the message in Figures 5 and 6. As seen in column (2), relative to the baseline estimated models, in models with no bias, we see no improvement in the informativeness of earnings, as firms substitute toward real manipulation. Although the cost of capital, R_f, rises, and firm value mechanically falls, welfare gains and growth largely do not. The convexity of managers contracts imply that with a great deal of real manipulation, average intangible investment levels rise. The externalities in the model imply that while welfare depends both on investment and value, the effect of investment is dominant because investment adds to the number of available varieties, thus raising productivity, growth, and consumer utility, that is, welfare. Thus, welfare moves less than value, and sometimes in the opposite direction, depending upon the exact parameterization and quantitative balance between higher investment distortions and higher average investment at this extreme.

In column (3), we report the results of an equally extreme environment with no earnings manipulation incentives, which is a situation unlikely to occur in practice, given the likely underlying agency conflicts that lead to short-term pressure in the first place. We find that zero earnings manipulation results in more informative earnings and meaningful reductions in the cost of capital. We also observe higher firm value, although only modest shifts in welfare because of the divergence between firm value and social welfare. The one exception to this pattern is the model estimated with the sample that includes only severe restatements. Here, the estimated incentives for earnings manipulation, θ_q and θ_f, are large enough to generate a nontrivial welfare gain from removing investment manipulation, even though firm value and social welfare are maximized at different levels of investment on average. In no cases do we observe counterfactual growth shifts of more than a few basis points, a result in line with the quantitatively moderate effects of short-term incentives on growth in Terry (2017).

We conclude from these counterfactual experiments that tighter firm disclosure regulation creates offsetting effects, improving the information content of earnings only up to a point beyond which substitution towards other forms of manipulation becomes more severe and results in more extreme investment distortions. Socially optimal punishment for misreporting is stronger than we estimate in the data, and the level of punishment that maximizes firm value is lower than the socially optimal level.

6. Conclusion

We quantify the real implications of managers' incentives to distort information to the public. Many features of compensation contracts, such as performance-based equity compensation and bonus plans, give managers short-term incentives to manipulate earnings disclosures. The interaction of these incentives with disclosure regulation implies that when managers find it costly to misreport earnings, they substitute opportunistic changes in investment. 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, Harvey, and Rajgopal 2005).

Given the scale of recent reforms to firm disclosure regulations, e.g. the Sarbanes-Oxley Act in the United States, quantifying the extent of this trade-off seems crucial. Our vehicle for addressing this question is estimation of a dynamic equilibrium model that incorporates all the ingredients necessary to generate the trade-off between misreporting and investment efficiency: a compensation structure with both short-term and long-term incentives, persistent investment opportunities that enhance firm growth and social welfare, punishment for misreporting, and an equilibrium effect of earnings informativeness on the cost of capital.

Our results are interesting and potentially useful for understanding disclosure regulation.

Two countervailing forces in our model imply a socially optimal level of disclosure regulation. On the one hand, regulation lowers accounting manipulation and lowers the cost of capital. On the other hand, too much regulation implies that firms substitute real investment manipulation for accounting manipulation, earnings informativeness drops, and the cost of capital rises. We find that the socially optimal level of disclosure regulation implied by our parameter estimates exceeds the estimated value, a result that enriches the discussion regarding disclosure regulation. Counterfactual analysis shows that eliminating misreporting completely through disclosure regulation incentivizes managers to distort real investment. Lower earnings informativeness raises the cost of capital, which results in a 5.7% drop in average firm value, but more modest effects on social welfare and aggregate growth.

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, we do not microfound manager compensation contracts, and the firm faces no financial frictions. 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, manager incentives, and the efficiency of the real economy.

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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 book values were biased upwards. Each solid line in the figure plots estimated coefficients $\beta_k, k = -2, ...2$ from the panel regression $X_{jt} = \sum_{k=-2}^{2} \beta_k \mathbb{I}(\text{Upward bias restated})_{jt+k} + f_s + g_t + \varepsilon_{jt}$, For firm j at time t in sector s, the variable X is selling, general, and administrative expenditures 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 book values for firm j at the horizon k from year t is included. The plotted error bands are 95% confidence intervals based on standard errors clustered by firm.

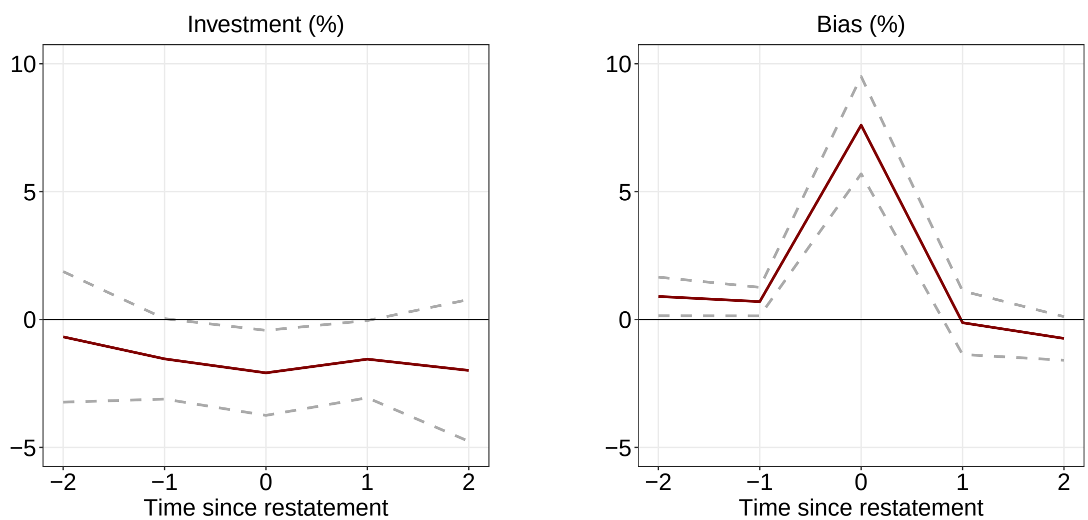

Figure 2: Investment and bias in the estimated model

Panel A plots optimal firm choices of investment, w, (top row) and bias, b (bottom row) as a function of the fundamental demand shock, z. Panel B plots the optimal choices of investment and bias as a function of the transitory profit shock, ν. Investment policies are expressed in percent deviations from the mean investment policy in the model, and bias policies are expressed as a percent of mean sales. The plotted policy functions are smoothed averages over the ergodic distribution of the model, conditioning upon the indicated values of the demand and profit shocks.

