Spillover Effects of Financial Reporting on Public Firms' Corporate Investment

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Abstract: I examine whether public firms' financial reporting has spillover effects on the amount and efficiency of *other* public firms' investment and quantify the relative importance of these indirect *spillover* effects vis-à-vis the *direct* effects due to firms' own financial reporting. Spillover effects are important for understanding (i) how financial reporting affects corporate investment, which is fundamental for generating firm value and macroeconomic growth, and (ii) whether positive externalities are a meaningful economic justification for financial reporting regulation. The primary empirical challenge for studying spillovers is that every public firm not only discloses its own financial report, but also simultaneously benefits from spillovers from other firms' financial reports, making it difficult to disentangle the observed combination of direct and spillover effects. I overcome this challenge by structurally estimating a model that links firms' financial reporting and investment, which I use to decompose the effect of financial reporting into its direct and spillover components. I examine the effect of financial reporting on aggregate output from the public corporate sector's investment, which combines the effects on both the amount and efficiency of investment, and estimate that a significant portion—roughly half of the total effect of financial reporting and a quarter of the marginal effect of an incremental change in financial reporting precision—is due to spillover effects. This evidence suggests that spillovers constitute a meaningful benefit of financial reporting for a wide range of public firms.

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1. Introduction

Corporate investment decisions are fundamental to the creation of firm value and are an important driver of macroeconomic growth (e.g., Solow, 1956; Swan, 1956), as evidenced by U.S. firms' annual capital expenditures in excess of $1.6 trillion in recent years (U.S. Census Bureau, 2019). Consequently, understanding how financial reporting, which is broadly defined as the collection, aggregation, and dissemination of financial information, affects corporate investment is an important and active area of research (Kanodia and Sapra, 2016; Roychowdhury et al., 2019). Although early studies largely focused on the direct effects of firms' own financial reporting on their investment decisions, the literature has recently begun to examine the *indirect* or *spillover* effects of other firms' financial reporting.[1] Within that stream of literature, some prior studies have provided evidence of beneficial information spillovers (e.g., from public to private firms: Badertscher et al., 2013; Shroff et al., 2017).

This study contributes to the study of beneficial information spillovers for investing decisions by (i) assessing whether public firms' financial reporting has spillover effects on both the amount and efficiency of *other public firms'* investment, and (ii) *quantifying* the relative importance of any such spillover effects vis-à-vis the direct effects of firms' own financial reporting. In order to assess whether there are beneficial spillovers among public firms and to quantify their relative importance, I empirically decompose the combined effect of all public firms' financial reporting on their corporate investment into its direct component (due to the investing firm's own reporting) and spillover component (due to all other firms' reporting). I perform this decomposition for both the total effect of financial reporting and the marginal effect that would

[1] Studies in this area include Durnev and Mangen (2009), Badertscher et al. (2013), Beatty et al. (2013), Chen et al. (2013), Shroff et al. (2014), Li (2016), and Shroff et al. (2017). Not all studies find spillover effects to be beneficial as some studies show that accounting misstatements also have spillover effects (Beatty et al., 2013; Li, 2016).

result from an incremental change in financial reporting precision from its current level.

Decomposing the combined effect of financial reporting into its direct and spillover components is the key innovation for achieving my two main research objectives. First, this decomposition allows me to examine spillover effects for the entire population of public firms, all of which simultaneously provide information through their own financial reports and receive information spillovers from other firms' financial reports. This simultaneous presence of direct and spillover effects has made it difficult to isolate spillover effects, which is why prior studies have largely focused on research settings that—for purposes of the study—provide a relatively sharp distinction between firms that are information providers and firms that are spillover recipients.[2] My decomposition adds to the important insights from these studies by providing broader evidence of spillover effects for the publicly traded corporate sector as a whole.

Second, this decomposition allows me to quantify the relative magnitudes of the direct and spillover effects, which is an important piece of evidence that bears on the economic justification of financial reporting regulation. Beneficial spillover effects constitute a positive externality and are frequently cited as one of the main justifications for financial reporting regulation (Beyer et al., 2010; Leuz and Wysocki, 2016; Minnis and Shroff, 2017). The argument is that since firms do not internalize positive externalities of their financial reporting, there is an undersupply of information compared to the social optimum (Dye, 1990; Admati and Pfleiderer, 2000), which may justify regulating—and, in particular, mandating a minimum level of—financial reporting. Assessing the benefits of financial reporting regulation on these grounds, however, requires estimates of the

[2] For example, the two groups may be public and private firms (Badertscher et al., 2013), already- and newly public firms (Shroff et al., 2017), misreporting firms and their peers (Durnev and Mangen, 2009; Beatty et al., 2013; Li, 2016), IFRS-adopting firms in one country and another (Chen et al., 2013), or subsidiaries and their foreign parents (Shroff et al., 2014). In each research setting, the firms in the first (second) group are the information providers (spillover recipients).

economic magnitude of spillover effects. My decomposition facilitates a comparison of the *relative* magnitudes of the direct and spillover effects—which correspond to private and social benefits of public financial information, respectively—and provides insight into whether spillover effects constitute a meaningful benefit of financial reporting regulation.[3]

To isolate these two effects, I develop and structurally estimate a parsimonious model that links financial reporting and corporate investment. The model features NPV-maximizing managers who make investment decisions after learning their firm's productivity (i.e., investment opportunities) from *both* their own firm's *and* other firms' financial reports.[4] Firms' productivity has both an idiosyncratic and a systematic component, and managers learn about the former from their own firm's report and the latter from all firms' (including their own) reports. Financial information affects managers' investment decisions in two ways: (i) it allows managers to make more profitable investment decisions ("Investment Efficiency Channel"), and (ii) it reduces their firm's cost of capital (Lambert et al., 2007), which, in turn, allows them to make larger investments ("Cost of Capital Channel").

The primary advantage of structural estimation for studying information spillovers is that it allows for the counterfactual "manipulation" of the amount and type of information available to managers when they make their investment decisions, which I employ to decompose the effect of financial reporting into its direct and spillover effects. Specifically, I decompose the total effect of financial reporting by examining counterfactual scenarios in which managers: (i) do not learn from

[3] For example, if spillover effects are dominated by direct effects, firms' voluntary supply of information is likely close to the social optimum, making it difficult to justify the extensive regulatory regime extant in the U.S. on the grounds of positive externalities.

[4] Although the only explicit decision-making agent in the model is the manager, I view the investment decision to be the manager's decision after being disciplined by external investors who also learn from financial reports. This joint learning by managers and external investors—along with evidence of managers learning from their own financial reports (Shroff, 2017; Choi, 2018)—alleviates the concern that the existence of direct effects is less credible when managers prepare financial reports themselves.

any contemporaneous financial reports; (ii) only learn from their own firm's financial report; and (iii) learn from both their own firm's financial report as well as financial reports from other firms in their industry and the overall economy. These alternative scenarios that sequentially expand managers' information sets allow me to decompose the combined change (from (i) to (iii)) in the amount and efficiency of firms' investment into its direct (from (i) to (ii)) and spillover (from (ii) to (iii)) components.[5] The difference in investment across (i) and (ii) is attributable to the firm's own reporting because other firms' reports are unavailable to managers in both scenarios, and the difference in investment across (ii) and (iii) is attributable to other firms' reporting because their own reports provide the same information to managers in both scenarios.

I estimate the structural parameters of my model using simulated method of moments (SMM) for essentially the population of publicly traded U.S. firms from the period 1990-2014. The primary parameters of interest are those that determine (i) co-movement in productivity across firms, which makes other firms' reports more valuable and hence increases spillover benefits, and (ii) the informativeness of financial reports, which reduces the incremental information other firms' reports provide over the firm's own report and hence decreases spillover benefits. SMM estimates these parameters by matching moments (e.g., variance, synchronicity) of the simulated model variables to their empirical counterparts in the observed data. The key observable inputs are: (i) firms' after-tax operating income, which is an accounting measure of productivity; (ii) a broad measure of firms' investment that includes expenditures on capital investment, mergers and acquisitions, research and development, and advertising; and (iii) firms' net payout to external investors, both creditors and shareholders. For example, synchronicity between firms' and the

[5] The decomposition of the marginal effect of financial reporting precision follows the same procedure with increase in reporting precision substituting for expansion of information sets. That is, the firm's own financial report gets an incremental boost in its precision (from (i) to (ii)) before all other firms' reports get that boost (from (ii) to (iii)).

market- or industry-wide operating income primarily identifies co-movement in fundamental productivity. The informativeness of financial reports, on the other hand, is primarily identified by the relative magnitude of the variance of operating income (i.e., the accounting signal about productivity) relative to the variance of firms' real actions (i.e., investment and net payout, which together constitute underlying productivity). The intuition is that more precise information allows managers to report operating income that more closely corresponds to—and therefore exhibits a more similar variability with—their firm's underlying productivity. I validate my estimates of these and other key model parameters by showing that they capture several stylized facts and inter-industry patterns that I do not require the SMM procedure to fit (e.g., stock return synchronicity and earnings-response coefficients).

I find that roughly half (54%) of the total effect of financial reporting on both the amount and efficiency of investment is attributable to spillover effects.[6] Considering that prior studies document economically significant direct effects (e.g., Botosan, 1997; Biddle and Hilary, 2006; Hail and Leuz, 2006; Biddle et al., 2009), the comparable magnitudes of the direct and spillover effects suggest that spillover effects among public firms are also economically meaningful. A more granular analysis at the industry level shows that most (68%) of the spillover effects are due to learning about industry-specific rather than economy-wide fluctuations in productivity. This analysis also shows that managers are able to learn an even larger proportion (83%) of this information from financial reports of firms in their industry, which convey both industry-specific and economy-wide information. This finding is consistent with the focus on within-industry spillovers in several prior reduced-form studies (e.g., Badertscher et al., 2013; Shroff et al., 2017).

[6] I examine simulated aggregate output of the public corporate sector to estimate the collective effect of financial reporting through both the investment efficiency and cost of capital channels. Spillover effects are more important for the cost of capital channel (67%) than for the investment efficiency channel (40%).

The preceding analysis provides insight into the full extent of spillover effects because I compare scenarios with and without spillover effects. Although this insight helps to understand the total spillover benefits inherent in the current financial reporting regime, it may be less relevant for understanding the spillover benefits from introducing a new financial reporting regulation to the existing regime. I provide additional insight in this respect by decomposing the marginal effect of financial reporting precision and find that roughly a quarter (23%) of the marginal effect is attributable to spillover effects, almost all of which is due to incremental learning about industry-specific fluctuations in productivity. It is not surprising that spillover effects comprise a smaller share at the current margin because systematic information quickly becomes subject to diminishing marginal returns due to its relative abundance compared to idiosyncratic information. [7] Nevertheless, spillover effects account for a meaningful portion of the marginal effect, suggesting that the rich information environment of the U.S. has not yet exhausted all of the potential spillover benefits of financial reporting.

My study contributes to the literature not only by answering the call for a better understanding of the spillover effects of financial reporting on corporate investment (Leuz and Wysocki, 2016; Roychowdhury et al., 2019) but also by providing some of the first quantitative evidence about the magnitude of spillover effects of financial reporting. Due to the empirical challenge posed by the simultaneous presence of direct and spillover effects among public firms, prior empirical studies have largely focused on research settings that feature two distinct sets of firms—a set of information providers and another distinct set of spillover recipients—rather than a broad sample of public firms. I build upon the important insights from these studies and provide more generalizable evidence of spillover effects for the entire population of publicly traded firms,

[7] This intuition is consistent with Shroff et al. (2017), who find that peer information has a weaker association with a firm's cost of capital as the firm accumulates its own public information.

which is typically the set of firms to which new financial reporting regulations apply. My study also provides quantitative evidence about the magnitude of spillover effects that sheds light on the role of positive externalities as a justification for financial reporting regulation. In this regard, my study adds to the emerging literature that focuses on quantifying market-wide effects of financial reporting (Breuer, 2018; Choi, 2018). In summary, the quantitative nature of my evidence coupled with the broad and more generalizable scope of my inferences suggest that spillover effects constitute a meaningful benefit of financial reporting for the population of public firms and provide new evidence about the economic justification of financial reporting regulation.

The remainder of the paper proceeds as follows. Section 2 discusses the empirical challenge to studying spillover effects, how prior studies address the challenge, and new insights that structural estimation can provide. Section 3 develops the model, and Section 4 describes the data. Section 5 explains how I identify and estimate parameters using SMM. Section 6 presents results from my quantitative analyses, and Section 7 extends the research design to perform industry-level analyses. Section 8 examines the robustness of my analyses. Section 9 concludes.

2. Background

This section outlines the empirical challenges with studying spillover effects, how prior studies address these challenges, and how my research methodology (i.e., structural estimation) is equipped to provide new insight. The primary empirical challenge to examining spillover effects—especially among public firms—is what is referred to as the "reflection problem" (Manski, 1993; Angrist, 2014). This refers to the endogeneity issue that arises when an observed correlation between a group's shared characteristics and its members' behavior is possibly due to a common underlying variable rather than spillovers. In other words, similarities in the individual group members' behavior *reflects* a shared common characteristic rather than the individual members influencing each other's decisions. In the context of my research question, the reflection problem amounts to the concern that a common contextual variable (e.g., growth opportunities) drives *both* the financial reporting (a group characteristic) and individual firms' (i.e., group members') investment decisions, thereby making it difficult to disentangle the direct effect of the underlying variable (potentially through the firm's own financial reporting) and spillovers from other firms' financial reporting.[8] Using a plausibly exogenous shock (e.g., a new regulation) does not resolve the reflection problem among firms subject to the shock because the shock becomes the contextual variable that causes the reflection problem.

Figure 1 illustrates the reflection problem using an exogenous information event as an example. The illustration has four firms: A and B, which are subject to the information event; C, which is a close peer of A and B in that it receives spillovers from A and B's financial reporting; and D, which is a remote peer of A and B in that it does not receive any spillovers from A and B. Firms A and B are subject to the information event, so they experience both (i) direct effects of the information event (potentially through changes in their own financial reporting) and (ii) spillover effects from the change in the other firm's financial reporting. The reflection problem in my setting pertains to the difficulty in separately identifying these two distinct effects from the observed combination of the two.

To address this reflection problem, prior studies have largely focused on settings where the spillover recipients are *not* members of the group of information providers. In the context of Figure 1, since Firm C experiences spillovers while Firm D does not, the difference between the two firms'

[8] For example, Badertscher et al. (2013) explain that examining the effect of public firm presence on public firms' (rather than private firms') investment efficiency may be more susceptible to endogeneity concerns because industry growth opportunities may drive both public firm presence (through initial public offerings) and investment decisions.

responses provide evidences about spillover effects. For example, Durnev and Mangen (2009) and Beatty et al. (2013) use this approach to document spillover effects of restatements/misstatements on peer firms' investment. In Durnev and Mangen (2009), Firm A corresponds to restating firms, Firm C corresponds to their four-digit SIC peers, and Firm D corresponds to firms belonging to four-digit SIC industries in which no firms restate during the sample period—and therefore receive no spillovers. In Beatty et al. (2013), Firm A corresponds to misstating firms (before the restatement), Firm C corresponds to their three-digit SIC peers, and Firm D corresponds to other two-digit SIC peers.[9]

Firm D is important in this approach because it is difficult to disentangle common time trends from spillovers solely by examining Firm C's response. However, some prior studies document spillover effects without an analogue of Firm D by examining multiple pairs of firms that correspond to A and C. In this case, evidence of spillovers is inferred from the association between Firm C's response and certain properties of Firm A's financial reporting that are potential sources of spillovers (e.g., earnings synchronicity). For example, Firms A and C could be, respectively, public and private firms (Badertscher et al., 2013), already- and newly public firms (Shroff et al., 2017), firms adopting the International Financial Reporting Standards in one country and another (Chen et al., 2013), or subsidiaries and their foreign parents (Shroff et al., 2014).

Although these and other studies provide important insight into spillover effects of financial reporting, their approach to addressing the reflection problem shifts the focus away from Firms A and B to Firm C. My research methodology of structural estimation builds upon and adds to this literature by providing an alternative approach to directly addressing the reflection problem

[9] Li (2016) extends Beatty et al. (2013) and finds evidence of spillover effects of misstatements more generally. In Li (2016), Firm A corresponds to misstating firms, Firm C corresponds to their Fama and French (1997) 48 industry classification peers, and Firm D corresponds to other firms in industries without misstatements in the.

that exists between Firms A and B. This shift in focus is crucial because it allows me to examine spillover effects among *all publicly traded firms* and quantify the *relative magnitude* of spillover effects against direct effects. Structural estimation makes this alternative approach feasible because it allows me to control how and to which firms the information event occurs in the counterfactual simulations.

An information event entails three simultaneous effects: (i) direct effects through the firm's own financial reporting; (ii) spillover effects through other firms' financial reporting; and (iii) effects of the event that are unrelated to financial reporting.[10] In my quantitative analyses, I can suppress (iii) and make (ii) and (iii) occur sequentially rather than simultaneously. Altering the occurrence and timing of these three effects allows me to overcome the reflection problem because Firms A and B's response to (i) represents the direct effects of financial reporting, while their response to (ii) represents the spillover effects. Section 6 describes this process in detail based on the model develop in Section 3 and estimate in Section 5. Appendix A provides an overview of structural estimation by way of an analogy to more common—and likely more familiar—reduced-form research designs.

3. Model

In this section, I develop a parsimonious model that links financial reporting and corporate investment. Since my aim is to understand spillover effects, my model explicitly captures managers' ability to learn from *other firms'* financial reports about some element that is common—and therefore induces co-movement—across firms. The baseline model features a

[10] The last category refers to confounding effects of real information events in the data. For example, major regulatory information events (e.g., the adoption of the Sarbanes-Oxley Act) can affect corporate investment through multiple channels, not only through financial reporting.

single aggregate (i.e., economy-wide) systematic productivity factor (i.e., investment opportunity) reflected in earnings, which managers can learn about from other firms' financial reports. In Section 7, I extend the model by adding additional industry-specific systematic productivity factors. My focus on learning about investment opportunity through other firms' earnings is largely consistent with the prior literature on peer information and spillover effects.[11]

3.1. Manager's objective

The economy consists of N firms, each with a manager who maximizes the net present value (NPV) generated by the firm's capital stock. I view this NPV-maximization to be the manager's objective after being disciplined by external investors, who are not explicitly in the model, so that "learning" in the model encompasses both that of the manager and external investors. The expected NPV that will be generated by firm i's capital stock in period t, k_{it}, is

$$\mathrm{E}\left[\tilde{\zeta}_{it}|\mathbb{I}_{it}\right]k_{it}-I_{it}k_{i,t-1}-\frac{\phi}{2}\frac{\left(I_{it}k_{i,t-1}\right)^{2}}{k_{i,t-1}}-\lambda k_{it}\mathrm{Cov}\left(\tilde{\zeta}_{it},\frac{1}{N}\sum_{j=1}^{N}\tilde{\zeta}_{jt}\,|\mathbb{I}_{it}\right) \tag{1}$$

Tilde indicates that the variable is random. I explain each term below.

Operating outcome. The first term in eqn. (1), $\mathrm{E}\left[\tilde{\zeta}_{it}|\mathbb{I}_{it}\right]k_{it}$, is the discounted sum of expected operating outcome generated by k_{it}. Here, $\tilde{\zeta}_{it}=\sum_{s=0}^{\infty}\frac{\tilde{\pi}_{i,t+s}(1-\delta)^{s}}{\left(1+r_{f}\right)^{s}}$ is a summary measure of the long-term productivity of k_{it}, while $\tilde{\pi}_{it}$ is short-term productivity for period t. The two parameters that define $\tilde{\zeta}_{it}$ are (i) the depreciation rate of capital stock $\delta\geq 0$, and (ii) the risk-free rate r_f. Finally, $\mathbb{I}_{it}$ is the manager's information set when making the investment decision in period t.

Investment expenditure. The second term in eqn. (1), $I_{it}k_{i,t-1}$, is investment expenditure for

[11] For example, prior studies on peer information mostly examine earnings announcements (Foster, 1981; Clinch and Sinclair, 1987; Han and Wild, 1990), management guidance (Baginski, 1987; Han et al., 1989), and restatements (often with an emphasis on revenue restatements: Gleason et al., 2008; Durnev and Mangen, 2009).

period t.[12] The investment rate I_{it} in period t is the key choice variable in my model. Capital stock evolves according to the equation $k_{it} = (1 - \delta + I_{it})k_{i,t-1}$.

