How Much Does Imprecision in Accounting Measurement Enhance Value?

Ying Liang *

*Baruch College – CUNY*

Current Draft: January 1, 2020

Abstract

Theory on real effects suggests that more precise accounting does not necessarily improve investment efficiency. However, with investment efficiency mostly unobservable, empirical assessment of the theory is rare. This paper develops an empirical framework based on Kanodia, Singh, and Spero (2005) to structurally estimate the effect of imprecision in accounting measurement on investment efficiency. My estimates suggest that imprecision in accounting measurement has mitigated over-investment in capital expenditures and R&D by 28.6% and 4.9%, respectively. On average, firms still over-invest relative to the first-best full-information benchmark. In counterfactual analyses, my estimates suggest that the optimal investment efficiency could be achieved by reducing the current accounting precision by 4 percentage points (19.5 percentage points) in capital expenditures (R&D), which would increase investor welfare by 4.2% (22%). My study is among the first to provide a quantitative assessment of real effects and presents early evidence of excessive precision in accounting measurement.

Keywords: accounting measurement; real effects; economic efficiency

JEL codes: D82, D83, G14, E22, M41.

*I am grateful to my dissertation committee members: Jeremy Bertomeu, Masako Darrough (Chair), Mingcherng Deng, Edward Li and Lin Peng. All errors are my own.
1. Introduction

Accounting measurements and disclosure rules have significant effects on firms’ real investment decisions, referred to as the real-effects theory (Kanodia, 2006; Kanodia and Sapra, 2016). One interesting finding in the real-effects theory is on the imprecision of accounting measurement. Because of the inescapable judgments, conventions and subjectivities involved in the application of accounting standards, most accounting measurements are imprecise. Both the FASB and the IASB view reducing the imprecision as one of their objectives.\(^1\) However, Kanodia, Singh, and Spero (2005) suggest that a certain degree of imprecision in measuring firms’ investments can be value-enhancing. The intuition is rooted in the postulate of the second-best theory (Lipsey and Lancaster, 1956): when there are two market frictions, for example, asymmetric information about both profitability and investment in this case, resolving one of the two could do more harm than good. More specifically, when profitability is only observable to the firm manager and investment is precisely measured, expecting that the market interprets high investment as high profitability, a firm will over-invest to signal its profitability, resulting in a loss in economic welfare.\(^2\) An imprecise investment measure weakens the market’s response to investment, reducing the firm’s incentive to over-invest. Excess imprecision is not ideal, either. If the market price is no longer sensitive to investment because the investment measure is too noisy, without the incentive from the market, the firm will invest in a myopic way, leading to under-investment. Therefore, there is an optimal level of imprecision in accounting measurement, in which the investment is made as if there is no information asymmetry.

Despite their broad intuitive appeal, real effects models are difficult to test. Investment decisions may be made in an economy described by the real-effects theory, where...
more information could distort decision-making. Investment decisions may also be made in a simple “Robinson Crusoe” economy where prices are exogenous,\(^3\) where more information improves decision-making (Demski, 1973). When these two types of investments co-exist in the data, distinguishing them becomes a major roadblock for empirical research. Moreover, even if one can identify investments made under the real-effects theory, it is difficult to conclude from data whether signal precision levels are above or below the optimal level. For this reason, most empirical research to date has focused on documenting real consequences from information dissemination.\(^4\) There is little evidence on the implications of the real-effects theory for optimal accounting precision.

My study employs structural estimation to link the real-effects theory to the empirical literature. Structural estimation incorporates theoretical restrictions required to identify a firm’s decision problem, thereby allowing me to quantify the potential loss in investment efficiency when information precision about investment varies. It also allows me to answer questions beyond the scope of theory: Do firms in general under- or over-invest? And would an increase in accounting precision improve or hurt investors’ welfare? By fitting empirical data to the model and obtaining parameter estimates, I can apply these estimates to study counterfactual situations, including a completely precise measurement scenario, as well as the first-best scenario with full information.

A clear link between theory and empirical measurements of real effects is crucial to accounting standard setting. The real-effects theory is acknowledged as one of the overriding criteria to evaluate potential accounting rules, but in practice, standard setters rarely use the theory to conduct economic analyses (Glover, 2014). This is partly due to the difficulties with empirical measurement, which render the real-effects theory untestable and largely ignored. As a result, standard-setting has been marred by debates about

---

\(^3\)The Robinson Crusoe Economy refers to an economy with two agents, one of which is a consumer, and the other is a producer. There are two goods produced in the economy. Both agents are price-takers. It is a simple framework used in the study in economics.

\(^4\)For instance, Biddle, Hilary, and Verdi (2009) document both reduction of over-investment and under-investment following a reduction of information asymmetry; Shroff (2017) examines the effects of forty-nine changes in GAAP on firm investment decisions. Some paper also study the role of reporting frequency on investment but come to different conclusions (Ernstberger, Link, Stich, and Vogler, 2017; Kraft, Vashishtha, and Venkatachalam, 2018; Fu, Kraft, Tian, Zhang, and Zuo, 2019; Kajüter, Klassmann, and Nienhaus, 2019; Nallareddy, Pozen, and Rajgopal, 2017).
whether accounting can suitably address the challenges caused by asymmetric information. In comparison to other forms of public policy evaluations that are based on welfare assessments, accounting standard setting lags behind in connecting theoretical models and empirical analysis to policy making.⁵

I start with a simple investment model in an overlapping generation setting that is closely anchored on Kanodia, Singh, and Spero (2005). The firm manager makes investment decisions on behalf of current shareholders. Investment generates both short-term and long-term revenues, both of which are linear in investment amount and profitability. Profitability is only observable to the manager, and investment is reported to the capital market but measured with noise. The current shareholders have to sell the firm before the long-term profit is realized. The manager chooses investment to maximize the firm price instead of terminal cash flows. This implies that given the firm’s private information, the price-maximizing investment policies need not be value-maximizing. In other words, price efficiency does not necessarily lead to economic efficiency.

The capital market sets the price of the firm according to an imprecise report of investment. The quality of the investment report depends entirely on the accounting standards, and the manager has no discretion to manipulate the report. The degree of imprecision in the investment report is the primary variable of interest in my estimation. After estimating the parameters, I conduct counterfactual analysis to calculate the degree of imprecision that would achieve optimal investment efficiency. This optimal degree of imprecision provides a benchmark to evaluate the imprecision estimated from data (i.e., too high or too low?).

To estimate the model, I collect data on stock returns, earnings, and investment and use simulated method of moments (SMM) to match moments from the model and those from the data. SMM simulates a dataset from the model solution from which selected moments are calculated for every possible parameter set. The optimal parameter values will return moments that best line up with those calculated using the empirical sample.

⁵Research on economic public policing is abundant. To name a few, see industrial organization (Gentzkow, 2007), labor (Autor, Palmer, and Pathak, 2014; Heckman and Vytlacil, 2007), monetary policy (Clarida, Gali, and Gertler, 2000; Mankiw and Reis, 2002) and international trade (Trefler, 1993).
With the parameter estimates, I conduct a series of counterfactual analyses to evaluate the effect of imprecision on over-investment and provide quantitative policy guidance to improve investment efficiency.

My estimation shows that the measurement imprecision accounts for 32% of the sample variation in capital expenditure, and 16.2% of R&D sample variation. Compared to a precise investment measure, the imprecision in the data mitigates over-investment by 28.6% in capital investment and 4.9% in R&D, implying that improving the quality of investment measurement will make firms significantly worse-off. Contrary to conventional wisdom, my result suggests that investment efficiency would be improved by reducing measurement precision about investments. The first-best level of investment efficiency is implemented when decreasing measurement imprecision by 4 percentage points for capital expenditures and by 19.5 percentage points for R&D. As noted in real effects theories (Kanodia and Sapra, 2016), more information is not always preferred. My result shows that, although using the optimal imprecision will cause a loss of information, firm values would rise by 4.2% for the capital expenditures sample and 22% for the R&D sample. These findings suggest that accounting measurement has a first-order effect on firm values through investment decisions.

My paper contributes to the literature in two main aspects. First, I attempt to address the call in Kanodia and Sapra (2016) for more study of predictions from the real-effects models. As a starting point, my study uses structural estimation to assess the real effects of imprecision in accounting measurement and provides directional guidance toward optimal investment efficiency. I also extend the model to obtain various measurements, such as the distance between current and optimal investment, the effect of over-investment on the firm and the investors’ welfare, and the loss of information due to accounting imprecision.

Second, the paper provides an empirical implementation of evaluating investment efficiency. I use the general approach of the real-effects models that focuses on managers maximizing prices. The objective of this study is to capture one plausible first-order trade-off. With the assumptions about functional forms and investment horizons, the
model yields mostly closed-form estimates that can be applied to many empirical settings. Also, the estimation only requires a moderate amount of computation and builds on pre-existing models whose trade-offs are well-understood. Nevertheless, I recognize that, by trying to adhere to a particular real-effects model as tightly as possible, I do not incorporate other empirical features nor other trade-offs in real-effects models. It would be challenging to write a model that reflects all such complexities, and future work on this general problem can build on my model and help facilitate the understanding of the quantitative implications of real effects.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 presents the general model as well as three benchmark cases. Section 4 describes the data and estimation method. Section 5 presents parameter estimates, assesses the model’s fit with the data, and provides validation tests. Section 6 examines the effects of altering accounting precision on the firm’s investment efficiency, on residual information uncertainty, and on the firm’s shareholders and the market’s welfare. The last section concludes.

