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Essays on ICT Standardization, Voluntary R&D Disclosure and Capital Market Valuation

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Abstract

This thesis consists of three chapters on innovation, focusing on firms' involvement in ICT standardization, capital market valuation of innovation, and firms' voluntary disclosures of innovation activities.

The first chapter empirically investigates the financial market's reaction to firms' participation in developing technology standards which is coordinated by Standard Setting Organizations (SSOs). We present the first evidence on the influence of SSO membership over a firm's implied cost of equity capital - the discount rate applied by investors to its expected future cash flows. Our analysis utilizes a sample of 3,350 U.S. public firms and their memberships in 183 SSOs operating in Information and Communications Technologies (ICT) fields between 1996 and 2014. We find that SSO membership results in a statistically significant reduction in the cost of equity using exogenous variations from SSO closures and instrumental variables. This negative correlation is more pronounced for a firm's first SSO membership, among members of the most influential SSOs as well as in ICT industries and certain technology domains. We empirically document the contingent role of three mechanisms – innovation intensity, market uncertainty and information environment – through which SSO membership can affect financial outcomes.

Chapter 2 investigates the relationship between analyst coverage and patent value. Using the listed U.S. firms' data from 1990 to 2015, we find an inverted-U relationship between analyst coverage and firms' patent value, as well as between analyst coverage and innovation efficiency (measured as patent value over R&D capital). Our results are robust to considerations of the endogenous nature of firms' analyst coverage and other sample compositions and adjustments to variables. Additionally, we find that the curvilinear influence of analyst coverage is contingent on firm participation in industrial organizations with regard to innovation and technology (Standard Setting Organizations), and product market competition.

The last chapter examines the effects of narrative R&D disclosure on investment efficiency. Using the enactment of the Leahy-Smith America Invents Act of 2011 (AIA) as a quasi-natural shock on narrative R&D disclosure, we provide strong evidence that firms' narrative R&D disclosure improves investment efficiency by reducing underinvestment in innovation-intensive firms. We argue that these firms are able to issue

more equity and are less likely to experience financial constraints in financing innovative projects, since narrative R&D disclosure reduces their cost of equity. In addition, we find that the positive effect of R&D disclosure on investment efficiency is more pronounced for firms with greater information asymmetry, poorer financial reporting quality, higher R&D intensity and more volatile cash flows.

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Finally, I dedicate this thesis to my father Rongzhu Diao. I hope that this achievement will complete the dream that you had for me and hope I do not let you down. I miss you so much and will love you forever.

Declaration

The first Chapter “Participation in Setting Technology Standards and the Implied Cost of Equity” is co-authored with my two supervisors Dr Cher Li and Dr Simona Mateut. The manuscript drawing on this chapter is under the second round of revisions with Research Policy and available as SSRN paper (following the link: <http://dx.doi.org/10.2139/ssrn.3910622>). This paper has been presented at the 16th Annual Conference of the European Policy for Intellectual Property Association on 8-10 September 2021, the 43rd Annual Congress of the European Accounting Association on 26-27 May 2021, ESCoE Conference on Economic Measurement on 11-13 May 2021 (pre-recorded poster presentation), the Summer School for Data & Algorithm on ST&I STUDIES on 16-18 September 2020 and the internal seminars at Nottingham University Business School. This Chapter 1 in the thesis presents additional analyses which are not contained in the manuscript submitted to the journal in order to offer a more extensive treatment of the research questions.

The third Chapter “Narrative R&D Disclosure and Investment Efficiency” has been presented at the Summer School for Data & Algorithm on ST&I STUDIES on 22 Sept 2021, and the 1st CRIBS Spring Workshop of the Centre for Research in the Behaviour Science of Nottingham University of Business School in April 2021.

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Introduction

This thesis consists of three chapters on innovation, focusing on firms' involvement in ICT standardization, capital market valuation of innovation, and firms' voluntary disclosures of innovation activities.