Investment adjustment cost. The third term in eqn. (1), $\frac{\phi}{2}\frac{\left(I_{it}k_{i,t-1}\right)^2}{k_{i,t-1}}$, is the investment adjustment cost for period t where $\phi \geq 0$ is the investment adjustment cost parameter. This represents the disruption of the firm's operations that accompanies the current period's investment.[13] The formula shows that larger investments are more disruptive albeit to a lesser extent for larger firms.

Risk premium. The final term in eqn. (1), $\lambda k_{it}\mathrm{Cov}\left(\tilde{\zeta}_{it}, \frac{1}{N}\sum_{j=1}^{N}\tilde{\zeta}_{jt}\,|\mathbb{I}_{it}\right)$, is the risk premium associated with the firm's operations where $\lambda \geq 0$ is the risk premium parameter. Instead of using the risk-adjusted cost of capital as the discount rate for the first term in eqn. (1), I use an additively separable risk premium.[14] Following common modeling conventions (Garman and Ohlson, 1980; Lambert et al., 2007), I use the covariance between firm-specific and systematic (economy-wide average) productivity. I use the posterior covariance following Lambert et al. (2007), who show that financial reporting can affect cost of capital by providing systematic information.[15]

Given the manager's objective of maximizing expected NPV in eqn. (1) and the evolution of capital stock $k_{it} = (1 - \delta + I_{it})k_{i,t-1}$, the optimal investment rate is

$$I_{it} = \frac{\mathrm{E}\left[\tilde{\zeta}_{it}|\mathbb{I}_{it}\right] - 1 - \lambda\mathrm{Cov}\left(\tilde{\zeta}_{it}, \frac{1}{N}\sum_{j=1}^{N}\tilde{\zeta}_{jt}\,|\mathbb{I}_{it}\right)}{\phi} \tag{2}$$

[12] The term "investment" encompasses disinvestment (e.g., downsizing) as well, i.e., I_{it} can be negative.
[13] An example is training expense for new machines. The cost also represents partial irreversibility of investment (Bloom et al., 2007; Badertscher et al., 2013).
[14] This specification is common in models that share the framework of the capital asset pricing model, in particular, with overlapping generations (e.g., Fischer et al., 2016; Dutta and Nezlobin, 2017).
[15] There is considerable debate about whether and how financial reporting affects cost of capital (Easley and O'Hara, 2004; Hughes et al., 2007; Lambert et al., 2007; Christensen et al., 2010; Gao, 2010; Zhang, 2013; Christensen and Frimor, 2019). However, the argument that more precise financial reporting leads to greater investment is less controversial. Therefore, my introduction of cost of capital is a representation of the effect of financial reporting on the amount of investment, not a statement about how financial reporting actually affects firms' cost of capital.

Eqn. (2) exhibits the intuitive property that favorable prospects (i.e., higher $\mathrm{E}\left[\tilde{\zeta}_{it}|\mathbb{I}_{it}\right]$) encourage investment, while greater systematic risk of investment (i.e., higher $\mathrm{Cov}\left(\tilde{\zeta}_{it}, \frac{1}{N}\sum_{j=1}^{N}\tilde{\zeta}_{jt}\,|\mathbb{I}_{it}\right)$) discourages investment. Moreover, eqn. (2) succinctly and explicitly shows how both the amount and quality of information affect managers' investment decisions.

However, for purposes of structural estimation in which I match *simulated* investment to *observed* investment in the data, I assume that managers' investment decisions deviate from the purely NPV-maximizing level and are instead given by

$$I_{it} = \frac{\mathrm{E}\left[\tilde{\zeta}_{it}|\mathbb{I}_{it}\right] - 1 - \lambda\mathrm{Cov}\left(\tilde{\zeta}_{it}, \frac{1}{N}\sum_{j=1}^{N}\tilde{\zeta}_{jt}\,|\mathbb{I}_{it}\right) + \tilde{s}_{it}}{\phi} \tag{3}$$

where the investment deviation term $\tilde{s}_{it}$ follows i.i.d. $N(0,\psi)$.[16] I use $\tilde{s}_{it}$ to parsimoniously capture any frictions and incentives (e.g., financing constraints, agency frictions) that cause managers' actual investment decisions to deviate from NPV maximization.[17]

3.2. Financial Reporting

Firms' financial reports provide a noisy signal of (short-term) productivity $\tilde{\pi}_{it}$, which is given by

$$\tilde{\pi}_{it} = m + \rho\left(\pi_{i,t-1} - m\right) + \tilde{f}_t + \tilde{\omega}_{it} \tag{4}$$

Here, $\tilde{\pi}_{it}$ follows an AR(1) process and has both a systematic innovation, $\tilde{f}_t$, which follows i.i.d. $N(0,\gamma\tau^{-1})$, and an idiosyncratic innovation, $\tilde{\omega}_{it}$, which follows i.i.d. $N(0,(1-\gamma)\tau^{-1})$. I assume

[16] Bertomeu et al. (2019, p.22) also introduces a similar white-noise variable that is "intended to capture other time-varying factors affecting the disclosure decision." This modeling convention is analogous to a residual in a reduced-form regression model that captures (ideally idiosyncratic) factors that are—either deliberately or inadvertently—omitted from the model, but that nevertheless influence the dependent variable.

[17] Representing all other investment frictions as an independent random variable does not mean that I view financial reporting to have no role in mitigating such frictions but rather means that I focus on how financial reporting affects corporate investment by aiding managers in making better NPV-maximizing decisions. This assumption is less of a concern because I am interested in the relative magnitude of spillover effects, which is more generalizable than the absolute magnitude to other channels through which financial reporting affects corporate investment.

that these two innovations are mutually independent. The economy-wide systematic innovation, $\tilde{f}_t$, is the source of spillover effects since it is the only term that captures relevant information that managers can learn from other firms. The four parameters that govern the distribution of $\tilde{\pi}_{it}$ are (i) mean productivity m, (ii) the autocorrelation of productivity $\rho \in [-1,1]$, (iii) the proportion of systematic (rather than idiosyncratic) variation in productivity $\gamma \in [0,1]$, and (iv) the precision of the productivity innovation $\tau \geq 0$. Eqn. (4) also shows that $\pi_{i,t-1}$ is eventually revealed at the end of period $t-1$ through other sources of information.

I define the accounting signal of productivity to be

$$\tilde{z}_{it} = \tilde{\pi}_{it} + q^{-\frac{1}{2}}\, \tilde{\varepsilon}_{it} \tag{5}$$

where $q \geq 0$ is the precision of financial reporting and $\tilde{\varepsilon}_{it}$ is standard normal white noise. Thus, the combined term $q^{-\frac{1}{2}}\, \tilde{\varepsilon}_{it}$ represents accounting noise, which has precision q. Applying Bayes' rule to $\tilde{\pi}_{it}$ and $\tilde{z}_{it}$ implies that the productivity innovation has prior precision τ and posterior precision $\tau + q$, which indicates that the accounting signal $\tilde{z}_{it}$ explains $\frac{q}{\tau+q}$ of the uncertainty in productivity $\tilde{\pi}_{it}$. This explanatory power of accounting signals increases when other firms' signals are also used in conjunction with the firm's own signal. This incremental resolution of uncertainty from using other firms' accounting signals leads to higher investment efficiency and lower cost of capital, which constitute the spillover effects of financial reporting.

For the main estimation (Section 5), I assume that the manager's information set $\mathbb{I}_{it}$ is the full vector of $\tilde{\mathbf{z}}_t$, which is equivalent to assuming that the manager will utilize all available information in the economy when making investment decisions. In counterfactual analyses (Section 6), I either reduce (or "coarsen") the manager's information set $\mathbb{I}_{it}$ or reduce the precision of certain accounting signals to analyze the various effects of financial reporting. Appendix B derives the conditional distributions of $\tilde{\pi}_{it}$ and $\tilde{\zeta}_{it}$, which are crucial in these analyses.

3.3. Variables for Estimation

I discuss the variables that I match with the data. Two variables, *Investment Rate*, I_{it}, and *Depreciation Rate*, δ, were previously defined. The other two variables are *ROA* and *Payout Rate*. I define *ROA* as operating income scaled by $k_{i,t-1}$. Operating income is

$$\mathrm{E}[\tilde{\pi}_{it}|z_{it}]k_{it} - \frac{\phi}{2}\frac{\left(I_{it}k_{i,t-1}\right)^2}{k_{i,t-1}} \qquad (6)$$

which has the following two components: (i) (accounting-based) operating outcome for period t, and (ii) investment adjustment cost. Using $\mathrm{E}[\tilde{\pi}_{it}|z_{it}]$ rather than z_{it} itself reflects the notion that the accounting standards require the financial report to provide reasonable estimates of firms' operating performances. Operating income also includes the investment adjustment cost, which is not part of the investment expenditure (e.g., training expense for new machines).

I define *Payout Rate* as net payout to investors scaled by $k_{i,t-1}$. Net payout to investors is

$$\pi_{it}k_{it} - I_{it}k_{i,t-1} - \frac{\phi}{2}\frac{\left(I_{it}k_{i,t-1}\right)^2}{k_{i,t-1}} \qquad (7)$$

which reflects the assumption that firms only retain cash or raise capital that is necessary to finance their investment expenditures. Because I abstract away the distinction between different types of capital providers, investors can be interpreted as including both creditors and shareholders.

4. Data

I collect data on financial reports, corporate investment, and transactions with capital providers from Compustat and Thomson Reuters SDC. My sample consists of U.S. firms in Compustat for fiscal years 1990-2014, excluding financial (SIC 6000-6999) and utility firms (SIC

4900-4999), which, due to their regulated nature, tend to have distinct investment policies.[18] I remove firms that have fewer than five observations.[19] I also remove firm-years that have missing value for either operating income or lagged total assets.[20] Finally, I remove firm-years for which I cannot obtain the long-run cash effective tax rate (ETR) due to missing pretax income or cash taxes paid. This procedure results in a final sample of 67,472 observations from 5,609 unique firms.

From this dataset, I construct four variables that correspond to the four model variables defined in Section 3.3. For the first variable, *ROA*, which I define as operating income scaled by lagged assets, I adjust operating income in Compustat to correspond to how it is defined in the model. Operating income in Section 3.3 only reflects the output generated by the firm's capital stock and excludes any expenses related to investment (e.g., depreciation $\delta k_{i,t-1}$ is not subtracted from operating outcome). Also, since productivity in the model is an after-tax construct that determines NPV and investment policy, its empirical counterpart should be measured on an after-tax basis. Therefore, I adjust operating income in Compustat by adding back investment-related expenses included in operating income (i.e., depreciation and amortization, research and development (R&D), and advertising) and applying the firm's ETR to obtain the after-tax amount. For this ETR, I use long-run cash ETR calculated over the surrounding five years (i.e., from year *t*-2 to *t*+2), which reflects the firm's overall tax burden with less noise (Dyreng et al., 2008). Finally, I add the tax shields from investment-related expenses and interest expense to operating income.[21]

For the second variable, *Investment Rate*, which I define as investment expenditure scaled

[18] I restrict the sample period to 1990-2014 to minimize the impact of the two major tax reforms around this sample period: the Tax Reform Act of 1986 and the Tax Cuts and Jobs Act of 2017. Since I use 5-year cash ETR around each year (i.e., from year *t*-2 to *t*+2), my data broadly covers the period of 1988-2016.
[19] This restriction is to ensure reliable firm-level regressions, which certain moments in Section 5 rely on.
[20] I assume the value is zero if other variables are missing (e.g., capital expenditure).
[21] Tax shields for investment-related expenses and interest expense are likely to be conforming tax avoidance strategies in the long run. Since ETR measures cannot reflect conforming avoidance (Hanlon and Heitzman, 2010), I separately adjust operating income.

by lagged assets, I use a broad measure of corporate investment that includes not only expenditures for capital investment (and finance leases), but also for mergers and acquisitions (M&A), R&D, and advertising.[22] For M&A, I include both cash expenditures from Compustat and non-cash expenditures (i.e., stock acquisition and liability assumption) from Thomson Reuters SDC. This broad measure mitigates the effect of differences in the relative importance of capital and non-capital investments across industries and better captures the many ways in which firms can and do alter their operating capacity in response to fluctuations in investment opportunities (Figure 2).

For the third variable, *Payout Rate*, which I define as net payout to investors scaled by lagged assets, I include most of the components of financing cash flows—dividend payments, debt issuances and repayments, and share sales and repurchases—as well as interest payments because my model abstracts away the distinction between different types of capital providers (e.g., shareholders and creditors). I also treat non-cash M&A expenditure and finance leases as combinations of investment expenditure and external financing, so I subtract them from net payout to investors. I define the last variable, *Depreciation Rate*, as investment-related expenses included in operating income (i.e., depreciation and amortization, R&D, and advertising) scaled by lagged assets.[23]

Appendix C explains in detail how I define each variable, and Table 1 presents descriptive statistics of the variables and their underlying components. I winsorize all variables at the 1st and 99th percentiles. This table shows that mean *ROA* is 19.4%, which is somewhat higher than that reported in prior studies because I add back investment-related expenses to operating income. The

[22] Many studies on corporate investment focus on capital expenditure, but several studies use a broader measure of corporate investment similar to mine (e.g., Biddle et al., 2009; Cheng et al., 2013; Goodman et al., 2014; Shroff, 2017).
[23] Since current U.S. GAAP requires immediate expensing of R&D and advertising, the expense amounts reflect little, if any, of the economic depreciation associated with the capital stock they create. However, to the extent that firms tend to exhibit persistence in their R&D and advertising policies, immediate expensing may produce a reasonable approximation of the total economic depreciation for a steady state firm with multiple layers of capital stock created by previous R&D and advertising expenditures.

correlation matrix presented in Panel B shows an economically significant correlation of 0.52 between *ROA* and *Investment Rate*. This preliminary finding is consistent with an important maintained assumption in the model that firms' productivity (reflected in *ROA*) is a major driver of their investment decisions.

5. Estimation and Identification

5.1. Estimation

My model has ten parameters, which I summarize in Panel A of Table 2. Broadly, there are three groups of parameters: (i) those that govern the distribution of productivity, $\tilde{\pi}_{it}$, which include its mean m and autocorrelation ρ, the proportion of systematic variation γ, and the precision of innovation τ; (ii) one that governs the accounting process, financial reporting precision q; and (iii) those that govern investment decisions, which include the annual depreciation rate δ, investment adjustment cost parameter ϕ, risk premium parameter λ, the variance of investment deviations ψ, and the risk-free rate r_f. Among these, the three parameters γ, τ, and q, which define the posterior covariance of $\tilde{\pi}_{it}$ (eqn. (B6) in Appendix B), are the primary parameters in examining the extent of spillover effects. Co-movement in productivity across firms, which γ represents, makes other firms' reports more informationally valuable (i.e., more spillovers); the informativeness of financial reports, which τ and q represent jointly, reduces the incremental information other firms' reports can provide over the firm's own report (i.e., less spillovers).

I use simulated method of moments (SMM) to estimate these parameters except for the risk-free rate, which I set to 4%.[24] SMM is an estimation technique that matches (i) the moments

[24] It is common to set the risk-free rate (or an equivalent discount rate) to a specific value in structural estimation. I choose 4% based on average treasury constant maturity rates released daily by the Federal Reserve Board (H.15). Based on 6,255 releases during my sample period from 1990-2014, the average rates for different maturities are 3.39% (1 year), 3.72% (2 years), 3.95% (3 years), 4.38% (5 years), 4.70% (7 years), 4.96% (10 years).

(e.g., mean, variance, correlation, synchronicity) of simulated variables from the model with (ii) the moments of their observed counterparts in the data. More formally, SMM searches for the set of parameters θ that minimizes the distance between the two sets of moments:

$$Q(d, \hat{d}, \theta) \equiv \left(m(d) - \widehat{m}(\hat{d}, \theta)\right)' \Omega^{-1} \left(m(d) - \widehat{m}(\hat{d}, \theta)\right) \tag{8}$$

$m(d)$ is the vector of data moments, which is a function of the observed data panel d, and $\widehat{m}(\hat{d}, \theta)$ is the vector of simulated moments, which is a function of the simulated data panel $\hat{d}$ and the parameters θ. I use the inverse of the covariance matrix, Ω, of $m(d)$ as the weight matrix to standardize this distance.[25] Appendix D describes my SMM estimation procedure and its analogy to reduced-form approaches (i.e., ordinary/generalized least squares) in greater detail.

5.2. Identification

A parameter is “identified” in SMM if the objective function in eqn. (8) has a *unique* minimum at its *true* value. This definition is essentially equivalent to its use in reduced-form settings, in which identification is often understood in a more applied context (because uniqueness is rarely a concern). In reduced-form settings, identification often means that the value of a model coefficient captures the appropriate source of variation in the data, rather than an unknown or spurious source of variation, allowing a researcher to rely on statistical estimates to draw (causal) inferences about theoretical constructs.

To have my parameter estimates capture appropriate sources of variation, my identification strategy primarily focuses on the main, intuitive role of each parameter in the model and uses the most relevant moment, which is sensitive to—and has a monotonic relationship with—the parameter. For example, the main role of the investment adjustment cost parameter ϕ is to reduce

[25] This weight matrix is also the efficient weight matrix, which minimizes the asymptotic variance of the parameter estimates. I use two-way clustering by firm and year when obtaining the covariance matrix of $m(d)$ following Cameron et al. (2011) and Thompson (2011).

the variability of investment, while that of the risk premium parameter λ is to suppress investment altogether. Therefore, ϕ and λ are primarily identified by their negative relationships with the variance and mean of *Investment Rate*, respectively. This identification strategy crucially relies on the model's validity, which I examine after the parameters are estimated.

I use eleven moments from the four main variables, most of which are based on the two key variables *ROA* and *Investment Rate*. These eleven moments are means, variances, autocorrelations, and synchronicities of *ROA* and *Investment Rate*; the correlation between *ROA* and *Investment Rate*; the variance of the sum of *Investment Rate* and *Payout Rate*; and the mean of *Depreciation Rate*. Synchronicity is defined as the explanatory power (i.e., R^2) of the economy-level variable against the firm-level variable.[26] I summarize these moments in Panel B of Table 2 along with the parameters to whose identification each moment contributes the most.

The first two parameters—mean m and autocorrelation ρ of productivity—are primarily identified by the mean and autocorrelation of *ROA*, respectively. This identification stems from the observation that $\mathrm{E}[\tilde{\pi}_{it}|z_{it}]$, which is the core of *ROA* in eqn. (6), has the same *ex ante* mean and autocorrelation as those of productivity $\tilde{\pi}_{it}$.

The precision of productivity innovation τ and reporting precision q are primarily identified by the (i) variance of *ROA* and (ii) the variance of the sum of *Investment Rate* and *Payout Rate*. The three variables *ROA*, *Investment Rate*, and *Payout Rate* roughly correspond to cash flows from operating, investing, and financing activities, respectively. However, *ROA* is based on earnings while the other two variables are more directly linked to cash flows and firms' real actions, so I assume that the sum of *Investment Rate* and *Payout Rate* better reveals productivity $\tilde{\pi}_{it}$ than

[26] For autocorrelation and synchronicity, I use the average of firm-level statistics (i.e., the coefficient of the lagged variable and the R^2 of the economy-level variable from each firm-level regression) as the respective moment in order to avoid estimating a single regression specification for a heterogeneous set of firms.

does *ROA*, which captures productivity with a layer of accounting noise. Therefore, variance of the sum of *Investment Rate* and *Payout Rate* primarily identifies τ, while the relative magnitudes of the two variances primarily identify q. The latter identification rests on the observation that the variance of $\mathrm{E}[\tilde{\pi}_{it}|z_{it}]$, on which *ROA* is based, approaches that of $\tilde{\pi}_{it}$ as q increases.