2. Related Literature

The real-effects literature starts with Kanodia (1980) and has grown substantially to incorporate various aspects of accounting features, including accounting conservatism (Gigler, Kanodia, Sapra, and Venugopalan, 2009), hedge accounting (Melumad, Weyns, and Ziv, 1999; Sapra, 2002; Gigler, Kanodia, and Venugopalan, 2007), mark-to-market accounting (Plantin, Sapra, and Shin, 2008; Allen and Carletti, 2008), alternative accounting measurement methods (Liang and Wen, 2007; Bertomeu and Cheynel, 2015), auditing (Lu and Sapra, 2009; Chen, Jiang, and Zhang, 2019), and reporting choices (Gao and Jiang, 2018; Kanodia, Sapra, and Venugopalan, 2004; Dutta and Nezlobin, 2017). There are two distinguished assumptions in the real-effects framework: first, the firm’s manager has superior information over the market when corporate decisions are made; and second, the manager maximizes the firm’s short-term price instead of terminal cash
flows.

Most of the empirical accounting literature on investment efficiency uses exogenous variations in financial reporting quality such as accounting disclosure, financial reporting efficiency, and transparency. The objective of this literature, as surveyed in Kothari, Ramanna, and Skinner (2010) and Roychowdhury, Shroff, and Verdi (2019), parallels mine in this paper, but the exact question answered by these studies is very different. Their main focus is on whether accounting generates desirable or undesirable economic consequences. This is different from what accounting theory refers to as real effects, since economic consequences can occur without the interaction between stock prices and firm decisions – the essential feature of real-effects theory. Unfortunately, finding an exogenous variation in price incentives that could render a clean reduced-form assessment of real effects is very difficult. Furthermore, the existing empirical papers mainly speak to real effects within the scope of observed variation, sometimes after a regulation has been enforced (Hope and Thomas, 2008; Chuk, 2013). Although my approach is less precise as a result of its assumptions on functional forms, it allows me to provide counterfactual analyses to evaluate a proposed policy before it is put in place.

To my knowledge, the only prior paper that quantitatively examines the real effect of imprecision on investment decision is Liang, Sun, and Tam (2019). They study a dynamic setting with information asymmetry on productivity shock as well as managerial myopia. The fundamental difference between their paper and this one is that in their paper, the market observes a perfectly measured investment and an imprecise report on earnings. They also develop and calibrate a dynamic model to evaluate the magnitude of real effects, while I use a simple over-lapping generation model and employ SMM to estimate the parameters. The stylized model allows me to compare the current equilibrium to several benchmark cases in closed forms, and conduct counterfactual policy analyses to provide insight on the optimal accounting precision to achieve first-best investment efficiency.

Several studies have used structural estimation to quantify the effect of accounting on investment. Two important papers in this area are Terry (2018) and Terry, Whited, and
Zakolyukina (2018). Both studies estimate a multi-period investment model of strategic accounting choice, and examine how accounting choices affect firm growth. These studies also build on insights from the existing finance literature, including capital market misvaluation, adjustment costs, and agency problems (Cooper and Haltiwanger, 2006; Warusawitharana and Whited, 2016; Hennessy and Whited, 2007; Nikolov and Whited, 2014). This literature is more ambitious as they aim at fully understanding dynamic investment patterns. However, the questions asked in these models are different, as they do not model the interactions between endogenous prices and the subsequent investment inefficiencies. I analyze a much simpler myopic investment model in order to explicitly solve the pricing function and conduct counterfactual analyses.

Several studies, such as Choi (2018) and Breuer and Windisch (2019), share the same objective – to estimate the effect of an accounting information flow on investment while setting aside strategic information management. In contrast to my paper, managers in these studies do not maximize short-term prices. In the context of accrual management and earnings quality, the studies by Gerakos and Kovrijnykh (2013), Beyer, Guttman, and Marinovic (2018) and Zakolyukina (2018) combine theory and empirical analysis to examine reporting discretion. Within this literature, Bertomeu, Cheynel, Li, and Liang (2018), Bird, Karolyi, and Ruchti (2019), and Bertomeu, Ma, and Marinovic (2019) focus specifically on estimating earnings management using cross-sectional properties of earnings and price. Unlike this paper, their studies do not explicitly model the investment technology. In other studies, Gerakos and Syverson (2015) develop a model on audit market and evaluate the effects of two potential policy changes: mandatory audit firm rotation and an increase in supply concentration if one of the “Big Four” firms exits the market. Zhou (2017) develops a dynamic disclosure model to study the effect of investors’ learning on managers’ disclosure decisions. Gayle, Golan, and Miller (2015) analyze various features of executive labor market, and Li (2019) studies contract design of top executives’ compensation. McClure (2019) estimates the key determinants of tax avoidance.

Lastly, other structural studies have investigated other channels for reporting discre-
tion, in the form of strategic selection of information. In Bertomeu, Beyer, and Taylor (2016), Zhou (2017), and Cheynel and Zhou (2018), managers decide to disclose or withhold information subject to proprietary costs, implying a potential loss of efficiency when bad information is withheld. In Bertomeu, Marinovic, Terry, and Varas (2017) and Bertomeu, Ma, and Marinovic (2019), managers strategically withhold information when they are informed (Dye, 1985). These approaches are different from my work because the manager does not make an investment decision but has discretion on voluntary disclosures. In line with theoretical work in this area, more analysis of the joint choice to disclose and invest may help estimate investment efficiency in contexts that involve voluntary disclosure.

3. The Model

The model is adapted from Kanodia, Singh, and Spero (2005) (hereafter KSS) and expand into an over-lapping generation model. In this section, I briefly describe the model notation, discuss the core intuition of the theory, and present three benchmark cases, which will be empirically evaluated later.

Consider an overlapping generation setting in which shareholders buy the firm from the previous generation, hold it for one period, and sell it to the next generation of investors at the end of the period. The shareholders delegate decision making to the firm’s manager who maximizes the current shareholders’ benefit. In each period, the manager chooses an amount $k_t$ to invest in a project. The project generates both short-term and long-term profits. Short-term profit equals economic revenue net of the cost of investment:

$$\tilde{x}_t = \tilde{\theta}_t k_t - \frac{1}{2} ck_t^2 + \frac{1}{2} \tilde{\eta}_t,$$  

(1)

where $\tilde{\theta}_t$ is the profitability of the project in which the firm invests. The term $\frac{1}{2} ck_t^2$ is the cost of investment, and $c$ is the marginal cost of investment. The profitability parameter
\( \tilde{\theta}_t \) follows an i.i.d normal distribution with mean zero and variance \( \sigma^2_{\tilde{\theta}} \), and \( \tilde{\theta}_t \in [\theta, +\infty) \). Before the manager makes the investment decision, he privately observes the project’s profitability \( \theta_t \). Lastly, \( \tilde{\eta}_t \) is the noise in earnings, which is normally distributed with mean zero and variance \( \sigma^2_{\tilde{\eta}} \). The earnings noise \( \tilde{\eta}_t \) and the profitability \( \tilde{\theta}_t \) are independent.

The short-term profit \( \tilde{x}_t \) is realized at the end of period \( t \) and consumed privately by the current shareholders, while the long-term profit is not realized until period \( t + 1 \). Define the long-term profit from the time \( t \) project as

\[
\tilde{y}_t = \gamma \tilde{\theta}_t k_t + \frac{1}{2} \tilde{\eta}_t,
\]

where \( \gamma \) can be viewed as a combination of earnings multiple, a discount factor or the correlation between short-term and long-term cash flows. The current shareholders also receive the long-term profit from last period investment. Define \( d_t \) as the total cash flow realized in period \( t \), which is the sum of the long-term profit from last period and the short-term profit of the current investment

\[
\tilde{d}_t = \tilde{x}_t + \tilde{y}_{t-1}.
\]

At the end of period \( t \), the firm issues an accounting report \( s_t \) about investment \( k_t \) to the market. The report \( s_t \) is imprecise on \( k_t \) due to the noise generated in the measurement process:

\[
\tilde{s}_t = k_t + \tilde{\epsilon}_t,
\]

where \( \tilde{\epsilon}_t \) is the noise in accounting measurement, which is normally distributed with mean zero and variance \( \sigma^2_{\tilde{\epsilon}} \). The distribution of \( \tilde{\epsilon}_t \) is common knowledge and \( \tilde{\epsilon}_t \) is independent from \( \tilde{\theta}_t \) and \( \tilde{\eta}_t \). This noise refers to the random errors generated by the subjective judgements, conventions and estimations involved in the measurement process. It is the result of the inherent limitation in financial reporting, not the firm’s intention for mendacity. In other words, the firm manager cannot intentionally manipulate \( \epsilon_t \).

\footnote{The assumption of a zero mean does not mean that the economy is stationary. A negative profitability should be viewed as lower than the average. Accordingly, the sample data used in the later estimation are controlled for firm and year variation and demeaned.}
All investors in the capital market are risk-neutral; the price is then set as the conditional expectation of the long-term profit $y_t$ given the investment report $s_t$

$$p(s_t) = \mathbb{E}(y_t|s_t).$$

(5)

Given the pricing function, the manager chooses $k_t$ to maximize the current shareholders’ total expected payoff. The manager’s optimization problem is:

$$\max_{k_t} \mathbb{E}(d_t + p_t).$$

(6)

The timeline is in Figure 1.

Figure 1: Model Timeline

Shareholders purchase the firm for $p_{t-1}$.

Manager observes $\theta_t$ and chooses $k(\theta_t)$.

Long-term profit $y_{t-1}$ and short-term profit $x_t$ are realized.

Accounting system generates a report $s_t$.

Shareholders sell the firm for $p(s_t)$.