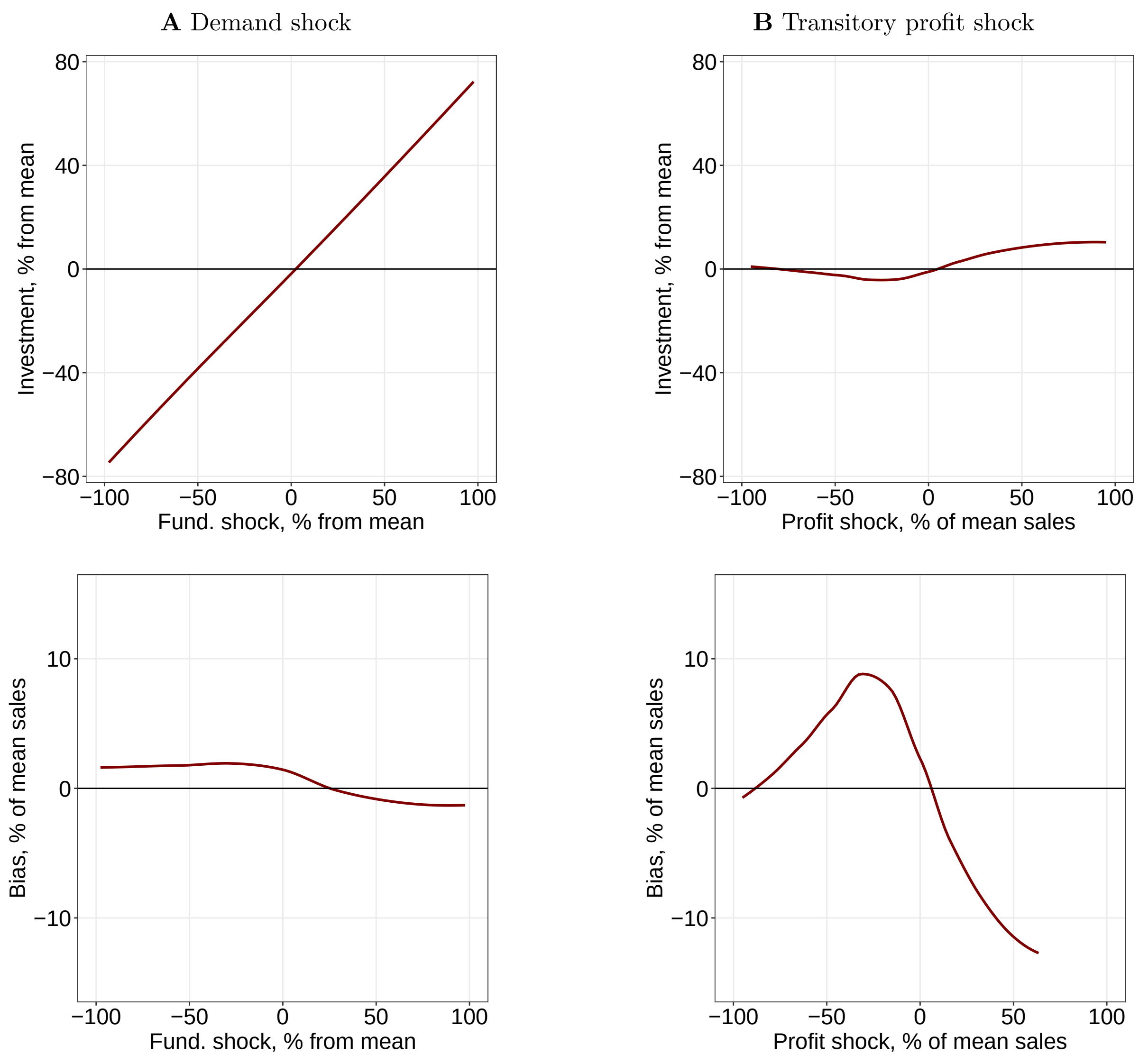

Figure 3: Comparative statics

Each panel of this figure plots the relation between a moment on the y-axis and a parameter on the x-axis.

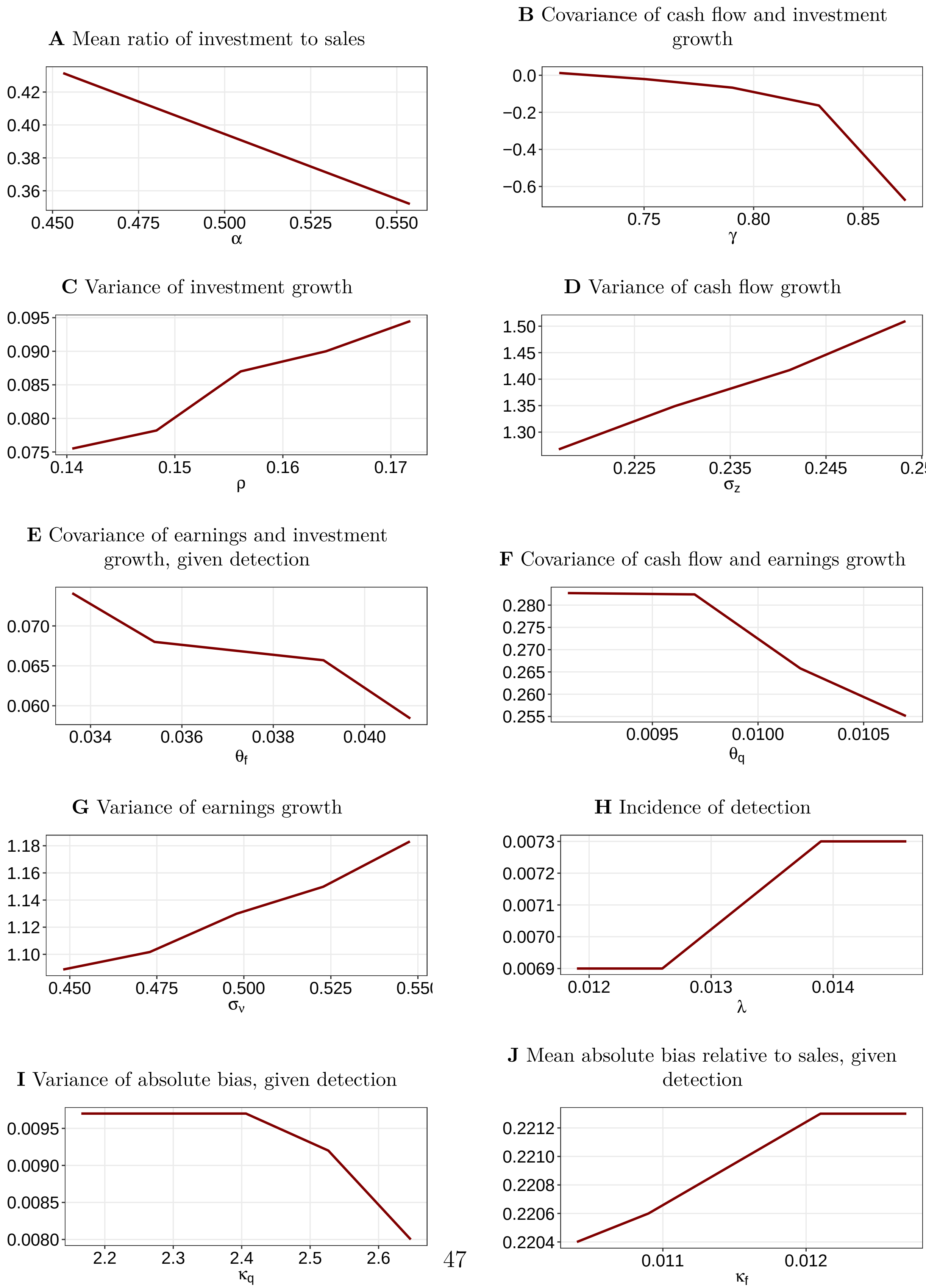

Figure 4: Dynamics around a restatement event: Simulated data

The figure plots the dynamics of intangible investment (left panel) and reporting bias (right panel) around firm restatement events in which book values were biased upwards for the simulated data. Each solid line in the figure plots estimated coefficients $\beta_k, k = -2, \ldots 2$ from the panel regression $X_{jt} = \sum_{k=-2}^{2} \beta_k \mathbb{I}(\text{Upward bias restated})_{jt+k} + f_j + g_t + \varepsilon_{jt}$. For firm j at time t, the variable X is investment, w, and reported bias in book value, b, both relative to sales. A full set of firm and time dummies together with indicators for public restatement of an upward bias in book values for firm j at the horizon k from year t is included. The plotted error bands are 95% confidence intervals based on standard errors clustered by firm.

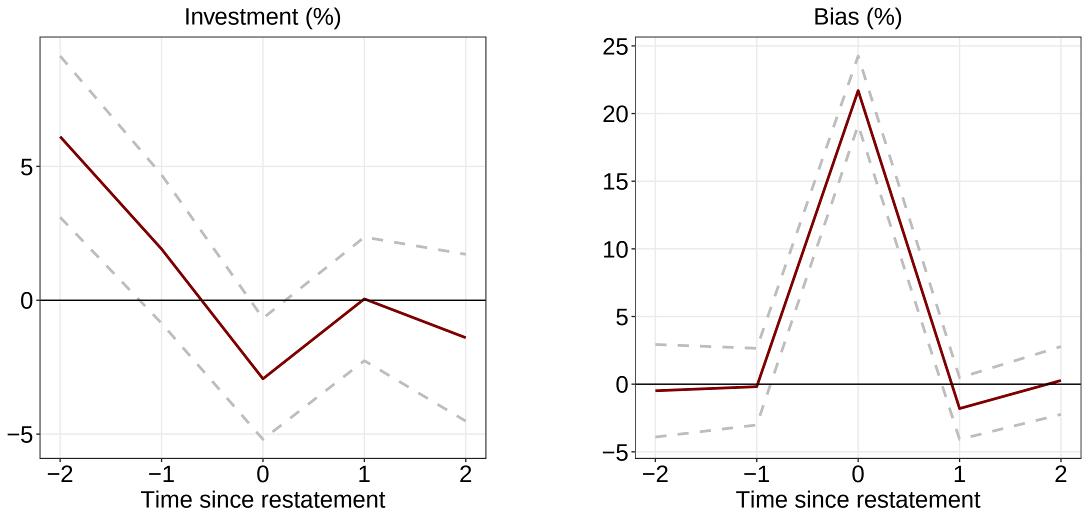

Figure 5: Counterfactual experiments: probability of detection

This figure plots the equilibrium probability of detection as a function of the quadratic manipulation cost parameter, κ_q. Each point on the curve reports the probability of detection 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 obtained by locally weighted smoothing of a discrete set of counterfactual experiments. The probability of detection in the baseline model is indicated by the grey circular dot.

