How Much Value Does Accounting Imprecision Enhance?

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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), in which there is information asymmetry about profitability and investment. I show 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, I show that the optimal investment efficiency can be achieved by reducing the current accounting precision by 6% (20%) in capital expenditures (R&D), which increases investor welfare by 4.2% (22%). My study is among the first to provide a quantitative assessment of real effects of accounting measurement and presents early evidence that demonstrates potential negative effects of excessive precision in accounting.

Keywords: accounting measurement; real effects; economic efficiency

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

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1. Introduction

Theory suggests that a certain degree of imprecision in measuring firms' investment can be value-enhancing (Kanodia, Singh, and Spero 2005). The postulate of the second-best theory (Lipsey and Lancaster, 1956) provides the intuition for this assertation: when there are two market frictions, in this case, asymmetric information about *both* profitability and investment level, resolving one of the two could do more harm than good. Specifically, expecting that the market will interpret high observable investment as high profitability, a firm will over-invest to signal its profitability.[1] An imprecise investment measure weakens the market's response to investment, reducing the incentive for over-investment. Excess imprecision is not ideal, either. Since the market price of the firm is no longer sensitive when the investment measure is too noisy, the firm will invest in a myopic way. Therefore, in a similar vein to real effects models (Kanodia, 2007; Kanodia and Sapra, 2016), the optimal level of imprecision is interior and a function of the characteristics of the decision problem.

Despite their broad intuitive appeal, real effects models are difficult to test. Investments can be made in an economy specified by real effect theory, where more information could cripple decision-making. They can also be made in a simple Robinson Crusoe economy where more information improves decision-making (Demski, 1973). When the two types of investments co-exist in the data, distinguishing them has eluded empirical researchers. Moreover, even if we can identify investments made under the real effects theory, it is difficult to conclude from empirical facts whether we are above or below the optimal precision. For this reason, most of the empirical literature has focused on documenting real consequences from information dissemination.[2] Yet, empirical literature has failed to propose accounting policies that would adequately address the optimal

[1]See also other applications of the signaling role of investment in the real effects literature, e.g., Spence (1974); Sapra (2002); Beyer and Guttman (2012); Bertomeu and Cheynel (2015); Gao and Jiang (2018).

[2]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).

accounting precision guided by real effects theory.

My study uses 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 also crucial to accounting standard setting. Admittedly, real effects theory is acknowledged as one of the overriding criteria to evaluate potential rules, but in practice, standard setters have given up utilizing the theory to conduct economic analyses (Glover, 2014). This is partly due to the difficulties with empirical measurement, which render real effects theory untestable and largely ignored. As a result, standard-setting has been marred by debates about whether accounting can suitably address the challenges caused by asymmetric information. In comparison to other forms of public policing that are evaluated by welfare assessments and economic policy implications, accounting standard setting lags behind in connecting theoretical models and empirical analysis to policy.[3]

To overcome this difficulty, I start with a simple investment model on an overlapping generation setting that is closely anchored on Kanodia, Singh, and Spero (2005). The firm manager makes investment decisions on behalf of the 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 shareholder has to sell the firm before the long-term profit evolves. In this model, the manager chooses

[3] Research 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).

investment to maximize the firm price instead of terminal profits. This implies that given the firm's private information, the price-maximizing investment policies need not be the value-maximizing policy. In other words, price efficiency does not necessarily lead to economic efficiency.

The capital market sets the price of the firm according to the imprecise investment report. The quality of the investment report depends entirely on the accounting standard, and the manager has no discretion to manipulate the report. Due to the unavoidable judgment and subjectivity of accounting methods, accounting measurement is fraught with imprecision (Hoogervorst, 2012). The degree of investment report imprecision is the primary variable of interest in my estimation. After estimating the parameters, I conduct counterfactual analysis to calculate the degree of imprecision that could help companies achieve optimal investment efficiency. This optimal degree of imprecision provides a benchmark for me to evaluate the estimated imprecision (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 can best line up with those calculated using the empirical sample. 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 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 policies, I find that investment efficiency would be improved by *reducing* measurement precision about investments. The first-best level of investment is implemented when decreasing investment efficiency by 6% for capital expenditures and by 20% for R&D. As noted in real effects theories (Kanodia and Sapra, 2016), more information is not always preferred. I show that, although using the optimal imprecision will cause a further loss of information, firm values would rise by 4.2% for capital expenditures sample and 22% for R&D sample. These findings show that accounting measurement has a first-order effect on firm values through investments.

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 on testing and quantifying predictions from real-effect models. As a starting point, I use structural estimation to assess the real effect of imprecision in the current accounting system and provide directional guidance towards 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 market's welfare, and the loss of information due to accounting imprecision.

Second, the paper provides an empirical implementation of investment efficiency. I use the general approach of real effect models that focuses on managers maximizing prices. Although the model makes several demanding assumptions about functional forms and horizons, my objective is to capture one plausible first-order trade-off. In return for the assumptions, I am able to develop 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 also recognize that, by trying to bind to a particular real effect model as tightly as possible, I do not incorporate other empirical features as well as other real effects trade-offs of the model. Although it would be challenging to write a model to reflect all such complexities, I hope that more work on this general problem can help facilitate the understanding over 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 the parameter estimates, assesses the model's fit with the data, and provides validation tests. Section 6 examines the effect of altering accounting precision on the firm's investment efficiency, residual information uncertainty, as well as the firm's shareholders and the market's welfare. The last section concludes.

2. Related Literature

Theory on real effects states that accounting rules on measurement and disclosure have significant effects on firms' real decisions (Kanodia and Sapra, 2016). Starting with Kanodia (1980), the literature on real effects of accounting 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), other 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). Among these literature, there are two distinguished features about the real effects framework: first, the firm's manager has superior information over the market upon the corporate decisions are made; and second, the firm manager maximizes the firm's short-term price instead of terminal cash flows.

Most of the empirical accounting literature on investment efficiency utilizes 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 whether accounting has 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 price and firm decisions – the essential feature of real effects theory. Unfortunately, finding an exogenous variation in price motives that could render a clean reduced-form assessment of real effects is very difficult. Besides, 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 functional assumptions, it allows me to provide counterfactual analyses to evaluate the 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 manager myopia. The fundamental difference in their paper is that the market observes a perfectly measured investment and an imprecise report on earnings. Besides, they develop and calibrate a dynamic model to evaluate the magnitude of real effects while I utilize 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.