3.1. Benchmark cases

There are two sources of information asymmetry in the model: the manager has private information about the project profitability $\theta_t$, and the firm’s investment $k_t$ is measured with noise. To better understand how the two frictions affect investment, it is helpful to first analyze three benchmark cases. I begin with a model where the firm and the market are perfectly informed, referred to as the first-best scenario. Next, I add a layer of friction by considering a setting where the profitability $\theta_t$ is common knowledge, but the firm’s investment is measured with noise. Then, I focus on the other source of friction by imposing information asymmetry on profitability but allowing the accounting system to measure the investment precisely.
3.1.1 Investment with full information

In the first-best benchmark profitability $\theta_t$ is common knowledge, and the firm’s is measured precisely. The price function is then

$$p_t = \mathbb{E}(y_t|k_t, \theta_t) = \gamma \theta_t k_t,$$

and the manager’s optimization problem defined in Equation (6) can be stated as

$$k_{FB}^* = \arg \max_{k_t} \mathbb{E}(d_t + p_t) = \arg \max_{k_t} \left\{ \theta_t k_t - \frac{1}{2} c k_t^2 + \gamma \theta_{t-1} k_{t-1} + \gamma \theta_t k_t \right\}.$$  \hspace{1cm} (8)

Investment is obtained by taking the first order condition of Equation (8) and is linear in $\theta_t$ as:

$$k_{FB}^* = \left( \frac{1 + \gamma}{c} \right) \theta_t.$$  \hspace{1cm} (9)

Denote the coefficient $\frac{1 + \gamma}{c}$ as $B_{FB}^*$, and it refers to the sensitivity of the investment function. Rewrite the first-best price as a function of investment $k$ by substituting $\theta_t$ with $k_t$ in Equation (7):

$$p_{FB}(k_t) = \frac{c \gamma}{1 + \gamma} k_t^2.$$  \hspace{1cm} (10)

3.1.2 Investment with known profitability and imprecise measurement

Next, consider a setting where the project profitability is publicly observed, but the firm’s investment is measured with noise. As in the main model, the imprecise investment report $s_t$ is $\hat{s}_t = k_t + \hat{\epsilon}_t$, with $\hat{\epsilon}_t \in N(0, \sigma^2_\epsilon)$. The market knows profitability $\theta_t$, observes the report $s_t$, and sets the price based on them. In a pure strategy equilibrium, the firm chooses an investment amount to maximize the expected cash flows, and the market price incorporates beliefs that are consistent with the investment strategy. The equilibrium investment strategy is:

$$k_{KP}(\theta_t) = \frac{1}{c} \theta_t.$$  \hspace{1cm} (11)
Denote the sensitivity $\frac{1}{c}$ as $B^{KP}$. The equilibrium pricing rule is:

$$p^{KP}(k_t) = c\gamma k_t^2.$$  \hfill (12)

The equilibrium investment sensitivity $B^{KP}$ is lower than $B^{FB}$. The reason for under-investment is that the equilibrium price is not set based on the firm’s actual investment. Instead, the market anticipates an investment level based on $\theta_t$ and sets the price according to its anticipation. Since the market a priori knows the profitability $\theta_t$, it can perfectly anticipate how the firm invests given $\theta_t$. When the market observes a report different from the anticipated level, it attributes the difference to measurement noise, and investment report is ignored in the pricing function. Since investment does not affect price, the manager chooses investment only to maximize the short-term profit, so the firm invests in an myopic way. In equilibrium, the market rationally anticipates the firm’s under-investment and adjusts the price accordingly.

### 3.1.3 Investment with unknown profitability and perfect measurement

Suppose now that profitability $\theta_t$ is private information of the firm, but the accounting system generates a precise investment report. In this case, investors update their belief on profitability $\theta_t$ when they observe the level of investment. Thus, the firm’s investment has an additional informational value, as denoted in KSS. Even though the firm does not consciously deliver information about its profitability, investment serves as a signal similar to Spence (1974): high investment is more attractive to firms with high profitability, and so the level of investment serves as a signalling device to separate low and high profitability types. Then, a Spence-like fully revealing signalling equilibrium exists, where investors correctly infer the profitability $\theta_t$. In this signalling equilibrium, the firm’s investment function is

$$k^{PM} = A^{PM} + B^{PM}\theta_t,$$ \hfill (13)
where $A^{PM} = -\frac{\gamma}{c}\theta$, and $B^{PM} = \frac{1 + 2\gamma}{c}$. The capital market’s pricing function can be expressed as a function of investment

$$p^{PM}(k_t) = \frac{c\gamma}{1 + 2\gamma} k_t^2 + \frac{\gamma^2 \theta}{1 + 2\gamma}.$$  

(14)

Since the investment sensitivity $B^{PM} = \frac{1 + 2\gamma}{c} > \frac{1 + \gamma}{c} = B^{FB}$, the firm over-invests compared to the first-best for any given profitability $\theta_t > \theta$. The result of over-investment is due to the belief that investment conveys information about the project’s profitability, where more investment is perceived by investors as a sign of higher profitability. The firm with a low profitability type is then inclined to choose a high investment level in an effort to be perceived as a high profitability type. Investors would be deceived first, but gradually revise their inferences until they perfectly conjecture the underlying profitability. In equilibrium, the price function is less sensitive to investment as is shown by comparing $p^{PM}(k_t)$ to $p^{FB}(k_t)$. This is a suboptimal equilibrium, as the firm over-invests and, once the firm price is fully adjusted, the cost of over-investment is borne by the current shareholders alone.

### 3.2. Unknown profitability and imprecise investment

The benchmark models provide good references, yet in practice both profitability and investment are privately known by a firm’s managers. Managers have access to firm-specific information that is not available to the capital market, and accounting measurements of investments are rarely 100% accurate. In this setting, KSS show that more efficient equilibria can be sustained. Below I define the KSS equilibrium and briefly explain the intuition.

Since investors only observe an accounting report $s_t$, they can no longer infer the actual investment amount perfectly. To set the price of the firm, the market forms a Bayesian posterior belief on the distribution of profitability conditional on the observed report, denoted as $g(\theta_t|s_t)$. The market also anticipates the firm’s investment function $\hat{k}(\theta_t)$ for each possible $\theta_t$. The market price is then set based on the posterior belief
g(θ_t | s_t) and ˆk(θ_t). The manager conjectures the price function ˆp(s_t) and chooses k_t to maximize the current shareholders’ expected payoff. In equilibrium, both the conjectured functions are correct: ˆp(s_t) = p(s_t) and ˆk(θ_t) = k(θ_t).

**Definition of Equilibrium** A noisy signalling equilibrium contains three functions: the manager’s investment strategy k(θ_t), investors’ Bayesian posterior belief g(θ_t | s_t), and a pricing rule p(s_t). The equilibrium functions satisfy the following three conditions:

1. For any given p(s_t), the optimal investment satisfies:

   \[
   k(θ_t) = \arg\max_k \left\{ d_t + \int_\theta^\infty p(s_t) f(s_t | k_t) ds_t \right\}; \quad (15)
   \]

2. Let h(.) be the pdf of θ. The posterior belief g(θ_t | s_t) is given by:

   \[
   g(θ_t | s_t) = \frac{f (s_t | k(θ_t)) h(θ_t)}{\int_{\theta}^{\infty} f(s_t | k(z)) h(z) dz}; \quad (16)
   \]

3. The pricing rule given s_t is:

   \[
   p(s_t) = E[γθ_t k(θ_t) | s_t] = γ \int_{\theta}^{\infty} θ_t k(θ_t) g(θ_t | s_t) dθ_t. \quad (17)
   \]

I focus on the case where k_t is linear in profitability parameter θ_t, which is consistent with the three benchmark models. The following proposition lists the pricing functions and investment functions in equilibrium.

**Proposition** A linear equilibrium investment strategy takes the form: k(θ_t) = B*θ_t, where B* is the root of equation:

\[
B^2 \sigma_θ^2 \left( \sqrt{\frac{2γ}{Bc - 1}} - 1 \right) - \sigma_θ^2 = 0. \quad (18)
\]

The market price at time $t$ is a quadratic form of the accounting report:

$$p(s_t) = \alpha_0 + \alpha_2 s_t^2,$$

where $\alpha_0 = (1 - \beta)B^*\gamma\sigma_\theta^2$, $\alpha_2 = \frac{B^*c - 1}{2B^*}$ and $\beta = \frac{B^*2\sigma_\theta^2}{B^*2\sigma_\theta^2 + \sigma^2}$. Equation (18) can also be expressed as $B^* = 1 + 2\gamma\beta^2$. Since $0 < \beta < 1$, and $\frac{1}{c} < B^* < \frac{1+2\gamma}{c}$, I can compare the equilibrium investment strategy to the benchmark cases:

$$B_{KP} < B^* < B_{PM}.$$  

Equilibrium investment is greater than the myopic investment in Section 3.1.2 but smaller than the over-investment case when investment is perfectly measured. In fact, when $2\beta^2 = 1$, the equilibrium investment is most efficient: $B^* = B^{FB}$. Since $\beta$ is a function of $B^*$, and there can be more than one root that solves Equation (18), I cannot analytically compare the current investment function with the first-best case. However, since the price-report relationship is uniquely defined as in Equation (19), I can identify empirically the equilibrium investment and price strategies under the assumption that the entire sample is generated from the same equilibrium. With the parameter estimates, I can recover the current investment function, the first-best investment function and the underlying level of reporting imprecision for the first-best.

4. Econometric Methodology

To evaluate the current investment function, I first estimate the parameter set of the model $\Phi = \{\sigma_\theta, \gamma, c, \sigma_\epsilon, \sigma_\eta\}$ using SMM. The five parameters include the uncertainty in profitability $\sigma_\theta$, the coefficient in long-term cash flow $\gamma$, marginal cost of investment $c$, imprecision in accounting measurement $\sigma_\epsilon$, and noise in earnings $\sigma_\eta$. In this section, I describe the data set used in the estimation and identification strategy.
4.1. Data

Table 1 reports the sample selection process. I employ financial data from Compustat North America Annual and stock return data from CRSP. The sample begins 1986 and ends in 2015. I only include firms listed in the main three stock exchanges: NYSE, American Stock Exchange, and Nasdaq. I exclude firms in financial and regulated industries (primary SIC codes 4800 – 4829, 4910 – 4949 or 6000 – 6999) because my investment model is not likely to be applicable to regulated or financial firms.