Business involvement in the development of technology standards (e.g., 5G mobile, Wi-Fi and internet standards) that is coordinated by Standard Setting Organizations (SSOs) has received increasing attention from corporate managers and policymakers alike. Notably, scholarly attention for the economic and strategic implications of firm engagement in open standardization has steadily increased (e.g., Waguespack and Fleming, 2009; Aggarwal et al., 2011). These studies provide useful insights for a narrow set of industries and specific technologies. A crucial question remains as to how the capital market responds to wider business participation in scores of SSOs. Therefore, Chapter 1 intends to address this knowledge gap by using the novel and comprehensive firm-level data from a broad set of industries involved in technology standardization to link firms' cost of equity with their participation in SSOs across a diverse range of technology domains. The cost of equity is the internal rate of return that the market applies to a firm's future cash flows to determine its current market value. If the capital market perceives that a firm's riskiness is attenuated by its participation in technology standardization, then the firm will likely be rewarded with a lower cost of equity and an attendant improvement in its overall economic performance. SSO participation can then be considered an important strategic factor to finance innovation.

To answer these research questions, the first chapter, "Participation in Setting Technology Standards and the Implied Cost of Equity", empirically investigates the financial outcomes of firms' participation in setting ICT standards. More specifically, we study the relationship between the cost of equity and firms' participation in Standard Setting Organizations. Utilizing a substantial sample of 3,350 U.S. listed firms and their membership in 183 SSOs operating in Information and Communications Technologies (ICT) fields over the period 1996-2014, we find robust evidence that membership of SSOs plays a significant role in lowering a member firm's implied cost of equity. Most notably, a firm's first SSO membership is associated with a greater reduction in its cost of capital. While firms operating across a range of industries participate in the development of ICT-based technology standards, our results indicate that firms

belonging to ICT industries, in particular, are associated with a lower cost of equity, compared with their non-ICT counterparts. We further document the contingent role of three mechanisms - innovation intensity, market uncertainty and information environment - through which SSO membership can affect a firm's cost of equity. We find that R&D- or patenting-intensive firms, or firms that own standard-essential patents (SEPs) enjoy a discounted cost of equity. SSO members operating in a more competitive market structure or having a more concentrated customer base also enjoy a lower cost of equity. Additionally, we find that SSO members with more financial constraints and a higher level of information opacity benefit more from their participation in SSOs.

To address the endogeneity issues in our paper, our identification strategy consists of several steps: propensity score matching, instrumental variables and a quasi-natural experiment based on SSO closures. Conditional on observable characteristics, our matched sample analysis reveals a highly significant negative association between participation in SSOs and a firm's implied cost of equity. Whilst considering potentially omitted variables and unobservable confounding factors, we subsequently utilize an exogenous variation in firm exposure to SSO availability in relevant industries to construct our instrumental variable, which is plausibly linked to a firm's membership decision, but uncorrelated with the error term in the model determining the implied cost of equity. This instrumental variable (IV) analysis corroborates our observed negative correlation between SSO membership and a firm's cost of equity. Our final step uses the closure of eight SSOs as external (supply-side) shocks, that can directly affect a firm's membership count, but are exogenous to firm-level activities, including firm-specific standardization strategies. The results from this difference-in-differences estimation show that the difference in the cost of equity between SSO members and non-members is indeed highly statistically significant and that the observed reduction in equity cost, as a result of SSO membership, has a causal interpretation.

Chapter 1 conceptualizes and subsequently empirically evaluates the channels through which SSO membership affects participating firms' cost of equity. We first unpack two sources of uncertainty stemming from technological innovation and product market. We further highlight the signalling effect of SSO membership that helps to improve the information environment of the member firms. We argue that disclosure of standard-setting initiatives by SSO member firms signals the quality of their technologies, thus reducing the level of information asymmetry in R&D projects as a source of capital-market failure; moreover, the ongoing disclosure of SSO memberships and standards-

developing activities can plausibly breed increased transparency in both operations and investments among member firms. Inefficiencies in the capital market can arise under asymmetric information as outside investors may not easily observe the quality of technologies possessed by innovators (which may result in under-investment). At the same time, firms may have an incentive to obfuscate information in their financial statements, as they may be involved in riskier R&D projects at the expense of investor profits (agency problem). Therefore, Chapter 2 and Chapter 3 intend to further study the nexus between firms' information environment and their investment efficiency. More specifically, Chapter 2 introduces an external information environment indicator, which is analyst coverage, and discusses how it affects innovation efficiency. Chapter 3 shifts from the focus on the role of the disclosure of standard-setting initiatives by SSO members and the disclosure of external financial analysts to that of firms' voluntary narrative disclosure on their innovation-related activities. The chapter aims to address whether and how disclosing more narrative information on R&D investment affects firms' investment efficiency due to the change in their information environment.