Some 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 much more ambitious along the dimensions of fully understanding dynamic investment patterns. However, the questions answered in these models are different, as they do not model the real effects between endogenous prices and the subsequent investment inefficiencies. I write 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 object to estimate the effect of an accounting information flow on investment while setting aside strategic information management. Different from my paper, managers do not maximize short-term prices in their studies. 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, Cheynel, Li, and Liang (2019) focus specifically on estimating earnings management using cross-sectional properties of earnings and price. Unlike in 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 "Big 4" firm 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 the features in executives' labor market and Li (2018) studies the 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 discretion, 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, Cheynel, Li, and Liang (2019); Bertomeu, Marinovic, Terry, and Varas (2017), managers strategically withhold information when they are informed (Dye, 1985). These approaches are different from my model because the manager does not make an investment decision but has discretion on voluntary disclosures. However, consistent 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

In this section, I briefly develop the model notation of Kanodia, Singh, and Spero (2005) (hereafter KSS), lay out the core intuitions in the theory and present three benchmark cases which will be empirically evaluated later. Note that these are not specific to my paper but they are critical to interpret the quantitative trade-offs.

Consider an overlapping generation setting where a representative shareholder buys the firm from the last generation, holds it for one period and sells it to the next generation of investors at the end. The shareholder delegates the decision making to the firm manager who maximizes the current shareholder's 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. The short-term profit is defined as the economic revenue net of the cost of investment

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

where $\tilde{\theta}_t$ represents 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 μ_θ and variance σ_θ^2. Before the manager makes the investment decision, he privately observes the project profitability θ_t. Lastly, $\tilde{\eta}_t$ is the noise in earnings, which is normally distributed with mean zero and variance σ_η^2. 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 shareholder, while the long-term profit is not realized until period $t+1$. Define the long-term profit from the time t project as

$$\tilde{y}_t = \gamma \tilde{\theta}_t k_t, \tag{2}$$

where γ can be viewed as a combination of earnings multiple, discount factor or the correlation between short-term and long-term cash flows. The current shareholder also receives 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

$$\tilde{d}_t = \tilde{x}_t + \tilde{y}_{t-1}. \tag{3}$$

At the end of period t, the firm issues an accounting report s_t about investment k_t. Due to the feature of the accounting system, the investment is measured with noise:

$$\tilde{s}_t = k_t + \tilde{\epsilon}_t, \tag{4}$$

where $\tilde{\epsilon}_t$ is normally distributed with mean zero and variance σ_ϵ^2. The distribution of $\tilde{\epsilon}_t$ is common knowledge. $\tilde{\epsilon}_t$ is independent from $\tilde{\theta}_t$ and $\tilde{\eta}_t$. The noise $\tilde{\epsilon}_t$ represents the estimation and random errors along with the measurement process. For example, depending on the business model, a debt security is measured at market value when it is held for trading purposes, but it is reported at historic cost if it is held to maturity. It is possible that a government bond held to maturity would be valued at a higher price than the same bond held in a trading portfolio, where it may be subject to a discount.

Assume all investors in the capital market are risk-neutral, the price is set as the conditional expectation of the long-term profit y_t given the investment report s_t

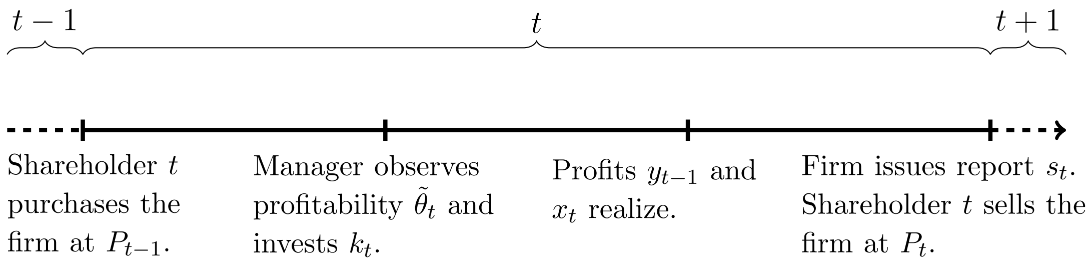
$$P(s_t) = E(y_t|s_t). \tag{5}$$

Given the pricing function, the manager chooses k_t to maximize current shareholder's total expected payoff. Define the manager's optimization problem as follows:

$$\max_{k_t} E(d_t + p_t). \tag{6}$$

The timeline of the game can be described in Figure 1.

Figure 1: Model Timeline



3.1. Benchmark Cases

There are two sources of information asymmetry in the model: the manager has private information about the project profitability θ_t and 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. Next, I add a layer of friction by considering a setting where the profitability θ_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 accounting system to measure investment precisely.

3.1.1 Investment with Full Information

The first-best scenario happens when the profitability θ_t is common knowledge and firm's investment k_t can be measured precisely. The price function can be expressed as

$$P_t = \mathbf{E}\left(y_t | k_t, \theta_t\right) = \gamma \theta_t k_t, \tag{7}$$

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

$$\max_{k_t} \mathbf{E}(d_t + P_t) = \max_{k_t} \left\{ \theta_t k_t - \frac{1}{2} c k_t^2 + \gamma \theta_{t-1} k_{t-1} + \gamma \theta_t k_t \right\}. \tag{8}$$

Take the first order condition of (8) is linear in θ_t:

$$K_t^{\text{FB}} = \left(\frac{1+\gamma}{c} \right) \theta_t, \tag{9}$$

Denote $B_t^{\text{FB}} = \dfrac{1+\gamma}{c}$ as the sensitivity of investment function. Substituting θ_t with k_t in equation in Equation (7):

$$P_t^{\text{FB}}(k_t) = \frac{c\gamma}{1+\gamma} k_t^2. \tag{10}$$

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 defined as $\tilde{s}_t = k_t + \tilde{\epsilon}_t$ and $\tilde{\epsilon}_t \in N(0, \sigma_\epsilon)$. The market knows profitability θ_t, observes report s_t and sets the price based on them. In a pure strategy equilibrium, the firm chooses 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 written as:

$$K^{\text{KP}}(\theta_t) = \frac{1}{c}\theta_t, \tag{11}$$

Denote $B^{\text{KP}} = \dfrac{1}{c}$. The equilibrium pricing rule is:

$$P^{\text{KP}}(k_t) = c\gamma k_t^2. \tag{12}$$

The equilibrium investment sensitivity B^{KP} is lower than B^{FB}. The reason for under-investment is that equilibrium price is not set based on firm's actual investment. Instead, the market anticipates an investment level based on θ_t and sets the price according to its anticipation. Since the market *a priori* knows the profitability θ_t, it can perfectly anticipates how the firm invests given θ_t. When the market observes a report different from the anticipated level, it attributes the difference to the noise in measurement 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 the profitability θ_t is private information to the firm, but the accounting system is able to generate a precise investment report. In this case, the capital market investors update their belief on profitability θ_t when they observe the size 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 (1973): high investment is more attractive to firms with high profitability and so investment serves to separate low and high profitability types. Then, a Spence-like fully revealing signalling equilibrium exists, where investors correctly infer the profitability θ_t. In this signalling equilibrium, the firm's investment function is defined as

$$K_t^{\mathrm{PM}} = \left(\frac{1+2\gamma}{c}\right)\theta_t. \tag{13}$$

Let $B^{\mathrm{PM}} = \dfrac{1+2\gamma}{c}$. The capital market's pricing function can be expressed as a function of investment