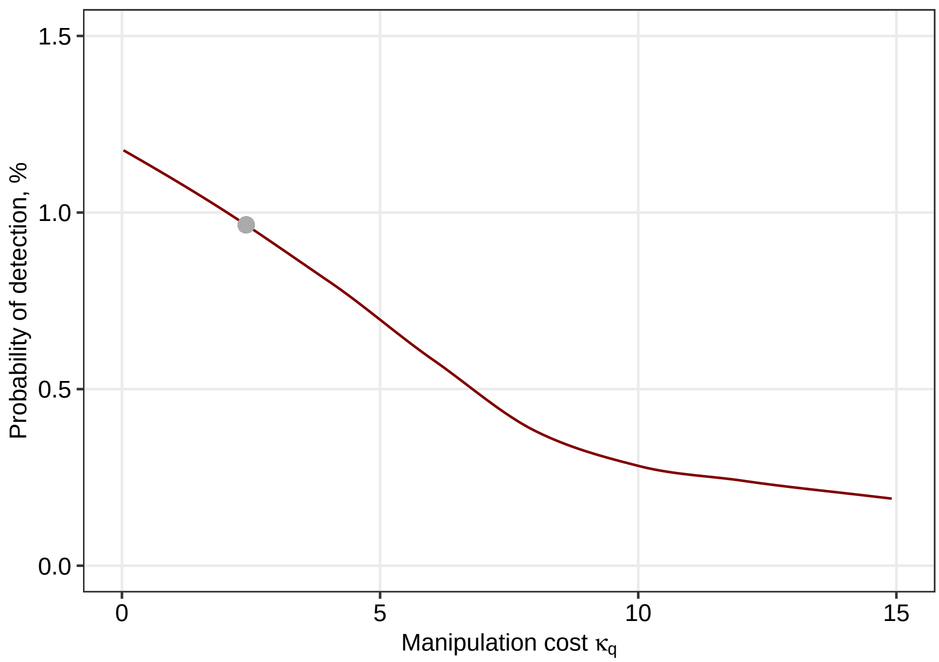

Figure 6: Counterfactual experiments

This figure plots the equilibrium outcomes as a function of the quadratic manipulation cost parameter, κ_q. Each point on the curve reports the outcome 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 obtained by locally weighted smoothing of a discrete set of counterfactual experiments. The outcome in the baseline model is indicated by the grey circular dot.

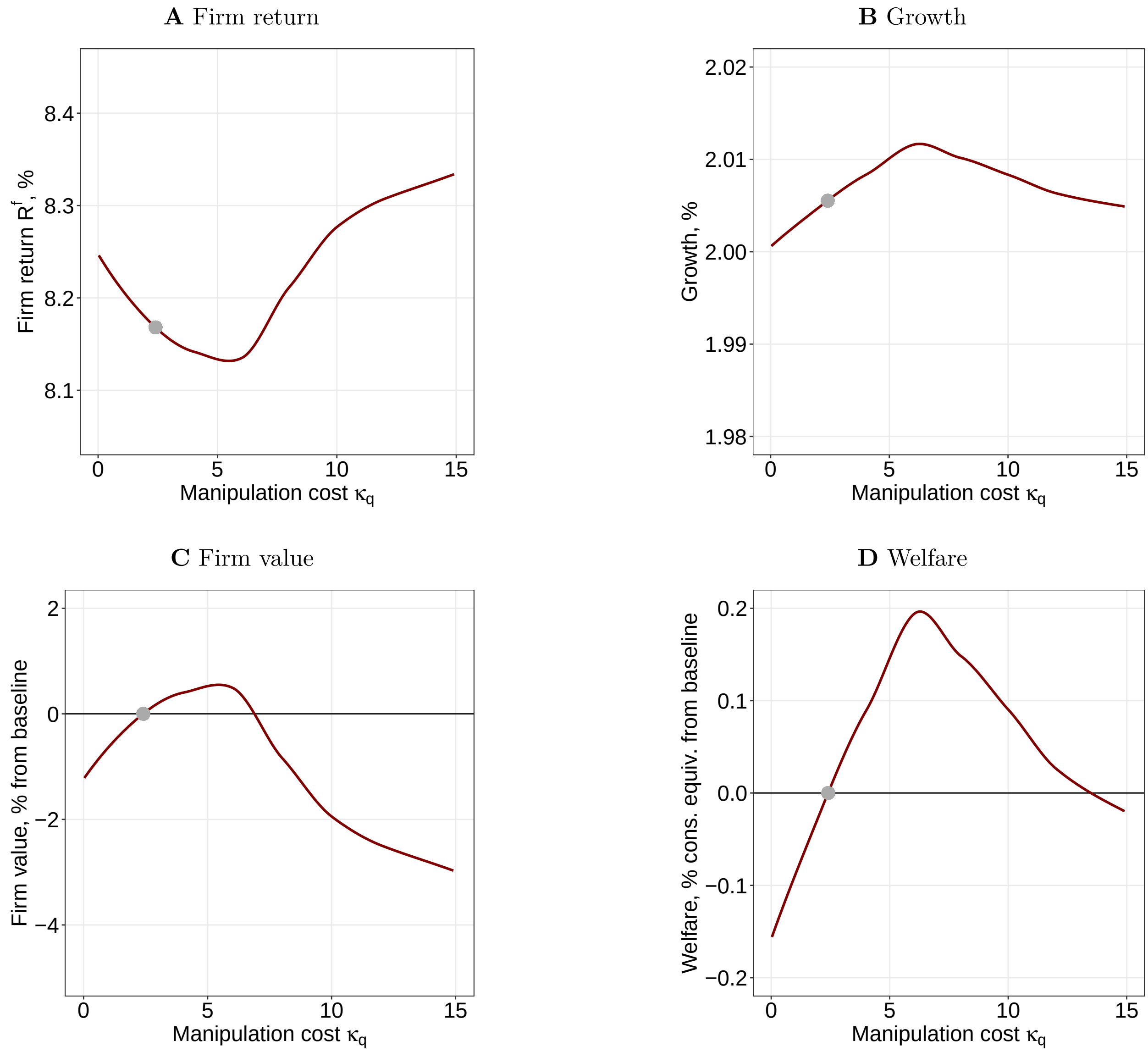

Table 1: Data definitions

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

A. Firm-specific variables	
y	Sale revenues (SALE). Compustat.
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. 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	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 Audit Analytics advanced restatements and Compustat. The sample covers the period from 1999 to 2015 at the 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. *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 (Number of firms = 646)						
Bias in book value ($mn)	2,143	57.049	262.182	0.869	6.398	30.482
Bias in book value to sales	2,143	0.067	0.237	0.002	0.011	0.055
Bias in earnings ($mn)	2,143	15.243	164.387	0.074	1.413	7.503
Bias in earnings to sales	2,143	1.726	106.558	0.000	0.002	0.014
Annual bias in earnings growth	2,143	0.293	1.525	-1.070	0.310	2.000
Irregularities (Number of firms = 433)						
Bias in book value ($mn)	1,531	76.330	307.387	1.615	10.626	41.727
Bias in book value to sales	1,531	0.079	0.266	0.003	0.015	0.073
Bias in earnings ($mn)	1,531	20.171	193.576	0.171	1.891	10.128
Bias in earnings to sales	1,531	2.404	126.075	0.000	0.003	0.016
Annual bias in earnings growth	1,531	0.273	1.510	-1.052	0.232	2.000
Firm characteristics (Number of firms = 5,918)						
Obs.	51,535	13.441	5.353	9.000	15.000	19.000
Market value ($bn)	51,012	2.567	7.391	0.041	0.262	1.339
Total assets ($bn)	51,535	2.823	10.184	0.049	0.285	1.378
Sales ($bn)	51,535	2.226	6.317	0.047	0.275	1.287
Market-to-book	51,012	2.397	4.672	1.086	1.486	2.310
Fiscal-year return	50,910	0.178	0.837	-0.282	0.023	0.370
Return on assets	51,535	-0.111	0.733	-0.059	0.028	0.073
SG&A to sales	51,535	0.395	0.649	0.122	0.243	0.418
Annual free cash flow growth	51,535	0.057	1.228	-0.699	0.071	0.863
Annual earnings growth	51,535	0.044	1.124	-0.535	0.101	0.638
Annual SG&A growth	51,535	0.057	0.333	-0.036	0.047	0.149
3-year sales growth	51,535	0.193	0.547	-0.063	0.190	0.474

Table 2: —*Continued*

B. R&D sample

	Obs.	Mean	Std.Dev	p25	p50	p75
Revenue recognition errors and irregularities (Number of firms = 397)						
Bias in book value ($mn)	1,320	61.264	249.101	0.900	7.732	35.077
Bias in book value to sales	1,320	0.096	0.303	0.003	0.020	0.097
Bias in earnings ($mn)	1,320	16.863	124.681	0.100	1.535	8.014
Bias in earnings to sales	1,320	2.797	135.781	0.000	0.004	0.023
Annual bias in earnings growth	1,320	0.290	1.535	-1.081	0.296	2.000
Irregularities (Number of firms = 280)						
Bias in book value ($mn)	1,003	77.675	283.291	1.750	12.049	44.869
Bias in book value to sales	1,003	0.109	0.333	0.003	0.030	0.129
Bias in earnings ($mn)	1,003	21.185	142.526	0.179	2.100	10.424
Bias in earnings to sales	1,003	3.665	155.776	0.000	0.005	0.027
Annual bias in earnings growth	1,003	0.250	1.515	-1.071	0.199	2.000
Firm characteristics (Number of firms = 3,542)						
Obs.	31,326	13.431	5.317	9.000	15.000	19.000
Market value ($bn)	31,145	2.706	7.980	0.037	0.220	1.210
Total assets ($bn)	31,326	2.735	10.993	0.032	0.176	0.974
Sales ($bn)	31,326	1.943	6.304	0.025	0.141	0.858
Market-to-book	31,145	2.906	5.635	1.196	1.706	2.789
Fiscal-year return	31,094	0.188	0.881	-0.307	0.014	0.378
Return on assets	31,326	-0.189	0.885	-0.143	0.018	0.071
R&D to sales	31,326	0.508	2.258	0.009	0.053	0.169
Annual free cash flow growth	31,326	0.066	1.186	-0.613	0.073	0.801
Annual earnings growth	31,326	0.052	1.121	-0.538	0.095	0.669
Annual R&D growth	31,326	0.033	0.470	-0.076	0.010	0.171
3-year sales growth	31,326	0.175	0.609	-0.100	0.185	0.488