I use capital expenditures (CapEx) as a proxy for firms’ tangible investments, and R&D expenses for intangible investments. I do not have a theory of the interactions between tangible and intangible assets so, as a simplifying assumption, I estimate the models separately.\footnote{Similar practice is in Terry, Whited, and Zakolyukina (2018), where they estimate their growth model with R&D and selling, general and administrative expenses separately.} Furthermore, since empirically R&D expenses are missing for many firms, the sample composition will be different for firms involved in both tangible investment and research and development that are measured in the accounting system. The final CapEx sample consists of 40,469 firm-year observations and 6,116 unique firms, and the R&D sample contains 25,403 firm-year observations and 3,996 unique firms.

Table 2 lists the definitions of related variables and model correspondence. Since both the CapEx and R&D data (and after scaling) have fat tails, I use natural logarithms to transform the investment distribution, denoted as $\ln\text{CAPEXP}$ and $\ln\text{XRDS}$. Specifically, $\ln\text{CAPEXP}$ is calculated as the natural logarithm of capital expenditures scaled by lagged property, plant and equipment (gross). $\ln\text{XRDS}$ is defined as the natural log of R&D expense scaled by sales in the last fiscal year. Because the simulation process generates independent and identically distributed firms, I run the following regressions to capture firm and year fixed effects to control for the possible firm or time trend related heterogeneity, as in Hennessy and Whited (2007):

$$ Variables_{it} = \sum_t \beta_t Year_t + \sum_i \gamma_i \text{Firm}_i + e_{it}, \quad (21) $$

where $Variables$ are $\text{EPS}$, $\text{Ret}$, $\ln\text{CAPEXP}$ and $\ln\text{XRDS}$, while $Year_{-t}$ and $\text{Firm}_{-i}$ are
indicator variables. I use the residual values $e_{it}$ in each regression to proxy for the corresponding variable in the estimation. I trim the residuals at 1% and 99% to remove extreme values. $EPS_r$, $Ret_r$, $CAPEXP_r$ and $XRDS_r$ are the four residual values. Panel B in Table 2 provides the correspondence of between model variables and data variables. I use three variables for the moment calculation. I define shareholders’ return as shareholders’ total gain divided by the price they paid at $t - 1$. Shareholders’ earnings $d_t$ is represented by $EPS_r$. $CAPEXP_r$ and $XRDS_r$ correspond to investment report $s_t$. Note that after controlling for firm-year fixed effects, the variables should be viewed in relative terms. For example, a negative value of investment $CAPEXP_r$ or $XRDS_r$ suggests that the investment report is lower than the sample average.

Table 3 reports the summary statistics. The average total assets for the CapEx sample in Panel A is $2.8$ billion (the median is $337.1$ million), very close to the Compustat Universe. The CapEx sample has a slightly higher $MarketCap$ with median $357.8$ million, and lower $Book-to-market$ ratio of 0.482. Higher market capitalization suggests the sample contains relatively larger companies, and low book-to-market ratio indicates the sample firms have larger growth opportunities. Panel B lists the summary statistics for the R&D investment sample. The observations are more disperse, as the standard deviations of both $Assets$ and $MarketCap$ are larger than those in the CapEx sample. The $Book-to-market$ ratio is also lower, suggesting that firms in the R&D sample have more intangible assets.

### 4.2. Identification and estimation

I estimate the parameter set $\Phi = \{\sigma_\theta, \gamma, c, \sigma_c, \sigma_q\}$ using simulated method of moments (SMM) (McFadden, 1989; Pakes and Pollard, 1989). The process of SMM estimation is as follows. For each possible parameter set, I simulate a time series of profitability ($\theta_t$), investment report ($s_t$), short-term and long-term earnings ($x_t$ and $y_t$) and price ($p_t$). I use the simulated data to compute seven moments related to the three variables as stated in Panel B of Table 2. The optimal parameter set returns the minimal weighted square error. Also see Strebulaev and Whited (2012) for identification and detailed procedures for SMM.
of distance between the actual and simulated moments:

\[ \hat{\Phi} = \arg \min_{\Phi} g(\Phi)Wg(\Phi)', \]

where \( g(\Phi) \) is the mean difference between moments from the actual data and moments from simulated data, and \( W \) is the weight matrix. I calculate \( W \) as the inverse of the bootstrap variance-covariance moment matrix.

Identification is achieved by choosing moments that are informative about the structural parameters. A moment is informative about a parameter if the sensitivity of the moment to the parameter is high (Strebulaev and Whited, 2012). In other words, a change in the parameter can “move” the moment. In practice, most of the moments are affected by more than one parameter, while some moments are more sensitive to specific parameters than others. I use seven moments to identify five parameters. These moments include the mean and variance of investments, the variance of earnings, the variance of stock returns, and covariances between investments, stock returns, and earnings. Because of the multiple roots in Equation (18), most of the relationships are not directly observed. I perform a series of comparative statics, and here I highlight the intuition behind the sensitivities of each moment.

The first moment of interest is the imprecision in measurement \( \sigma_\theta \). This parameter determines the noise in measuring investment and thus maps positively into the variance of the investment report. Intuitively, stock price reacts more to the investment report if the investment report is more precise, which reflects on the negative correlation between the covariance between stock price and investment report and imprecision \( \sigma_\theta \). The second parameter is the long-term earnings multiple \( \gamma \). A large \( \gamma \) reflects that the cash flows generated by the project are more concentrated in the future. A higher coefficient of long-term profit increases the variance of stock price and the covariance of investment and stock price. Moreover, the mean of investment decreases in \( \gamma \) through \( B \). The variance of earnings and the covariance of earnings and investment also increase in \( \gamma \) through the component of long-term profit. The third parameter is the marginal cost of investment \( c \), which directly reduces incentive of investment. Both the variances and covariances
moments decrease in \( c \), with greater effect on the variance of investment. Imprecision in measurement \( \sigma_\epsilon \) is identified by two covariances jointly: covariance of return and earnings is increasing in \( \sigma_\epsilon \), while the covariance of investment and earnings is decreasing in \( \sigma_\epsilon \). Finally, \( \sigma_\eta \) is identified by the variance of return which is only increasing in \( \sigma_\eta \).

5. Results

This section presents the estimation results for capital expenditures and R&D samples, and evaluates the fit of the model.

5.1. Parameter estimates

CapEx Sample Panel A of Table 4 reports the parameter estimates from the SMM procedure and their standard errors using the CapEx sample. To interpret the estimates within the context of the model, I first calculate the investment sensitivity to profitability by plugging the parameter estimates into the polynomial equation of \( B \), as in Equation (18). The equation has only one real root, denoted as \( B^* = 1.05 \). For every unit change in profitability, the actual investment in capital expenditures changes by 1.05.

With the magnitude of investment sensitivity \( B^* \), I next examine profitability uncertainty and accounting imprecision. The estimate of the uncertainty in profitability \( \sigma_\theta \) is 0.50, comparable to Strebulaev and Whited (2012). Given the investment sensitivity of 1.05, the standard deviation of actual investment is calculated as 0.525 (1.05 \( \times \) 0.50). The estimate of accounting imprecision is 0.25. Since the investment report is a combination of actual investment and imprecision, an imprecision of 0.25 explains 32% \(( \frac{0.25}{\sqrt{0.525^2 + 0.25^2}} \) of the observed investment report variance. This suggests that for when the investment report changes by one standard deviation, there is an average of 32% noise, and the actual investment may change only by 68%. Accounting imprecision imposes significant informational friction. The estimate of the standard deviation of earnings noise is 0.29. Given that the model implied variation of earnings \( std(d_t) \) is 1.15, the imprecision in earnings is about 25% \((0.29/1.15) \) of the observed variation.
The coefficient $\gamma$ on the long-term profit is 2.57, indicating that the discounted long-term payoff is about 79% of the total payoff from the investment. Given that the sample of CapEx is composed of long-term tangible assets, it is reasonable that more than two thirds of the revenues are generated in more than one year. The marginal cost of investment $c$ is 4.19. This estimate is within the range of investment cost estimated in Liu, Whited, and Zhang (2009) (even though I do not model accumulation of capital stock). To interpret these estimates, I compare the short-term profit (loss) $x_t$ and long-term profit $y_t$. First, on average the short-term profit $x_t$ is negative for any realized profitability because of the high marginal cost of investment $c$. Second, the ratio of short-term and long-term payoff is $-1$ to 2.14. For one unit short-term loss, the long-term payoff is 2.14 units. The magnitudes of the payoffs are increasing in the absolute value of profitability. The net profit is on average positive. Lastly, the long-term profit $y_t$ is found to be more volatile than the short-term payoff $x_t$, as $\frac{\sigma_x}{\sigma_\theta} = 0.89$ and $\frac{\sigma_y}{\sigma_\theta} = 1.90$. For 100% variation in profitability, the variation in short-term payoff is 89%, while the long-term payoff varies for 190%.

R&D Sample Parameter estimates for the R&D sample are reported in Panel B of Table 4. I use the estimates to calculate the investment sensitivity to profitability from Equation (18). The polynomial equation again has only one real solution: $B^* = 0.98$. This means, for any realized profitability, the actual investment is 0.98 times of the profitability. The estimate of standard deviation of profitability $\sigma_\theta$ is 0.31, and thus the actual investment, which can be expressed as $B^*\theta$, has a standard deviation of 0.304. The degree of imprecision in the investment report $\sigma_\epsilon$ is 0.05, imposing a noise on the investment report of about $16.2\% \left( \frac{0.05}{\sqrt{0.304^2 + 0.05^2}} \right)$. This suggests that the actual investment variation accounts for 73.8% of the observed investment report. The estimate of the standard deviation of earnings noise is 0.16. The standard deviation of earnings implied by the model is 1.08, and the noise in earnings accounts for 15% (0.16/1.08) of the total variation.