$$P_t^{\mathrm{PM}}(k_t) = \frac{c\gamma}{1+2\gamma}k_t^2. \tag{14}$$

Since $B^{\mathrm{PM}} = \dfrac{1+2\gamma}{c} > \dfrac{1+\gamma}{c} = B^{\mathrm{FB}}$, the firm over-invests compared to the first-best for any given profitability θ_t. The intuition behind the over-investment is that investment conveys information about the project profitability. In this case, the firm with a low profitability type is inclined to choose a high investment level in an effort to be perceived as a high type. Investors revise their inferences in equilibrium until they perfectly conjecture the underlying profitability. In equilibrium, the price function is less sensitive to investment as is shown by comparing $P_t^{\mathrm{PM}}(k_t)$ to $P_t^{\mathrm{FB}}(k_t)$. This is a suboptimal equilibrium as the firm is induced to over-invest and, once the firm price is fully adjusted, the cost of over-investment is borne by the current shareholder alone.

3.2. Unknown profitability and imprecise investment

The benchmark models provide good references, yet in practice it is more realistic to assume information asymmetry on both profitability and investment. Managers have access to more firm-specific information that is not available to the capital market and accounting measurements of investments are not 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 θ_t. The market price is then set based on the posterior belief $g(\theta_t|s_t)$ and $\hat{K}(\theta_t)$. The manager, then, conjectures the price function $\hat{P}(s_t)$ and chooses k_t to maximize the current shareholder's expected payoff. In equilibrium, both the conjectured functions are correct: $\hat{P}(s_t) = P(s_t)$ and $\hat{K}(\theta_t) = K(\theta_t)$.

Definition of Equilibrium A noisy signalling equilibrium contains three functions: the manager's investment strategy $K(\theta_t)$, investors' Bayesian posterior belief $g(\theta_t|s_t)$ and a pricing rule $P(s_t)$, and they satisfy the following three conditions:

[1] For any given $P(s_t)$, the optimal investment satisfies:

$$K(\theta_t) = \arg\max_{k_t} \left\{ \theta k_t - \frac{c}{2}k_t^2 + d_t + \int_{\underline{s}}^{\bar{s}} P(s_t) f(s_t|k_t) ds_t \right\}; \tag{15}$$

[2] Let $h(.)$ be the pdf of θ. The posterior belief $g(\theta|s)$ is defined as:

$$g(\theta_t|s_t) = \frac{f\left(s_t|K_t(\theta_t)\right) h(\theta_t)}{\int_{\underline{\theta}}^{\bar{\theta}} f(s_t|K(z))h(z)dz}; \tag{16}$$

[3] The pricing rule given s_t is:

$$P(s_t) = E\big[\gamma\theta_t K(\theta_t)|s_t\big] = \gamma \int_{\underline{\theta}}^{\bar{\theta}} \theta_t K(\theta_t) g(\theta_t|s_t) d\theta_t. \tag{17}$$

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: $K(\theta_t) = B^*\theta_t$, where B^* is the root of equation:[4]

$$B^2\sigma_\theta^2 \left(\sqrt{\frac{2\gamma}{Bc-1}} - 1\right) - \sigma_\epsilon^2 = 0. \tag{18}$$

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

$$P(s_t) = \alpha_0 + \alpha_2 s_t^2, \tag{19}$$

where $\alpha_0 = (1-\beta)B^*\gamma\sigma_\theta^2$, $\alpha_2 = \dfrac{B^*c-1}{2B^*}$ and $\beta = \dfrac{{B^*}^2\sigma_\theta^2}{{B^*}^2\sigma_\theta^2 + \sigma_\epsilon^2}$.

Equation (18) can also be expressed as $B^* = \dfrac{1+2\gamma\beta^2}{c}$. Since $0 < \beta < 1$, so $\dfrac{1}{c} < B^* < \dfrac{1+2\gamma}{c}$ and I can compare the equilibrium investment strategy to the benchmark cases:

$$B^{\text{KP}} < B^* < B^{\text{PM}}. \tag{20}$$

Equilibrium investment is greater than the myopic investment in Section 3.1.2 but also smaller than the over-investment case when invesment is perfectly measured. In fact, when $2\beta^2 = 1$, the equilibrium investment is most efficient: $B^* = B^{\text{FB}}$. Since β 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 which equilibrium is being played under the assumption that the entire sample

[4]See Kanodia, Singh, and Spero (2005) for the detailed proof.

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 σ_θ, the coefficient in long-term cash flow γ, marginal cost of investment c, imprecision in accounting measure σ_ϵ and noise in earnings σ_η. 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 starts from 1986 and ends in 2015. I only include firms listed in the main three stock exchanges: NYSE, American Stock Exchange and Nasdaq. I also 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 expenditure (CAPX) to proxy for firm's tangible investment and R&D expenses for intangible investment. I do not have a theory of the interactions between tangible and intangible assets so, as a simplifying assumption, I estimate the models separately. [5] 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 CAPX 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

[5] Similar practice can be found in Terry, Whited, and Zakolyukina (2018), where they estimate their growth model with R&D and sales general and administrative expenses separately.

both the CAPX and R&D data have heavy tails, I use natural logarithm to transform the investment distribution, denoted as *lnCAPXP* and *lnXRDS*. Specifically, *lnCAPXP* is calculated as the natural logarithm of capital expenditure scaled by lagged property, plant and equipment (gross). *lnXRDS* 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):

$$Variables_{it} = \sum_t \beta_t Year_t + \sum_i \gamma_i Firm_i + e_{it}, \tag{21}$$

where $Variables$ are *EPS*, *Ret*, *lnCAPXP* and *lnXRDS*, while *Year_t* and *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*, *CAPXP_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 shareholder's total gain divided by the price she paid at $t-1$. Shareholder's earnings d_t is represented by *EPS_r*. *CAPXP_r* and *XRDS_r* correspond to investment report s_t.

Table 3 reports the summary statistics. The average total assets for the CAPX sample in Panel A is $2.8 billions and median $337.1 millions, very close to the Compustat Universe. The CAPX 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 R&D investment sample. The observations are more disperse, as the standard deviations of both *Assets* and *MarketCap* are larger than those in the CAPX sample. The *Book-to-market* ratio is also lower, suggesting that firms the R&D sample consist of more intangible assets.