Table 3: Baseline estimation results: SG&A sample

The estimation is done with a simulated minimum distance estimator, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data in the SG&A sample. Panel A reports the simulated and actual moments and the t-statistics for the differences between the corresponding moments. Panel B reports the estimated structural parameters with standard errors in parentheses. ρ is the serial correlation of the persistent productivity shock. σ_z is the volatility of the persistent productivity shock. σ_ν 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 manipulation. γ is the curvature of the innovation production function. λ is the probability of manipulation detection. θ_f is the manager incentive to beat average profits. θ_q is the manager incentive to smooth profits. α is the elasticity of final good output to intermediate varieties. The standard errors are double-clustered by firm and year in both panels.

A. Moments

	Data moments	Simulated moments	t-stat
Mean ratio of investment to sales	0.398	0.392	-0.66
Incidence of detection	0.013	0.007	-2.40
Mean absolute bias relative to sales, given detection	0.090	0.217	8.45
Variance of cash flow growth	1.331	1.417	3.28
Covariance of cash flow and earnings growth	0.291	0.266	-1.73
Covariance of cash flow and investment growth	-0.019	-0.067	-14.15
Variance of earnings growth	1.126	1.130	0.10
Covariance of earnings and investment growth	-0.020	0.004	6.48
Variance of investment growth	0.084	0.087	0.40
Variance of cash flow growth, given detection	1.515	1.258	-4.38
Covariance of cash flow and earnings growth, given detection	0.294	0.112	-2.73
Covariance of cash flow and investment growth, given detection	-0.019	-0.068	-3.23
Covariance of cash flow and earnings bias growth, given detection	0.062	-0.265	-3.53
Variance of earnings growth, given detection	1.244	2.203	12.34
Covariance of earnings and investment growth, given detection	-0.023	0.068	6.90
Covariance of earnings and earnings bias growth, given detection	0.152	-0.013	-3.52
Variance of investment growth, given detection	0.070	0.089	1.26
Covariance of investment growth and earnings bias growth, given detection	-0.003	0.040	2.52
Variance of earnings bias growth, given detection	2.110	2.790	6.10
Variance of absolute bias, given detection	0.059	0.010	-3.80
Skewness of absolute bias, given detection	5.583	1.679	-7.14

B. Parameter estimates

ρ	σ_z	σ_ν	κ_q	κ_f	γ	λ	θ_f	θ_q	α
0.156	0.241	0.498	2.406	0.012	0.790	0.013	0.037	0.010	0.503
(0.004)	(0.004)	(0.004)	(0.095)	(0.005)	(0.007)	(0.000)	(0.017)	(0.000)	(0.018)

Table 4: Estimation results: R&D sample

The estimation is done with a simulated minimum distance estimator, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data in the R&D sample. Panel A reports the simulated and actual moments and the t-statistics for the differences between the corresponding moments. Panel B reports the estimated structural parameters with standard errors in parentheses. ρ is the serial correlation of the persistent productivity shock. σ_z is the volatility of the persistent productivity shock. σ_ν 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 manipulation. γ is the curvature of the innovation production function. λ is the probability of manipulation detection. θ_f is the manager incentive to beat average profits. θ_q is the manager incentive to smooth profits. α is the elasticity of final good output to intermediate varieties. The standard errors are double-clustered by firm and year in both panels.

A. Moments

	Data moments	Simulated moments	t-stat
Mean ratio of investment to sales	0.539	0.455	-2.43
Incidence of detection	0.014	0.007	-2.30
Mean absolute bias relative to sales, given detection	0.127	0.274	6.06
Variance of cash flow growth	1.252	1.535	10.86
Covariance of cash flow and earnings growth	0.343	0.312	-2.21
Covariance of cash flow and investment growth	-0.042	-0.140	-21.80
Variance of earnings growth	1.121	1.012	-2.93
Covariance of earnings and investment growth	-0.055	-0.005	6.99
Variance of investment growth	0.173	0.130	-5.83
Variance of cash flow growth, given detection	1.397	1.638	3.02
Covariance of cash flow and earnings growth, given detection	0.380	0.364	-0.23
Covariance of cash flow and investment growth, given detection	-0.049	-0.140	-2.58
Covariance of cash flow and earnings bias growth, given detection	0.107	-0.351	-6.08
Variance of earnings growth, given detection	1.318	2.124	8.38
Covariance of earnings and investment growth, given detection	-0.065	-0.022	2.06
Covariance of earnings and earnings bias growth, given detection	0.168	0.227	0.66
Variance of investment growth, given detection	0.137	0.108	-2.56
Covariance of investment growth and earnings bias growth, given detection	0.005	0.066	2.14
Variance of earnings bias growth, given detection	2.114	2.883	5.17
Variance of absolute bias, given detection	0.087	0.019	-3.50
Skewness of absolute bias, given detection	4.513	2.043	-5.04

B. Parameter estimates

ρ	σ_z	σ_ν	κ_q	κ_f	γ	λ	θ_f	θ_q	α
0.183	0.252	0.416	2.904	0.026	0.785	0.013	0.051	0.011	0.426
(0.009)	(0.003)	(0.003)	(0.710)	(0.004)	(0.005)	(0.001)	(0.003)	(0.001)	(0.043)

Table 5: Less versus more serious restatements

The estimation is done with a simulated minimum distance estimator, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data in the SG&A sample for less serious, i.e., revenue recognition errors and irregularities, versus more serious, i.e., irregularities only, restatements. Less serious restatements is our baseline specification in Table 3. Panel A reports the simulated and actual moments and the t-statistics for the differences between the corresponding moments. Panel B reports the estimated structural parameters with standard errors in parentheses. ρ is the serial correlation of the persistent productivity shock. σ_z is the volatility of the persistent productivity shock. σ_ν 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 manipulation. γ is the curvature of the innovation production function. λ is the probability of manipulation detection. θ_f is the manager incentive to beat average profits. θ_q is the manager incentive to smooth profits. α is the elasticity of final good output to intermediate varieties. The standard errors are double-clustered by firm and year in both panels.

A. Moments

	Less serious restatements			More serious restatements		
	Data moments	Simulated moments	t-stat	Data moments	Simulated moments	t-stat
Mean ratio of investment to sales	0.398	0.392	-0.66	0.398	0.394	-0.37
Incidence of detection	0.013	0.007	-2.40	0.009	0.009	-0.18
Mean absolute bias relative to sales, given detection	0.090	0.217	8.45	0.105	0.238	7.22
Variance of cash flow growth	1.331	1.417	3.28	1.331	1.324	-0.26
Covariance of cash flow and earnings growth	0.291	0.266	-1.73	0.291	0.261	-2.06
Covariance of cash flow and investment growth	-0.019	-0.067	-14.15	-0.019	-0.001	5.34
Variance of earnings growth	1.126	1.130	0.10	1.126	1.082	-1.08
Covariance of earnings and investment growth	-0.020	0.004	6.48	-0.020	0.009	7.66
Variance of investment growth	0.084	0.087	0.40	0.084	0.078	-0.78
Variance of cash flow growth, given detection	1.515	1.258	-4.38	1.462	1.266	-2.73
Covariance of cash flow and earnings growth, given detection	0.294	0.112	-2.73	0.323	0.200	-1.69
Covariance of cash flow and investment growth, given detection	-0.019	-0.068	-3.23	-0.024	-0.024	0.03
Covariance of cash flow and earnings bias growth, given detection	0.062	-0.265	-3.53	0.096	-0.055	-1.61
Variance of earnings growth, given detection	1.244	2.203	12.34	1.257	2.032	7.43
Covariance of earnings and investment growth, given detection	-0.023	0.068	6.90	-0.035	0.059	5.85
Covariance of earnings and earnings bias growth, given detection	0.152	-0.013	-3.52	0.158	0.282	2.67
Variance of investment growth, given detection	0.070	0.089	1.26	0.060	0.078	1.08
Covariance of investment growth and earnings bias growth, given detection	-0.003	0.040	2.52	-0.017	0.009	0.92
Variance of earnings bias growth, given detection	2.110	2.790	6.10	2.139	2.348	1.40
Variance of absolute bias, given detection	0.059	0.010	-3.80	0.065	0.017	-2.47
Skewness of absolute bias, given detection	5.583	1.679	-7.14	5.317	1.781	-6.74