Innovation productivity is an issue of significant interest to a wide range of stakeholders in the market from company managers, outside investors to policymakers. It can determine the long-term growth and even the survival of the firm. Financial analysts improve the information environment of the firm by providing additional information to the market such as earnings forecasts, which are also performance benchmarks set by these analysts. The second chapter, "Analyst Coverage and Patent Value: An Inverted-U Relationship", examines the role of financial analysts in firms' innovation efficiency. The chapter intends to shed light on how financial analysts, being a key ingredient of the capital market, affect firms' market value of innovation and their innovation efficiency. In this chapter, I follow the measure, recently developed by Kogan et al. (2017), to compute the commercial value of innovation. Compared to the technological value of innovation measured by patent forward citations, the commercial value more accurately captures the true value of innovation for shareholders in the capital market. Moreover, this paper considers both innovative inputs and outputs in terms of the commercial value of innovation, focusing on innovation efficiency, when discussing the nexus between financial analysts and innovation productivity.

Using the sample of 26,926 firm-year observations of 2,674 listed U.S. firms from 1990 to 2015, I identify inverted-U relationships between analyst coverage and firms' patent commercial value, as well as between analyst coverage and innovation efficiency

(a variable measured using the patent value and the R&D capital). The results are robust to different sample compositions and variable adjustments, and considerations of the endogenous nature of firms' analyst coverage. More specifically, I first conduct the analysis on samples of patenting-only firms, active innovative firms, and high-tech firms. The inverted-U relationships between analyst coverage and firms' patent value, and analyst coverage and innovation efficiency, remain consistent across different sample compositions. Second, considering that the innovative process may take more than one year, I conduct the analysis using different sample periods and lags of analyst coverage. The curvilinear influence of analyst coverage is unaffected. To address the endogeneity concerns in the paper, I further utilize an exogenous variation in firms' expected analyst coverage as an instrumental variable. This IV analysis corroborates the observed inverted-U relationships between analyst coverage and firms' patent value, and between analyst coverage and innovation efficiency. Finally, in the additional analysis, I find that the curvilinear influence of analyst coverage on firms' patent value, and its influence on innovation efficiency, is contingent on firms' participation in industrial organizations, with regard to innovation and technology, and product market competition. The industrial organizations membership is identified using firms' participation status in Standard Setting Organization (SSOs), discussed in Chapter 1.

In the third chapter, "Narrative R&D disclosure and Investment Efficiency", I intend to examine the role of narrative R&D disclosure in firms' public, annual 10-K documents in relation to their investment efficiency. This paper shifts the focus on the impact of the disclosure of standard-setting initiatives by SSO members and the disclosure of financial analysts to that of firms' voluntary narrative reporting on innovation activities. As discussed earlier, Inefficiencies occur due to the friction of the capital market, such as agency problem, information asymmetries, or other deficiencies in firms' financing status. Since investment efficiency is one of the most fundamental and important factors that determine firm value and investor wealth, it is of pivotal importance to understand potential factors that can improve the investment efficiency, possibly through attenuating information asymmetry and improving transparency of the firm.

The chapter emphasizes the narrative disclosure on innovation activities as a factor affecting investment efficiency mainly for two reasons. On the one hand, R&D is highly firm-specific and uncertain. Managers have access to inside information on R&D investment carried out by the firm. Producing and disclosing more narrative R&D information to the market, particularly for innovation-intensive firms, can substantially

attenuates information asymmetry and opacity. On the other hand, firms attain competitive advantages through innovation. Disclosing innovation-related information inevitably increases the proprietary cost, which can dampen the positive influence of disclosure on the innovating firms. Consequently, managers face a trade-off between disclosing more narrative R&D information to improve information environment and losing competitive advantages due to knowledge leakage.