4.2. Identification and Estimation

I estimate the parameter set $\Phi = \{\sigma_\theta, \gamma, c, \sigma_\epsilon, \sigma_\eta\}$ using SMM (McFadden, 1989; Pakes and Pollard, 1989).[6] The process of SMM estimation is as follows. For each possible parameter set, I simulate a time series of profitability (θ_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 should return the minimal weighted square of distance between the actual and simulated moments:

$$\hat{\Phi} = \arg\min_{\Phi} g(\Phi) W g(\Phi)', \tag{22}$$

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 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 utilize seven moments to identify five parameters. These moments include the mean and variance of investment, the variance of earnings, the variance of stock return, and covariances between investment, stock return, 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 σ_θ. This parameter determines the noise in measuring investment and thus maps positively into the variance of investment report. It also affects investment sensitivities B, which in turn affects the

[6] Also see Strebulaev and Whited (2012) for identification and detailed procedures for SMM.

mean of investment report (negatively), variance of investment report (positively) and the covariance of investment report and earnings (positively). The second parameter is the long-term earnings multiple γ. A large γ represents that the cash flows generated by the project is 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 γ through B. The variances of earnings and the covariance of earnings and investment also increase in γ 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 decreases with c, with stronger effect on the variance of investment. Imprecision in measurement σ_ϵ is identified by two covariances jointly: covariance of return and earnings is increasing in σ_ϵ while the covariance of investment and earnings is decreasing in σ_ϵ. Finanlly, σ_η is identified by the variance of return which is only increasing in σ_η.

5. Results

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

5.1. Parameter Estimates

CAPX Sample Panel A of Table 4 reports the parameter estimates from the SMM procedure and their standard errors using the CAPX sample. To interpret the estimates within the context of our model, I first calculate the investment sensitivity to profitability by plugging the parameter estimates to 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 look at profitability uncertainty and accounting imprecision. The estimate of the uncertainty in profitability σ_θ 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 (1.05×0.50). The estimate of accounting imprecision is 0.25, explaining 32.3% ($0.25/(0.25 + 0.525)$) of the investment report variation, suggesting that accounting imprecision imposes significant informational friction. The estimate of the standard deviation of earnings noise is 0.29, very close to the imprecision in investment.

The coefficient γ on the long-term profit is 2.57, indicating that the discounted long-term revenue is 2.57 times larger than the short-term. Given that our sample of CAPX is composed of long-term tangible assets, it is reasonable to see that more than two thirds of the revenues generated concentrates on the long-term. 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 capital stock to be cumulative. Next, I compare the short-term profit and long-term revenue stated as functions of profitability θ_t:

$$x(\theta_t) = (B^* - \frac{1}{2}cB^{*2})\theta_t^2 \tag{23}$$

and

$$y(\theta_t) = \gamma B^* \theta_t^2. \tag{24}$$

Plugging in the parameter estimates to the equations above, the results suggest that investment in capital expenditures generates a short-term profit as $x_t = -1.26\,\theta_t^2$ and long-term profit of $y_t = 2.7\,\theta_t^2$. The negative coefficient -1.26 on x_t suggests the the cost of investment outweighs the short-term revenue. The coefficient of long-term profit is 2.7, and thus the total profit of investment has a coefficient of 1.44 ($2.70 - 1.26$). This suggests that the average total profit generated by investments is positive.

R&D Sample Parameter estimates for 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). Same as capital expenditure, the polynomial equation has only one real solution: $B^* = 0.98$. Both the CAPX and R&D investment sensitivities are close to one.

The estimate of standard deviation of profitability σ_θ is 0.31,[7] and thus the actual investment, which can be expressed as $B^*\theta$, has a standard deviation of 0.304. The degree of imprecision in investment report σ_ϵ is 0.05, imposing a noise on the investment report for about 16.2% $(0.05/(0.304+0.05)$. The estimate of the standard deviation of earnings noise is 0.16. The difference between earnings noise and investment imprecision estimates is caused by the difference in standard deviations of the two data measures.

The estimates for long-term earnings multiple γ and the marginal cost of investment c are both larger than those in the CAPX sample. The estimate of γ is 5.83, indicating a more concentrated profits in the long-term period. 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. To better interpret the implications of γ and c, I next examine the revenues and profits generated by R&D investment in both periods.

Similarly, I plug in estimates to Equations (23) and (24). The short-term profit x_t can be expressed as $x_t = -4.94\,\theta_t^2$ and the long-term profit is $y_t^{RD} = 5.71\,\theta_t^2$. Investment in R&D also cannot generate positive short-term profit on average, as the coefficient on x_t is -4.94. The long-term profit coefficient 5.71 is positive, which yields a positive net total profits with coefficient of 0.77. Comparing the patterns of the profits, the magnitudes of both the short-term and long-term profit coefficients on R&D investments are larger than those on CAPX, suggesting more volatility in profits. This is consistent with the fact that the early stage of R&D activities are mostly research oriented, which seldom brings in revenues. The main cash flows are realized after R&D investment successful, resulting in a volatile profit pattern, as reflected in large estimates γ and c.

Two patterns in the results are worth mentioning. The first pattern is that the accounting imprecision in capital expenditures is larger than in R&D. Two possible reasons can explain this pattern. First, under the guidance of the US Generally Accepted Accounting Principles (GAAP), capital expenditures are recorded as assets on the balance

[7] Note that the difference in σ_θ in the two samples is mainly due to the difference in investment data: the standard deviation of *CAPXP_r* is 0.6 while the standard deviation of *XRDS_r* is 0.321, and it should not to be interpreted as difference in the profitability uncertainty.

sheet and then depreciated over time, while R&D are expensed. In addition to the purchase of the asset, the US GAAP allows companies to capitalize the associated initial setup cost, land and equipment improvement and interest expense 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 accounting imprecision in reporting investment. On the other hand, since R&D expenditures are fully expensed in the same reporting period, there is less discretion involved and thus less imprecision in the report. Secondly, 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. Unfortunately, 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.

The second pattern is that the capital expenditures seem to generate higher returns than R&D investment ($1.44\,\theta^2$ for CAPX *v.s.* $0.77\,\theta^2$ for R&D). One has to be cautious in interpreting these coefficients because my model assumes an identical payback period for all types of investments. In practice, capital expenditures and R&D have very different payback period. According to PhRMA, a trade group representing the US pharmaceutical industry, on average, it takes at least ten years for a new medicine to complete the journey from initial discovery to the marketplace.[8] In contrast, the construction of a new building usually takes less than five years and the payback period for assets purchases should be negligible. Therefore, the longer payback period for R&D naturally results in a smaller coefficient (0.77 *v.s.* 1.44).

[8]See PhRMA (2015).

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 data. In the CAPX sample, four out of seven pairs of moments are insignificantly different from each other, including the mean of investment report, the variance of stock return, the covariance between stock return and investment report, and covariance between stock return and earnings. The model underestimates the variance of investment report (Moment 4), but when I simulate the histogram of 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 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 θ_t is assumed to be *i.i.d.*. Because of the negative coefficient in Equation (23) and thus 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 current investment k_t. This correlation is positive as indicated by Equation (24) 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 reports, 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 *ret_r* is distributed around zero, although the actual mean of stock returns should be positive (sample average return is 2.6 according to Table 3. The does not affect my estimation as the mean is not selected as one of the moments.