B. Parameter estimates

ρ	σ_z	σ_ν	κ_q	κ_f	γ	λ	θ_f	θ_q	α
Less serious restatements									
0.156	0.241	0.498	2.406	0.012	0.790	0.013	0.037	0.010	0.503
(0.004)	(0.004)	(0.004)	(0.095)	(0.005)	(0.007)	(0.000)	(0.017)	(0.000)	(0.018)
More serious restatements									
0.158	0.275	0.523	2.334	0.008	0.757	0.013	0.053	0.010	0.483
(0.012)	(0.006)	(0.014)	(0.503)	(0.121)	(0.004)	(0.002)	(0.004)	(0.002)	(0.017)

Table 6: Post-SOX versus pre-SOX period

The estimation is done with a simulated minimum distance estimator, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data in the SG&A sample for the post-SOX versus pre-SOX period. Post-SOX period is our baseline specification in Table 3. Panel A reports the simulated and actual moments and the t-statistics for the differences between the corresponding moments. Panel B reports the estimated structural parameters with standard errors in parentheses. ρ is the serial correlation of the persistent productivity shock. σ_z is the volatility of the persistent productivity shock. σ_ν 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 manipulation. γ is the curvature of the innovation production function. λ is the probability of manipulation detection. θ_f is the manager incentive to beat average profits. θ_q is the manager incentive to smooth profits. α is the elasticity of final good output to intermediate varieties. The standard errors are double-clustered by firm and year in the post-SOX period and by firm only in the pre-SOX period.

A. Moments

	Post-SOX period			Pre-SOX period		
	Data moments	Simulated moments	t-stat	Data moments	Simulated moments	t-stat
Mean ratio of investment to sales	0.398	0.392	-0.66	0.387	0.392	0.58
Incidence of detection	0.013	0.007	-2.40	0.010	0.008	-1.98
Mean absolute bias relative to sales, given detection	0.090	0.217	8.45	0.086	0.202	5.54
Variance of cash flow growth	1.331	1.417	3.28	1.407	1.357	-2.64
Covariance of cash flow and earnings growth	0.291	0.266	-1.73	0.253	0.334	5.03
Covariance of cash flow and investment growth	-0.019	-0.067	-14.15	-0.027	-0.065	-9.25
Variance of earnings growth	1.126	1.130	0.10	1.035	1.230	11.32
Covariance of earnings and investment growth	-0.020	0.004	6.48	-0.030	0.008	10.07
Variance of investment growth	0.084	0.087	0.40	0.088	0.089	0.09
Variance of cash flow growth, given detection	1.515	1.258	-4.38	1.457	1.249	-1.32
Covariance of cash flow and earnings growth, given detection	0.294	0.112	-2.73	0.307	0.090	-1.60
Covariance of cash flow and investment growth, given detection	-0.019	-0.068	-3.23	-0.001	-0.048	-1.13
Covariance of cash flow and earnings bias growth, given detection	0.062	-0.265	-3.53	-0.098	-0.170	-0.45
Variance of earnings growth, given detection	1.244	2.203	12.34	1.186	2.196	7.08
Covariance of earnings and investment growth, given detection	-0.023	0.068	6.90	-0.050	0.077	4.68
Covariance of earnings and earnings bias growth, given detection	0.152	-0.013	-3.52	0.219	-0.508	-4.72
Variance of investment growth, given detection	0.070	0.089	1.26	0.084	0.083	-0.06
Covariance of investment growth and earnings bias growth, given detection	-0.003	0.040	2.52	-0.009	0.036	1.07
Variance of earnings bias growth, given detection	2.110	2.790	6.10	1.916	3.005	5.78
Variance of absolute bias, given detection	0.059	0.010	-3.80	0.049	0.005	-1.36
Skewness of absolute bias, given detection	5.583	1.679	-7.14	6.304	1.014	-5.13

B. Parameter estimates

ρ	σ_z	σ_ν	κ_q	κ_f	γ	λ	θ_f	θ_q	α
Post-SOX period									
0.156	0.241	0.498	2.406	0.012	0.790	0.013	0.037	0.010	0.503
(0.004)	(0.004)	(0.004)	(0.095)	(0.005)	(0.007)	(0.000)	(0.017)	(0.000)	(0.018)
Pre-SOX period									
			2.310	0.009		0.016			
			(0.325)	(0.132)		(0.234)			

Table 7: Counterfactual experiments

This 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 from a model with no accounting bias (identical to the baseline with bias costs $\kappa_f = \kappa_q = \infty$), and the third column reports moments from a value-maximizing model with no incentives to distort earnings (identical to the baseline with earnings incentive parameters $\theta_f = \theta_q = 0$). The first row reports the mean absolute bias relative to sales conditional upon detection. The second row reports the growth. The third row reports the cost of capital. The fourth row reports the average change in fundamental firm value relative to the baseline model. The fifth row reports the average consumption-equivalent change in welfare relative to the baseline model. All counterfactual moments are computed using the ergodic distribution of the respective models.

	Estimated	No bias ($\kappa_f = \kappa_q = \infty$)	Value maximizing ($\theta_f = \theta_q = 0$)
SG&A sample			
Mean bias, %	21.745	0.000	0.000
Growth, %	2.000	2.003	1.999
Cost of capital R^f, net %	8.216	8.564	8.078
Firm value change from baseline, %	0.000	-5.674	2.382
Welfare change from baseline, %	0.000	0.099	-0.019
R&D sample			
Mean bias, %	27.356	0.000	0.000
Growth, %	2.000	1.999	2.002
Cost of capital R^f, net %	8.359	8.867	8.363
Firm value change from baseline, %	0.000	-8.271	0.314
Welfare change from baseline, %	0.000	-0.018	0.048
SG&A sample with more serious restatements			
Mean bias, %	23.837	0.000	0.000
Growth, %	2.000	2.014	2.034
Cost of capital R^f, net %	8.216	8.501	7.419
Firm value change from baseline, %	0.000	-4.385	13.949
Welfare change from baseline, %	0.000	0.440	1.126
Pre-SOX SG&A sample			
Mean bias, %	20.151	0.000	0.000
Growth, %	2.000	2.000	1.999
Cost of capital R^f, net %	8.216	8.564	8.093
Firm value change from baseline, %	0.000	-5.748	2.164
Welfare change from baseline, %	0.000	-0.005	-0.017

Internet Appendix for "Information versus Investment"

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A. Model appendix

This appendix provides more detail on our theoretical model. We define a stationary general equilibrium on a balanced growth path, characterize normalized stationary versions of value functions, the cross-sectional distribution, the earnings-based pricing function, and the variety growth rate in this equilibrium, demonstrate that all aggregates grow at an identical rate equal to the growth rate of aggregate varieties, characterize household bond returns and welfare in closed form, provide an expression for the realized household equity return as an aggregate across stationary firm outcomes, and describe the numerical solution method we employ.

A.1 Equilibrium definition

A stationary general equilibrium on a balanced growth path (balanced growth path) is a collection of:

- intermediate goods prices, p_{jt},
- intermediate goods quantities, x_{jt},
- land prices, P_t^L,
- land quantities demanded, L_t
- a manager value function, $V^m(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$, an intangible investment policy, $W(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$, a bias policy, $B(z_{kt}, \nu_{kt}, M_{kt}, Q_t)$,
- a fundamental firm value function, $V^f(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$,
- aggregate output, Y_t,
- intangible investment, W_t,
- intermediate goods production, X_t,
- consumption, C_t,
- aggregate newly innovated variety levels, M_t,
- aggregate total variety levels, Q_t,
- household bond savings, S_t,
- household equity investments, E_t,

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- a household bond return, R^f,
- a household equity return, $\tilde{R}^h$,
- a firm average equity return, R^f,
- a profit target, $\bar{\pi}$,
- an aggregate growth rate, g,
- and a stationary distribution, $F(z, \nu, b_{-1}, m)$.