Given the identification of these four parameters, the remaining parameters are identified in a sequential manner (Strebulaev and Whited, 2012). To illustrate, the proportion of systematic variation γ is primarily identified by the synchronicity of *ROA*. Although *ROA* is less synchronous than is productivity due to accounting noise, given that τ and q are identified (i.e., I know the relative weights of synchronous productivity and asynchronous accounting noise in *ROA*), I can extract the underlying synchronicity of productivity from the observed synchronicity of *ROA*.

I similarly identify the four other parameters that govern investment decisions. First, depreciation rate δ is primarily identified by the mean of *Depreciation Rate*. Second, the variance of investment deviations ψ represents the variation in *Investment Rate* that is not productivity-driven (i.e., due to $\tilde{s}_{it}$) and is primarily identified by the correlation between *ROA* and *Investment Rate*. Third, investment adjustment cost parameter ϕ determines the variability of investment and is primarily identified by the variance of *Investment Rate*. Finally, risk premium parameter λ determines the amount of investment and is primarily identified by the mean of *Investment Rate*.[27]

The final two moments—i.e., the autocorrelation and synchronicity of *Investment Rate*—contribute to the identification of multiple parameters (e.g., ψ, which is the source of divergent patterns across *ROA* and *Investment Rate*), and they also provide evidence that the model is able to capture various aspects of observed investment decisions.

[27] This ordering of sequential identification is natural given the investment decision in eqn. (3). In the model, (i) depreciation rate is not a function of ψ, ϕ, and λ; (ii) the relative proportion of productivity-driven (i.e., due to $\tilde{\pi}_{it}$) and residual (i.e., due to $\tilde{s}_{it}$) variations in investment rate is not a function of ϕ and λ; and (iii) the variance of investment rate is not a function of λ.

5.3. Results

Panel A of Table 3 presents the parameter estimates of the baseline model with a single aggregate (i.e., economy-wide) systematic productivity factor. I discuss the estimates and assess their validity using stylized facts from the literature that are not artifacts—and are therefore independent—of my parameter estimates. This section focuses on the validity of the primary parameters γ, τ, and q, while Appendix E discusses the validity of other parameters.

The first four parameters that govern the distribution of productivity $\tilde{\pi}_{it}$ show that the estimated mean m is 0.21, autocorrelation ρ is 0.41, the proportion of systematic variation γ is 0.42, and the precision of innovation τ is 44 (which implies a standard deviation of $\sqrt{\tau^{-1}} = 0.15$). The corresponding values for observed *ROA* are mean 0.19, autocorrelation 0.37, synchronicity 0.23, and standard deviation of innovation 0.12. The values show that financial information (i.e., observed *ROA*) approximates the underlying productivity process, but the different synchronicities also show that firm-specific accounting processes hamper comparability across firms.

The estimate of the proportion of systematic variation in productivity γ of 0.42 also corresponds to patterns of systematic risk in equity returns. Factor models of monthly equity returns result in varying levels of average explanatory power (i.e., R^2), ranging from 21.8% for the single-factor model (i.e., the capital asset pricing model) to 40.3% for the Fama and French (1993) three-factor model and to 48.7% for the Carhart (1997) four-factor model.[28] Since γ's role is to succinctly represent all systematic variation in productivity, it is reasonable to expect the estimate to be comparable to the explanatory power of the three- and four-factor models.

The estimate of financial reporting precision q is 21. In conjunction with the estimate of τ,

[28] I use the WRDS Beta Suite to obtain the R^2's of factor models. I use twelve monthly equity returns (at least six) preceding the fiscal year end date. The average R^2 is based on a sample of 56,981 firm-years that have sufficient equity return data to estimate the factor models.

which is 44, this estimate implies that a firm's own financial report explains $\frac{q}{\tau+q} = \frac{21}{44+21} = 33\%$ of the uncertainty in latent productivity $\tilde{\pi}_{it}$. Although there is no observable input that directly corresponds to $\tilde{\pi}_{it}$, considering its delayed revelation in the model compared to the accounting signal, it resembles one-year-ahead operating cash flows. Prior studies find varying degrees with which earnings explain one-year-ahead operating cash flows, but the range is roughly 30~50%, which is consistent with my estimated explanatory power of 33%.[29]

For the other four parameters that govern investment decisions, I explain the implication of their estimates here but their validity in Appendix E. First, the estimated depreciation rate δ of 0.098 corresponds to roughly 15 years (150%-declining-balance) or 20 years (double-declining-balance) of useful life under the model's declining-balance depreciation. Second, the estimated investment adjustment cost parameter ϕ of 1.8 implies that the adjustment cost is roughly 15% of investment expenditure. 15% is the ratio of adjustment cost $\frac{\phi}{2}\frac{(I_{it}k_{i,t-1})^2}{k_{i,t-1}}$ to investment expenditure $I_{it}k_{i,t-1}$ estimated at the mean Investment Rate of 16.6% (i.e., $\frac{\phi I_{it}}{2} = \frac{1.8\times 16.6\%}{2}$ =15%). Third, the estimated risk premium parameter λ of 4 roughly corresponds to a risk-adjusted weighted average cost of capital (WACC) of 7.5% under the transformation of the additively separable risk premium to a risk-adjusted discount rate using

$$\sum_{s=0}^{\infty} \frac{\mathrm{E}[\tilde{\pi}_{it}|\mathbf{z}_t](1-\delta)^s}{\left(1+r_f\right)^s} - \lambda \mathrm{Cov}\left(\tilde{\zeta}_{it}, \frac{1}{N}\sum_{j=1}^{N}\tilde{\zeta}_{jt} \,|\mathbb{I}_{it}\right) = \sum_{s=0}^{\infty} \frac{\mathrm{E}[\tilde{\pi}_{it}|\mathbf{z}_t](1-\delta)^s}{(1+r_a)^s} \qquad (9)$$

where r_a is the risk-adjusted WACC. The expectation $\mathrm{E}[\tilde{\pi}_{it}|\tilde{\mathbf{z}}_t]$ is replaced with its *ex ante* expectation m to derive 7.5%. The final parameter—the variance of investment deviations ψ—

[29] For example, Subramanyam and Venkatachalam (2007) find an R^2 as low as 29.0%, but Kim and Kross (2005) find an R^2 as high as 52.8%.

has an estimate of 0.099. Comparison of the relative variations in $\mathrm{E}\left[\tilde{\zeta}_{it}|\mathbf{z}_t\right]$ and $\tilde{s}_{it}$, both in the numerator of eqn. (3), imply that roughly 29% of the total variation in investment is productivity-driven (i.e., due to $\tilde{\pi}_{it}$), while the remaining 71% is residual variation (i.e., due to $\tilde{s}_{it}$).

5.4. Model Fit and Analysis of Identification

Panel B of Table 3 presents the model's fit. No simulated moment shows a statistically significant difference with its observed counterpart, nor does there seem to be an economically significant difference. The largest absolute (proportional) difference between the data and the simulation is for synchronicity (autocorrelation) of *ROA* at 0.013 (6.7%). Panel B also presents the results from the test of overidentifying restrictions. The *J*-statistic is 1.5 with a *p*-value of 0.48, indicating that the null hypothesis that the model fits all eleven moments cannot be rejected. Overall, my baseline model with a single aggregate (i.e., economy-wide) systematic productivity factor provides not only a reasonable fit with the observed data, but also produces parameter estimates that correspond to other empirical regularities that are independent of the model.

I also examine the identification of parameter estimates. Panel A of Table 3 shows that all parameter estimates have high *t*-statistics, alleviating the concern of poor identification. In addition, Figure 3 presents the sensitivities of parameter estimates to perturbations in moment conditions (Andrews et al., 2017). These sensitivities roughly correspond to the number of standard deviations by which the parameter estimate would change if a moment increased by one standard deviation, albeit of an infinitesimal scale. These sensitivities are useful in assessing (local) identification because if a moment primarily identifies a certain parameter, that parameter is expected to be most sensitive to that moment. The results show that the pattern of the sensitivities largely coincides with my discussion of identification in Section 5.2. For the first six parameters, the patterns almost exactly follow the discussion. For example, I expect the proportion of systematic variation γ to be primarily identified by the synchronicity of *ROA*, and indeed the estimate of γ is most sensitive to the synchronicity of *ROA*. The last three parameters are sensitive not just to the moments that I expect to primarily identify them because they are identified in a sequential manner. Still, the patterns are largely consistent with the discussion in Section 5.2 (e.g., investment adjustment cost parameter ϕ is most sensitive to the variance of *Investment Rate*). Overall, the SMM estimation appears to identify the parameters in a manner that is consistent with my *ex ante* expectations.

6. Quantitative Analysis

6.1. Total Effect of Financial Reporting

In this section, I decompose the total effect of financial reporting on corporate investment into its direct and spillover components. My structural model allows this decomposition because, once I have estimates of the "deep" (i.e., invariant) structural parameters, I can (counterfactually) manipulate managers' information sets to assess their investment decisions under various alternative information structures. Specifically, I use the investment decision formula in eqn. (3)

$$I_{it}(\mathbb{I}_{it}) = \frac{\mathrm{E}\left[\tilde{\zeta}_{it}|\mathbb{I}_{it}\right] - 1 - \lambda \mathrm{Cov}\left(\tilde{\zeta}_{it}, \frac{1}{N}\sum_{j=1}^{N} \tilde{\zeta}_{jt}\,|\mathbb{I}_{it}\right) + \tilde{s}_{it}}{\phi} \tag{10}$$

to simulate investment decisions I_{it} under various alternative information sets $\mathbb{I}_{it}$.[30] Three information sets are of particular interest: (i) the null set $\emptyset$, which corresponds to lack of learning from any contemporaneous financial reports; (ii) the firm's own report z_{it}, which corresponds to managers learning only from their own firm's financial report; and (iii) the full set of all financial reports in the economy $\mathbf{z}_t$, which corresponds to managers learning from their own firm's financial

[30] This manipulation is possible because the parameters that I estimate in Section 5 are "deep" structural parameters that do not depend on (i.e., are invariant to) managers' information set $\mathbb{I}_{it}$. In contrast, more observable inputs (e.g., WACC) are not invariant, making it difficult to extrapolate results from reduced-form studies into counterfactual economies that we cannot observe.

report as well as financial reports from other firms in the economy.[31] The difference in the amount and efficiency of investment between the first two scenarios captures the direct effects of financial reporting (i.e., due to a firm's own financial reporting), while the difference between the last two scenarios captures the spillover effects (i.e., due to other firms' financial reporting).

Figure 4 illustrates the general pattern of this counterfactual analysis. Panel A displays the incremental investment rates for one firm in the simulated panel, which is representative of the whole economy due to homogeneity across firms in the simulation. The red crosses, which are $I_{it}(\mathbb{I}_{it} = z_{it}) - I_{it}(\mathbb{I}_{it} = \emptyset)$, represent the direct effects, while the blue circles, which are $I_{it}(\mathbb{I}_{it} = \mathbf{z}_t) - I_{it}(\mathbb{I}_{it} = \emptyset)$, represent the sum of the direct and spillover effects. Panel B reveals the pattern in Panel A (i.e., the effect of financial reporting) more clearly. Compared to the baseline of no learning from contemporaneous financial reports (black solid horizontal line), expanding the manager's information set increases both (i) investment sensitivity to productivity (upward-sloping dashed lines; investment efficiency channel) and (ii) investment amount (horizontal dotted lines; cost of capital channel). The first channel ("Investment Efficiency Channel") shows that managers better understand their firm's investment opportunities and time their investment decisions more efficiently. The second channel ("Cost of Capital Channel") shows that managers can invest more because of the reduction in their firm's cost of capital. Panel B shows that *other firms'* financial reporting has incremental spillover effects above and beyond the direct effects of the firm's own financial reporting through both of these channels (i.e., the blue lines deviate more from the baseline than the red lines).

To quantify the combined spillover effects through these two channels, I examine the

[31] Since I retain the assumption that the realization of $\tilde{\pi}_{it}$ is revealed at the end of period t, the counterfactual analysis focuses on the effect of changing managers' access to *contemporaneous* financial reports (while preserving managers' access to *historical* financial reports).

aggregate output of the public corporate sector, i.e., the sum of $\pi_{it}k_{it}$ across all firm-years (scaled by $\sum_{j=1}^{N} k_{j,t-1}$ to ensure comparable magnitude across years), which increases in both the amount and efficiency of investment. Panel A of Table 4 presents the decomposition of the total effect of financial reporting on the aggregate output of the public corporate sector based on 1,000 simulations of the whole economy. The last row shows that roughly half (54%) of the total effect is attributable to spillover effects, providing evidence that spillover effects are just as important as direct effects of financial reporting.[32] Considering that prior studies document economically significant direct effects (e.g., Botosan, 1997; Biddle and Hilary, 2006; Hail and Leuz, 2006; Biddle et al., 2009), this finding implies that public firms' financial reporting has economically significant spillover effects on other firms' investment.

A closer inspection shows that spillovers account for roughly two-thirds (67% = 33.85% ÷ 50.39%) of the total effect through the cost of capital channel, but only one-third (40% = 19.99% ÷ 49.61%) through the investment efficiency channel. In other words, information spillovers primarily affect the *amount* of firms' investment and only secondarily affect the *efficiency* of their investment decisions. For a given year, (cross-sectional) investment efficiency is about whether more productive firms invest more, which requires knowledge about a firm's relative (i.e., idiosyncratic) productivity vis-à-vis the average productivity of the economy as a whole. In contrast, cost of capital stems from non-diversifiable risk, which depends on the systematic productivity factor. Therefore, spillover effects, which primarily relate to learning about the systematic productivity factor from other firms' financial reports, should be more important for the cost of capital channel.

[32] Figure 5 presents the comparative statics of the relative importance of total spillover effects with regard to changes in parameter values. The figure confirms that the three primary parameters γ, τ, and q, which define the posterior covariance of productivity, drive the result.

This quantitative evidence also provides insight into the role of spillover effects in the debate on the economic justification of financial reporting regulation. Positive spillover externalities are frequently cited as a main justification for regulation (Beyer et al., 2010; Leuz and Wysocki, 2016; Minnis and Shroff, 2017), in line with the public goods argument that firms only internalize the private benefit (i.e., direct effects) of their financial reporting, which leads to an undersupply of information than the social optimum that also considers the social benefit (i.e., spillover effects). My finding that spillover effects constitute a meaningful benefit of financial reporting, which is even comparable to direct effects, supports the endeavor to justify financial reporting regulation using positive spillover externalities.

6.2. Marginal Effect of Financial Reporting Precision

The preceding counterfactual analysis eliminated managers' ability to learn from certain contemporaneous financial reports. However, estimates from my structural model also allow for other, more subtle, manipulations of managers' information sets. In particular, I can decompose the effect of changing firms' reporting *precision* from one value to another (e.g., from q_1 to q_2).[33] In this analysis, three alternative information sets are of particular interest: (i) all firms' financial reports are of precision q_1; (ii) the firm's own financial report is of precision q_2, while other financial reports are of precision q_1; and (iii) all firms' financial reports are of precision q_2.

An interesting and informative scenario is when $q_1 = 21$, which corresponds to the reporting precision estimated from the data, and q_2 is a marginally larger value. This change provides evidence about the effect of a *marginal* change in reporting precision. The finding that spillover effects account for roughly half of the total effect of financial reporting provides insight into the total spillover benefits inherent in the current regulatory regime, but it may be less relevant

[33] Manipulating managers' access to financial reports in Section 6.1 can be viewed as a special case of this change: q_1 is zero and q_2 is the estimated reporting precision 21.

for understanding the spillover benefits from introducing a new regulation to the existing regime. The marginal effect of financial reporting precision is more relevant for the latter purpose.

Panel B of Table 4 presents the decomposition of the effect of a 1% increase in reporting precision from the estimate 21 on the aggregate output of the public corporate sector. The estimates show that spillover effects at this particular margin are trivial compared to the direct effects. The intuition for the stark difference between my estimates of the total spillover effects (Panel A) and the marginal spillover effects (Panel B) is that systematic information quickly becomes subject to diminishing marginal returns because of its relative abundance compared to idiosyncratic information.[34] To illustrate, consider the acquisition of systematic information: a marginal increase in reporting precision is analogous to accessing the financial reports of a few more firms. However, after already having access to thousands of firms' financial reports, these new reports will provide little, if any, systematic information that was not already known. This intuition suggests that if the model included more systematic productivity factors that only some firms are exposed to, spillover effects would not have been exhausted so quickly. Therefore, I re-discuss marginal spillover effects after I introduce another layer of industry-level productivity factors in the next section.[35]

7. Industry Analysis

In this section, I conduct an industry-level analysis using an expanded model that also

[34] Given the parameter estimates, the *prior* variances of the systematic and idiosyncratic productivity innovations are $\mathrm{Var}(\tilde{f}_t) = 0.0097$ and $\mathrm{Var}(\widetilde{\omega}_{it}) = 0.0132$, which are roughly similar in magnitude. However, the *posterior* variances have very different magnitudes. In fact, $\mathrm{Var}(\widetilde{\omega}_{it}|\mathbf{z}_t)$ is more than 400 times larger than $\mathrm{Var}(\tilde{f}_t|\mathbf{z}_t)$.

[35] Having only a single economy-wide systematic factor without industry-level factors results in underestimation for marginal spillover effects but not for total spillover effects because the moment conditions capture average (rather than marginal) characteristics of the data. As a simple analogy, consider a firm with multiple types of income subject to different tax rates. The total tax amount can be derived from total pretax income and the average tax rate, but the marginal tax amount cannot be estimated without also knowing the income type. In the context of my study, total pretax income corresponds to the estimated reporting precision, average tax rate to the moment conditions, and the income type to the layer of productivity factors.

includes industry-specific systematic productivity factors, which allows me to estimate separate parameters and draw quantitative inferences for each industry. This industry-level analysis serves several purposes. First, this analysis shows that my main finding—that spillover and direct effects are of comparable economic magnitude—is robust to relaxing the homogeneity assumption across all firms in the industry. Second, assessing the extent to which spillover effects are due to industry-specific versus economy-wide information provides corroborating evidence to prior studies' focus on within-industry spillover effects (e.g., Badertscher et al., 2013; Shroff et al., 2017). Third, this analysis allows me to examine marginal spillover effects from industry-specific information, which is less susceptible to diminishing marginal returns than economy-wide information.

7.1. Model

The model in Section 3 assumes that the same set of parameters govern all firms in the economy (e.g., m is every firm's mean productivity). In this section, I relax this homogeneity assumption and instead assume that the firms in each industry are governed by their own set of parameters. Productivity $\tilde{\pi}_{ijt}$ for firm i in industry j at time t is now defined as

$$\tilde{\pi}_{ijt} = m_j + \beta_j \tilde{\pi}_t^{econ} + \tilde{\pi}_{jt}^{ind} + \tilde{\pi}_{ijt}^{firm} \tag{11}$$

where the three components follow AR(1) processes

$$\tilde{\pi}_t^{econ} = \rho_e \tilde{\pi}_{t-1}^{econ} + \tilde{f}_t \tag{12}$$

$$\tilde{\pi}_{jt}^{ind} = \rho \tilde{\pi}_{j,t-1}^{ind} + \tilde{g}_{jt} \tag{13}$$

$$\tilde{\pi}_{ijt}^{firm} = \rho \tilde{\pi}_{ij,t-1}^{firm} + \widetilde{\omega}_{ijt} \tag{14}$$

There are three mutually independent innovations: (i) an economy-wide innovation, $\tilde{f}_t$, which follows i.i.d. $N(0, \tau_e^{-1})$; (ii) an industry-specific innovation, $\tilde{g}_{jt}$, which follows i.i.d. $N\left(0, \gamma_j \tau_j^{-1}\right)$; and (iii) an idiosyncratic innovation, $\widetilde{\omega}_{ijt}$, which follows i.i.d. $N\left(0, \left(1-\gamma_j\right)\tau_j^{-1}\right)$. The new parameter β_j accounts for heterogeneous exposure to the economy-wide productivity factor across industries. When β_j equals zero, eqns. (11) to (14) collapse to eqn. (4), showing that the addition of $\beta_j \tilde{\pi}_t^{econ}$ is the core of the extension. The autocorrelation ρ_e and innovation precision τ_e of $\tilde{\pi}_t^{econ}$ are parameters that do not vary by industry because there is only one economy-wide systematic productivity factor. Hereinafter, I drop the industry subscript (e.g., j in $\tilde{\pi}_{ijt}$ and γ_j) for brevity and consistency with the preceding sections.