Both the model-simulated distribution and data distribution have heavy right tails. On the whole, despite the overidentification of matching seven moments with five parameters, the fit is quite good.[9]

The fitness of moments for R&D sample performs similarly well to the CAPX sample. The seven targeted model and empirical moments for R&D sample are reported in Panel B of Table 5. In general, moments are matched nicely with five out of seven moments do not display significant difference. The difference in the covariance of earnings and investment report (Moment 7) is similar to the CAPX sample, due to *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 shareholder's return. The two earnings distributions match each other nicely. The shareholder's return distribution generated by the model mimics the heavy right tail in the data but has a higher kurtosis and less asymmetry.

6. Counterfactual Analysis

The parameter estimates allow me to answer three questions. First, does the current imprecision in accounting leads to under- or over-investment? Furthermore, what is the optimal imprecision in accounting measurement that corresponds to the optimal investment strategy? Second, 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?

[9]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.

The last two questions combined appeal to the key message in real effects theory that more information is not always desirable by providing quantification evidence. I first quantify the information loss due to the estimated accounting imprecision and the counterfactual degree of imprecision in which the optimal investment efficiency can be achieved. And next I compute the difference in ex-ante welfare for investors between the two cases above.

6.1. Optimal Imprecision

For the first question, the benchmark cases in Section 3.1 provide closed form expressions on investment sensitivities B. I calculate B^{FB}, B^{KP} and B^{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 problem 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 shows that in general, firms still over-invest. Similarly, we calculate the benchmark case when profitability is known, as $B^{KP} = 0.24$. Figure 4 plots the current investment-profitability relationship as well as the three benchmark cases.

I next look for the accounting imprecision that allows the firm to achieve the first-best investment $B = B^{\text{FB}}$. Recall that for any parameter set Φ, B is the solution to Equation (18): $B^2\sigma_\theta^2\left(\sqrt{\frac{2\gamma}{B^{\text{FB}}c-1}}-1\right)-{\sigma_\epsilon}^2=0$. 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}

$$\sigma_\epsilon^2 = {B^{\text{FB}}}^2\hat{\sigma}_\theta^2\left(\sqrt{\frac{2\hat{\gamma}}{B^{\text{FB}}\hat{c}-1}}-1\right). \tag{25}$$

The corresponding imprecision $\sigma_\epsilon^{\text{FB}}$ is 0.28, greater than the current imprecision of 0.25. In fact, for any given investment sensitivity B, Equation (25) suggests that there is a corresponding accounting imprecision σ_ϵ as long as $Bc - 1 > 0$ and $\sqrt{\dfrac{2\gamma}{Bc-1}} - 1 \geq 0$. I plot the $\sigma_\epsilon - B$ relationship in Figure 5. Investment sensitivity B is decreasing in σ_ϵ 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 measure is precise, firms invest with B^{PM} as 1.03, suggesting that a fully precise measure in R&D would worsen over-investment problem by 4.9%. The first-best investment sensitivity B^{FB} is 0.55, smaller than the current sensitivity B^*. Thus, similar to the capital expenditures sample, firms also over-invest in R&D, and the degree of over-investment is more significant than CAPX sample. Given the substantial cost of investment in R&D, the myopic investment under the situation of known profitability is very inelastic, with B^{KP} being only 0.08.

Figure 6 plots the current investment function with references to the three benchmark cases. As illustrated above, the current estimated investment function is very close to the case of Precise Measurement. I further plot the investment-imprecision relationship in Figure 7. The current imprecision estimate is 0.05, as indicated in the round dot. To achieve the first-best investment level, the imprecision of accounting measure should increase to 0.11, which accounts for 35.5% of the uncertainty in profitability. Consistent with the CAPX sample, the trajectory of (σ_ϵ, B) is decreasing from the current investment to the first-best investment.

6.2. Information Loss

To motivate the second question, note that in all the benchmark cases, the market either observes or correctly conjecture the actual investment, and they can infer the profitability of the project correctly 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 the spirit of earnings management literature and focus on the capital market's unresolved uncertainty about the profitability θ upon observing the investment report s.[10] Defined the measure residual uncertainty as

$$\sigma_{\theta|s} \equiv \frac{\sqrt{Var(\theta|s)}}{\sigma_\theta}. \tag{26}$$

If the investment report s is accurate, investors can perfectly infer the value of the profitability θ from the report. In this case, no uncertainty remains since $Var(\theta|s) = 0$ 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 θ at all, the uncertainty on profitability will not change before or after observing the report s. In this case, $\sqrt{Var(\theta|s)} = \sigma_\theta$ and our measure of residual uncertainty is one. 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 the optimal imprecision, there will be a further loss in information by 21.9%, 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.

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 the optimal imprecision would lead to a residual uncertainty of 74.2%, a more significant loss in information compared to the capital expenditure investment.

[10] See Beyer, Guttman, and Marinovic (2018); Bertomeu, Ma, and Marinovic (2019) and Bertomeu, Cheynel, Li, and Liang (2019).

6.3. Welfare Change

To motivate the third question, recall that in the benchmark cases, the cost of deviating from the first-best scenario is solely borne by the firm owner because the market successfully anticipates the actual investment and thus profitability. It is no longer the case under 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 the capital market investors by comparing the current equilibrium to the first-best. Note that unlike the literature in earnings management (Fischer and Verreechia, 2000; Bertomeu, Cheynel, Li, and Liang, 2019), the firm owner may not necessarily benefit from the accounting noise in this framework. Recall that the firm 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 infer the project profitability ideally, the firm owner also incurs a loss in the short-term profit x_t due to over-investment. Thus, it is not clear whether the benefit from price can fully offset the loss in the short-term profit.

Define the change in ex-ante expected welfare for the current shareholders and the market investors as ΔW_{Firm} and ΔW_{Market}, respectively:

$$\Delta W_{Firm} \equiv \frac{\mathbf{E}[d_t + P_t - (d_t^{\text{FB}} + P^{\text{FB}})]}{\sqrt{Var(d_t^{\text{FB}} + P^{\text{FB}})}}, \tag{27}$$

and

$$\Delta W_{Market} \equiv \frac{\mathbf{E}[P_t - P^{\text{FB}}]}{\sqrt{Var(P^{\text{FB}})}} \tag{28}$$

Table 8 presents the results. In the CAPX sample, the firm's shareholders benefit from the noisy equilibrium by 0.4%, yet not significantly different from zero. However, market investors' overpays 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 CAPX 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

In this study, I incorporate information on stock prices, investment report, and earnings to estimate the real effect of accounting measure under the framework of Kanodia, Singh, and Spero (2005). The primary conclusion of this paper is that, on average, firms over-invest, but the imprecision in investment reporting has significantly reduced the degree of over-investment. The current imprecision in the investment report is smaller than the optimal level that corresponds to the first-best investment efficiency. Counterfactual analyses show that easing the imprecision in CAPX investment by 6% of the profitability uncertainty can result in an improvement of the market's welfare by 4.2%. By allowing the noise in R&D investment to increase by 20% can raise shareholders' welfare by 12.1% and the market's welfare by 22%.