Note that the difference in $\sigma_\theta$ in the two samples is mainly due to the difference in investment data: the standard deviation of $\text{CAPEXP}_r$ is 0.6 while the standard deviation of $\text{XRDS}_r$ is 0.321, and it should not to be interpreted as a difference in the profitability uncertainty.
The estimates for long-term earnings multiple $\gamma$ and the marginal cost of investment $c$ are both larger than those in the CapEx sample. The estimate of $\gamma$ is 5.83, indicating that profits are more concentrated in the long-term. Given a realized level of profitability, the long-term revenue from R&D investment is almost six times larger than its short-term revenue. The cost of investment $c$ is 12.32, suggesting that R&D investment requires a heavy initial input. Although the magnitudes of $\gamma$ and $c$ are larger than those for CapEx, it is not obvious compare across samples since the R&D sample is more concentrated.

To better interpret the implications of $\gamma$ and $c$, I next examine the payoffs generated by R&D investment in both periods. I find that R&D investment generates a negative average short-term payoff (loss) and a positive long-term profit. The ratio between short-term and long-term payoffs ($x_t$ vs. $y_t$) is $-1$ to $1.16$. The net profit is positive, but the difference between the two payoffs is not as big as that in the CapEx investment.

In terms of volatility, I compare the standard deviation of $x_t$ and $y_t$ to the variation of R&D profitability, and find that short-term payoff is twice more volatile than R&D profitability, as $\frac{\sigma_x}{\sigma_\theta} = 2.07$, and the variation of the long-term payoff is more than five times of the profitability, as $\frac{\sigma_y}{\sigma_\theta} = 5.4$.

It is worth mentioning that the accounting imprecision in capital expenditures is larger than in R&D. There are two possible explanations. First, under the guidance of the US Generally Accepted Accounting Principles (GAAP), capital expenditures are recorded as assets on the balance sheet and then depreciated over time, while R&D are expensed. In addition to the purchase price of the asset, GAAP allows companies to capitalize the associated initial setup cost, land and equipment improvements, and interest expenses incurred to construct the asset. The process of capitalizing these items inevitably involves subjective judgement and estimation that may not accurately reflect the economic facts, resulting in additional imprecision in reporting investment. On the other hand, GAAP requires that R&D expenditures be fully expensed in the period incurred; thus, there is less discretion involved and less reporting imprecision. Second, the limitation in my R&D data also contributes to the difference in accounting imprecision between the two samples. My R&D sample excludes firm-year observations with missing R&Ds. Koh and Reeb
(2015) point out that 10.5% of the missing R&Ds have patents (the ratio in my sample is 9.5%), suggesting that some firms conduct R&D activities without reporting them. In other words, the exclusion of observations without R&D cleans out part of the accounting imprecision in R&D reporting. As a result, the estimated degree of imprecision in R&D investment in my model is biased downward. Because the missing R&D observations account for 42% of my total sample, and when I replace the missing observations with zeros, the imprecision becomes too large for my model to accommodate.

5.2. Goodness of fit

Table 5 reports the seven simulated and estimated moments, and Figure 2 displays the histograms of the three main variables. The model replicates some salient characteristics of the data. In the CapEx sample, four out of seven pairs of moments are insignificantly different from each other, including the mean of the investment report, the variance of stock return, the covariance between stock return and the investment report, and the covariance between stock return and earnings. The model underestimates the variance of the investment report (Moment 4), but when I simulate the histogram of the investment report in Panel A of Figure 2, the difference is not economically significant. The model also underestimates the variance of earnings (Moment 5). Panel B of Figure 2 plots the histogram of earnings from actual data and model-simulated data. The actual earnings have more small negative observations in the range $[-5,-1]$ and fewer small positive observations in $[1.5,5]$. The simulated earnings also contain some large positive outliers. Nevertheless, the discrepancy is not large.

For the covariance between earnings and the investment report (Moment 7), the covariance of sample data is 0.118, while the model predicts a negative covariance of -0.003. In the model, the current investment $k_t$ only correlates with the short-term profit of $x_t$ in total earnings. The other part in the earnings $y_{t-1}$ is not related to current investment since $\theta_t$ is assumed to be i.i.d. Because of the negative short-term payoff for any given $\theta$ and thus the negative relation between $x_t$ and $k_t$, the covariance between total earnings and investment must be negative. In practice, however, profitability is likely to be serially
correlated, and so is investment. The long-term profit from last investment $y_{t-1}$ will be correlated with the current investment $k_t$. This correlation is positive and larger than that between $k_t$ and $x_t$ in absolute value, leading to an overall positive covariance of $k_t$ and total profits. In the model, each generation of investors only observes the current period investment report, and relaxing the i.i.d. assumption does not affect the analysis. Lastly, the histogram of stock return is plotted in Panel C of Figure 2. Note that after fixed effect regression, stock return $r_{t,r}$ is distributed around zero, although the actual mean of stock returns should be positive (sample average return is 2.6 in Table 3). This does not affect my estimation as the mean is not selected as one of the moments.

Both the model-simulated distribution and the data distribution have heavy right tails. On the whole, despite the overidentification of matching seven moments with five parameters, the fit is quite good.\textsuperscript{11}

The fitness of moments for the R&D sample performs similarly well to the CapEx sample. The seven targeted model and empirical moments for the R&D sample are reported in Panel B of Table 5. In general, moments are matched nicely – five out of seven moments do not display significant differences. The difference in the covariance of earnings and the investment report (Moment 7) is similar to the CapEx sample, due to the i.i.d. assumption for profitability. The model also overestimates the variance of the investment report. Panel A in Figure 3 plots the distribution of model and data investment reports. R&D investment in the data distribution has a higher kurtosis than a normal distribution, while the model assumes a normal distribution. The higher kurtosis also reflects on the variance as a higher kurtosis generates observations more concentrated around the mean. Panel B in Figure 3 is the earnings distribution, and Panel C plots the shareholders’ return. The two earnings distributions match each other nicely. The shareholders’ return distribution generated by the model mimics the heavy right tail in the data but has a higher kurtosis and less asymmetry.

\textsuperscript{11}Tests of the overidentifying restrictions are not reported for the usual reason of the large sample size (Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018; Terry, Whited, and Zakolyukina, 2018). Because the sample size is quite large, any minor deviation from the moments would lead to a rejection of the overidentifying restrictions.
6. Counterfactual Analysis

The parameter estimates allow me to answer four questions. Does the current imprecision in accounting lead to under- or over-investment? What is the optimal imprecision in accounting measurement that corresponds to the optimal investment strategy? How much information is lost due to the imprecision in the accounting report? Lastly, how are investors in the capital market affected by the imprecision?

These questions are inspired by and test the key message in real-effects theory: more information is not always desirable. I first quantify the information loss due to estimated accounting imprecision and the counterfactual degree of imprecision that allows optimal investment efficiency. Next I compute the difference in ex-ante welfare for investors between these two imprecision estimates.

6.1. Optimal imprecision

The benchmark cases in Section 3.1 provide closed form expressions on investment sensitivities $B$. I calculate $B^{FB}$, $B^{KP}$ and $B^{PM}$ (and $A^{PM}$) using the parameter estimates and report their values in Table 6. The current imprecision of accounting measurement is 0.25, corresponding to investment sensitivity $B^{*}$ of 1.05. When accounting measurement is precise, firms over-invest with sensitivity $B^{PM}$ of 1.47, suggesting that the degree of imprecision in the current accounting system has mitigated over-investment incentive by a substantial amount of 28.6%. The first-best investment sensitivity $B^{FB}$ is 0.85, which is smaller than the current sensitivity of $B^{*}$. This suggests that in general, firms still over-invest. Similarly, in the benchmark case when profitability is known $B^{KP} = 0.24$. Figure 4 plots the current investment-profitability relationship compared to the first-best scenario.

I next look for the accounting imprecision that allows the firm to achieve the first-best investment $B = B^{FB}$. Recall that for any parameter set $\Phi$, $B$ is the solution to Equation

\[12\] $A^{PM}$ is calculated as 0.92, suggesting that in the case when profitability is privately observed by the manager and investment is precisely measured, manager will invest 0.92 even when the profitability is realized as zero.
\[(18): B^2 \sigma^2_\theta \left( \sqrt{\frac{2 \gamma}{B^{FB} c - 1}} - 1 \right) - \sigma^2_\epsilon = 0. \] The optimal accounting imprecision can be calculated by plugging the estimates of \( \sigma_\epsilon, \gamma, c \) into the equation and substitute \( B \) with \( B^{FB} \)

\[
\sigma^2_\epsilon = B^{FB^2} \sigma^2_\theta \left( \sqrt{\frac{2 \gamma}{B^{FB^2} c - 1}} - 1 \right). \tag{23}
\]

The corresponding imprecision \( \sigma^{FB}_\epsilon \) is 0.28, which is 36\% of the total sample variation, greater than the current imprecision of 0.25 or 32\% of the sample variation. In fact, for any given investment sensitivity \( B \), Equation (23) suggests that there is a corresponding accounting imprecision \( \sigma_\epsilon \) as long as \( Bc - 1 > 0 \) and \( \sqrt{\frac{2 \gamma}{Bc - 1}} - 1 \geq 0. \) I plot the \( \sigma_\epsilon - B \) relationship in Figure 5. Investment sensitivity \( B \) is decreasing in \( \sigma_\epsilon \) in the trajectory from the estimated imprecision (0.25) to the optimal imprecision (0.28). Thus, increasing the imprecision in accounting measurement within an appropriate range can mitigate over-investment and increase investment efficiency.