To unravel the relationship between narrative R&D disclosure and investment efficiency, the paper utilizes a substantial sample of 48,027 firm-year observations of 6,355 U.S. firms between 1996 to 2018, and finds strong evidence that firms' narrative R&D disclosure positively affects investment efficiency. Moreover, when considering the two scenarios relating to firm investment (underinvestment vs. overinvestment), I find that narrative R&D disclosure is positively related to underinvestment and negatively related to overinvestment. The results are robust when I conduct the analysis on R&D investment efficiency, or use alternative measures of investment efficiency and narrative R&D disclosure. When considering the quality of narrative R&D disclosure, I find that firms with more positive and readable R&D disclosures experience a further increase in their investment efficiency.

To address the endogeneity concerns and to establish causality, I implement a quasi-natural experiment in the difference-in-differences (DiD) framework, by comparing the change in investment efficiency around the time of the enactment of the Leahy-Smith America Invents Act of 2011 (AIA) on March 16, 2013. I find that the investment efficiency of innovation-intensive firms decreases after the enactment, compared to non-innovation-intensive firms. This finding is primarily driven by the negative relationship between narrative R&D disclosure and underinvestment. In order to further understand firms' investment adjustments around the time of the enactment of the AIA, the paper also conducts the DiD analysis on firms' patenting and external financing activities. The results show an increase in patent applications immediately after the enactment by innovation-intensive firms, and reveal that these firms also face diminishing patent quality. As for firms' financing activities, I find that innovation-intensive firms are less likely to issue new equity after the enactment, as the cost of equity increases. Finally, the paper discusses three possible mechanisms, namely information environment, R&D intensity, and cash flow volatility, in an attempt to further disentangle the possible mechanisms between the observed relationship. I find that the positive relationship between narrative R&D disclosure and investment efficiency is more pronounced for

firms with greater information asymmetry, poorer financial reporting quality, higher R&D intensity, and increased cash flow volatility.

The limitations and further proposals for future work of our studies are addressed in the conclusion of each chapter.

Chapter 1:
**Participation in Setting Technology Standards
and the Implied Cost of Equity**

Participation in Setting Technology Standards and the Implied Cost of Equity

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Abstract

This chapter empirically investigates the financial market's reaction to firms' participation in developing technology standards which is coordinated by Standard Setting Organizations (SSOs). We present the first evidence on the influence of SSO membership over a firm's implied cost of equity capital - the discount rate applied by investors to its expected future cash flows. Our analysis utilizes a panel of 3,350 U.S. public firms and their memberships in 183 SSOs operating in Information and Communications Technologies (ICT) fields between 1996 and 2014. We find that SSO membership results in a statistically significant reduction in the cost of equity using exogenous variations from SSO closures and instrumental variables. This negative correlation is more pronounced for a firm's first SSO membership, among members of the most influential SSOs as well as in ICT industries and certain technology domains. We empirically document the contingent role of three mechanisms – innovation intensity, market uncertainty and information environment – through which SSO membership can affect financial outcomes.

Keywords: cost of equity; uncertainty; technology standards; Standard Setting Organizations (SSOs)

1 Introduction

Standard Setting Organizations (SSOs) are largely self-governed public organizations or industry consortia which coordinate the development of innovative technology standards (e.g., 5G mobile, Wi-Fi and internet standards). As members of SSOs, firms collaborate to collectively define common rules, technical specifications, and regulations for players in the market while promoting these as voluntary consensus-based standards in relevant industry domains (Simcoe, 2012). *De jure* standards emerging from this process serve a distinctive set of functions ranging from minimum quality, variety reduction, interoperability, to health and safety etc. (for a comprehensive review, see Swann, 2010).

Our study focuses on technology standards which are developed by SSOs operating in the domains of Information and Communications Technologies (ICT). Business participation in ICT standardization has received increasing attention from corporate managers and policymakers alike alongside greater media coverage. For instance, when AT&T and seven other companies joined the Telecommunications Industry Association (TIA) in 2015, the media emphasized a suite of benefits ranging from better industry intelligence to improved network opportunities. Publicly traded U.S. firms frequently disclose participation in standards setting in their annual 10-K reports to provide crucial business and financial information to investors.¹ This research seeks to advance our understanding of how investors perceive a firm's participation in developing open technology standards. More specifically, to what extent a firm's participation in SSOs impacts on its cost of equity.