Several unique features of my approach is worth mentioning. First, I try the 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 the linear production function and no asset accumulation. This simplification is designed for the purpose of illustrating 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 assessment on the economic importance of such a trade-off.

This paper serves as an initial attempt to quantify the real effect 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 possible with extra signals such as earnings. Moreover, this easy-to-implement methodology can be applied to evaluate certain accounting rules. For instance, development expenditure is capitalized in the UK after the adoption of IFRS, which renders a more precise measurement of the productive R&D investment. 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.

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Table 1: Sample Selection

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

		CAPX	*R&D*
Compustat/CRSP Observations from 1986-2015		115,885	115,885
Less:	Missing earnings data	(971)	(971)
	Missing stock return data	(36,012)	(36,012)
	Missing investment data	(11,913)	(39,623)
	Financial and regulated firms	(7,866)	(2,999)
	Not listed in NYSE, AMEX or NASDAQ	(14,922)	(8,653)
	Missing residuals from fixed-effect regressions	(1,209)	(737)
	Trim variables at 1% and 99%	(2,523)	(1,577)
Final Sample Size		40,469	25,403

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

Variables	Definitions
Assets	Total Assets in millions (Compustat AT).
Ret	One plus buy-and-hold return from nine months before to three months after the fiscal-year-end date ($exp(\sum_i log(1 + ret_i))$).
EPS	Income before extraordinary items divided by common shares outstanding (Compustat $IB \times CSHO$), measured in millions.
MarketCap	Market capitalization in millions (Compustat $MKVALT$).
Book-to-Market	Common equity divided by *MarketCap* (Compustat $CEQ/MKVALT$).
lnCAPXP	The natural log of capital expenditure scaled by lagged property, plant, and equipment (gross). (Compustat $log(CAPX/l.PPEGT)$).
lnXRDS	The natural log of R&D expense scaled by lagged sales (Compustat $XRD/l.SALE$).
EPS_r	The residual values of *EPS* regression on firm and year fixed effects.
Ret_r	The residual values of *Ret* regression on firm and year fixed effects.
$CAPXP\_r$	The residuals of *lnCAPXP* regression on firm and year fixed effects.
$XRDS\_r$	The residual of *lnXRDS* regression on firm and year fixed effects.

Panel B. Variable Correspondence

Variables	Model Correspondence	Data Correspondence
Accounting report	s_t	$CAPXP\_r$, $XRDS\_r$
Earnings	d_t	EPS_r
Shareholder's return	$\frac{P_t + d_t}{P_{t-1}}$	*Ret_r*

Table 3: Summary Statistics

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

Variables	**N**	**Mean**	**SD**	**25%**	**50%**	**75%**
Panel A. CAPX Sample						
Assets	40,469	2,810	7,937	84.72	337.1	1,566
Ret	40,469	2.607	3.891	0.524	1.161	2.654
EPS	40,469	0.871	1.822	-0.049	0.651	1.687
Market Cap	40,440	3,298	10,204	77.31	357.8	1,646
Book-to-market	40,422	0.600	0.514	0.278	0.482	0.781
lnCAPXP	40,469	-2.289	0.886	-2.811	-2.275	-1.735
Data used in estimation:						
EPS_r	40,469	0.014	1.217	−0.492	0.031	0.568
Ret_r	40,469	−0.071	3.302	−1.903	−0.565	0.673
CAPXP_r	40,469	0.002	0.600	−0.351	0.003	0.356
Panel B. R&D Sample						
Assets	25,403	3,221	10,363	70.58	282.4	1,420
Ret	25,403	2.762	4.320	0.510	1.162	2.709
EPS	25,403	0.838	1.741	-0.104	0.577	1.650
Market Cap	25,381	4,117	13,524	76.82	345.8	1,725
Book-to-market	25,378	0.557	0.473	0.255	0.445	0.722
lnXRDS	25,403	−2.833	1.444	−4.010	−2.963	−1.916
Data used in estimation:						
EPS_r	25,403	0.016	1.087	-0.462	0.0327	0.523
Ret_r	25,403	−0.075	3.614	−2.041	−0.557	0.755
XRDS_r	25,403	−0.003	0.321	−0.126	−0.005	0.117

Table 4: Parameter Estimates

This table presents the estimates of the parameter set Φ 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 CAPX Sample, and Panel B is for R&D sample.

Panel A. CAPX Sample

#	**Parameter**	**Description**	**Value**	**St. Errors**
1.	σ_θ	Uncertainty in profitability	0.50	(0.005)
2.	γ	Multiple of long-term earnings	2.57	(0.076)
3.	c	Marginal cost of investment	4.19	(0.057)
4.	σ_ϵ	Measurement imprecision	0.25	(0.003)
5.	σ_η	Earnings noise	0.29	(0.008)

Panel B. R&D Sample

#	**Parameter**	**Description**	**Value**	**St. Errors**
1.	σ_θ	Uncertainty in profitability	0.31	(0.010)
2.	γ	Multiple of long-term earnings	5.83	(0.508)
3.	c	Marginal cost of investment	12.32	(0.413)
4.	σ_ϵ	Measurement imprecision	0.05	(0.013)
5.	σ_η	Earnings noise	0.16	(0.011)

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 CAPX Sample, and Panel B is about the R&D sample.

Panel A. CAPX Sample

#	**Moments**	**Data**	**Model**	***t*-stat**
1.	Variance of stock return	10.903	11.040	-0.68
2.	Covariance of stock return and investment report	0.003	0.022	-0.96
3.	Mean of Investment report	0.002	0.001	0.34
4.	Variance of Investment report	0.360	0.345	4.08
5.	Variance of earnings	1.481	1.309	6.44
6.	Covariance of stock return and earnings	0.004	0.043	-1.44
7.	Covariance of earnings and investment report	0.118	-0.003	23.36

Panel B. R&D Sample

#	**Moments**	**Data**	**Model**	***t*-stat**
1.	Variance of stock return	12.990	13.064	0.24
2.	Covariance of stock return and investment report	0.001	0.013	1.02
3.	Mean of Investment report	-0.005	-0.003	0.67
4.	Variance of Investment report	0.098	0.103	3.39
5.	Variance of earnings	1.167	1.182	0.58
6.	Covariance of stock return and earnings	0.081	0.047	-0.96
7.	Covariance of earnings and investment report	0.001	-0.029	-7.36

Table 6: Counterfactual Analysis

This table presents the results of counterfactual analysis. Results for CAPX 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: $\sigma_\epsilon^2 = B^2\sigma_\theta^2\left(\sqrt{\frac{2\gamma}{Bc-1}} - 1\right)$. Standard errors are in parentheses.