In the R&D Sample, the current investment sensitivity \( B^* \) is 0.98. When accounting measurement is precise, firms invest with \( B^{PM} \) as 1.03, suggesting that a fully precise measure in R&D would worsen over-investment by 4.9\%.\(^{13}\) The first-best investment sensitivity \( B^{FB} \) is 0.55, smaller than the current sensitivity \( B^* \). Thus, as with the capital expenditures sample, firms over-invest in R&D, and the degree of over-investment is more significant than in the CapEx sample. Given the substantial cost of investment in R&D, the myopic investment under the situation of known profitability is highly inelastic, with \( B^{KP} \) being only 0.08. Figure 6 plots the sample investment function and the first-best investment function.

I plot the investment-imprecision relationship in Figure 7. The sample imprecision estimate is 0.05, or 16.2\% of the sample variation, as indicated in the round dot. To achieve the first-best investment level, imprecision of the accounting measurement should increase to 0.11, which corresponds to 35.7\% of the sample variation, greater than the sample imprecision by 19.5 percentage points. Consistent with the CapEx sample, the

\(^{13}\)For R&D sample, when there is information asymmetry on profitability but true investment is observable, the manager will still invest \( k = 0.44 \) even when profitability \( \theta = 0. \)
trajectory of \((\sigma, B)\) is decreasing from the current investment to the first-best investment.

6.2. Information loss

In all the benchmark cases, the market participants either observe or correctly conjecture the actual investment, and correctly infer the profitability of the project in equilibrium. In the current framework, however, the investment report is contaminated by accounting noise, and thus the market’s inference on profitability is no longer perfect.

To measure information loss, I follow the spirit of the earnings-management literature and focus on the capital market’s unresolved uncertainty about the profitability \(\theta\) upon observing the investment report \(s\).\(^{14}\) Define the measure of residual uncertainty as

\[
\sigma_{\theta|s} \equiv \sqrt{\text{Var}(\theta|s) / \sigma_\theta}.
\] (24)

If investment report \(s\) is accurate, investors can perfectly infer the value of profitability \(\theta\) from the report. In this case, no uncertainty remains since \(\text{Var}(\theta|s) = 0\) and thus \(\sigma_{\theta|s} = 0\). For the benchmark case with unknown profitability and perfect measurement, the residual uncertainty is zero. If \(s\) contains no information about \(\theta\) at all, the uncertainty on profitability will not change before or after observing the report \(s\). In this case, \(\sqrt{\text{Var}(\theta|s)} = \sigma_\theta\), and the measure of residual uncertainty \(\sigma_{\theta|s} = 1\). In fact, the residual uncertainty \(\sigma_{\theta|s}\) is increasing in the accounting imprecision, ranging from zero to one.

Table 7 reports the results. I compare the residual uncertainty estimated using the data and the residual uncertainty using optimal imprecision. The remaining uncertainty on profitability after observing the imprecise investment report is 38.9%. This suggests that information asymmetry caused a loss of 38.9% of information. Using optimal imprecision will cause a further loss in information of 21.9 percentage points, leading to a residual uncertainty of 60.8%. The large magnitude of residual uncertainty further supports the argument that achieving the optimal investment efficiency does not require precise measurement.

\(^{14}\)See Beyer, Guttman, and Marinovic (2018); Bertomeu, Cheynel, Li, and Liang (2019) and Bertomeu, Ma, and Marinovic (2019).
The R&D sample shows a similar pattern. A 21.1% residual uncertainty indicates that to the capital market, the imprecise investment report contains 21.1% less information on profitability. Using optimal imprecision would lead to a residual uncertainty of 74.2%, a more significant loss in information compared to the capital expenditures investment.

6.3. Welfare change

Recall that in the benchmark cases, the cost of deviating from the first-best scenario is solely borne by the firm’s owner because the market fully anticipates actual investment and thus profitability. This is no longer the case in the current noisy signaling equilibrium. Unable to perfectly conjecture the actual investment, the market has to bear part of the cost from over-investment. Thus, it is worthwhile to investigate the change in welfare for the firm’s shareholders and for capital market investors (shareholders in the next generation) by comparing the current equilibrium to the first-best. Note that unlike the literature in earnings management (Fischer and Verreechia, 2000; Bertomeu, Ma, and Marinovic, 2019), the firm’s owner does not necessarily benefit from the accounting noise in this framework. Recall that the owner’s objective function consists of the current period profit and the price of selling the firm. Although the firm is sold at a ‘premium’ because the capital market cannot perfectly infer the project profitability, the firm’s owner also incurs a loss in the short-term profit $x_t$ due to over-investment. Thus, it is not clear whether the selling price benefit can fully offset the loss in the short-term profit.

Define the difference between the equilibrium ex-ante expected welfare and first-best welfare for the current shareholders and the market investors as $\Delta W_{Firm}$ and $\Delta W_{Market}$, respectively:

$$\Delta W_{Firm} = \frac{\mathbb{E} [x_t + p_t - (x_t^{FB} + p^{FB})]}{\sqrt{\text{Var}(x_t^{FB} + p^{FB})}},$$ (25)

and

$$\Delta W_{Market} = \frac{\mathbb{E} [p^{FB} - p_t]}{\sqrt{\text{Var}(p^{FB})}}$$ (26)

Table 8 presents the results. In the CapEx sample, the firm’s owner benefits from the noisy equilibrium by 0.4%, yet this is not significantly different from zero. However,
market investors overpay by 4.2%. On the whole, the results suggest that the firm can offload all the cost of over-investment to the market. For the R&D sample, both the firm and the market are worse off compared to the first-best. The firm owner’s welfare drops by 12.1%, and the market’s welfare is reduced by 22%. Both parties incur greater losses than in the CapEx sample because of the significant amount of over-investment in R&D. Although the firm owner’s welfare drops, the noisy equilibrium still allows the firm to transfer a large portion of the cost to the market.

7. Conclusion and Future Work

In this study, I incorporate information on stock prices, investment reports, and earnings to estimate the real effects of accounting measurement under the framework of Kanodia, Singh, and Spero (2005). The main conclusion is that, the imprecision in measuring investment under the US accounting system has significantly reduced the degree of over-investment, but compared to the first-best, firms on average over-invest. Counterfactual analyses show that increasing the level of imprecision in CapEx investment by 4 percentage points of the profitability uncertainty can improve the market’s welfare by 4.2%. Allowing the noise in R&D investment to increase by 19.5 percentage points can raise the next generation of shareholders’ welfare by 22%.

My study contributes to the literature by quantifying the real effects of imprecision in accounting measurement and its impact on investors’ welfare. Such quantification analysis is important to the application of the real-effects theory. As stated in Kanodia and Sapra (2016), “identifying the real economic consequences of alternative accounting standards is of first-order importance to the accounting discipline.” However, such identification has been difficult to empirical research due to the lack of observable proxies. As a result, the real-effects theory stays largely untested, limiting its application to guide public policy on alternative disclosure standards. Structural estimation is well suited for this task, as it can quantify the predictions of a fully specified model that directly studies the effect of accounting choices on the behavior of the real economy. My paper is among the first
to meet the demand.

Several unique features of my approach are worth emphasizing. First, I try to keep the model simple by avoiding numerical dynamic estimation or heavy computational intensity such that the model can be applied to many samples and different settings. Second, the model assumes a linear production function and no asset accumulation. This simplification is imposed to illustrate the core trade-off in closed-form expressions. Third, I use the model to estimate the effects on information loss and welfare changes for both parties, providing an assessment of the economic importance of such a trade-off.

This paper serves as an initial attempt to quantify the real effects of accounting measurement. I focus on a simple semi-dynamic model where shareholders are fully myopic. Future researchers can extend the analysis to capture more frictions in the dynamic relation between accounting measurement and investment, and possibly with extra signals such as earnings. Moreover, this easy-to-implement methodology can be applied to evaluate certain accounting rules. For instance, development expenditures are capitalized in the UK after the adoption of IFRS; this provides a more precise measurement of firms’ productive R&D investments. My model will be suitable to this setting, as it can evaluate the effect of this decomposition of R&D reporting on corporate investment efficiency.
References


Table 1: Sample Selection

This table presents the sample selection process. Both CapEx and R&D sample start with the Compustat-CRSP merged dataset. I require non-missing lagged PPEGT for CapEx sample and non-missing lagged SALE for R&D sample.

<table>
<thead>
<tr>
<th></th>
<th>CapEx</th>
<th>R&amp;D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compustat/CRSP Observations from 1986-2015</td>
<td>115,885</td>
<td>115,885</td>
</tr>
<tr>
<td>Less: Missing earnings data</td>
<td>(971)</td>
<td>(971)</td>
</tr>
<tr>
<td>Missing stock return data</td>
<td>(36,012)</td>
<td>(36,012)</td>
</tr>
<tr>
<td>Missing investment data</td>
<td>(11,913)</td>
<td>(39,623)</td>
</tr>
<tr>
<td>Financial and regulated firms</td>
<td>(7,866)</td>
<td>(2,999)</td>
</tr>
<tr>
<td>Not listed in NYSE, AMEX or NASDAQ</td>
<td>(14,922)</td>
<td>(8,653)</td>
</tr>
<tr>
<td>Missing residuals from fixed-effect regressions</td>
<td>(1,209)</td>
<td>(737)</td>
</tr>
<tr>
<td>Trim variables at 1% and 99%</td>
<td>(2,523)</td>
<td>(1,577)</td>
</tr>
<tr>
<td><strong>Final Sample Size</strong></td>
<td>40,469</td>
<td>25,403</td>
</tr>
</tbody>
</table>
Table 2: Data Definitions and Variable Correspondence

This table presents data definitions for variables used in the estimation. Panel A describes the variable definition and data sources. Panel B summarizes the correspondence between model variables and data variables.