Since I do not make any other changes to the model, the investment decision in eqn. (3), the specification of accounting signals in eqn. (5), and the definitions of operating income and payout to investors in eqns. (6) and (7) are the same as before. The conditional distributions of $\tilde{\pi}_{it}$ and $\tilde{\zeta}_{it}$ do change, which I explain in Appendix B.

7.2. Estimation and Validation

7.2.1. Estimation

I classify firms into 28 of Fama and French's (1997) 48 industries. The industries I use are listed in Panel A of Table 5. I exclude five industries of the original 48 because they consist of financial and utility firms. I exclude the other 15 industries are excluded due to the low number of observations. For stability of the estimation, I require an industry to have at least 625 observations (i.e., an average of 25 observations per year) in total and at least 10 observations in each fiscal year. The resulting 28 industries have 60,775 observations, which accounts for 90% of the full sample used to estimate the baseline model in Section 5.

Using this classification, I estimate the parameters for each industry in isolation. Since all firms are exposed to the same economy-wide productivity factor, every firm's accounting signal matters in forming the posterior distribution of productivity. Therefore, in principle, estimation for any particular industry depends on the parameters of all industries, which requires simultaneous estimation of the parameters of every industry. However, to reduce the complexity of the estimation, I make the simplifying assumption that managers know the realization of the economy-wide productivity factor $\tilde{\pi}_t^{econ}$. The parameter estimates in Section 5 imply that the posterior variance of the economy-wide systematic factor, $\mathrm{Var}(\tilde{f}_t|\mathbf{z}_t)$, is only 0.23% of the prior variance in the baseline model, so assuming that managers are able to accurately infer $\tilde{\pi}_t^{econ}$ after observing all other financial reports in the economy is relatively innocuous. This assumption eliminates the need to consider other industries when estimating parameters for an industry.

Parameter estimation by industry requires the autocorrelation ρ_e and innovation precision τ_e of the economy-wide productivity factor. I extract these two parameters from the observed annual average *ROA* across all firms in the data, consistent with the simplifying assumption that observed annual average *ROA* reveals the true economy-wide systematic productivity factor. The extracted parameter values are ρ_e = 0.7987 and τ_e = 10,889 (i.e., standard deviation of 0.0096).

For each industry, the estimation technique and the identification strategy are largely the same as in Section 5 except that there is an additional parameter to estimate: the industry's exposure to the economy-wide productivity factor, β. To identify this parameter, I include industry synchronicity of *ROA* as an additional moment to match. This moment is the R^2 from regressing industry-average *ROA* on economy-wide average *ROA*. I explain other changes in the SMM estimation procedure in Appendix D.

Panel B of Table 5 presents the SMM estimation result for each industry. Columns (2) - (11) present the parameter estimates, which display industry heterogeneity but are on average similar to the estimates from the baseline model (Section 5) evidenced by the last two rows. Column (12) presents the *p*-values from the test of overidentifying restrictions. The *p*-value is less than 0.05 in 15 industries, indicating worse model fit in these industries than for the economy-wide model in Section 5. The untabulated moment comparison indicates that the estimation for most industries fails to match two moments at most, except for the business services industry (code 34), which fails to match six. The most frequent mismatch occurs for the autocorrelation of *Investment Rate* (in 11 industries), where the simulated autocorrelation tends to be higher than the observed autocorrelation in the data.[36] Since no parameter primarily relies on this moment for identification and my research objective focuses on the relative importance of various *contemporaneous* sources of information, mismatch of this autocorrelation is less of a concern. Figure 6 graphically presents the overall model fit across industries.

7.2.2. Validation

I provide further evidence of the validity of my model and parameter estimates by examining how my industry-level parameter estimates capture inter-industry patterns that are not artifacts of my estimation procedure. In particular, I focus on the three primary parameters—proportion of systematic variation in productivity γ, precision of productivity innovations τ, and financial reporting precision q—and the industry's exposure to economy-wide productivity, β, which is only used in the industry-level analysis. Since productivity $\tilde{\pi}_{it}$ represents firm fundamentals, I use measures based on stock returns, which is another measure that reflects firm fundamentals, for validation. This test is an extension of Section 5.3, which uses stylized facts that are not artifacts of my model to assess the reasonableness of the baseline parameter estimates.

For γ, τ, and β, I compare directly corresponding measures of $\tilde{\pi}_{it}$ in the model and stock returns in the data—synchronicity for γ, total volatility for τ, and the industry's exposure to the market for β. Panel A of Table 6 shows that the industry-level measures from the model and stock

[36] This result shows that the smooth investment adjustment cost in my model does not properly capture the lumpiness in observed investment, which is better captured by a discontinuous adjustment cost (typically discontinuous at zero investment). However, a discontinuous adjustment cost is less tractable and less compatible with randomness in investment (i.e., the randomness due to the investment deviation $\tilde{s}_{it}$).

returns are positively associated. For q, since it is a measure of reporting precision, I compare it with earnings-response coefficients (ERCs), which closely reflect the definition of q (i.e., how precisely financial reports convey decision-useful information). Panel B of Table 6 shows that q is positively associated with industry-level ERCs measured across whole fiscal periods (but not those measured just around earnings announcements). Overall, these results further support my model's validity. Appendix E describes the validation tests in detail, and Figure 7 graphically displays the results in Table 6.

Examination of specific industries corroborates the validity of my parameter estimates. For example, Panel B of Table 5 shows that the estimated γ is highest at 0.67 for the petroleum and natural gas industry (code 30) and lowest at 0.06 for the electrical equipment industry (code 22). Indeed, Minton and Schrand (2016) designate these two industries as a high- and low-homogeneity industry, respectively. Panel B of Table 5 also shows that the four industries that have the lowest estimated τ are computers (code 35), pharmaceutical products (code 13), medical equipment (code 12), and electronic equipment (code 36) industries, consistent with the view that industries that experience more technological revolutions are more volatile (e.g., Pastor and Veronesi, 2009).

7.3. Quantitative Analysis

7.3.1. Total Effect of Financial Reporting

The quantitative analysis at the industry level is also largely the same as that for the baseline model (Section 6). To decompose the total effect of financial reporting into its direct and spillover components, I simulate investment decisions under three information sets: (i) the null set $\emptyset$, (ii) the firm's own report z_{it}, and (iii) the full set of all financial reports in the economy $\{\mathbf{z}_t^{ind}, \pi_t^{econ}\}$. Here, $\mathbf{z}_t^{ind}$ is the full set of all financial reports in the industry, and the realization of the economy-wide productivity factor, π_t^{econ}, summarizes the information in all other financial reports.

Panel A of Table 7 presents the decomposition of the total effect of financial reporting on the aggregate output of the public corporate sector based on 1,000 simulations of the whole economy, which is an aggregation of all the simulated industries. The last row shows that spillover effects again account for roughly half (55%) of the total effect. This differs from the estimate in Section 5 (54%) by only 0.7% points, which is statistically insignificant, and provides evidence that my finding that total spillover effects are similarly important as total direct effects of financial reporting is robust to industry-level estimation. Moreover, I continue to find that spillovers are more important for the cost of capital channel than for the investment efficiency channel.

A more detailed analysis shows which information (i.e., industry-specific vs. economy-wide) is primarily responsible for these spillover effects. For this decomposition, I expand the information set from z_{it} to $\{z_{it}, \pi_t^{econ}\}$ and then to $\{\mathbf{z}_t^{ind}, \pi_t^{econ}\}$. Since π_t^{econ} only provides economy-wide information, the expansion from z_{it} to $\{z_{it}, \pi_t^{econ}\}$ captures spillover effects due to acquisition of economy-wide information. The expansion from $\{z_{it}, \pi_t^{econ}\}$ to $\{\mathbf{z}_t^{ind}, \pi_t^{econ}\}$ captures the residual spillover effects due to acquisition of industry-specific information. Panel B of Table 7 shows that most (68%) of the spillover effects are due to learning about industry-specific information, suggesting that industry-specific fluctuations in productivity are the main driver.

Since financial reports of firms in the same industry also provide information about the economy-wide productivity factor, within-industry spillover effects are even more important. Progressively expanding the information set from z_{it} to $\mathbf{z}_t^{ind}$ and then to $\{\mathbf{z}_t^{ind}, \pi_t^{econ}\}$ shows that managers learn a significant portion of economy-wide information from financial reports within the industry. Panel C of Table 7 shows that almost all (83%) of the spillover effects are attributable to intra-industry learning, which is consistent with prior studies that often focus on within-industry spillover effects (e.g., Badertscher et al., 2013; Shroff et al., 2017).

7.3.2. Marginal Effect of Financial Reporting Precision

Next, I conduct a counterfactual analysis that parallels the one in Section 6.2. Specifically, I examine the effect of increasing firms' financial reporting precision by 1% to estimate marginal spillover effects from *industry-specific* information. In contrast to the negligible marginal spillover effects from economy-wide information in Section 6.2, Panel D of Table 7 shows that spillover effects from industry-specific information are economically meaningful, accounting for 23% of the marginal effect of financial reporting precision.

Marginal spillover effects from industry-specific information are much larger than those from economy-wide information because an industry consists of fewer firms than does the economy as a whole. In my sample, industries have an average of 87 firms each versus 2,699 firms in the entire economy. Therefore, the marginal return of industry-specific information, though diminishing, has not been exhausted at the estimated level of reporting precision that prevails in the data. This result implies that spillover effects—particularly those that stem from industry-specific information—constitute an economically meaningful benefit. Moreover, this is the case even if a new financial reporting regulation were to be introduced into the current information environment, which is widely considered to be rich for publicly traded U.S. firms.

8. Robustness Analysis

To mitigate the concern that my findings are highly sensitive to some of my specific measurement choices, I re-estimate the model with alternative measurement choices, which fall into three categories: (i) alternative definitions of *ROA*; (ii) alternative definitions of *Investment Rate*; and (iii) alternative definitions of cash ETR.

I measure *ROA* based on operating income, but managers and external investors may focus on alternative measures of profitability, making my findings deviate from spillover effects they experience. To alleviate this concern, I examine the sensitivity of my results to measuring *ROA* based on net income. Columns (2)-(4) of Table 8 present how my results change when I define *ROA* with net income measures that increasingly get distant from operating income: net income before special and extraordinary items for Column (2); net income before extraordinary items for Column (3); and net income for Column (4). The results show that my general inference—that total spillover effects are comparable in magnitude to total direct effects and that marginal spillover effects account for a smaller, yet meaningful portion—is not highly sensitive to such measurement choices. Furthermore, the *J*-statistic increases as the basis of *ROA* gets more distant from operating income, implying that operating income is the appropriate measure to estimate my model.

Alternative definitions of *Investment Rate* concern missing R&D and advertising expenses. The two variables are frequently missing, and my treatment of missing values as zero may not be the most appropriate. For example, Koh and Reeb (2015) find that firms with missing R&D expense also show signs of innovation activity and that industry-average R&D expense may be a better filler than zero. Following their suggestion, Column (5) of Table 8 presents how my results change when I fill missing R&D expense with its industry average, and Column (6) applies that treatment to advertising expense as well. Alternatively, Column (7) excludes advertising expense from *Investment Rate*, considering that prior studies least include it in investment expenditure among the four components I have. The results again show that my general inference is not highly sensitive to such measurement choices, and the *J*-statistic in Column (7), which is lower than that from my main result (Column 1), alleviates the concern that my measurement choices result from a single pursuit of maximal model fit without their economic context carefully scrutinized.

As for cash ETR, my original measurement uses a five-year window surrounding the focal year (i.e., years t-2 to t+2) to capture the firm's long-term tax environment, but that window includes future years, which may be influenced by firms' decisions. I change this window to years t-2 to t in Column (8) of Table 8 and to year t in Column (9). The results, as in other columns, show that my general inference is not highly sensitive to the ETR measurement windows.

9. Conclusion

Notwithstanding the pervasive and extensive nature of financial reporting regulation, there is little evidence that speaks to the economic justification of this regulation (Berger, 2011; Leuz and Wysocki, 2016). One stream of literature focuses on positive externalities of financial reporting, which may result in an undersupply of information relative to the social optimum absent regulation, to explain this economic justification. I extend this literature by examining whether public firms' financial reporting has spillover effects on the amount and efficiency of other public firms' investment. I do so by developing and structurally estimating a parsimonious model that links firms' financial reporting and corporate investment in order to decompose the combined effect of financial reporting into its direct and spillover components. This decomposition is the key innovation that allows me to overcome the difficulty associated with isolating spillover effects among public firms, which not only disclose their own information, but also benefit from other firms' disclosures. With this decomposition, I contribute to the literature by providing *quantitative* evidence about the spillover effects of financial reporting *in toto* as opposed to spillovers from specific or isolated information events (e.g., accounting misstatements).

My quantitative estimates suggest that roughly half (54%) of the total effect of financial reporting and a smaller, but still meaningful, portion (23%) of the marginal effect of financial reporting precision is attributable to spillover effects. Considering that prior studies document economically significant direct effects of financial reporting, my estimates suggest that spillovers are of comparable importance among public firms. Further analyses show that most (68%) of the total spillovers are due to learning about industry-specific rather than economy-wide information, with an even larger proportion (83%) due to intra-industry learning because economy-wide information is also contained in industry peers' financial reports. These findings are consistent with prior reduced-form studies that often focus on within-industry spillover effects.

Although my study is closely related to—and relies on similar motivation as—prior studies that argue that positive spillover externalities are one of the major justifications for financial reporting regulation, my findings and inferences are subject to several important caveats. First, my inferences are not decisive about the economic justification of regulation because I only focus on a specific benefit of regulation without considering its other costs and benefits. Second, my model does not explicitly consider other sources of information that might substitute for financial reporting. Therefore, a more literal interpretation of my findings is that they are about the relative decision-usefulness of information conveyed by other firms' financial reports compared to that in firms' own financial reports, regardless of whether managers and external investors learn such information from financial reports *per se*. However, my estimates of *marginal* spillovers are much less susceptible to this concern because they relate to information that is incremental to that in the prevailing information environment, which includes—and therefore accounts for—any substitute sources. Moreover, several characteristics of the financial reporting environment alleviate this concern for *total* spillovers: (i) to the extent that information from other sources provides both systematic and idiosyncratic information, any bias in my estimates of the direct and spillover effects is potentially offset when I assess their relative magnitude; (ii) other information sources may derive from financial reports, implying that learning from those sources can be construed as indirect learning from financial reports; and (iii) other information sources may not influence corporate investment until they are corroborated by financial reports (i.e., other information may not be a perfect substitute for financial reports, which are also audited). Nevertheless, identifying the incremental value of financial reporting above and beyond alternative sources of information is important for accurately identifying spillovers, as well as any other (e.g., direct) effects of financial reporting. Although this investigation is beyond the scope of my study, it is a fruitful avenue for future research.

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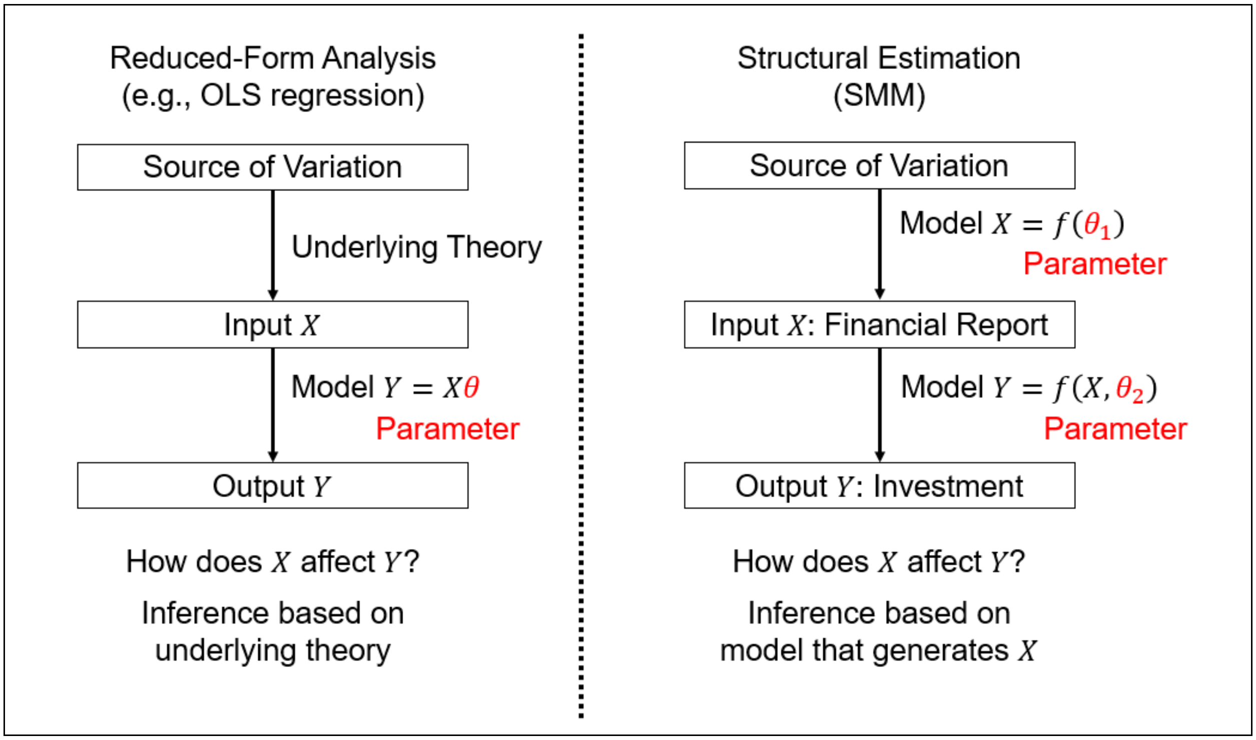
Appendix A. Overview of Structural Estimation



The above figure illustrates the overview of my structural estimation and its analogy to reduced-form analyses (e.g., OLS). My study's objective is to understand how an independent variable X (i.e., financial reporting) affects a dependent variable Y (i.e., investment), similar to most reduced-form studies. To answer this research question, I construct a model that links the two variables, $Y = f(X, \theta_2)$, which is analogous to the OLS specification $Y = X\theta$, albeit the latter is closer to a statistical relationship.

To answer the research question with parameter estimates of these models, an inference based on underlying theory is necessary to identify the source of the variation in X. Verbal theory or a motivating model provides that inference in reduced-form analyses, whereas I have another layer of the model $X = f(\theta_1)$, which is formally estimated unlike its counterparts (i.e., verbal theory, motivating model), to identify the source of the variation. In particular, I control one of the parameters in θ_1 (i.e., financial reporting precision q) for different firms each time, to achieve my research objective. Section 6 provides details of this approach.

Appendix B. Posterior Distribution of Productivity

The investment decision in eqn. (3) is governed by the posterior mean $\mathrm{E}[\tilde{\zeta}_{it}|\mathbb{I}_{it}]$ and covariance $\mathrm{Cov}(\tilde{\zeta}_{it},\tilde{\zeta}_{jt}|\mathbb{I}_{it})$ of long-term productivity. I derive the closed-form expressions of these statistics in this appendix.

B.1. Baseline Model

I first derive the posterior distribution of $\tilde{\zeta}_{it}$ based on the vector of accounting signals with firm-specific reporting precision q_i, i.e., $\mathbb{I}_{it}$ is a vector of $\tilde{z}_{it} = \tilde{\pi}_{it} + q_i^{-\frac{1}{2}}\tilde{\varepsilon}_{it}$. Plugging in appropriate values for q_i gives all of the conditional statistics I need in my analyses.