Together these objects satisfy the following conditions:

- taking as given demand from the final goods producer, intermediate goods prices, p_{jt}, for newly innovated on-patent goods are set optimally by intermediate goods firms under monopolistic competition to maximize their static profits,

- taking as given the marginal cost of production, intermediate goods prices, p_{jt}, for previously innovated off-patent goods are optimally set equal to marginal cost by intermediate goods firms under perfect competition to maximize their static profits,

- taking as given the intermediate goods prices, p_{jt}, the final goods producer optimally chooses intermediate goods quantities, x_{jt}, to maximize their static profits,

- taking as given the land price, P_t^L, the final goods producer optimally chooses the quantity of land demanded, L_t, to maximize their static profits,

- taking as given the firm average equity return, R^f, and the profit target, $\bar{\pi}$, firm managers choose policies for intangible investment, $W(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$, and bias, $B(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$, in order to optimize the expected present discounted value of their payoffs, D_{kt}^m, given by the manager value function, $V^m(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$,

- fundamental firm value, $V^f(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$, is equal to the present discounted value of firm cash flows, D_{kt}^f, taking as given the firm cost of capital, R^f, as well as manager optimal policies for intangible investment, $W(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$, and bias, $B(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$,

- taking as given the bond return, R^f, the household optimally chooses bond savings, S_{t+1}, to maximize their welfare,

- taking as given the equity return, $\tilde{R}^h$, the household optimally chooses equity savings, E_{t+1}, to maximize their welfare,

- taking as given manager intangible investment, $W(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$, and bias, $B(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$, policies as well as fundamental ex-dividend firm value functions, $\tilde{V}^f(z_{kt}, \nu_{kt}, B_{kt-1}, M_{kt}, Q_t)$, which imply an earnings-based firm pricing function, $\mathbb{E}\left(\tilde{V}_{kt}^f | \Pi_{kt}\right)$, household realized equity returns, $\tilde{R}^h$, reflect intermediary information rents causing overpayment for purchases and underpayment for sales by the fraction τ for every firm k

$$\tilde{R}^h = \int \frac{D_{kt+1}^f + \tilde{V}_{kt+1}^f - \tau \left[\tilde{V}_{kt+1}^f - \mathbb{E}\left(\tilde{V}_{kt+1}^f | \Pi_{kt+1}\right)\right]^+}{\tilde{V}_{kt}^f + \tau \left[\mathbb{E}\left(\tilde{V}_{kt}^f | \Pi_{kt}\right) - \tilde{V}_{kt}^f\right]^+} dk,$$

- aggregate output, Y_t, is given by the final goods producer technology as a function of the land, L_t, and intermediate goods, x_{jt}, inputs,
- aggregate final goods used in intermediate goods production, X_t, is equal to the total demand across all intermediate varieties j adjusted for marginal cost

$$X_t = \int \psi x_{jt} dj,$$

- aggregate intangible investment, W_t, is equal to the total intangible investment across all firms k

$$W_t = \int w_{kt} dk,$$

- the mass of newly innovated varieties is given by the total newly innovated varieties across all firms k

$$M_{t+1} = \int M_{kt+1} dk,$$

- the market for final goods clears, i.e., the resource constraint

$$Y_t = C_t + X_t + W_t$$

  is satisfied,
- the zero net supply bond market clears with savings, $S_t = 0$,
- the land market clears with the land demand, L_t, equal to the inelastic supply 1 in each period,
- the average profit target, $\bar{\pi}$, is equal to the average scaled profit level across firms, i.e.,

$$\bar{\pi} = \mathbb{E}\left(\frac{\Pi_{kt}}{Q_t}\right),$$

- total aggregate variety levels respect the accumulation equation

$$Q_{t+1} = M_{t+1} + Q_t,$$

- growth of the total variety level is constant and given by g, i.e.,

$$g = \frac{M_{t+1}}{Q_t},$$

- aggregate quantities C_t, Y_t, X_t, and W_t all grow at the constant rate g,
- and the constant stationary distribution of scaled firm state variables in each period is $F(z_t, \nu_t, b_{t-1}, m_t)$, where $b_{t-1} = B_{t-1}/Q_t$, $m_t = M_t/Q_t$, and $F(\cdot)$ respects manager optimal intangible investment and bias policies together with the exogenous stochastic processes for z_t and ν_t.

A.2 Stationary optimization, cross-sectional distributions, earnings-based pricing functions, and the variety growth rate

First, note that from this point forward we often drop the k and t notation, replacing it with state vectors and $_{-1}$, prime notation when it is possible to do so without loss of clarity. Also note that the value functions V^f and V^m above have unbounded, nonstationary inputs because Q grows without bound on a balanced growth path. This nonstationarity makes numerical dynamic programming difficult in practice, so we exploit the fact that the firm and manager flow payoffs are homogeneous in Q to write the value functions and nonstationary inputs in stationary, normalized form.

$$V^m(z,\nu,B_{-1},M,Q) =$$

$$\max_{W,B}\begin{bmatrix} \mathbb{I}(B=0)\left(D^m+\frac{1}{R^f}\mathbb{E}\left[V^m(z',\nu',0,M',Q')|z\right]\right) \\ \mathbb{I}(B\neq 0)(1-\lambda)\left(D^m+\frac{1}{R^f}\mathbb{E}\left[V^m(z',\nu',B,M',Q')|z\right]\right) \\ \mathbb{I}(B\neq 0)\lambda\left(D^m|_{B=0}-MC(B,Q)+\frac{1}{R^f}\mathbb{E}\left[V^m(z',\nu',0,M',Q')|z\right]\right) \end{bmatrix}$$

$$= Q\max_{w,b}\begin{bmatrix} \mathbb{I}(b=0)\left(d^m+\frac{1}{R^f}\frac{1}{Q}\mathbb{E}\left[V^m(z',\nu',0,M',Q')|z\right]\right) \\ \mathbb{I}(b\neq 0)(1-\lambda)\left(d^m+\frac{1}{R^f}\frac{1}{Q}\mathbb{E}\left[V^m(z',\nu',B,M',Q')|z\right]\right) \\ \mathbb{I}(b\neq 0)\lambda\left(d^m|_{b=0}-MC(b,1)+\frac{1}{R^f}\frac{1}{Q}\mathbb{E}\left[V^m(z',\nu',0,M',Q')|z\right]\right) \end{bmatrix}$$

where lowercase variables are the same as uppercase variables scaled by Q, i.e.,

$$m=\frac{M}{Q}, w=\frac{W}{Q}, b=\frac{B}{Q}$$

$$d^m=\frac{D^m}{Q}=\theta^d d^f+\theta_\pi\mathbb{I}(\pi\geq\bar{\pi})-\theta_q(\pi-\bar{\pi})^2, d^f=\frac{D}{Q}=\pi_m(z)m-w$$

$$mc(b)=\frac{MC(B,Q)}{Q}=\kappa_f+\kappa_q b^2, \pi=\frac{\Pi}{Q}=\pi_m(z)m-w+\nu+b-b_{-1}$$

$$v^m(z,\nu,b_{-1},m)=\frac{V^m(z,\nu,B_{-1},M,Q)}{Q}.$$

We obtain that

$$v^m(z,\nu,b_{-1},m)Q = Q\max_{w,b}\begin{bmatrix} \mathbb{I}(b=0)\left(d^m + \frac{1}{R^f}\frac{Q'}{Q}\mathbb{E}\left[v^m(z',\nu',0,m')|z\right]\right) \\ \mathbb{I}(b\neq 0)(1-\lambda)\left(d^m + \frac{1}{R^f}\frac{Q'}{Q}\mathbb{E}\left[v^m(z',\nu',b,m')|z\right]\right) \\ \mathbb{I}(b\neq 0)\lambda\left(d^m|_{b=0} - mc(b) + \frac{1}{R^f}\frac{Q'}{Q}\mathbb{E}\left[v^m(z',\nu',0,m')|z\right]\right) \end{bmatrix}$$

$$v^m(z,\nu,b_{-1},m) = \max_{w,b}\begin{bmatrix} \mathbb{I}(b=0)\left(d^m + \frac{1+g}{R^f}\mathbb{E}\left[v^m(z',\nu',0,m')|z\right]\right) \\ \mathbb{I}(b\neq 0)(1-\lambda)\left(d^m + \frac{1+g}{R^f}\mathbb{E}\left[v^m(z',\nu',b,m')|z\right]\right) \\ \mathbb{I}(b\neq 0)\lambda\left(d^m|_{b=0} - mc(b) + \frac{1+g}{R^f}\mathbb{E}\left[v^m(z',\nu',0,m')|z\right]\right) \end{bmatrix}$$

where g is the growth rate of varieties Q. Similarly, we can write fundamental firm value in normalized form as

$$v^f(z,\nu,b_{-1},m) = \begin{bmatrix} \mathbb{I}(b=0)\left(d + \frac{1+g}{R^f}\mathbb{E}\left[v^f(z',\nu',0,m')|z\right]\right) \\ \mathbb{I}(b\neq 0)(1-\lambda)\left(d + \frac{1+g}{R^f}\mathbb{E}\left[v^f(z',\nu',b,m')|z\right]\right) \\ \mathbb{I}(b\neq 0)\lambda\left(d + \frac{1+g}{R^f}\mathbb{E}\left[v^f(z',\nu',0,m')|z\right]\right) \end{bmatrix},$$

where we substitute in the optimal policies from the manager's problem, v^m, and where $v^f Q = V^f$. Given values for the aggregate growth rate, g, the profit target, $\bar{\pi}$, and the firm cost of capital, R^f, the normalized or stationary Bellman equations above are computable using standard numerical dynamic programming techniques.