### Panel A. Variable Definition

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Assets</strong></td>
<td>Total Assets in millions (Compustat $AT$).</td>
</tr>
<tr>
<td><strong>Ret</strong></td>
<td>One plus buy-and-hold return from nine months before to three months after the fiscal-year-end date ((\exp(\sum_i \log(1 + \text{ret}_i)))).</td>
</tr>
<tr>
<td><strong>EPS</strong></td>
<td>Income before extraordinary items divided by common shares outstanding (Compustat $IB \times CSHO$), measured in millions.</td>
</tr>
<tr>
<td><strong>MarketCap</strong></td>
<td>Market capitalization in millions (Compustat $MKVALT$).</td>
</tr>
<tr>
<td><strong>Book-to-Market</strong></td>
<td>Common equity divided by $MarketCap$ (Compustat $CEQ/MKVALT$).</td>
</tr>
<tr>
<td><strong>lnCAPEXP</strong></td>
<td>The natural log of capital expenditures scaled by lagged property, plant, and equipment (gross). (Compustat $\log(\text{CapEx}/l.PPEGT)$).</td>
</tr>
<tr>
<td><strong>lnXRDS</strong></td>
<td>The natural log of R&amp;D expense scaled by lagged sales (Compustat $XRD/l.SALE$).</td>
</tr>
<tr>
<td><strong>EPS$_r$</strong></td>
<td>The residual values of $EPS$ regression on firm and year fixed effects.</td>
</tr>
<tr>
<td><strong>Ret$_r$</strong></td>
<td>The residual values of $Ret$ regression on firm and year fixed effects.</td>
</tr>
<tr>
<td><strong>CAPEXP$_r$</strong></td>
<td>The residuals of $lnCAPEXP$ regression on firm and year fixed effects.</td>
</tr>
<tr>
<td><strong>XRDS$_r$</strong></td>
<td>The residual of $lnXRDS$ regression on firm and year fixed effects.</td>
</tr>
</tbody>
</table>

### Panel B. Variable Correspondence

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model Correspondence</th>
<th>Data Correspondence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accounting report</td>
<td>$s_t$</td>
<td>$CAPEXP_r$, $XRDS_r$</td>
</tr>
<tr>
<td>Earnings</td>
<td>$d_t$</td>
<td>$EPS_r$</td>
</tr>
<tr>
<td>Shareholders’ return</td>
<td>$p_t + d_t$</td>
<td>$p_t / p_{t-1}$</td>
</tr>
<tr>
<td>Shareholders’ return</td>
<td>$p_t / p_{t-1}$</td>
<td>$Ret_r$</td>
</tr>
</tbody>
</table>
Table 3: Summary Statistics

This table presents the summary statistics of the samples. Panel A reports the statistics for CapEx sample and Panel B summarizes the R&D sample. The definitions are provided in Table 2. The last three variables in each panel are used in the estimation.

<table>
<thead>
<tr>
<th>Variables</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. CapEx Sample</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Assets</td>
<td>40,469</td>
<td>2,810</td>
<td>7,937</td>
<td>84.72</td>
<td>337.1</td>
<td>1,566</td>
</tr>
<tr>
<td>Ret</td>
<td>40,469</td>
<td>2.607</td>
<td>3.891</td>
<td>0.524</td>
<td>1.161</td>
<td>2.654</td>
</tr>
<tr>
<td>EPS</td>
<td>40,469</td>
<td>0.871</td>
<td>1.822</td>
<td>-0.049</td>
<td>0.651</td>
<td>1.687</td>
</tr>
<tr>
<td>Market Cap</td>
<td>40,440</td>
<td>3.298</td>
<td>10,204</td>
<td>77.31</td>
<td>357.8</td>
<td>1,646</td>
</tr>
<tr>
<td>Book-to-market</td>
<td>40,422</td>
<td>0.600</td>
<td>0.514</td>
<td>0.278</td>
<td>0.482</td>
<td>0.781</td>
</tr>
<tr>
<td>lnCAPEXP</td>
<td>40,469</td>
<td>-2.289</td>
<td>0.886</td>
<td>-2.811</td>
<td>-2.275</td>
<td>-1.735</td>
</tr>
<tr>
<td><strong>Data used in estimation:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EPS$_r$</td>
<td>40,469</td>
<td>0.014</td>
<td>1.217</td>
<td>-0.492</td>
<td>0.031</td>
<td>0.568</td>
</tr>
<tr>
<td>Ret$_r$</td>
<td>40,469</td>
<td>-0.071</td>
<td>3.302</td>
<td>-1.903</td>
<td>-0.565</td>
<td>0.673</td>
</tr>
<tr>
<td>CAPEXP$_r$</td>
<td>40,469</td>
<td>0.002</td>
<td>0.600</td>
<td>-0.351</td>
<td>0.003</td>
<td>0.356</td>
</tr>
<tr>
<td><strong>Panel B. R&amp;D Sample</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Assets</td>
<td>25,403</td>
<td>3.221</td>
<td>10,363</td>
<td>70.58</td>
<td>282.4</td>
<td>1,420</td>
</tr>
<tr>
<td>Ret</td>
<td>25,403</td>
<td>2.762</td>
<td>4.320</td>
<td>0.510</td>
<td>1.162</td>
<td>2.709</td>
</tr>
<tr>
<td>EPS</td>
<td>25,403</td>
<td>0.838</td>
<td>1.741</td>
<td>-0.104</td>
<td>0.577</td>
<td>1.650</td>
</tr>
<tr>
<td>Market Cap</td>
<td>25,381</td>
<td>4.117</td>
<td>13,524</td>
<td>76.82</td>
<td>345.8</td>
<td>1,725</td>
</tr>
<tr>
<td>Book-to-market</td>
<td>25,378</td>
<td>0.557</td>
<td>0.473</td>
<td>0.255</td>
<td>0.445</td>
<td>0.722</td>
</tr>
<tr>
<td>lnXRDS</td>
<td>25,403</td>
<td>-2.833</td>
<td>1.444</td>
<td>-4.010</td>
<td>-2.963</td>
<td>-1.916</td>
</tr>
<tr>
<td><strong>Data used in estimation:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EPS$_r$</td>
<td>25,403</td>
<td>0.016</td>
<td>1.087</td>
<td>-0.462</td>
<td>0.0327</td>
<td>0.523</td>
</tr>
<tr>
<td>Ret$_r$</td>
<td>25,403</td>
<td>-0.075</td>
<td>3.614</td>
<td>-2.041</td>
<td>-0.557</td>
<td>0.755</td>
</tr>
<tr>
<td>XRDS$_r$</td>
<td>25,403</td>
<td>-0.003</td>
<td>0.321</td>
<td>-0.126</td>
<td>-0.005</td>
<td>0.117</td>
</tr>
</tbody>
</table>
### Table 4: Parameter Estimates

This table presents the estimates of the parameter set $\Phi$ using SMM. The five parameters are $\{\sigma_\theta, \gamma, c, \sigma_\epsilon, \sigma_\eta\}$ with descriptions listed in Column 3. Column 4 reports their estimated values with standard errors from bootstrap in Column 5. Panel A reports estimates based on CapEx Sample, and Panel B is for R&D sample.

#### Panel A. CapEx Sample

<table>
<thead>
<tr>
<th>#</th>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>St. Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>$\sigma_\theta$</td>
<td>Uncertainty in profitability</td>
<td>0.50</td>
<td>(0.005)</td>
</tr>
<tr>
<td>2.</td>
<td>$\gamma$</td>
<td>Multiple of long-term earnings</td>
<td>2.57</td>
<td>(0.076)</td>
</tr>
<tr>
<td>3.</td>
<td>$c$</td>
<td>Marginal cost of investment</td>
<td>4.19</td>
<td>(0.057)</td>
</tr>
<tr>
<td>4.</td>
<td>$\sigma_\epsilon$</td>
<td>Measurement imprecision</td>
<td>0.25</td>
<td>(0.003)</td>
</tr>
<tr>
<td>5.</td>
<td>$\sigma_\eta$</td>
<td>Earnings noise</td>
<td>0.29</td>
<td>(0.008)</td>
</tr>
</tbody>
</table>

#### Panel B. R&D Sample

<table>
<thead>
<tr>
<th>#</th>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>St. Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>$\sigma_\theta$</td>
<td>Uncertainty in profitability</td>
<td>0.31</td>
<td>(0.010)</td>
</tr>
<tr>
<td>2.</td>
<td>$\gamma$</td>
<td>Multiple of long-term earnings</td>
<td>5.83</td>
<td>(0.508)</td>
</tr>
<tr>
<td>3.</td>
<td>$c$</td>
<td>Marginal cost of investment</td>
<td>12.32</td>
<td>(0.413)</td>
</tr>
<tr>
<td>4.</td>
<td>$\sigma_\epsilon$</td>
<td>Measurement imprecision</td>
<td>0.05</td>
<td>(0.013)</td>
</tr>
<tr>
<td>5.</td>
<td>$\sigma_\eta$</td>
<td>Earnings noise</td>
<td>0.16</td>
<td>(0.011)</td>
</tr>
</tbody>
</table>
Table 5: Model and Data Moments

This table reports the values of seven targeted moments calculated from actual data and the model. Column 3 is the empirical moment, while Column 4 uses data simulated from the model. The last column reports the $t$-statistics for the null hypothesis that the difference between each pair of moments equals zero. Panel A reports the moment values based on the CapEx Sample, and Panel B is about the R&D sample.