Panel A. CAPX Sample

Scenarios	B		σ_ϵ
	Model	Estimate	Corresponding estimate
Noisy Signalling	-	*1.05*	*0.25*
		(0.011)	(0.003)
First-Best Investment	$\frac{1+\gamma}{c}$	0.85	0.28
		(0.023)	(0.004)
Known Profitability	$\frac{1}{c}$	0.24	
		(0.004)	
Perfect Measurement	$\frac{1+2\gamma}{c}$	1.47	
		(0.044)	

Panel B. R&D Sample

Scenarios	B		σ_ϵ
	Model	Estimate	Corresponding estimate
Noisy Signalling	-	0.98	0.05
		(0.024)	(0.013)
First-Best Investment	$\frac{1+\gamma}{c}$	0.55	0.11
		(0.059)	(0.006)
Known Profitability	$\frac{1}{c}$	0.08	-
		(0.003)	
Perfect Measurement	$\frac{1+2\gamma}{c}$	1.03	
		(0.117)	

Table 7: Information Loss

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

	Residual Uncertainty $\sigma_{\theta\|s}$	
	Estimated imprecision	Optimal Imprecision
	Panel A. CAPX Sample	
Estimates	0.389	0.608
sd.error	(0.002)	(0.012)
	Panel B. R&D Sample	
Estimates	0.211	0.742
sd.error	(0.004)	(0.027)

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 $\Delta W_{Firm} \equiv \frac{\mathbf{E}[d_t + P_t - (d_t^{\mathrm{FB}} + P^{\mathrm{FB}})]}{\sqrt{Var(d_t^{\mathrm{FB}} + P^{\mathrm{FB}})}}$. The change in investors' welfare is $\Delta W_{Market} \equiv \frac{\mathbf{E}[P_t - P^{\mathrm{FB}}]}{\sqrt{Var(P^{\mathrm{FB}})}}$. Standard errors are reported in parentheses.

	Welfare Change	
	Firm	Market
	Δ_{Firm}	Δ_{Market}
	Panel A. CAPX Sample	
Estimates	0.004	-0.042
St.error	(0.016)	(0.003)
	Panel B. R&D Sample	
Estimates	-0.121	-0.220
St.error	(0.014)	(0.023)

Figure 2: Data and Simulated Variables – CAPX Sample

This figure includes the histograms of data simulated variables for the CAPX sample. In Panel A, investment report for data sample uses variable *CAPXP_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 shareholder's return distributions. The data histogram is from the variable *Ret_r* and the simulated variable is calculated as $\frac{P_t + d_t}{P_{t-1}}$. See Panel B of Table 2 for the definitions.

(a) Accounting Report

capx-s-eps-converted-to.pdf

(b) Earnings

capx-d-eps-converted-to.pdf

(c) Shareholder's return

capx-ret-eps-converted-to.pdf

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 *XRDs_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 shareholder's return distributions. The data histogram is from the variable *Ret_r* and the simulated variable is calculated as $\dfrac{P_t + d_t}{P_{t-1}}$. See Panel B of Table 2 for the definitions.

(a) Investment Report

rd-s-eps-converted-to.pdf

(b) Earnings

rd-d-eps-converted-to.pdf

(c) Shareholder's return

rd-ret-eps-converted-to.pdf

Figure 4: Investment Strategy – CAPX Sample

This figure displays the investment functions. The solid line is the estimated investment function using CAPX sample with a slope $B = 1.05$. The dashed line is the counterfactual investment function when accounting measurement is completely precise, *i.e.* $\sigma_\epsilon = 0$. The slope of this investment function is $B^{\mathrm{PM}} = 1.47$. 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 $B^{\mathrm{FB}} = 0.85$. The dash-dotted line is the investment function in the benchmark case when profitability is known but investment report is not precise. The slope for the dash-dotted line is $B^{\mathrm{KP}} = 0.24$.

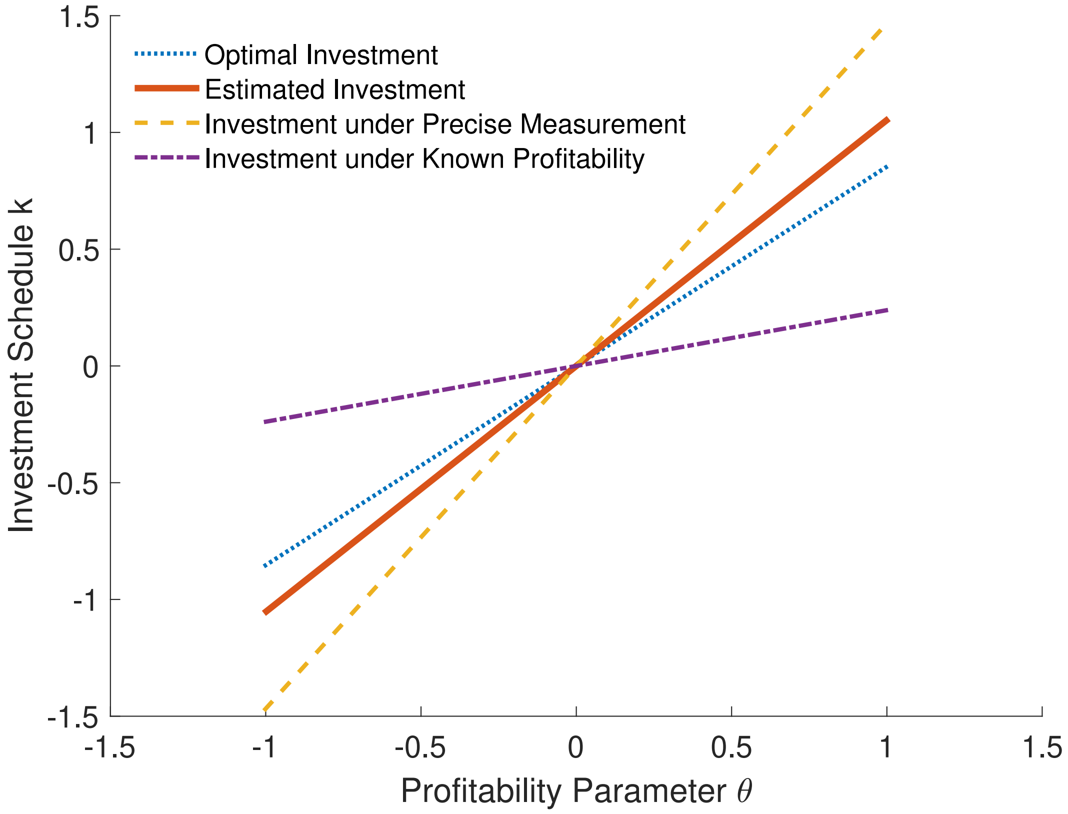

Figure 5: Imprecision and Investment Sensitivities – CAPX Sample

This figure plots the relation between accounting measurement noise σ_ϵ and investment sensitivity B, calculated using Equation (18): $B^2\sigma_\theta^2\left(\sqrt{\frac{2\gamma}{Bc-1}}-1\right)-\sigma_\epsilon^2=0$, where the parameters σ_θ, γ and c are substituted with estimates from the CAPX sample. The round dot is the estimated relation, with σ_ϵ 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, $B^{\text{FB}} = 0.85$.