Note that given this stationary formulation of the manager dynamic optimization problem, the stationary cross-sectional distribution, $F(z,\nu,b_{-1},m)$, is simply a function of the implied investment and bias policies, together with the exogenous stochastic processes for z and ν.

Also note that the nonstationary earnings-based firm valuation or pricing function, $\mathbb{E}(\tilde{V}^f_{kt}|\Pi_{kt}) = \mathbb{E}(\tilde{v}^f_{kt}Q_t|\pi_{kt}Q_t)$, is implied by the stationary earnings-based firm valuation function, $\mathbb{E}(\tilde{v}^f|\pi)$, given common knowledge of the nonstochastic aggregate variety level Q_t. In addition, the normalized firm pricing function is a function of computable stationary objects through the formula

$$\mathbb{E}(\tilde{v}^f|x) = \frac{\int \mathbb{I}(\pi(z,\nu,b_{-1},m)=x)\tilde{v}^f(z,\nu,b_{-1},m)dF(z,\nu,b_{-1},m)}{\int \mathbb{I}(\pi(z,\nu,b_{-1},m)=x)dF(z,\nu,b_{-1},m)}.$$

Finally, to characterize the variety growth rate, note that the total mass of varieties satisfies the accumulation equation

$$Q_{t+1} = \int M_{kt+1}dk + Q_t$$

$$Q_{t+1} = \int m'(z,\nu,b_{-1},m) Q_t dF(z,\nu,b_{-1},m) + Q_t$$

$$g = \frac{Q_{t+1} - Q_t}{Q_t} = \int m'(z,\nu,b_{-1},m) dF(z,\nu,b_{-1},m)$$

$$g = \int \bar{\xi} \left(w(z,\nu,b_{-1},m)\right)^{\gamma} dF(z,\nu,b_{-1},m),$$

Also, note that since the growth rate is constant in any period we also have

$$g = \int m dF(z,\nu,b_{-1},m) = \frac{Q_t - Q_{t-1}}{Q_{t-1}},$$

a formula that is sometimes easier to compute.

A.3 Balanced growth at rate g

In the background, we assume that there are lump-sum transfers from intermediaries and managers to the household that are chosen to ensure that, on aggregate, neither intermediaries nor managers consume positive amounts of resources. This assumption implies that neither manager consumption nor intermediaries' consumption enter the resource constraint or final goods clearing condition. Therefore, the final goods market-clearing condition is given as noted above by

$$Y_t = C_t + X_t + W_t.$$

We now show that each of these terms is proportional to Q_t, which implies common or balanced growth of all aggregate quantities at the rate g.

Note that output consumed in the production of intermediate varieties, X_t, satisfies

$$X_t = \int_{Q_{t-1}}^{Q_t} \psi x_{jt} dj + \psi \int_0^{Q_{t-1}} x_{jt} dj = M_t \int \psi x_m(z) dF(z,\nu,b_{-1},m) + Q_{t-1} \psi x_c$$

$$= \frac{g}{1+g} Q_t \int \psi x_m(z) dF(z,\nu,b_{-1},m) + \frac{1}{1+g} Q_t \psi x_c \propto Q_t$$

Aggregate investmen,t W_t, satisfies

$$W_t = \int_0^1 W_{kt} dk = \int_0^1 w_{kt} Q_t dk = Q_t \int w(z,\nu,b_{-1},m) dF(z,\nu,b_{-1},m) \propto Q_t.$$

Total output, Y_t, satisfies

$$Y_t = L_t^{1-\alpha} \int_0^{Q_t} z_{jt}^{1-\alpha} x_{jt}^{\alpha} dj = M_t \int z^{1-\alpha} x_m(z)^{\alpha} dF(z,\nu,b_{-1},m) + Q_{t-1} x_c^{\alpha}$$

$$= \frac{g}{1+g} Q_t \int z^{1-\alpha} x_m(z)^{\alpha} dF(z,\nu,b_{-1},m) + \frac{1}{1+g} Q_t x_c^{\alpha} \propto Q_t.$$

Since $C_t = Y_t - X_t - W_t$, we also conclude that $C_t \propto Q_t$. Given that Q_t grows at the constant rate g, we obtain common or balanced growth at rate g.

A.4 Household risk-free bond returns

The household optimality condition for savings, S_{t+1}, on a risk-free bond is given by

$$C_t^{-\eta} = \beta R^h C_{t+1}^{-\eta}.$$

But because C_t grows at the constant rate g, we have $\frac{C_{t+1}}{C_t} = 1 + g$, and therefore we can write the household return on risk-free bonds in closed form as

$$R^h = \frac{1}{\beta}(1+g)^{\eta}.$$

Next, because the household faces no aggregate uncertainty, the household must be indifferent between saving in the bond and equity investment E_{t+1}. This indifference requires that the household return on equity, $\tilde{R}^h = R^h$, is the same as the bond return.

A.5 Household welfare

Substituting the common growth rate g into the household welfare objective, and summing the implied geometric series, we have that welfare is given at time t by

$$\frac{C_t^{1-\eta}}{1-\eta}\frac{1}{1-\beta(1+g)^{1-\eta}}.$$

The first term represents static elements of welfare, and the second term represents dynamic components. Further note that under the innocuous normalizing assumption, $Q_t = 1$, we have from the derivations above that on a balanced growth path, C_t is given by the computable formulas

$$C_t = Y_t - X_t - W_t$$
$$Y_t = \left(\frac{g}{1+g}\int z^{1-\alpha}x_m(z)^{\alpha}dF(z,\nu,b_{-1},m) + \frac{1}{1+g}x_c^{\alpha}\right)$$
$$X_t = \left(\frac{g}{1+g}\int \psi x_m(z)dF(z,\nu,b_{-1},m) + \frac{1}{1+g}\psi x_c\right)$$
$$W_t = \left(\int w(z,\nu,b_{-1},m)dF(z,\nu,b_{-1},m)\right).$$

A.6 Household realized equity returns

The household's implied diversified equity return, $\tilde{R}^h$, accounting for information costs is given in computable stationary form by

$$\tilde{R}^h = (1+g)\int \frac{d^{f'} + \tilde{v}^{f'} - \tau\left[\tilde{v}^{f'} - \mathbb{E}\left(\tilde{v}^{f'}|\pi'\right)\right]^+}{\tilde{v}^f + \tau\left[\mathbb{E}\left(\tilde{v}^f|\pi\right) - \tilde{v}^f\right]^+}dG(z',\nu',b,m',z,\nu,b_{-1},m),$$

where $\tilde{v}^f = v^f - d^f$ and $G(\cdot)$ is the joint stationary distribution of outcomes in one period and the next.

A.7 Computational strategy

When numerically solving and estimating the model described above, we impose the following fixed points to guarantee consistency between model and empirical growth rates and firm returns:

- Average investment productivity, $\bar{\xi}$, is chosen so that $g = \hat{g}$, where the target growth rate, $\hat{g}$, is average real GDP growth in the data.
- The information rent parameter, τ, is chosen so that the firm's cost of capital is equal to the target empirical value, $\hat{R}^f$, i.e.,

$$R^f = \hat{R}^f.$$

With these targets in place, stationary general equilibrium along a balanced growth path involves only three aggregate fixed points that require numerical calculation, all of which are a function of the aggregate triplet, $(\tau, \bar{\xi}, \bar{\pi})$. The first fixed point requires that

$$g(\tau, \bar{\xi}, \bar{\pi}) = \hat{g},$$

i.e., that the growth rate implied by the model is equal to the target growth rate. So we must have that

$$\hat{g} = \int \bar{\xi} \, (w)^{\gamma} \, dF(z, \nu, b_{-1}, m).$$

The second fixed point is

$$\tilde{R}^h(\tau, \bar{\xi}, \bar{\pi}) = R^h = \frac{1}{\beta}(1 + \hat{g})^{\eta},$$

i.e., we must have that the household's implied diversified equity return accounting for information costs is equal to the analytically tractable formula for R^h. Given the normalized formulation for the households implied return on equity above, we can rewrite this second fixed point in a more computationally useful fashion as

$$\frac{1}{\beta}(1 + \hat{g})^{\eta} = (1 + \hat{g}) \int \frac{d^{f'} + \tilde{v}^{f'} - \tau \left[\tilde{v}^{f'} - \mathbb{E}\left(\tilde{v}^{f'}|\pi'\right)\right]^{+}}{\tilde{v}^f + \tau \left[\mathbb{E}\left(\tilde{v}^f|\pi\right) - \tilde{v}^f\right]^{+}} dG(z', \nu', b, m', z, \nu, b_{-1}, m)$$

The third fixed point is that average profits appearing in firm incentives are indeed average profits observed at firms, i.e.,

$$\bar{\pi} = \int \pi(z, \nu, b_{-1}, m) dF(z, \nu, b_{-1}, m).$$

We are now in a position to explicitly describe our algorithm for solving the GE model for estimation purposes:

1. Guess a triplet of the investment productivity shifter, $\bar{\xi}$, the information rent parameter, τ, and the average profit level $\bar{\pi}$.
   (a) Solve the manager problem, v^m, assuming the discounter, $R^f = \hat{R}^f$, from the data.
   (b) Compute the implied firm value, v^f, assuming the discounter, $R^f = \hat{R}^f$, from the data.
   (c) Compute the stationary distribution, F, (and the two-period equivalent, G).
   (d) Compute the inferred earnings-based pricing schedule, $\mathbb{E}\left(\tilde{v}^f|\pi\right)$.
2. Evaluate the three fixed point equations above. If they are all solved to some numerical tolerance, stop. If not, update the guesses for the values of the triplet and return to top.