Instead of using noisy *ex-post* returns, we follow recent studies and employ a developed method to estimate the *ex-ante* required return/implied cost of equity (e.g., Dhaliwal et al., 2016; Pham, 2019). Our interest in cost of equity capital is motivated by three reasons. First, a firm's cost of equity is the discount rate applied to its expected future cash flows to determine current stock prices. It reflects equity holders' perception of the firm's riskiness. If the perceived riskiness of SSO member firms is different to that of non-members, we should expect their cost of equity capital to vary systematically with SSO memberships. Despite the importance of standards setting for technological progress and its crucial implication for the financial management of the firms involved,

¹ For instance, ACI Worldwide Inc., a large technology company in payment systems, discloses in its 2018 10-K report its membership in several SSOs such as the International Organization for Standardization (ISO) and the Accredited Standards Committees (ASC) X9 responsible for developing financial service standards. The Online Appendix presents excerpts from such 10-K reports and examples of media reports.

there is surprisingly a dearth of research on whether participation in SSOs influences the market's expectation of firms' future cash flows and riskiness. Our research bridges these knowledge gaps. Secondly, the cost of equity is a direct measure of external equity financing costs, and as such it affects both investment decisions and financing decisions (Shleifer and Vishny, 2003). Third, the ICT industries have witnessed a surge in standard-setting activities as ICT technologies have experienced fast paced evolution and these industries are disproportionately dependent on external finance (Acharya and Xu, 2017). Hence, a better understanding of the causal links between the cost of equity and SSO participation holds the key to addressing innovation financing issues in some of the most dynamic industries of the economy.

Our empirical analysis utilizes a panel of 3,350 U.S. listed firms observed over the period 1996-2014. Information on firm-level affiliations with 183 SSOs spanning a range of ICT-based technology domains is drawn from the Searle Centre Database on SSOs (see Baron and Spulber, 2018 and a recent application in Baron et al., 2019). We find robust evidence that membership of SSOs plays a significant role in lowering a member firm's implied cost of equity. Most notably, a firm's first SSO membership is associated with a stronger reduction in its cost of capital. While firms operating across a range of industries participate in developing ICT-based technology standards, our results indicate that firms belonging to ICT industries are particularly associated with a lower cost of equity vis-à-vis their non-ICT counterparts.

To the best of our knowledge, this study presents a first analysis of the relationship between SSO membership and firm-level financial returns in terms of the cost of equity capital by utilizing robust evidence from a large sample of firms which are active in scores of SSOs and diverse technological domains. We exploit two types of exogenous variations in SSO membership to address the endogeneity concerns in our study. We first utilize the variation in a firm's exposure to SSO availability in relevant industries to construct our instrumental variable (IV), which is plausibly linked to a firm's membership decision but uncorrelated with the error term in the model used to determine the implied cost of equity. This IV analysis corroborates our observed negative correlation between SSO membership and a firm's cost of equity. Our second identification strategy relies on the difference-in-differences (DiD) method. In this setting, the closures of eight SSOs represent an external (supply-side) shock that in some instances directly affects a firm's membership count but is exogenous to business activities, including firm-specific standardization strategies. Our DiD results establish

that exogenous reductions in firms' membership count caused by SSO closures statistically significantly affected their cost of equity.

In a recent study, Blind et al. (2017) shed light on the role of formal standards in enhancing the innovation efficiency of firms in markets with high uncertainty. A critical issue that remains poorly understood is to what extent participation in developing these standards improves firms' financial performance by attenuating technological and market uncertainty. We address this question by first developing a conceptual framework with three potential channels whereby SSO memberships can affect firms' financial outcomes, namely, innovation intensity, market uncertainty, and information environment, before empirically testing them.