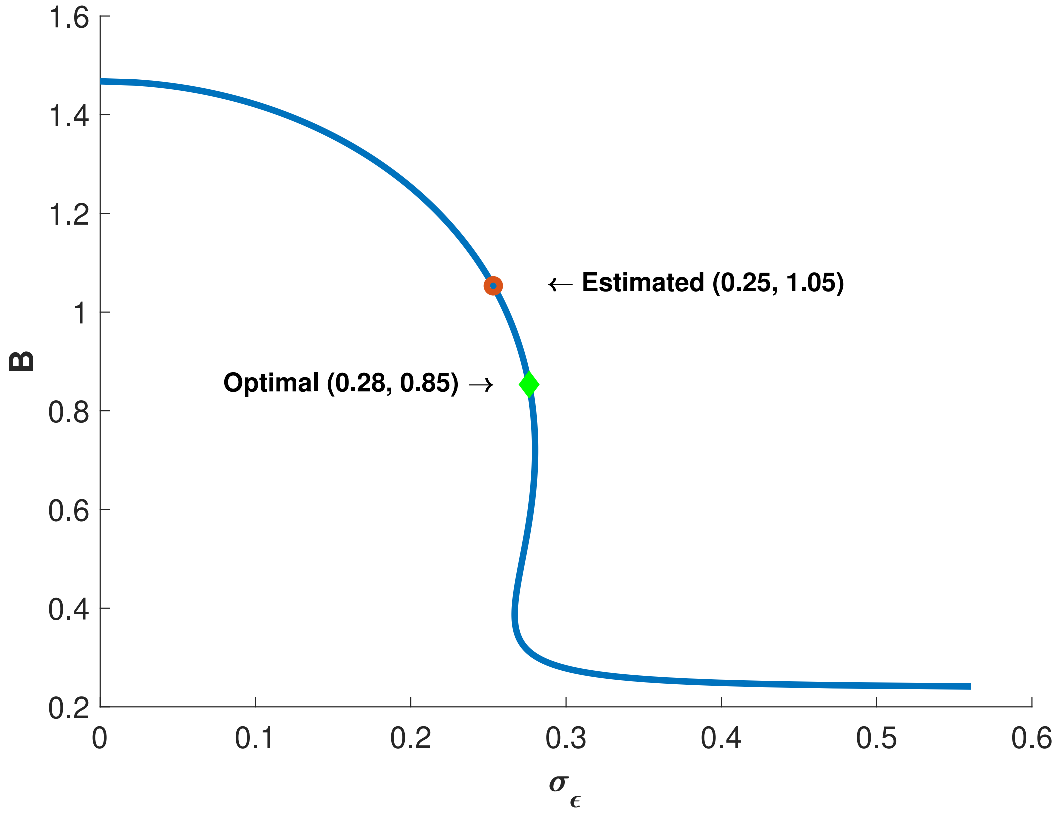

Figure 6: Investment Strategy – R&D Sample

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 dashed line is the counterfactual investment function when accounting measurement is completely precise, *i.e.* $\sigma_\epsilon = 0$. The slope of this investment function is $B^{\text{PM}} = 1.03$. 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 $B^{\text{FB}} = 0.55$. The dash-dotted line is the investment function in the benchmark case when profitability is known but investment report is not precise. The slope for the dash-dotted line is $B^{\text{KP}} = 0.08$.

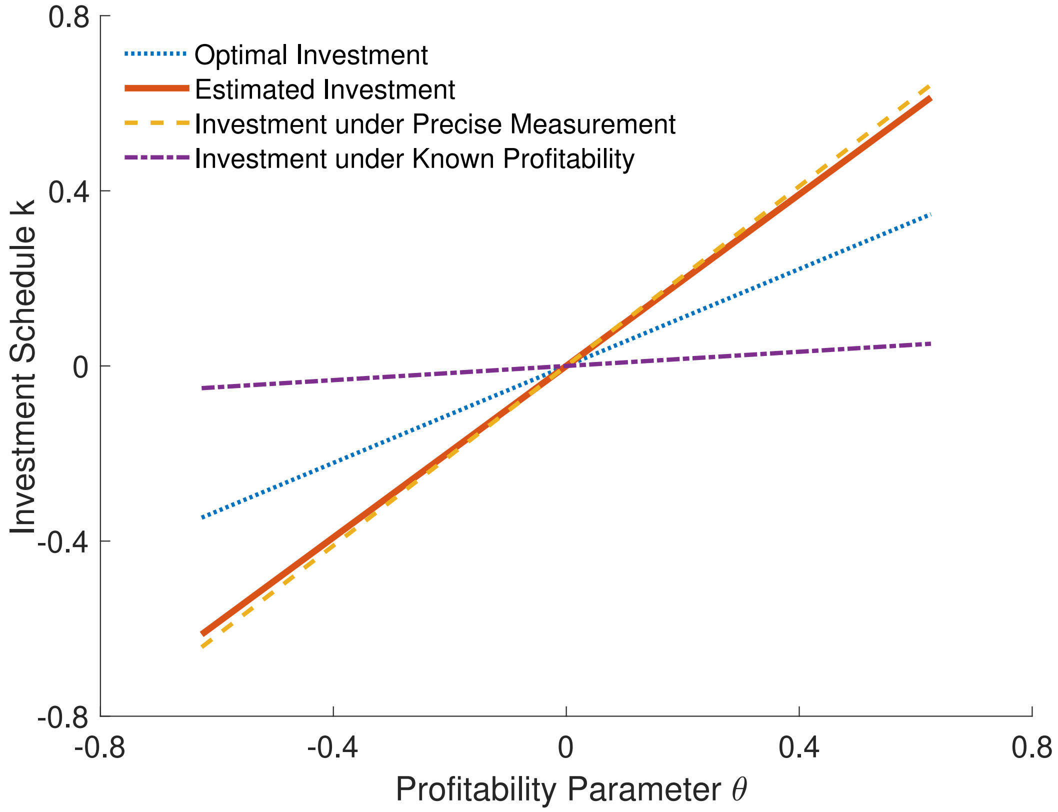

Figure 7: Imprecision and Investment Sensitivity – R&D Sample

This figure plots the relation between accounting measurement noise σ_ϵ and R&D investment sensitivity B. It is calculated using Equation (18): $B^2\sigma_\theta^2\left(\sqrt{\frac{2\gamma}{Bc-1}}-1\right)-\sigma_\epsilon^2=0$, where the parameters σ_θ, γ and c are substituted with estimates from the R&D sample. The round dot is the estimated relation, with σ_ϵ 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, $B^{\mathrm{FB}} = 0.55$.