Given information up to period $t-1$, short-term productivity can be expressed as

$$\tilde{\pi}_{i,t+s} = m + \rho^s(\mu_{it} - m) + \sum_{l=0}^{s} \rho^{s-l}\left(\tilde{f}_{t+l} + \tilde{\omega}_{i,t+l}\right) \tag{B1}$$

where $\mu_{it} = m + \rho\left(\pi_{i,t-1} - m\right)$ is the expectation of $\tilde{\pi}_{it}$ given information up to period $t-1$. Plugging in eqn. (B1) into $\tilde{\zeta}_{it} = \sum_{s=0}^{\infty}\frac{\tilde{\pi}_{i,t+s}(1-\delta)^s}{\left(1+r_f\right)^s}$, long-term productivity can be expressed as

$$\tilde{\zeta}_{it} = \frac{m\left(1+r_f\right)}{r_f+\delta} + \frac{(\mu_{it}-m)\left(1+r_f\right)}{1+r_f-\rho(1-\delta)} + \sum_{s=0}^{\infty}\frac{(1-\delta)^s\left(\tilde{f}_{t+s}+\tilde{\omega}_{i,t+s}\right)}{\left(1+r_f\right)^{s-1}\left(1+r_f-\rho(1-\delta)\right)} \tag{B2}$$

Since productivity innovations are independent across time, $\mathbb{I}_{it}$ can only provide information about the innovation for period t. Therefore, the posterior mean and covariance of $\tilde{\zeta}_{it}$ are

$$\mathrm{E}[\tilde{\zeta}_{it}|\mathbb{I}_{it}] = \frac{m\left(1+r_f\right)}{r_f+\delta} + \frac{\left(1+r_f\right)(\mu_{it}-m)}{1+r_f-\rho(1-\delta)} + \frac{\left(1+r_f\right)\mathrm{E}[\tilde{f}_t+\tilde{\omega}_{it}|\mathbb{I}_{it}]}{1+r_f-\rho(1-\delta)} \tag{B3}$$

and

$$\begin{aligned}\mathrm{Cov}\left(\tilde{\zeta}_{it},\tilde{\zeta}_{jt}|\mathbb{I}_{it}\right) = {}& \frac{\left(1+r_f\right)^2\mathrm{Cov}\left(\tilde{f}_t+\tilde{\omega}_{it},\tilde{f}_t+\tilde{\omega}_{jt}|\mathbb{I}_{it}\right)}{\left(1+r_f-\rho(1-\delta)\right)^2} \\ & + \sum_{s=1}^{\infty}\frac{(1-\delta)^{2s}\mathrm{Cov}\left(\tilde{f}_{t+s}+\tilde{\omega}_{i,t+s},\tilde{f}_{t+s}+\tilde{\omega}_{j,t+s}\right)}{\left(1+r_f\right)^{2(s-1)}\left(1+r_f-\rho(1-\delta)\right)^2}\end{aligned} \tag{B4}$$

Therefore, the posterior distribution of long-term productivity depends on the posterior distribution of period t productivity innovation. The information set $\mathbb{I}_{it}$ is jointly normal with period t

productivity innovation, so the posterior mean and covariance are

$$\mathrm{E}\left[\tilde{f}_t + \tilde{\omega}_{it} | \mathbb{I}_{it}\right] = \frac{q_i(1-\gamma)(z_{it}-\mu_{it})}{\tau + q_i(1-\gamma)} + \frac{\frac{\tau\gamma}{\tau + q_i(1-\gamma)} \sum_{n=1}^{N} \frac{q_n(z_{nt}-\mu_{nt})}{\tau + q_n(1-\gamma)}}{1 + \gamma \sum_{n=1}^{N} \frac{q_n}{\tau + q_n(1-\gamma)}} \tag{B5}$$

and

$$\mathrm{Cov}\left(\tilde{f}_t + \tilde{\omega}_{it}, \tilde{f}_t + \tilde{\omega}_{jt} | \mathbb{I}_{it}\right) = \frac{(1-\gamma)\mathbf{1}_{i=j}}{\tau + q_i(1-\gamma)} + \frac{\frac{\tau\gamma}{\left(\tau + q_i(1-\gamma)\right)\left(\tau + q_j(1-\gamma)\right)}}{1 + \gamma \sum_{n=1}^{N} \frac{q_n}{\tau + q_n(1-\gamma)}} \tag{B6}$$

where $\mathbf{1}_{i=j}$ is an indicator that equals one if $i = j$. Given that $\mathrm{Cov}\left(\tilde{f}_{t+s} + \tilde{\omega}_{i,t+s}, \tilde{f}_{t+s} + \tilde{\omega}_{j,t+s}\right)$ in eqn. (B4) equals $\tau^{-1}\left(\gamma + (1-\gamma)\mathbf{1}_{i=j}\right)$, eqns. (B3)-(B6) fully define the posterior mean and covariance of long-term productivity as closed-form expressions of the parameters.

In the counterfactual analysis in Section 6.1, I compare investment decisions under three information sets: $\mathbb{I}_{it} = \emptyset$ corresponds to $q_i = 0$ for all firms, $\mathbb{I}_{it} = z_{it}$ corresponds to $q_i = q$ for firm i and $q_j = 0$ for all other firms, and $\mathbb{I}_{it} = \mathbf{z}_t$ corresponds to $q_i = q$ for all firms. The counterfactual analysis in Section 6.2 replaces 0 and q in the previous sentence with q and $1.01\times q$.

B.2. Industry Model

Deriving the posterior distribution of $\tilde{\zeta}_{it}$ in the industry model is more complicated because (i) productivity is governed by two AR(1) processes with different autocorrelation coefficients and (ii) the full information set has two sources of conditioning variables $\mathbf{z}_t^{ind}$ and π_t^{econ}. However, the general procedure to derive the posterior distribution is the same. Long-term productivity can be expressed as

$$\begin{aligned}\tilde{\zeta}_{it} = {} & \frac{m(1+r_f)}{r_f + \delta} + \frac{\rho_e \beta \pi_{t-1}^{econ}(1+r_f)}{1 + r_f - \rho_e(1-\delta)} + \sum_{s=0}^{\infty} \frac{(1-\delta)^s \beta \tilde{f}_{t+s}}{(1+r_f)^{s-1}\left(1 + r_f - \rho_e(1-\delta)\right)} \\ & + \frac{\rho\left(\pi_{t-1}^{ind} + \pi_{t-1}^{firm}\right)(1+r_f)}{1 + r_f - \rho(1-\delta)} + \sum_{s=0}^{\infty} \frac{(1-\delta)^s\left(\tilde{g}_{t+s} + \tilde{\omega}_{i,t+s}\right)}{(1+r_f)^{s-1}\left(1 + r_f - \rho(1-\delta)\right)}\end{aligned} \tag{B7}$$

Therefore, the posterior distribution of long-term productivity again depends on the posterior distribution of period t productivity innovation, which is derived in the same manner using the joint normality of the innovations and the conditioning information. The posterior means and covariances expressed as closed-form functions of the parameters are available upon request.

Appendix C. Variable Definitions

Variables with names not in italics are directly from the data (e.g., CAPX is a variable in Compustat while *Lease* is a variable that I derive from FATL). All variables are scaled by lagged total assets (AT) except for *CashETR*, albeit the definitions do not explicitly mention the scaling.

Panel A. Variables derived from databases

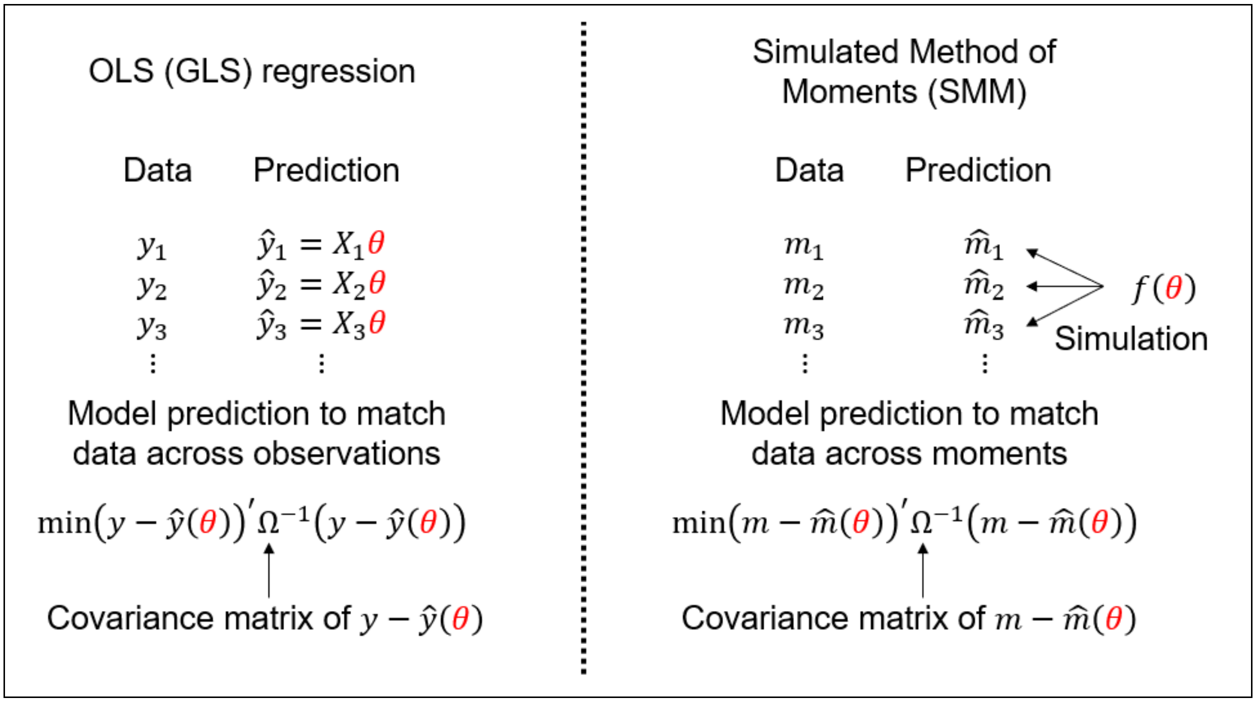
Variable	Definition
	Main variables
ROA	(OIADP + DPC + XRD + XAD) × (1 – *CashETR*) + (DPC + XRD + XAD + INTPN) × *CashETR* I add back investment-related expenses (DPC, XRD, and XAD) and apply the tax rate (*CashETR*) to operating income (OIADP). Next, I add back tax shields from investment-related expenses and interest expense (INTPN).
Investment Rate	CAPX – SPPE + *Lease* + AQC + *NonCashM&A* + XRD + XAD I aggregate expenditures on capital investment (CAPX – SPPE + *Lease*), M&A (AQC + *NonCashM&A*), R&D (XRD), and advertising (XAD).
Payout Rate	INTPN – DLTIS – DLCCH + DLTR + DVC + DVP – SSTK + PRSTKC – *NonCashM&A* – *Lease* I aggregate transactions with creditors (INTPN, DLTIS, DLCCH, and DLTR) and shareholders (DVC, DVP, SSTK, and PRSTKC). I also treat non-cash M&A expenditure and finance leases as combinations of investment expenditure and external financing, so I subtract them from the net payout to investors.
Depreciation Rate	DPC + XRD + XAD
	Variables derived from data sources
CashETR	Long-run cash ETR calculated over 5 years surrounding the focal year. The numerator is the sum of tax payments (TXPD), and the denominator is the sum of pretax income (PI) over that period. I require TXPD and PI to exist at least for the 3 years surrounding the focal year. I do not define this measure if the sum of pretax income is negative for the 5-year period. I restrict this variable to be between 0 and 1.
Lease	Change in gross value of lease assets (FATL) if non-negative. I include finance leases in *Investment Rate* because payment of finance lease liabilities will be included in *Payout Rate*.
NonCashM&A	M&A deal value paid in stock or in the form of liability assumption. I use Thomson Reuters SDC data for completed M&A deals. I measure stock payment with deal value (RANKVAL) and percentage of consideration paid in stock (PCT_STK). I measure liability assumption as the sum of (i) excess of enterprise value of the target (ENTVAL) sought by the acquirer (PSOUGHT) over the deal value, and (ii) excess of deal value over the equity value of the target (EQVAL) sought by the acquirer.

Panel B. Variables directly from Compustat

Variable	Variable description in Compustat
OIADP	Operating income after depreciation I use OIBDP (operating income before depreciation) instead of the sum of OIADP and DPC if OIBDP is available. In almost all cases, OIADP (OIBDP) equals the Compustat variable EBIT (EBITDA).
DPC	Depreciation and amortization (cash flow) If DPC is missing, I use DP (depreciation and amortization) from the income statement.
XRD	Research and development expense
XAD	Advertising expense
INTPN	Interest paid net If INTPN is missing, I use XINT (interest and related expense – total) from the income statement.
CAPX	Capital expenditures
SPPE	Sale of property
AQC	Acquisitions This variable is from the cash flow statement, representing cash M&A expenditures.
DLTIS	Long-term debt issuance
DLCCH	Current debt changes
DLTR	Long-term debt reduction
DVC	Dividends common/ordinary
DVP	Dividends – preferred/preference
SSTK	Sale of common and preferred stock
PRSTKC	Purchase of common and preferred stock

Appendix D. SMM Estimation Procedure

D.1. Overview of SMM



The above figure illustrates the overview of my SMM procedure and its analogy to ordinary or generalized least squares (OLS/GLS). SMM's objective is to match moments of the data variables to their predicted counterparts from the model's simulation, analogous to OLS/GLS matching observed values of the dependent variable to their predicted counterparts from the model (i.e., regression specification) and the independent variables.

My SMM procedure minimizes the standardized squared distance between the data and simulated moments using the covariance matrix of the moment vector difference $m(d) - \hat{m}(\hat{d}, \theta)$, which is equivalent to the covariance matrix of the data moment vector $m(d)$ because the simulated moment vector is not from the data and thus cannot contribute to the covariance matrix. This procedure is analogous to GLS, which minimizes the standardized squared distance between the observed and predicted dependent variable values using the covariance matrix of the vector difference $y - \hat{y}(\theta) = y - X\theta$. OLS is a special case when this covariance matrix is assumed to be proportional to the identity matrix.

This analogy between the minimization procedures leads to an analogy between the overall assessment of the model's performance. The standardized squared distance that is being minimized forms the basis of the *J*-test of overidentifying restrictions in SMM and the *F*-test of overall significance in OLS/GLS. The difference is that the *J*-statistic is proportional to this distance while the *F*-statistic has the distance in its denominator, leading to opposite interpretations when the test rejects the null hypothesis (i.e., rejection is a sign of poor model fit for SMM but is a sign of good model fit for OLS/GLS).

D.2. Simulation of the Baseline Model

The description of the baseline model in Section 3 shows that I only need to simulate four i.i.d. normal variables to simulate all the variables I need. The four fundamental random variables are the systematic innovation of productivity $\tilde{f}_t$, the idiosyncratic innovation of productivity $\widetilde{\omega}_{it}$, accounting noise $\tilde{\varepsilon}_{it}$, and investment deviation $\tilde{s}_{it}$. All other state variables, such as productivity $\tilde{\pi}_{it}$, accounting signal $\tilde{z}_{it}$, and investment I_{it}, are combinations of these four random variables. Productivity $\tilde{\pi}_{it}$ and capital stock k_{it} require initial values for period 0. I simulate $\tilde{\pi}_{i,0}$ from the unconditional distribution (i.e., distribution without knowledge of any past information), and set $k_{i,0} = 1$.

My data contains on average 2,699 firms (67,472 observations ÷ 25 years) each year, so I simulate an economy with 2,699 firms (i.e., $N = 2{,}699$). To follow Michaelides and Ng's (2000) finding that good simulation performance requires the simulated dataset to be at least 10 times larger than the real dataset, I simulate the economy for 500 periods (i.e., 20 times the number of years in the economy). I increase the number of years in order to keep the number of firms in the economy constant because the number of firms is an important determinant of the magnitude of spillover effects. I denote the relative size of the simulated dataset (i.e., 20) as S. The simulated dataset has $N \times S \times 25$ observations.

D.3. Simulation of the Industry Model

The simulation of the industry model is largely the same as that of the baseline model. The major difference is that there is an economy-wide productivity factor $\tilde{\pi}_t^{econ}$. Since all industries are exposed to this economy-wide factor, I first simulate it based on the estimates of its autocorrelation ρ_e and innovation precision τ_e. Each industry-level estimation then only requires four fundamental random variables: the industry-specific innovation of productivity $\tilde{g}_t$, the idiosyncratic innovation of productivity $\widetilde{\omega}_{it}$, accounting noise $\tilde{\varepsilon}_{it}$, and investment deviation $\tilde{s}_{it}$. All other state variables are combination of $\tilde{\pi}_t^{econ}$ and these four random variables.

For each industry, N is the average number of firms in the industry. For example, the food products industry has 1,799 observations, so N is 72 (1,799 observations ÷ 25 years). The relative size of the simulated dataset to the observed dataset, S, is still 20.

D.4. Estimation Results

The objective of my SMM procedure is to find a set of parameters θ that minimizes

$$Q\left(d, \hat{d}, \theta\right) \equiv \left(m(d) - \widehat{m}\left(\hat{d}, \theta\right)\right)' \Omega^{-1} \left(m(d) - \widehat{m}\left(\hat{d}, \theta\right)\right) \tag{D1}$$

The data moment vector $m(d)$ and its covariance matrix Ω (derived using influence functions and two-way clustering) are from the data. The simulated moment vector $\widehat{m}\left(\hat{d}, \theta\right)$ comes from the above simulation procedure. I use a combination of simulated annealing, which is good at approximating the global minimum, and the Nelder-Mead simplex method, which is good at locating the exact local minimum, to find the set of parameters θ that minimizes the objective function $Q(d, \hat{d}, \theta)$. I denote the set of parameters that minimizes the objective function as $\hat{\theta}$, i.e., $\hat{\theta} = \arg\min_{\theta} Q(d, \hat{d}, \theta)$. This $\hat{\theta}$ is the set of parameter *estimates*.

I obtain the standard errors of the parameter estimates from the asymptotic covariance matrix of $\hat{\theta}$, which is

$$\mathrm{aVar}(\hat{\theta}) = \left(1 + \frac{1}{S}\right)\left(\widehat{m}_{\theta}(\hat{d}, \hat{\theta})\Omega^{-1}\widehat{m}_{\theta}(\hat{d}, \hat{\theta})'\right)^{-1} \tag{D2}$$

where $\widehat{m}_{\theta}(\hat{d}, \hat{\theta})$ is the gradient matrix of $\widehat{m}(\hat{d}, \theta)$ with regard to θ evaluated at $\theta = \hat{\theta}$. I approximate this gradient matrix by perturbing each parameter estimate by 1% both upward and downward. For example, to obtain the gradient vector of $\widehat{m}(\hat{d}, \theta)$ with regard to parameter ρ, I assess $\widehat{m}(\hat{d}, \theta)$ once for ρ 1% higher than its estimate and again for ρ 1% lower than its estimate. The difference in $\widehat{m}(\hat{d}, \theta)$ in these two cases divided by 2% of the estimate of ρ is the estimated gradient vector with regard to ρ.

The *J*-statistic is $J = \frac{S}{1+S} Q(d, \hat{d}, \theta)$, which follows a χ^2 distribution with degree of freedom equal to the number of moments in excess of the number of parameters under the null hypothesis that the model does not fail to match all moments. In my estimation, this degree of freedom is two.

The sensitivity of parameter estimates to moments (Andrews et al., 2017) is based on

$$-\left(\widehat{m}_{\theta}(\hat{d}, \hat{\theta})\Omega^{-1}\widehat{m}_{\theta}(\hat{d}, \hat{\theta})'\right)^{-1} \widehat{m}_{\theta}(\hat{d}, \hat{\theta})\Omega^{-1} \tag{D3}$$

The elements of this matrix conceptually are derivatives of parameters to moments, i.e., $\frac{\partial \theta}{\partial m}$, evaluated at $\theta = \hat{\theta}$. To make the elements scale invariant (i.e., transform derivatives into sensitivities), I multiply each element by the respective moment's standard error and divide it by the respective parameter's standard error. Then, the elements conceptually become $\frac{\partial \theta}{s.e.(\theta)} \div \frac{\partial m}{s.e.(m)}$, which roughly convey the number of standard deviations by which the parameter estimate would change if a moment increased by one standard deviation, albeit of an infinitesimal scale.

Appendix E. Validation of Parameter Estimates

E.1. Validation of the Baseline Model

I assess the validity of the four parameters that govern investment decisions using stylized facts from the literature that are not artifacts of my estimation procedure. First, the estimated depreciation rate δ is 9.8% for a declining-balance depreciation scheme. This estimate is broadly consistent with those from other structural estimations of dynamic investment models, which also employ declining-balance depreciation. Some examples include 10.0% in Hennessy and Whited (2005), 13.0% in Nikolov and Whited (2014), and 6.7% in Bazdresch et al. (2018).