<table>
<thead>
<tr>
<th>#</th>
<th>Moments</th>
<th>Data</th>
<th>Model</th>
<th>$t$-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Variance of stock returns</td>
<td>10.903</td>
<td>11.040</td>
<td>-0.68</td>
</tr>
<tr>
<td>2.</td>
<td>Covariance of stock returns and investment reports</td>
<td>0.003</td>
<td>0.022</td>
<td>-0.96</td>
</tr>
<tr>
<td>3.</td>
<td>Mean of investment reports</td>
<td>0.002</td>
<td>0.001</td>
<td>0.34</td>
</tr>
<tr>
<td>4.</td>
<td>Variance of investment reports</td>
<td>0.360</td>
<td>0.345</td>
<td>4.08</td>
</tr>
<tr>
<td>5.</td>
<td>Variance of earnings</td>
<td>1.481</td>
<td>1.309</td>
<td>6.44</td>
</tr>
<tr>
<td>6.</td>
<td>Covariance of stock returns and earnings</td>
<td>0.004</td>
<td>0.043</td>
<td>-1.44</td>
</tr>
<tr>
<td>7.</td>
<td>Covariance of earnings and investment reports</td>
<td>0.118</td>
<td>-0.003</td>
<td>23.36</td>
</tr>
</tbody>
</table>

Panel B. R&D Sample

<table>
<thead>
<tr>
<th>#</th>
<th>Moments</th>
<th>Data</th>
<th>Model</th>
<th>$t$-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Variance of stock returns</td>
<td>12.990</td>
<td>13.064</td>
<td>0.24</td>
</tr>
<tr>
<td>2.</td>
<td>Covariance of stock returns and investment reports</td>
<td>0.001</td>
<td>0.013</td>
<td>1.02</td>
</tr>
<tr>
<td>3.</td>
<td>Mean of investment reports</td>
<td>-0.005</td>
<td>-0.003</td>
<td>0.67</td>
</tr>
<tr>
<td>4.</td>
<td>Variance of investment reports</td>
<td>0.098</td>
<td>0.103</td>
<td>3.39</td>
</tr>
<tr>
<td>5.</td>
<td>Variance of earnings</td>
<td>1.167</td>
<td>1.182</td>
<td>0.58</td>
</tr>
<tr>
<td>6.</td>
<td>Covariance of stock return and earnings</td>
<td>0.081</td>
<td>0.047</td>
<td>-0.96</td>
</tr>
<tr>
<td>7.</td>
<td>Covariance of earnings and investment reports</td>
<td>0.001</td>
<td>-0.029</td>
<td>-7.36</td>
</tr>
</tbody>
</table>
Table 6: Counterfactual Analysis

This table presents the results of counterfactual analysis. Results for CapEx Sample is reported in Panel A and Results for the R&D Sample. Column One list the models including the noisy signaling (the current investment strategy) and the three benchmark cases. Column Two is the expressions of the investment sensitivity $B$ in each benchmark case. Column Three is the value of $B$ according to the parameter estimated by the model. Column Four is the level of imprecision in accounting in the noisy signal model given the investment sensitivity $B$. The level of imprecision is calculated using: $\sigma_e^2 = B^2\sigma_\theta^2 \left( \sqrt{\frac{2\gamma}{Bc+1}} - 1 \right)$. Standard errors are in parentheses.

### Panel A. CapEx Sample

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>$B$</th>
<th>$\sigma_e$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model</td>
<td>Estimate</td>
</tr>
<tr>
<td>Noisy Signalling</td>
<td>-</td>
<td>1.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.011)</td>
</tr>
<tr>
<td>First-Best Investment</td>
<td>$\frac{1 + \gamma}{c}$</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.023)</td>
</tr>
<tr>
<td>Known Profitability</td>
<td>$\frac{1}{c}$</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Perfect Measurement</td>
<td>$\frac{1 + 2\gamma}{c}$</td>
<td>1.47</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.044)</td>
</tr>
</tbody>
</table>

### Panel B. R&D Sample

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>$B$</th>
<th>$\sigma_e$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model</td>
<td>Estimate</td>
</tr>
<tr>
<td>Noisy Signalling</td>
<td>-</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.024)</td>
</tr>
<tr>
<td>First-Best Investment</td>
<td>$\frac{1 + \gamma}{c}$</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.059)</td>
</tr>
<tr>
<td>Known Profitability</td>
<td>$\frac{1}{c}$</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Perfect Measurement</td>
<td>$\frac{1 + 2\gamma}{c}$</td>
<td>1.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.117)</td>
</tr>
</tbody>
</table>
Table 7: Information Loss

This table reports the estimates of residual uncertainty in profitability and price. The residual uncertainty in profitability is defined as $\sigma_{\theta|s} \equiv \frac{\sqrt{\text{Var}(\theta|s)}}{\sigma_\theta}$. Standard errors are reported in parentheses. Panel A displays results for the CapEx sample and Panel B is for the R&D sample.

| Residual Uncertainty $\sigma_{\theta|s}$ | Estimated imprecision | Optimal Imprecision |
|----------------------------------------|-----------------------|---------------------|
| **Panel A. CapEx Sample**              |                       |                     |
| Estimates                              | 0.389                 | 0.608               |
| sd.error                               | (0.002)               | (0.012)             |
| **Panel B. R&D Sample**                |                       |                     |
| Estimates                              | 0.158                 | 0.541               |
| sd.error                               | (0.018)               | (0.000)             |

Table 8: Welfare change

This table reports the change in ex-ante welfare compared to First-best model. The change in welfare for the firm’s current shareholders is defined as $\Delta W_{\text{Firm}} \equiv \frac{E[x_t + p_t - (x_{FB} + p_{FB})]}{\sqrt{\text{Var}(x_{FB} + p_{FB})}}$. The change in investors’ welfare is $\Delta W_{\text{Market}} \equiv \frac{E[p_{FB} - p_t]}{\sqrt{\text{Var}(p_{FB})}}$. Standard errors are reported in parentheses.

<table>
<thead>
<tr>
<th>Welfare Change</th>
<th>Firm</th>
<th>Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta_{\text{Firm}}$</td>
<td>0.004</td>
<td>-0.042</td>
</tr>
<tr>
<td>St.error</td>
<td>(0.016)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Panel B. R&amp;D Sample</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimates</td>
</tr>
<tr>
<td>St.error</td>
</tr>
</tbody>
</table>
This figure includes the histograms of data simulated variables for the CapEx sample. In Panel A, investment report for data sample uses variable $CAPEXP_r$, which corresponds to $s_t$ in the model. Panel B plots the distributions of earnings, which is $EPS_r$ in the data and $d_t$ in the model. Panel C displays the shareholders’ return distributions. The data histogram is from the variable $Ret_r$ and the simulated variable is calculated as $\frac{p_t + d_t}{p_{t-1}}$. To better compare the distribution, I demeaned the simulated return data. See Panel B of Table 2 for the definitions.

(a) Accounting Report

(b) Earnings

(c) Shareholders’ return
Figure 3: Data and Simulated Variables – R&D Sample

This figure includes the histograms of data simulated variables for the R&D sample. In Panel A, investment report for data sample uses variable \( XRD_{s,t} \), which corresponds to \( s_t \) in the model. Panel B plots the distributions of earnings, which is \( EPS_{s,t} \) in the data and \( d_t \) in the model. Panel C displays the shareholders’ return distributions. The data histogram is from the variable \( Ret_{s,t} \) and the simulated variable is calculated as \( \frac{p_t + d_t}{p_{t-1}} \). See Panel B of Table 2 for the definitions.

(a) Investment Report

(b) Earnings

(c) Shareholders’ return
Figure 4: Investment Strategy – CapEx Sample

This figure displays the investment functions. The solid line is the estimated investment function using CapEx sample with a slope $B = 1.05$. The dotted line is the optimal investment function as in the first-best benchmark case, which can also be achieved when $\sigma_\epsilon = 0.28$. The slope of the optimal investment function is $B^{FB} = 0.85$. 
Figure 5: Imprecision and Investment Sensitivities – CapEx Sample

This figure plots the relation between accounting measurement noise $\sigma_\epsilon$ and investment sensitivity $B$, calculated using Equation (18): $B^2 \sigma_\theta^2 \left( \frac{2\gamma}{Bc - 1} - 1 \right) - \sigma_\epsilon^2 = 0$, where the parameters $\sigma_\theta$, $\gamma$ and $c$ are substituted with estimates from the CapEx sample. The round dot is the estimated relation, with $\sigma_\epsilon$ of 0.25 and $B$ of 1.05. The diamond dot corresponds to the accounting measurement noise $\sigma_\epsilon = 0.28$ and the sensitivity of the optimal investment function, $B^{FB} = 0.85$. 
This figure displays the investment functions. The solid line is the estimated investment function using R&D sample with a slope $B = 0.98$. The dotted line is the optimal investment function as in the first-best benchmark case, which can also be achieved when $\sigma_x = 0.28$. The slope of the optimal investment function is $B^{FB} = 0.55$. 
Figure 7: Imprecision and Investment Sensitivity – R&D Sample

This figure plots the relation between accounting measurement noise $\sigma_\epsilon$ and R&D investment sensitivity $B$. It is calculated using Equation (18): $B^2 \sigma_\theta^2 \left( \frac{2\gamma}{Bc - 1} - 1 \right) - \sigma_\epsilon^2 = 0$, where the parameters $\sigma_\theta$, $\gamma$, and $c$ are substituted with estimates from the R&D sample. The round dot is the estimated relation, with $\sigma_\epsilon$ of 0.05 and $B$ of 0.98. The diamond dot corresponds to the accounting measurement noise $\sigma_\epsilon = 0.11$ and the sensitivity of the optimal investment function, $B^{FH} = 0.55$. 