In practice, we implement this solution algorithm with a (joint) dampened fixed point iteration on the triplet, $(\tau, \bar{\xi}, \bar{\pi})$.

For counterfactuals rather than estimation, the values of $\bar{\xi}$ and τ are taken as given from the estimated model while g and R^f must now be endogenously determined. In that case, the household's return is given by

$$R^h = \frac{1}{\beta}(1+g)^{\eta},$$

where g is not fixed to an outside benchmark. General equilibrium numerically reduces to a system of three fixed points in the triplet, $(g, R^f, \bar{\pi})$. The first fixed point is that equilibrium growth must be generated by optimal policies

$$g = \int \bar{\xi}\,(w)^{\gamma}\, dF(z, \nu, b_{-1}, m).$$

The second fixed point is that the household's realized diversified equity return must be equal to their analytically tractable risk-free bond return, i.e.,

$$\frac{1}{\beta}(1+g)^{\eta} = (1+g)\int \frac{d^{f'} + \tilde{v}^{f'} - \tau\left[\tilde{v}^{f'} - \mathbb{E}\left(\tilde{v}^{f'}|\pi'\right)\right]^{+}}{\tilde{v}^{f} + \tau\left[\mathbb{E}\left(\tilde{v}^{f}|\pi\right) - \tilde{v}^{f}\right]^{+}} dG(z', \nu', b, m', z, \nu, b_{-1}, m).$$

The third fixed point is the same as above, i.e., that $\bar{\pi}$ is equal to the average level of normalized earnings, π, across the stationary distribution, F. For these counterfactual exercises, we modify the explicit numerical algorithm above in the obvious way.

B. Model specification with variable detection probability

In this Appendix, we present results from a robustness check in which we consider the possibility that the probability of detection is a function of bias. First, we estimate logistic regressions for the probability of detection for both the pre-SOX and post-SOX periods, as well as for both less and more serious restatements. The results are in Table IA.1. In these regressions, the outcome variable is an indicator variable for detection. Defining this variable requires care because restatements of financial statements typically correct financial results for several years. We set this indicator variable equal to one in the last year of a restatement span and zero in the prior years of a restatement span. In other words, if a restatement spans just one year, this indicator variable is set to one in that year. If a restatement spans multiple years, this indicator variable equals a sequence of zeros that ends with one. Note that if certain years are not restated, one cannot conclude whether these years were manipulated or not because detection is not perfect. For this reason, the sample in Table IA.1 is restricted to restated years only.

Interestingly, Table IA.1 shows that the probability of detection does not increase with the magnitude of manipulation in either of the periods or for either type of restatement. While the coefficient on the absolute value of bias is positive (but statistically insignificant) for the pre-SOX period, it is *negative* (again, statistically insignificant) for the post-SOX period. Thus, there is no evidence that the probability of detection increases in the magnitude of bias.

One drawback of this analysis is the rare nature of restatements and thus a relatively small sample of restated years in Table IA.1. Because of the associated low power, we take a second approach to understanding the effect of the magnitude of bias on the probability of detection by completely reestimating the structural model for the less serious restatements (our main specification) for the pre-SOX period by letting the probability of detection be a logistic function of bias in which we set the value of the slope coefficient to 0.595, which is the value from Table IA.1. Similar to our main analysis for the pre-SOX period, we re-estimate κ_f, κ_q, as well as a new parameter λ_0, which is the intercept in the logistic function for the probability of detection.

These results are reported in Table IA.2. Briefly, the average implied detection probabilities are similar in our baseline pre-SOX estimation and this expended estimation. The point estimate for the detection probability in our baseline pre-SOX estimation is 0.016, while for the estimation of this augmented model, the average detection probability is:

$$\frac{1}{1+e^{-\lambda_0-\lambda_1|b/y|}}\Big|_{\lambda_0=-4.698,\ \lambda_1=0.595,\ |b/y|=0.172} = 0.010.$$

Table IA.1: Probability of detection as a function of bias

This table presents estimates of the probability of detection as a logistic function of the absolute value of bias in book value scaled by sales. The sample contains firm-year observations in which financial statements were, restated. The outcome variable is an indicator for detection that equals one in the last restated year and zero in prior restated years.

	Less serious restatements		More serious restatements	
	Pre-SOX	Post-SOX	Pre-SOX	Post-SOX
(Intercept)	-1.490^{***}	-0.651^{***}	-1.568^{***}	-0.727^{***}
	(0.111)	(0.058)	(0.135)	(0.070)
Bias in book value to sales, abs()	0.595	−0.109	0.488	−0.221
	(0.497)	(0.223)	(0.531)	(0.250)
AIC	585.299	1985.486	402.784	1389.168
BIC	594.087	1996.172	410.893	1399.184
Log Likelihood	−290.650	−990.743	−199.392	−692.584
Deviance	581.299	1981.486	398.784	1385.168
Num. obs.	598	1545	426	1105

Table IA.2: Pre-SOX period: probability of detection as a function of bias

The estimation is done with a simulated minimum distance estimator, which chooses structural model parameters by matching the moments or functions of moments from a simulated panel of firms to the corresponding moments or functions of moments from the data. The sample is the SG&A sample for the pre-SOX period. All parameters describing firm fundamentals are set to our baseline parameters from Table 3. Panel A reports the simulated and actual moments and the t-statistics for the differences between the corresponding moments. Panel B reports the estimated structural parameters with standard errors in parentheses. κ_q is the quadratic cost of manipulation. κ_f is the fixed cost of manipulation. λ is the probability of manipulation detection. λ_0 is the intercept in the logistic function used for the probability of manipulation detection. The standard errors are clustered by firm.

A. Moments

	Constant prob. of detection			Prob. of detection as a function of bias		
	Data moments	Simulated moments	t-stat	Data moments	Simulated moments	t-stat
Mean ratio of investment to sales	0.387	0.392	0.58	0.387	0.390	0.37
Incidence of detection	0.010	0.008	-1.98	0.010	0.006	-3.49
Mean absolute bias relative to sales, given detection	0.086	0.202	5.54	0.086	0.172	3.15
Variance of cash flow growth	1.407	1.357	-2.64	1.407	1.354	-2.92
Covariance of cash flow and earnings growth	0.253	0.334	5.03	0.253	0.288	1.77
Covariance of cash flow and investment growth	-0.027	-0.065	-9.25	-0.027	-0.032	-1.28
Variance of earnings growth	1.035	1.230	11.32	1.035	1.088	1.47
Covariance of earnings and investment growth	-0.030	0.008	10.07	-0.030	0.021	14.57
Variance of investment growth	0.088	0.089	0.09	0.088	0.076	-2.90
Variance of cash flow growth, given detection	1.457	1.249	-1.32	1.457	1.272	-0.97
Covariance of cash flow and earnings growth, given detection	0.307	0.090	-1.60	0.307	0.317	0.03
Covariance of cash flow and investment growth, given detection	-0.001	-0.048	-1.13	-0.001	-0.045	-1.07
Covariance of cash flow and earnings bias growth, given detection	-0.098	-0.170	-0.45	-0.098	-0.063	0.20
Variance of earnings growth, given detection	1.186	2.196	7.08	1.186	1.988	3.79
Covariance of earnings and investment growth, given detection	-0.050	0.077	4.68	-0.050	0.015	2.25
Covariance of earnings and earnings bias growth, given detection	0.219	-0.508	-4.72	0.219	-0.261	-3.17
Variance of investment growth, given detection	0.084	0.083	-0.06	0.084	0.061	-0.88
Covariance of investment growth and earnings bias growth, given detection	-0.009	0.036	1.07	-0.009	0.002	0.26
Variance of earnings bias growth, given detection	1.916	3.005	5.78	1.916	2.270	1.35
Variance of absolute bias, given detection	0.049	0.005	-1.36	0.049	0.011	-1.16
Skewness of absolute bias, given detection	6.304	1.014	-5.13	6.304	2.546	-3.30

B. Parameter estimates

	κ_q	κ_f	λ	λ_0
Constant prob. of detection				
	2.310	0.009	0.016	
	(0.325)	(0.132)	(0.234)	
Prob. of detection as a function of bias				
	2.405	0.046		-4.698
	(0.149)	(0.051)		(0.019)