Second, I assess the estimated investment adjustment cost parameter ϕ of 1.8 using a different angle to view the parameter. This parameter also captures the elasticity of investment to its returns. The numerator of investment rate in eqn. (3) is roughly the net present value from a dollar of investment. Since the denominator is ϕ, eqn. (3) shows that a 1% increase in investment returns results in a $\frac{1\%}{\phi} = \frac{1\%}{1.8} = 0.55\%$ increase in investment. This elasticity of 0.55 is largely consistent with investment-cash flow sensitivity estimates in prior studies (e.g., Kaplan and Zingales, 1997; Malmendier and Tate, 2005), albeit more recent studies find much lower investment-cash flow sensitivities (e.g., Chen and Chen, 2012).

Third, the estimated risk premium parameter λ of 4 implies a risk-adjusted WACC of 7.5%, or a risk premium of 3.5% given that the risk-free rate is set to 4%. Fernandez (2011) examines 150 finance textbooks and finds that they collectively suggest an average equity risk premium of 6.5%, which has been decreasing in more recent years. Since WACC is less than the cost of equity, a risk premium of 3.5% for WACC does not seem unreasonably low.

Lastly, the estimated variance of investment deviations ψ of 0.099 implies that roughly 29% of the total variation in investment is driven by productivity. This explanatory power of 29% is largely consistent with prior studies that regress investment amount on some financial reporting characteristic (and other control variables). For example, Biddle et al. (2009) report explanatory power of roughly 22% in their Table 2, Cheng et al. (2013) report explanatory power in the range of 20~25% in their Table 3, and Shroff (2017) reports explanatory power in the range of 15~40% in his Table 4.

E.2. Validation of the Industry Model

The industry-level validation test is a cross-sectional subsample test examining whether parameters are high (low) when they are expected to be high (low). I focus on validating the three primary parameters that drive spillover effects (γ, τ, and q) and β, the validity of which cannot be explored in Section 5.3. I use measures from stock returns for validation because they are similar to productivity $\tilde{\pi}_{it}$ in two respects: (i) both reflect firm fundamentals, and (ii) both are similar in scale. Therefore, a directly matched pair of measures from $\tilde{\pi}_{it}$ and stock returns, respectively, is expected to be positively associated and similar in scale. For γ, τ, and β, the three measures are: synchronicity, total volatility, and the industry's exposure to the market. These three measures are almost directly proportional to γ, τ, and β, respectively.

The measures from $\tilde{\pi}_{it}$ are based on analytical formulas, not simulations. Using eqn. (11), I define synchronicity as $\frac{\mathrm{Var}(\beta\tilde{\pi}_t^{econ}+\tilde{\pi}_t^{ind})}{\mathrm{Var}(\tilde{\pi}_{it})}$ (i.e, proportion of systematic over total variation), total volatility as $\mathrm{Var}(\tilde{\pi}_{it})$, and the industry's exposure to the market as β (i.e., regression coefficient of industry-level productivity, $\beta\tilde{\pi}_t^{econ} + \tilde{\pi}_t^{ind}$, on market productivity, $\tilde{\pi}_t^{econ}$).

The measures from stock returns are based on CRSP data. For synchronicity (R^2 from regressing firm returns on market and industry returns) and total volatility, I measure them for each firm-year observation in my sample using 12 monthly stock returns during the fiscal period and obtain industry averages. For industry-average exposure to the market, I regress 12 monthly industry returns on corresponding market returns to obtain the regression coefficient for each year-month in my sample period of 1990-2014 and obtain industry averages.

Since q does not govern the distribution of $\tilde{\pi}_{it}$, there is no directly corresponding measure from stock returns alone. However, using q's definition, which is how precisely financial reports convey decision-useful information, I examine its relationship with ERCs. Since decision-usefulness is determined by both q and τ, I regress ERCs on both parameters. I measure ERCs using the specification:

$$CAR = \alpha_0 + \alpha_1 UE + \alpha_2 Controls + \alpha_3 UE \times Controls + \eta \qquad \text{(E1)}$$

Here, α_1 from an industry-specific regression is that industry's ERC. I measure both long-term ERC based on stock returns during the whole fiscal period and short-term ERC based on stock returns around earnings announcements. For each horizon, I measure ERCs with and without control variables in eqn. (E1). When control variables are included, I standardize them for each industry so that α_1 becomes the industry's representative ERC. I define the variables I use in my ERC calculation in the table that is at the end of this section.

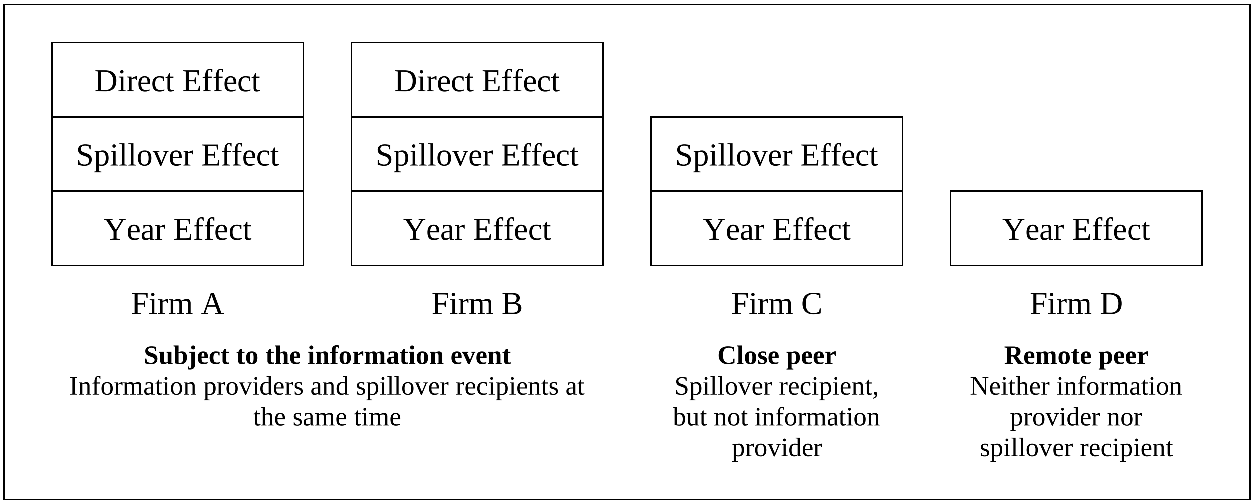
Table 6 presents the results. Panel A shows that the measures from $\tilde{\pi}_{it}$ and stock returns are positively associated, providing corroborating evidence that the estimates of γ, τ, and β are capturing their prescribed role in the model. Panel B shows that long-term ERCs are positively (negatively) associated with q (τ), as expected. However, short-term ERCs show no association with the two parameters. The long-term ERC result supports the validity of q's estimates, but the short-term ERC result suggests that the model not explicitly incorporating other sources of information may hinder the model's capacity to examine incremental information in earnings announcements. Figure 7 graphically displays the results in Table 6. For scatter plots for q, I residualize ERC and q against τ to succinctly display the association between ERC and q (Frisch-Waugh-Lovell theorem).

Panel A. Definition of variables used in ERC calculation

I generally follow Samuels et al.'s (2018) definition of long-term ERC and Gipper et al.'s (2015) definitions of short-term ERC and control variables.

Variable	Definition
	Long-term ERC
CAR	CRSP buy-and-hold return from the start of the 4th month of the fiscal year until the end of the 3rd month of the following fiscal year, in excess of market returns
UE	Change in Compustat EPS (before extraordinary items) from the previous year
	Short-term ERC
CAR	CRSP stock return in excess of market return for the 3-day period centered around the earnings announcement date
UE	Difference between I/B/E/S actual annual EPS and median I/B/E/S annual EPS forecast for the 95-day period before the earnings announcement date, scaled by CRSP price from 2 days prior to the earnings announcement
	Control variables
Size	Log of market value of equity, from Compustat
Market-to-book	Ratio of market value of equity to book value of equity, from Compustat
Beta	Market beta from single-factor model using daily returns during the fiscal year, from WRDS Beta Suite
Leverage	Ratio of total liabilities to book value of equity, from Compustat
Persistence	Coefficient from regressing annual Compustat EPS (before extraordinary items) on its lagged value using up to 10 years of observations
Loss	Indicator variable that equals one when Compustat EPS (before extraordinary items) is negative

Figure 1. Illustration of the Reflection Problem

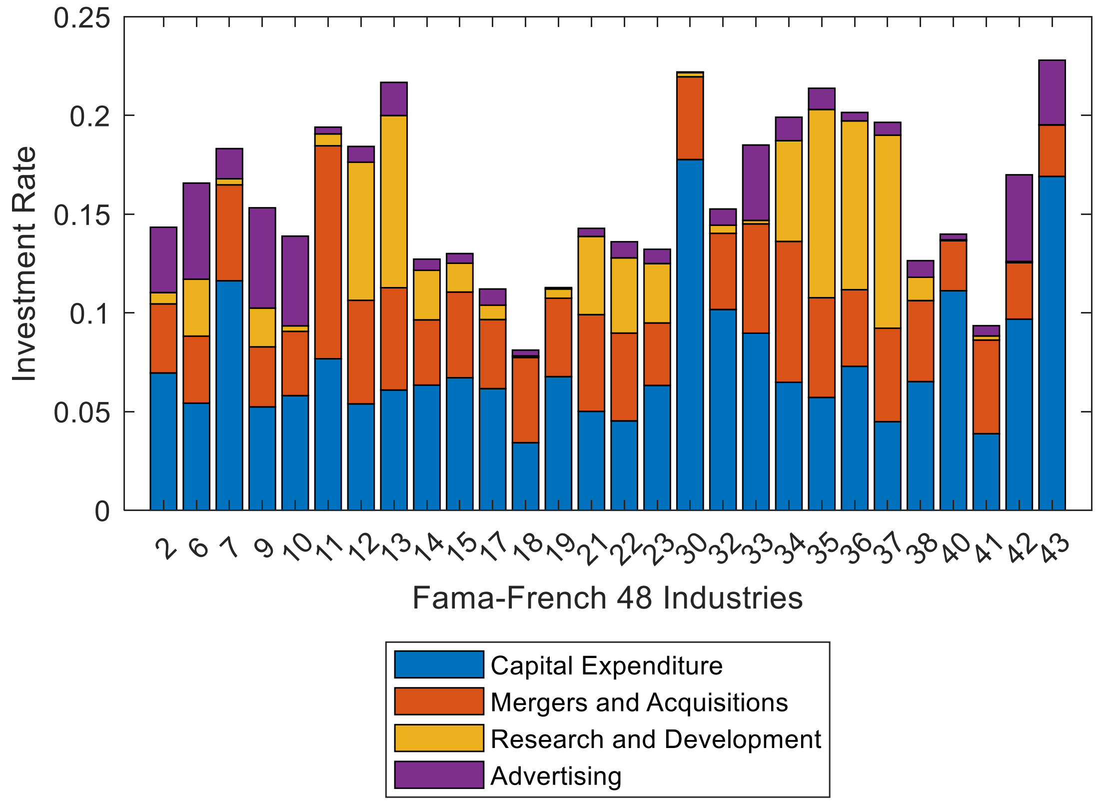


This figure illustrates the reflection problem (Manski, 1993; Angrist, 2014) using an (exogenous) information event as an example. The event affects firms A and B, which change their financial reporting in response. As a result, both firms experience the direct effects of the information event (potentially through changes in their own financial reporting) and the spillover effects from the changes of each other's financial reporting. The reflection problem refers to the difficulty in disentangling these two effects.

Therefore, prior studies often use firms that are not directly affected by the event to identify spillovers effects. Firm C is a close peer that receives spillover effects from changes in firms A and B's financial reporting, while Firm D is a remote peer that does not. Firm C cannot by itself play a role in identifying spillover effects because the SUTVA will attribute all of its (i.e., the control firm's) response to year effects. Therefore, Firm D is necessary to identify spillover effects Firm C experiences.

However, such research designs cannot directly tackle the reflection problem and examine spillovers among Firms A and B. Since spillover effects from ordinary financial reporting (rather than specific events such as restatements) among public firms require disentangling the direct and spillover effects among Firms A and B, I use structural estimation rather than reduced-form research designs in this study.

Figure 2. Decomposition of Investment Expenditure by Industry



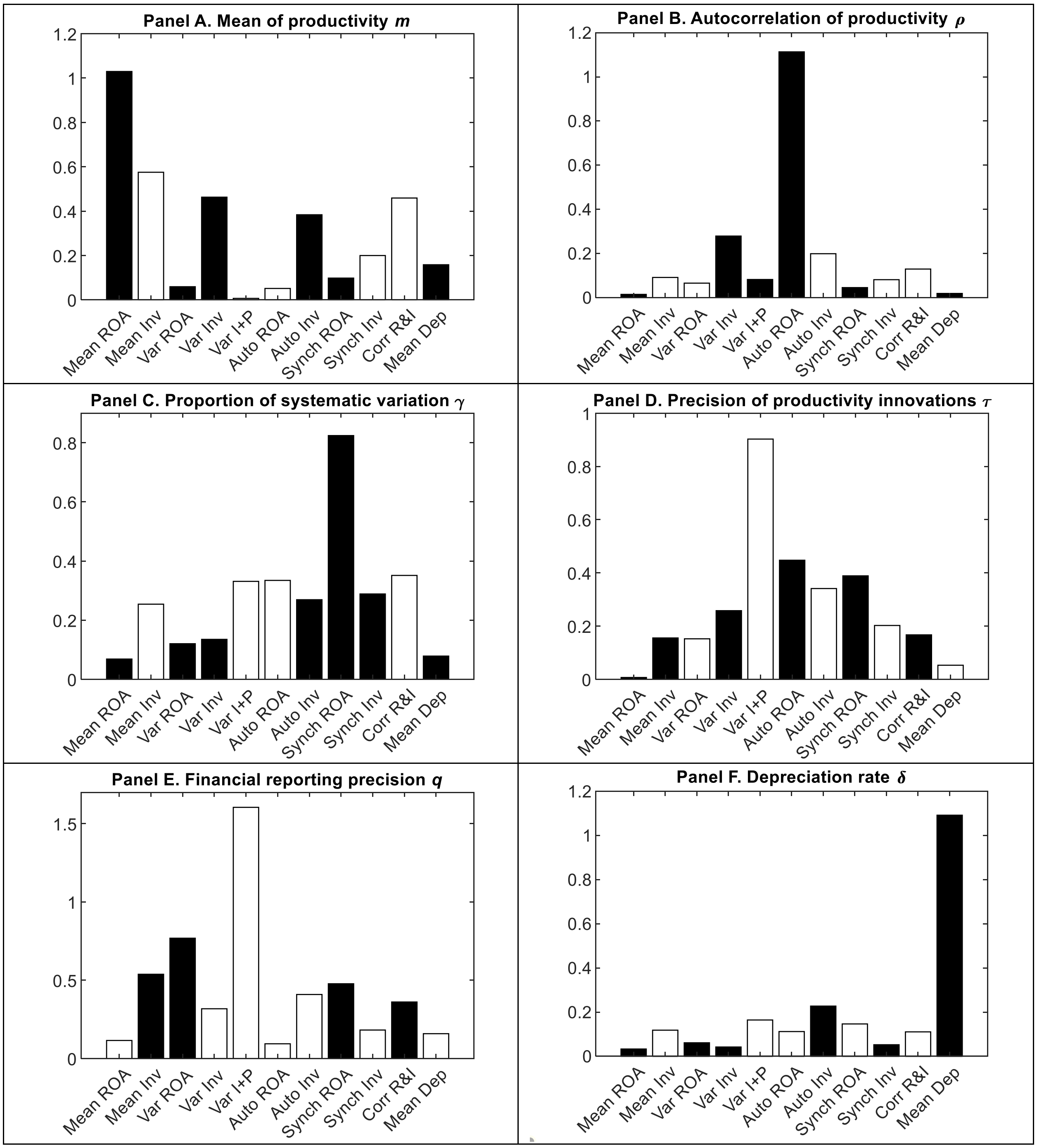
This figure displays the decomposition of investment expenditure into its four components: capital (CAPX – SPPE + *Lease*), M&A (AQC + *NonCashM&A*), R&D (XRD), and advertising (XAD) expenditures. See Appendix C for variable definitions. See Panel A of Table 5 for the list of industries included in this figure.

The summary statistics of the 28 industry-average rates show that capital expenditure has standard deviation (0.0345) as large as 46% of the mean (0.0745), while the broader investment measure has standard deviation (0.0439) only 27% of the mean (0.1641). This pattern suggests that the broader measure mitigates the systematic difference in the relative importance of capital versus non-capital investments across industries.[37]

[37] The proportion of capital expenditure among total investment is as low as 22.88% (industry 37: Measuring and Control Equipment) and as high as 80.33% (industry 30: Petroleum and Natural Gas).

Figure 3. Sensitivity of Parameter Estimates to Moments

This figure displays the sensitivity of parameter estimates to changes in moment conditions following Andrews et al. (2017). A(n) filled (unfilled) bar represents positive (negative) sensitivity. A strong sensitivity (with larger absolute value) indicates that the parameter is primarily identified by that moment. The parameters and moments are described in Table 2. See Appendix D for how the sensitivities are obtained.



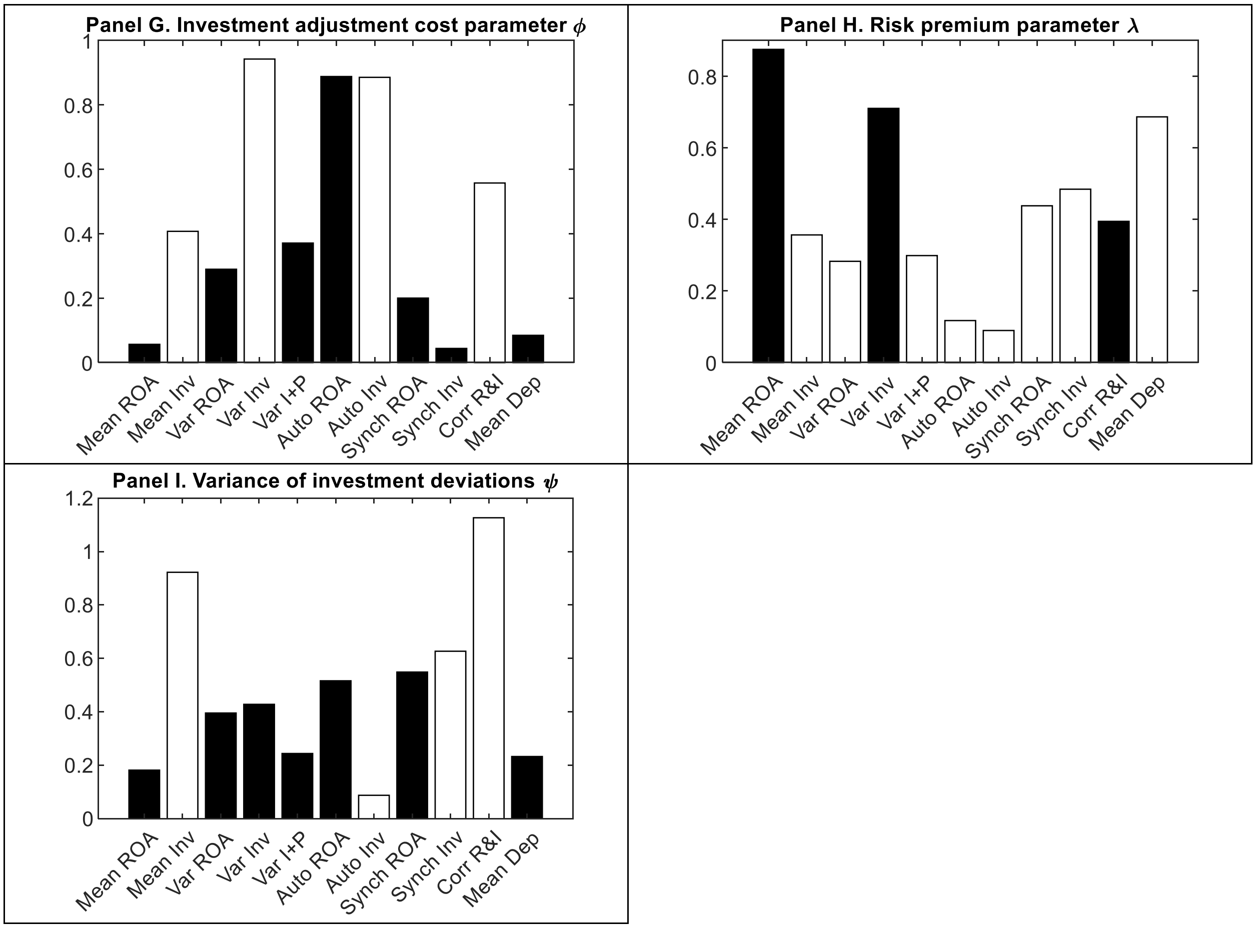

Panel G. Investment adjustment cost parameter ϕ
0
0.2
0.4
0.6
0.8
1
Mean ROA
Mean Inv
Var ROA
Var Inv
Var I+P
Auto ROA
Auto Inv
Synch ROA
Synch Inv
Corr R&I
Mean Dep
Panel H. Risk premium parameter λ
0
0.2
0.4
0.6
0.8
Mean ROA
Mean Inv
Var ROA
Var Inv
Var I+P
Auto ROA
Auto Inv
Synch ROA
Synch Inv
Corr R&I
Mean Dep
Panel I. Variance of investment deviations ψ
0
0.2
0.4
0.6
0.8
1
1.2
Mean ROA
Mean Inv
Var ROA
Var Inv
Var I+P
Auto ROA
Auto Inv
Synch ROA
Synch Inv
Corr R&I
Mean Dep

Figure 4. Illustration of Counterfactual Analysis

This figure illustrates the counterfactual analysis in Section 6.1. Panel A displays the incremental investment rate from the baseline rate without learning from contemporaneous financial reports (100 simulated observations for a single firm). Panel B summarizes Panel A using regression lines and average levels.