To measure innovation intensity, we use information relating to R&D intensity, narrative R&D-related disclosure in firms' 10-K filings, and patents. Our findings reveal that SSO members with above industry average R&D-intensity invariably enjoy a significantly lower cost of equity, implying a more important role of membership when technological uncertainty stemming from riskier R&D projects is high. Utilizing information on patent applications and ownership of standard-essential patents (SEPs) to distinguish between developers and implementers, we find that technology owners that actively contribute to standards development are associated with lower cost of equity. In a similar vein, in the case of uncertainty arising from product markets, we find that SSO members facing higher levels of uncertainty, in terms of product-market competition and customer-base concentration, also benefit more from a reduction in their cost of equity. Finally, using three measures to capture firms' information environment, we find that SSO members suffering from higher levels of information asymmetry (i.e., more financially constrained, producing less readable 10-K reports or less transparent) tend to gain more through their membership in terms of lower cost of equity.

Consistent with our conceptualization, our empirical results also underline that the extent to which an SSO member firm is associated with reduced cost of equity is contingent on which SSOs it chooses to join. Utilizing network analysis, we derive a centrality-based measure of SSO influence within the standardization network and show that firms participating in (one or multiple) influential SSOs have lower cost of equity vis-à-vis members of more peripheral SSOs. As our centrality measure is likely correlated with SSO size, our result resonates with prior evidence documented by Aggarwal et al. (2011) in their seminal study of the standardization and financial risk nexus. Using an event-study approach in the context of IT standards-setting events from

1996-2005, the authors show a significant return on stock price to a standard-setting initiative; most notably, a larger standardization group size decreases the risk-adjusted abnormal return and the market risk of individual firms (i.e., beta) while increasing their idiosyncratic risk (i.e., variance of returns).

Our study also sheds light on the heterogeneity across SSOs in our sample in terms of their technological specialization as well as their technology-centric versus market-centric focus (Delcamp and Leiponen, 2014; Baron et al., 2019). As a firm may participate in multiple SSOs and an SSO may develop standards in different technological categories, we identify the dominant SSO technological specialization for each member firm to allow more meaningful comparisons. This analysis reveals that the lowest cost of equity is associated with membership in *Electronics* domain across the full sample and associated with *Information Technology* among ICT firms, respectively. We then separate firms' SSO memberships into single versus multiple technological categories, where the latter can stem from participation in one or several SSOs. Our results suggest that multiple SSO memberships across technological categories seem to be important overall, while SSO membership in a single technological domain (*Information Technology*) matters especially in the ICT sector. Additionally, accounting for the technology- versus market-based focus of SSOs, our study points to a stronger correlation with lower cost of equity when firms combine memberships from both types of SSOs. Lastly, membership of technology-centric SSOs has more prominent effects on the cost of equity for ICT firms.

Our study thus contributes to the small but fast-growing body of research on firm-level involvement in SSOs which has to date primarily focused on understanding the motives of firms' participation in standards setting (e.g., Blind and Mangelsdorf, 2016; Baron et al., 2019) instead of evaluating its impact. This chapter particularly contributes to the empirical literature on the determinants of the cost of equity. Recent studies have emphasized the role of various factors such as corporate social responsibility (El Ghoul et al., 2011), political connections (Boubakri et al., 2012), financial reporting frequency (Fu et al., 2012), customer concentration (Dhaliwal et al., 2016), and corporate derivatives use (Ahmed et al., 2018). Little is known about the effect of innovation-related drivers except for the study by Lui et al. (2016) which shows a negative relationship between the adoption of (disruptive) information technology and a firm's cost of equity. Therefore, this chapter adds to this literature by highlighting an important

yet neglected factor in determining the cost of equity, i.e., collaborative innovation as measured by firms' participation in collectively developing open technology standards.

The remainder of the chapter is organized as follows. Section 2 presents our analytical framework building on related studies in the literature. Section 3 describes our data and baseline models. We discuss our main empirical results and robustness checks as well as explore key mechanisms in Section 4. We consider SSO-level heterogeneity in Section 5 and present our identification strategy in Section 6, before concluding in the last section.