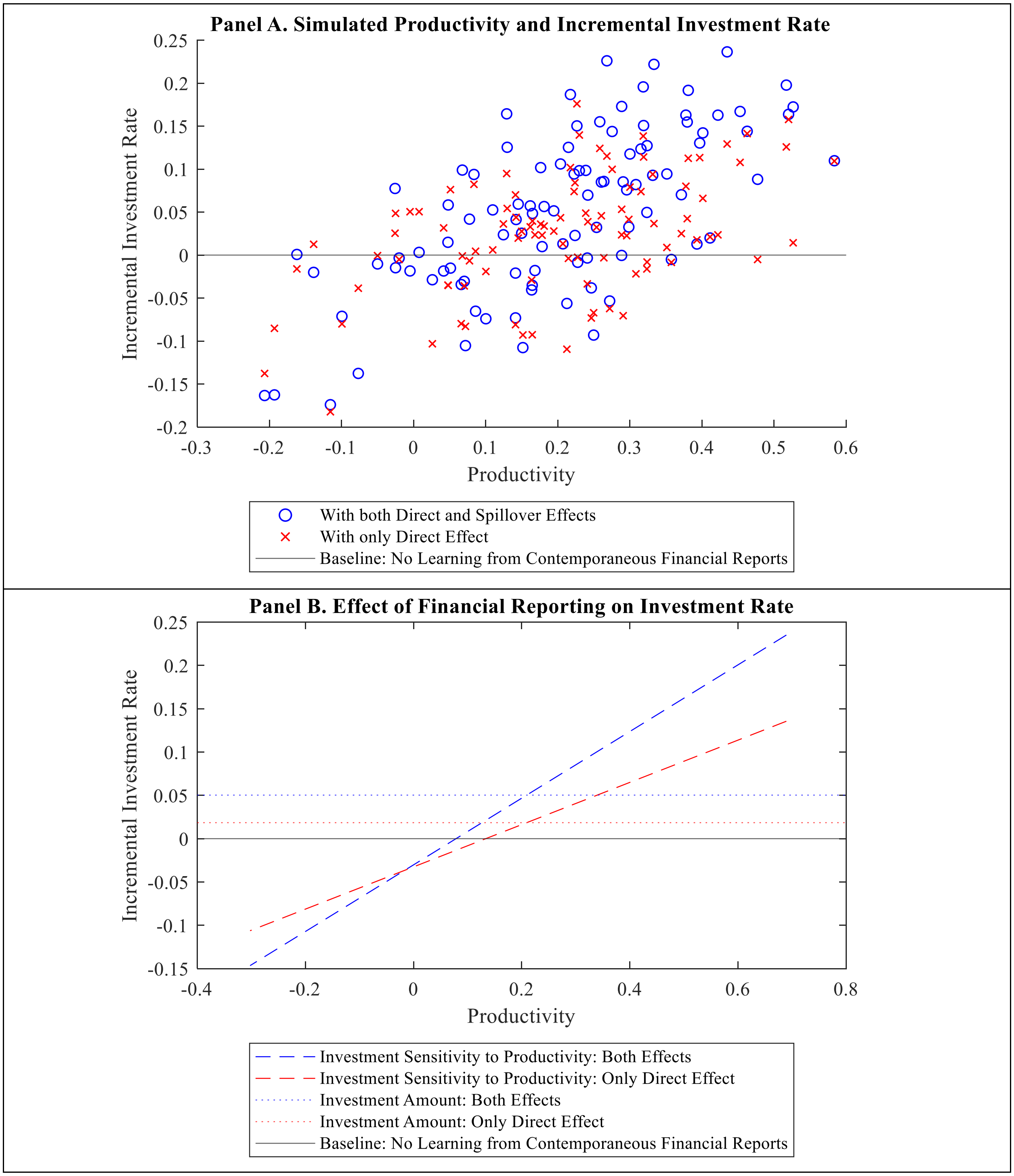


Figure 5. Comparative Statics of Total Spillover Effects

This figure displays how the relative importance of total spillover effects (Table 4 Panel A) responds to changes in parameter estimates. In each panel, one parameter is perturbed from (estimate – 8 × standard error) to (estimate + 8 × standard error) while the other parameters are kept at their estimated values. The parameters are described in Table 2, and the estimates and standard errors are from Table 3 Panel A.

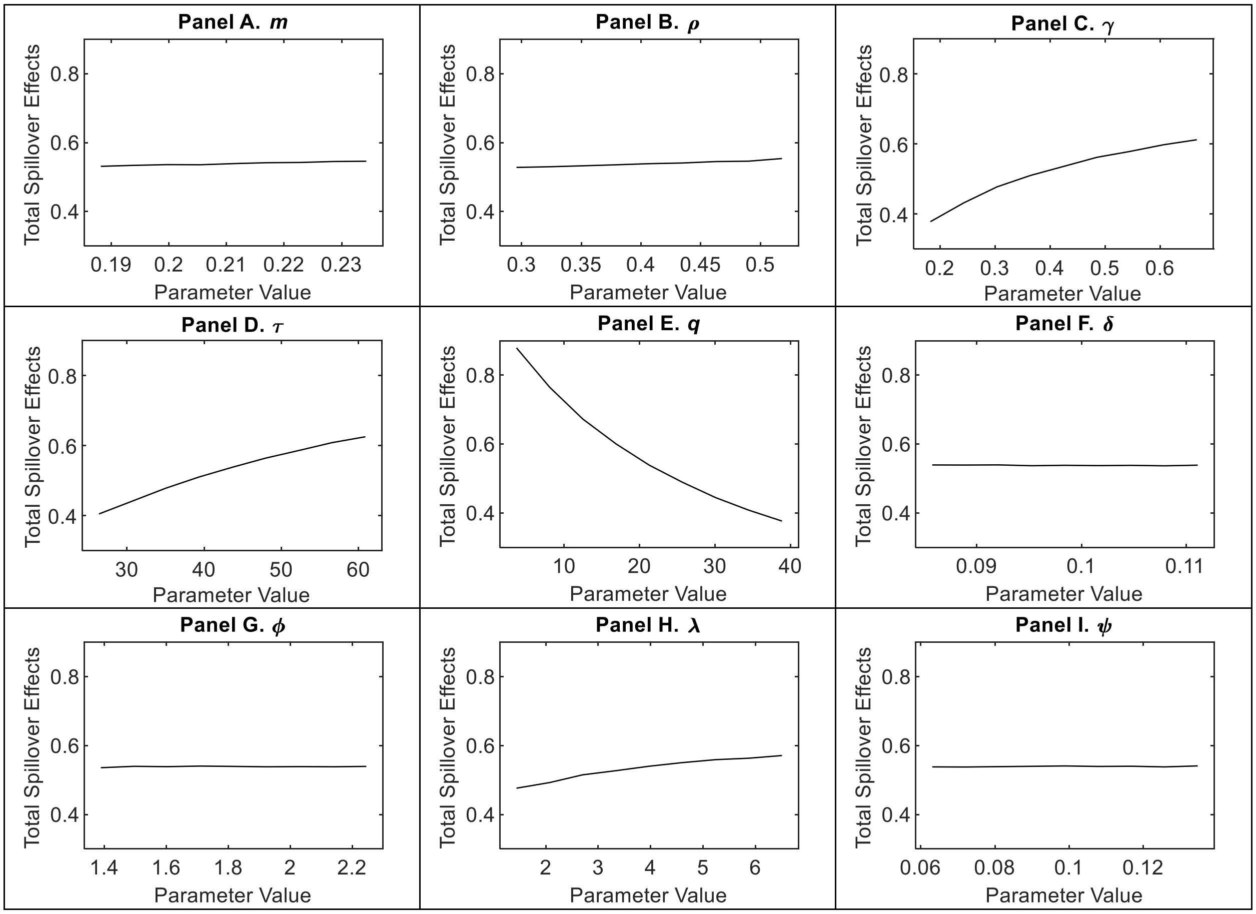
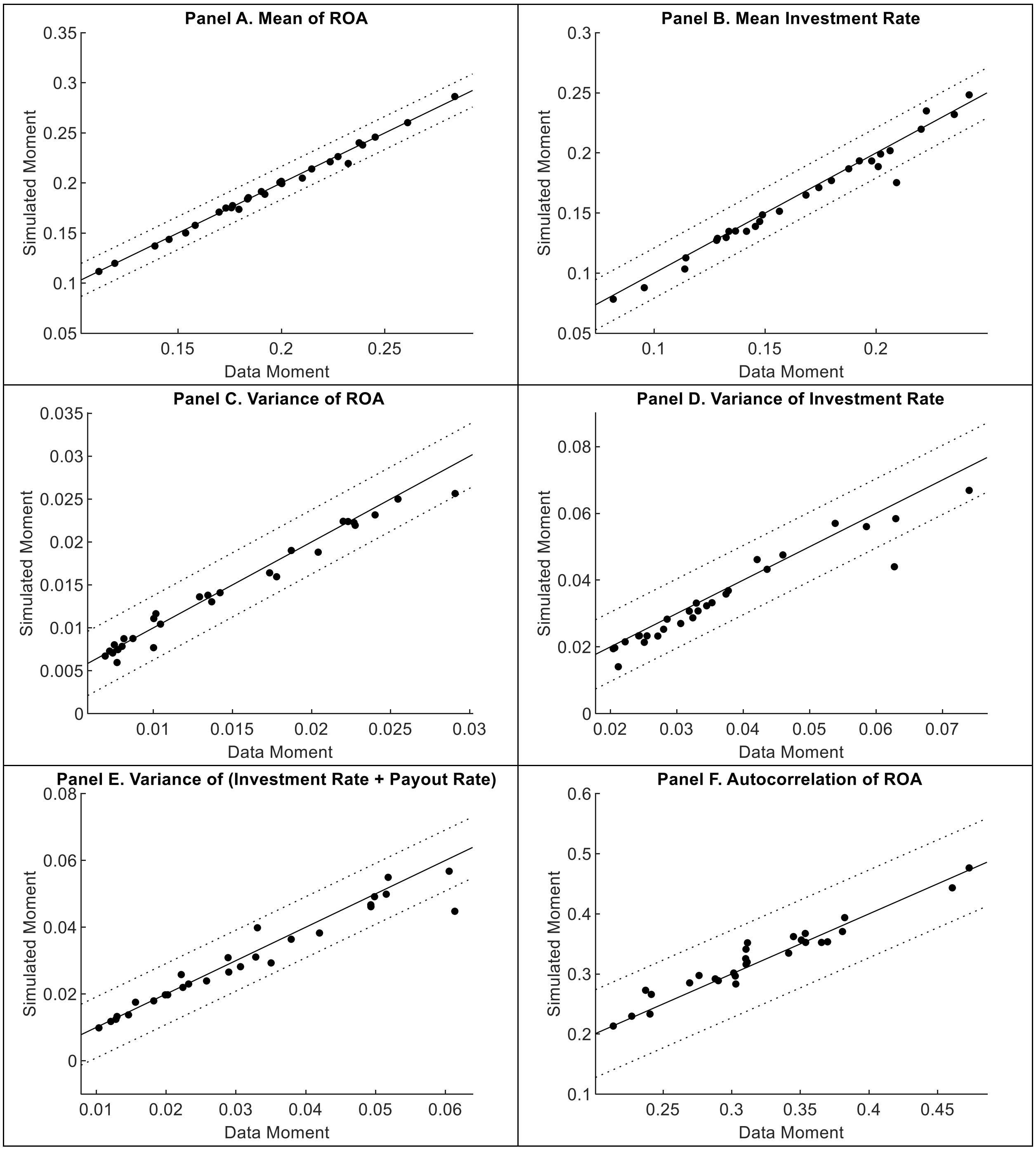
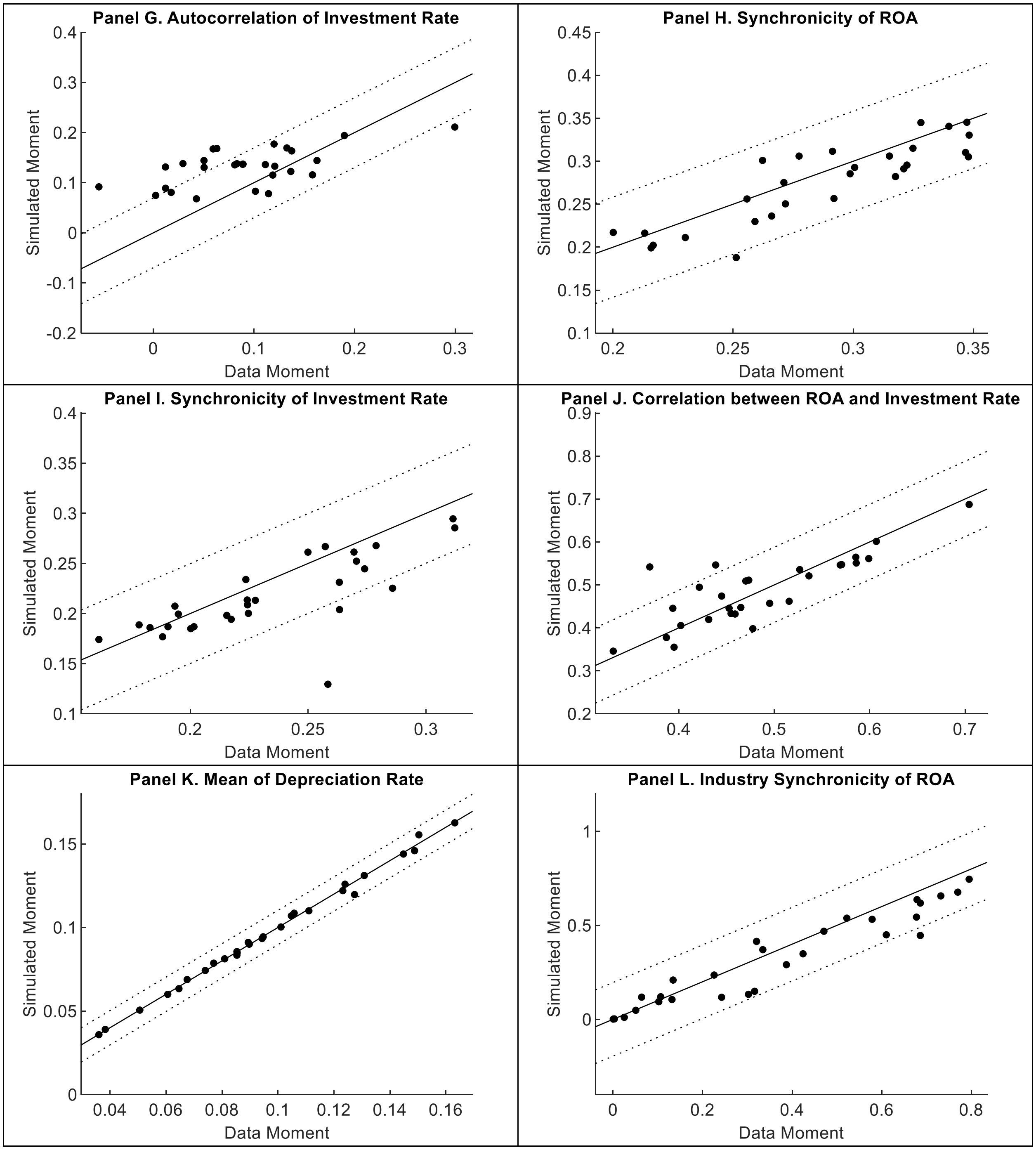


Figure 6. Industry-level Model Fit

This figure displays the model fit of the industry-level estimation in Section 7. In each panel, a dot represents an industry. The solid line is a 45º line that emanates from the origin, which means the data moment and the simulated moment are equal. The two dotted lines around the solid line form the 95% confidence interval band based on average standard error of the data moment across industries. Therefore, dots outside the band indicate a poor match between the two moments.





Panel G. Autocorrelation of Investment Rate
Panel H. Synchronicity of ROA
Panel I. Synchronicity of Investment Rate
Panel J. Correlation between ROA and Investment Rate
Panel K. Mean of Depreciation Rate
Panel L. Industry Synchronicity of ROA
Simulated Moment
Data Moment

Figure 7. Validation Test

This figure displays the results from the industry-level validation tests (Table 6). Appendix E describes the validation tests in detail. Each observation in the scatter plot represents an industry. For scatter plots for q, I residualize ERC and q against τ to succinctly display the association between ERC and q (Frisch-Waugh-Lovell theorem).

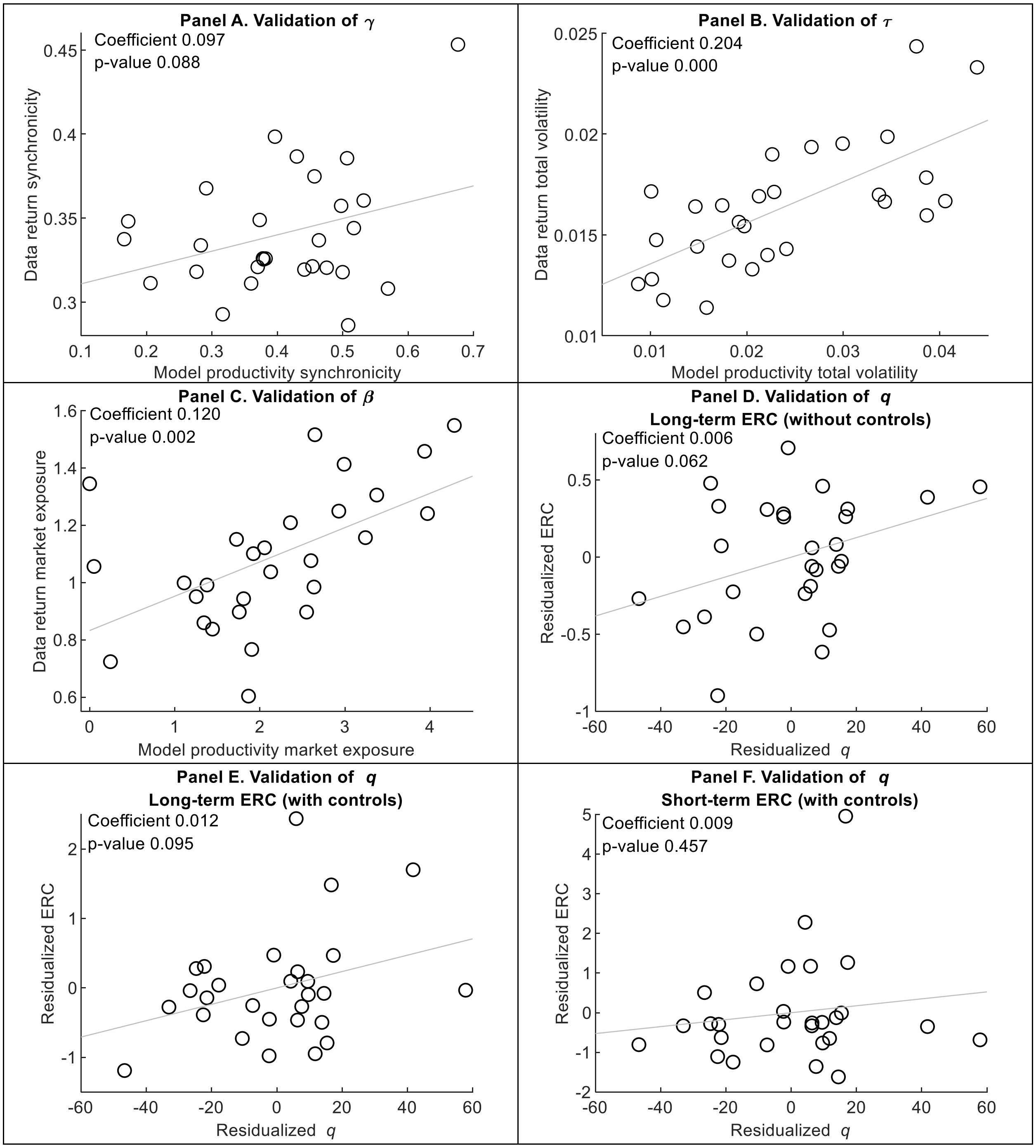


Table 1. Descriptive Statistics

This table presents descriptive statistics of the four main variables and their components. All variables (except for *CashETR*) are scaled by lagged total assets and winsorized at the 1st and 99th percentiles. The number of observations for all variables is 67,472. See Appendix C for variable definitions.

Panel A. Descriptive statistics

Variable	Mean	S.D.	P5	Q1	Median	Q3	P95
Main variables							
ROA	0.194	0.128	0.052	0.112	0.164	0.239	0.448
Investment Rate	0.166	0.190	0.012	0.055	0.109	0.199	0.528
Payout Rate	-0.024	0.237	-0.428	-0.032	0.025	0.074	0.177
Depreciation Rate	0.097	0.081	0.019	0.045	0.074	0.123	0.258
Components of the main variables							
OIBDP	0.181	0.120	0.034	0.107	0.159	0.229	0.406
CashETR	0.297	0.225	0.000	0.146	0.282	0.381	0.808
DPC	0.054	0.034	0.013	0.031	0.046	0.066	0.121
CAPX	0.075	0.084	0.006	0.025	0.049	0.092	0.237
SPPE	0.004	0.012	0.000	0.000	0.000	0.001	0.018
Lease	0.004	0.013	0.000	0.000	0.000	0.000	0.022
AQC	0.033	0.096	0.000	0.000	0.000	0.013	0.194
NonCashM&A	0.006	0.041	0.000	0.000	0.000	0.000	0.000
XRD	0.028	0.055	0.000	0.000	0.000	0.030	0.151
XAD	0.014	0.036	0.000	0.000	0.000	0.008	0.080
INTPN	0.017	0.018	0.000	0.003	0.013	0.025	0.053
DLTIS	0.121	0.265	0.000	0.000	0.008	0.113	0.624
DLCCH	0.000	0.032	-0.041	0.000	0.000	0.000	0.043
DLTR	0.101	0.214	0.000	0.001	0.022	0.090	0.489
DVC	0.016	0.032	0.000	0.000	0.000	0.019	0.069
DVP	0.001	0.002	0.000	0.000	0.000	0.000	0.002
SSTK	0.044	0.158	0.000	0.000	0.003	0.014	0.228
PRSTKC	0.019	0.045	0.000	0.000	0.000	0.013	0.112

Panel B. Correlation between main variables

The lower-left (upper-right) part of the table presents Pearson (Spearman) correlations. All correlation coefficients are significant at the 1% level.

	ROA	Investment Rate	Payout Rate	Depreciation Rate
ROA		0.6011	-0.0563	0.7016
Investment Rate	0.5247		-0.4383	0.6503
Payout Rate	-0.2438	-0.6680		-0.0919
Depreciation Rate	0.7545	0.5400	-0.2217	

Table 2. Parameters and Moments

This table presents descriptions of the structural parameters and the moment conditions I use in the SMM estimation of the baseline model with a single aggregate (i.e., economy-wide) systematic productivity factor. See Appendix C for definitions of variables on which the moments are based.

Panel A. Structural parameters

Parameter	Description
m	Mean of productivity
ρ	Autocorrelation of productivity
γ	Proportion of systematic variation in productivity
τ	Precision of productivity innovations
q	Financial reporting precision (precision of accounting signal)
δ	Depreciation rate
ϕ	Investment adjustment cost parameter
λ	Risk premium parameter
ψ	Variance of investment deviations

Panel B. Moment Conditions

Moment	Primarily identifying parameter
Mean of *ROA*	m
Mean of *Investment Rate*	λ
Variance of *ROA*	q
Variance of *Investment Rate*	ϕ
Variance of (*Investment Rate* + *Payout Rate*)	τ
Autocorrelation of *ROA*	ρ
Autocorrelation of *Investment Rate*	
Synchronicity of *ROA*	γ
Synchronicity of *Investment Rate*	
Correlation between *ROA* and *Investment Rate*	ψ
Mean of *Depreciation Rate*	δ

Each parameter's identification does not rely on any single moment condition. The "Primarily identifying parameter" column indicates that each parameter's final identification in the whole process of sequential identification relies the most on that specific moment condition.

Table 3. Estimation Results

This table presents SMM estimation results for the baseline model with a single aggregate (i.e., economy-wide) systematic productivity factor. All standard errors are clustered by firm and year. See Appendix D for a description of the SMM estimation procedure.

Panel A. Parameter estimates

Parameter	Description	Estimate	Standard Error	*t*-statistic
m	Mean of productivity	0.2112	0.0029	73.3010
ρ	Autocorrelation of productivity	0.4069	0.0139	29.2728
γ	Proportion of systematic variation	0.4244	0.0303	14.0281
τ	Precision of productivity innovations	43.6310	2.1567	20.2301
q	Financial reporting precision	21.2720	2.1991	9.6729
δ	Depreciation rate	0.0984	0.0016	62.1019
ϕ	Investment adjustment cost parameter	1.8174	0.0535	33.9427
λ	Risk premium parameter	3.9734	0.3166	12.5496
ψ	Variance of investment deviations	0.0989	0.0045	22.1158

Panel B. Moment conditions

Moment	Data	Simulated	Standard Error	*t*-statistic
Mean of *ROA*	0.1944	0.1957	0.0029	-0.4211
Mean of *Investment Rate*	0.1678	0.1716	0.0058	-0.6451
Variance of *ROA*	0.0169	0.0172	0.0006	-0.4070
Variance of *Investment Rate*	0.0392	0.0410	0.0028	-0.6309
Variance of (*Investment Rate* + *Payout Rate*)	0.0338	0.0352	0.0020	-0.7121
Autocorrelation of *ROA*	0.3736	0.3704	0.0116	0.2771
Autocorrelation of *Investment Rate*	0.1327	0.1237	0.0104	0.8579
Synchronicity of *ROA*	0.2320	0.2445	0.0217	-0.5767
Synchronicity of *Investment Rate*	0.2030	0.2029	0.0132	0.0033
Correlation between *ROA* and *Investment Rate*	0.5169	0.5216	0.0126	-0.3790
Mean of *Depreciation Rate*	0.0978	0.0984	0.0017	-0.3861
Observations: 67,472	*J*-statistic 1.4687 (*p*-value 0.4798)			

Table 4. Quantitative Analysis

This table presents the decomposition of the total and marginal effects of financial reporting on the simulated aggregate output of the public corporate sector in the baseline model with a single aggregate (i.e., economy-wide) systematic productivity factor. The main value is the mean across 1,000 simulations, while the values in parentheses represent 95% confidence intervals based on those simulations.

Panel A. Decomposition of the total effect of financial reporting

	Direct Effects	Spillover Effects	Total
Investment Efficiency Channel	29.62% (27.96%, 31.53%)	19.99% (16.69%, 23.09%)	49.61% (46.73%, 52.47%)
Cost of Capital Channel	16.55% (15.61%, 17.49%)	33.85% (31.92%, 35.78%)	50.39% (47.53%, 53.27%)
Total	46.16% (44.37%, 48.32%)	53.84% (51.68%, 55.63%)	

Panel B. Decomposition of the marginal effect of financial reporting precision

	Direct Effects	Spillover Effects	Total
Investment Efficiency Channel	98.54% (97.29%, 99.84%)	0.47% (-0.85%, 1.73%)	99.01% (98.93%, 99.09%)
Cost of Capital Channel	0.22% (0.20%, 0.24%)	0.77% (0.71%, 0.84%)	0.99% (0.91%, 1.07%)
Total	98.76% (97.51%, 100.1%)	1.24% (-0.06%, 2.49%)	

Table 5. Estimation Results (Industry Analysis)

Panel A. List of Industries

This panel presents 28 of the Fama-French 48 industries that I examine in the industry analysis. I exclude five industries because they consist of either financial or utility firms. I exclude the other 15 industries based on the number of observations criteria. I require an industry to have at least 625 observations in total and at least 10 observations in each fiscal year.

Code	Description	Observations
2	Food Products	1,799
6	Recreation	627
7	Entertainment	1,119
9	Consumer Goods	1,551
10	Apparel	1,351
11	Healthcare	1,269
12	Medical Equipment	2,013
13	Pharmaceutical Products	1,946
14	Chemicals	1,983
15	Rubber and Plastic Products	750
17	Construction Materials	1,844
18	Construction	996
19	Steel Works etc.	1,459
21	Machinery	3,091
22	Electrical Equipment	1,304
23	Automobiles and Trucks	1,508
30	Petroleum and Natural Gas	3,297
32	Communication	2,877
33	Personal Services	956
34	Business Services	7,096
35	Computers	2,273
36	Electronic Equipment	4,164
37	Measuring and Control Equipment	1,794
38	Business Supplies	1,283
40	Transportation	2,804
41	Wholesale	3,490
42	Retail	4,548
43	Restaurants, Hotels, Motels	1,583
	Total	60,775

Panel B. Estimation Result

This panel presents parameter estimates for each industry. The last column contains the p-values for the test of overidentifying restrictions. For the last column, * denotes statistical significance at the 0.05 level (one tail). The penultimate row presents the average value of parameter estimates weighted by the number of observations in each industry, and the last row repeats the results for the baseline model with a single economy-wide productivity factor (Table 3).

Ind.	Parameters										*J*-test *p*-val.
	m	ρ	γ	τ	q	δ	ϕ	λ	ψ	β	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
2	0.20	0.33	0.32	75	116	0.09	1.97	6.85	0.09	1.87	0.39
6	0.24	0.36	0.50	39	31	0.13	2.13	1.43	0.11	1.73	0.80
7	0.22	0.29	0.47	35	18	0.09	1.67	3.65	0.14	2.93	0.09
9	0.23	0.38	0.28	48	43	0.12	1.67	5.50	0.06	0.24	0.21
10	0.22	0.35	0.38	33	14	0.08	2.66	5.44	0.12	0.05	0.13
11	0.20	0.26	0.44	41	15	0.07	1.42	7.85	0.09	1.34	0.06
12	0.27	0.33	0.56	30	9	0.13	2.60	2.13	0.21	1.76	0.05*
13	0.31	0.31	0.46	28	10	0.16	2.07	2.29	0.16	1.90	0.00*
14	0.19	0.32	0.36	123	116	0.08	2.18	8.13	0.07	2.13	0.04*
15	0.19	0.24	0.13	109	105	0.08	2.11	17.09	0.10	1.92	0.00*
17	0.16	0.23	0.22	150	193	0.06	2.63	7.28	0.07	2.60	0.00*
18	0.12	0.33	0.40	64	23	0.04	1.84	6.75	0.06	0.00	0.74
19	0.16	0.27	0.40	130	132	0.05	2.49	7.04	0.11	2.65	0.41
21	0.20	0.19	0.24	86	65	0.08	2.35	5.84	0.12	3.24	0.00*
22	0.20	0.22	0.06	60	18	0.09	2.42	6.23	0.11	2.99	0.05*
23	0.18	0.22	0.48	78	52	0.09	2.06	4.03	0.06	2.36	0.28
30	0.20	0.22	0.67	56	47	0.09	1.34	4.28	0.08	1.44	0.24
32	0.22	0.36	0.48	58	20	0.11	2.01	3.66	0.09	1.81	0.00*
33	0.23	0.43	0.46	32	11	0.11	1.94	2.25	0.12	1.11	0.78
34	0.25	0.33	0.37	37	25	0.12	2.24	2.55	0.16	3.97	0.00*
35	0.28	0.13	0.47	25	12	0.16	2.05	0.00	0.13	3.94	0.04*
36	0.26	0.14	0.19	31	18	0.14	2.16	1.09	0.12	4.29	0.00*
37	0.26	0.30	0.28	56	32	0.15	2.20	0.00	0.13	3.37	0.00*
38	0.17	0.37	0.40	112	78	0.07	2.24	6.04	0.09	2.06	0.59
40	0.17	0.35	0.08	69	5	0.06	1.74	9.25	0.08	2.64	0.01*
41	0.14	0.24	0.26	54	11	0.04	2.39	6.49	0.10	2.55	0.00*
42	0.21	0.51	0.27	61	16	0.10	1.94	4.29	0.08	1.25	0.61
43	0.21	0.49	0.36	61	8	0.11	1.23	2.73	0.05	1.38	0.01*
Avg.	0.21	0.30	0.35	60	39	0.10	2.08	4.49	0.11	2.43	
Econ.	0.21	0.41	0.42	44	21	0.10	1.82	3.97	0.10		0.48

Table 6. Validation Test

This table presents results from validation tests using industry-level parameter estimates. Appendix E describes the validation tests in detail. Each observation in the regression represents an industry. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Panel A. Validation of γ, τ, and β

Dependent variable	Data moment from stock returns		
Validating parameter	γ	τ	β
Moment	Synchronicity	Total volatility	Industry exposure to the market
	(1)	(2)	(3)
Model moment	0.097*	0.204***	0.120***
	(1.77)	(4.81)	(3.36)
Constant	0.301***	0.012***	0.833***
	(13.00)	(10.55)	(9.80)
Observations	28	28	28
R-squared	0.108	0.471	0.303

Panel B. Validation of q

Dependent variable	ERC			
ERC horizon	Long-term		Short-term	
Controls in ERC	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
q	0.006*	0.012*	0.003	0.009
	(1.95)	(1.74)	(0.86)	(0.75)
τ	-0.016***	-0.025**	-0.007	-0.018
	(-3.52)	(-2.59)	(-1.65)	(-1.12)
Constant	2.433***	3.344***	1.187***	2.137***
	(12.77)	(8.42)	(6.33)	(3.15)
Observations	28	28	28	28
R-squared	0.424	0.243	0.149	0.056

Table 7. Quantitative Analysis (Industry Analysis)

This table presents the decomposition of the total and marginal effects of financial reporting on the simulated aggregate output of the public corporate sector based on industry-level estimation. The main value is the mean across 1,000 simulations, while the values in the parentheses represent 95% confidence intervals based on those simulations.

Panel A. Decomposition of the total effect of financial reporting

	Direct Effects	Spillover Effects	Total
Investment Efficiency Channel	31.72% (30.34%, 33.06%)	19.31% (16.98%, 21.74%)	51.03% (49.70%, 52.32%)
Cost of Capital Channel	13.70% (13.31%, 14.10%)	35.27% (34.37%, 36.19%)	48.97% (47.68%, 50.30%)
Total	45.42% (43.77%, 47.03%)	54.58% (52.97%, 56.23%)	

Panel B. Relative importance of industry-specific v. economy-wide information

	Industry-specific Information	Economy-wide Information	Total
Investment Efficiency Channel	29.14% (26.37%, 31.77%)	6.20% (0.87%, 11.40%)	35.34% (32.01%, 38.66%)
Cost of Capital Channel	39.11% (36.83%, 41.41%)	25.55% (24.47%, 26.63%)	64.66% (61.34%, 67.99%)
Total	68.25% (63.94%, 72.59%)	31.75% (27.41%, 36.06%)	

Panel C. Relative importance of intra-industry v. inter-industry learning

	Intra-industry Learning	Inter-industry Learning	Total
Investment Efficiency Channel	34.87% (33.11%, 36.63%)	0.47% (-3.17%, 4.12%)	35.34% (32.01%, 38.66%)
Cost of Capital Channel	48.33% (45.70%, 51.00%)	16.32% (15.63%, 17.03%)	64.66% (61.34%, 67.99%)
Total	83.21% (80.04%, 86.39%)	16.79% (13.61%, 19.96%)	

Panel D. Decomposition of the marginal effect of financial reporting precision

	Direct Effects	Spillover Effects	Total
Investment Efficiency Channel	73.75% (72.76%, 74.77%)	9.32% (8.33%, 10.23%)	83.07% (82.53%, 83.58%)
Cost of Capital Channel	3.74% (3.62%, 3.86%)	13.19% (12.79%, 13.61%)	16.93% (16.42%, 17.47%)
Total	77.49% (76.52%, 78.46%)	22.51% (21.54%, 23.48%)	

Table 8. Robustness Analysis

This table presents results from robustness analyses. Column (1) presents the original estimation (Tables 3, 4, and 7). Columns (2)-(4) are based on alternative measurements of *ROA*: Column (2) is based on net income before special and extraordinary items; Column (3) is based on net income before extraordinary items; and Column (4) is based on net income. Columns (5)-(7) are based on alternative measurements of *Investment Rate*: Column (5) fills missing R&D expense with its industry-average value; Column (6) extends this treatment to advertising expense as well; and Column (7) excludes advertising expense from investment expenditure. Columns (8)-(9) are based on alternative measurements of *CashETR*: Column (8) reduces the measurement window to years *t*-2 to *t*, while Column (9) reduces it only to year *t*.

Alternative Measurements of:			*ROA*			*Investment Rate*			*CashETR*	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parameter Estimates										
m	Mean of productivity	0.21	0.22	0.22	0.22	0.22	0.25	0.20	0.21	0.21
ρ	Autocorrelation of productivity	0.41	0.38	0.37	0.38	0.40	0.39	0.38	0.43	0.38
γ	Proportion of systematic variation	0.42	0.46	0.47	0.46	0.44	0.48	0.45	0.41	0.43
τ	Precision of productivity innovations	43.63	40.19	38.35	38.21	43.80	43.71	44.90	44.62	41.00
q	Financial reporting precision	21.27	23.08	21.79	23.31	21.86	22.50	17.72	23.59	23.61
δ	Depreciation rate	0.10	0.10	0.10	0.10	0.11	0.14	0.08	0.10	0.10
ϕ	Investment adjustment cost parameter	1.82	1.81	1.87	1.93	1.81	1.79	1.85	1.93	1.79
λ	Risk premium parameter	3.97	4.18	3.74	3.62	3.20	1.66	4.80	4.09	4.15
ψ	Variance of investment deviations	0.10	0.11	0.12	0.12	0.10	0.10	0.10	0.11	0.10
J-statistic		1.47	9.88	18.95	23.57	2.56	5.65	0.65	2.45	6.50
	p-value	0.48	0.01	0.00	0.00	0.28	0.06	0.72	0.29	0.04
Total Spillover Effects		53.8%	51.1%	51.2%	48.8%	52.7%	50.0%	60.9%	51.7%	50.0%
Marginal Spillover Effects		22.5%	20.3%	17.4%	15.2%	24.2%	22.7%	36.1%	22.1%	19.9%