2 Analytical framework

2.1 Motivation and barriers to participation in ICT-based SSOs

The literature on technological standardization often points to a key benefit of standards in promoting a focus on specific product/service options and technologies (Farrell and Saloner, 1985; Narayanan and Chen, 2012; Blind et al., 2017). This focusing is essential for the creation of new markets, building critical mass, attracting further investment, and developing complementary knowledge and technologies. It follows that much scholarly attention has been devoted to the role of technology standards in catalyzing innovation from the perspectives of both standards adopters and developers. By adopting technology standards, on the one hand, firms can perform better in delivering incremental innovation while catching up to the technology frontier defined by standards (see Foucart and Li, 2021, for recent theoretical and empirical evidence). By setting standards, on the other hand, firms can gain access to new markets while improving their innovation performance through compatibility standards (David and Steinmueller, 1994; Soh, 2010); and they can furthermore contribute to the emergence of new product markets through anticipatory standards (Blind and Mangelsdorf, 2016).

Prior literature on competitive strategy offers valuable insight into the benefits of the cooperative standards-setting process in network markets which allows firms to compete *in* the market by enabling compatibility, as opposed to a market-based standardization process which often entails fierce standards battle leading to highly uncertain returns (Besen and Farrell, 1994). Voluntary SSOs thus arise to provide solutions to the fundamental coordination problems in system markets which prevail in the presence of network externalities (Katz and Shapiro, 1994). In addition to mitigating winner-take-all competition, firms participate in these open standards organizations to benefit from state-

of-art technology, knowledge exchange, and anticipate the trajectories of future technology advancement. Although technology standards developed by an SSO are non-proprietary and open to all, formal members of the SSO can have early access to technologies built into emerging standards to drive lead time as a source of competitive advantage in developing their standard-compliant technologies and new products (Baron et al., 2019). Moreover, SSO members can have further say in the organization's governance as well as its rules and policies to subsequently influence the direction of technology development.

Not all firms, however, partake in standards development that is coordinated by SSOs nor is it feasible for a firm to join all pertinent SSOs in the domains where it operates.² Several arguments have been put forth to explain such selective participation including considerable pecuniary costs in terms of travel expenses for meeting attendance and membership fees (costing between \$10,000-\$60,000 per membership depending on the tier of membership and business size), non-pecuniary costs in terms of technical personnel and human resources as well as R&D investment required to develop technical contributions to the standard or to create new technologies which are relevant to the standard under development (Updegrove, 2006; Baron and Spulber, 2018). In a recent study, Baron et al. (2019) provide additional conjectures on the barriers to joining SSOs including unintended leakage of proprietary knowledge in collaborative development of technology standards, unwanted obligations of members around the disclosure of potential standard-essential patents (SEPs) and the licensing requirements stipulated by individual SSOs to make members' SEPs available to implementers (often on less profitable terms) in order to promote adoption. Lastly, Lerner and Tirole (2006) use a forum shopping framework to emphasize the matching between a firm's assets and the SSO forum to which it takes its ideas to develop. Our empirical extensions allow the financial returns to membership relationship to be influenced by SSO heterogeneity. In doing so, we offer finer-grained insight into this relationship being contingent on characteristics such as the centrality or influence of SSOs, their orientation towards technology versus market, their goals or technological specializations, as well as their domains (e.g., according to Aggarwal et al., 2011, group size is found to constitute a key determinant of financial returns for firms involved in IT standardization events).

² We thank the editor and a reviewer for suggesting this point.

2.2 Linking SSO participation and financial-market returns

Collaboration in developing technologies is perceived to mitigate uncertainty facing firms emanating from both technology- and market-based sources. In many system markets, technology standards (e.g., web standards and telecommunication standards) are known to encompass an industry's technological base and offer a non-proprietary (public) technical infrastructure upon which modular parts can be integrated to build more complex system-level technologies and products. The “infrastructure technology” embodied in these standards can thus reduce technological and product-market uncertainty arising from the use of complex technologies and market competition in a firm's innovation process from initial R&D to technology commercialization (Tassey, 2000; Foucart and Li, 2021).

Innovation intensity. Firstly, participation in developing standards can minimize uncertainty facing innovation-intensive firms and maximize their R&D effort by levelling the playing field, enabling learning through spillovers and aligning the firm's investment decision with the future trajectory of technology development in the industry (Waguespack and Fleming, 2009; Delcamp and Leiponen, 2014). Rysman and Simcoe (2008), for instance, show that SSOs are able to identify and subsequently influence the wider diffusion of higher quality technologies. Simcoe (2012) further argues that coordinated standards setting circumvents the uncertainty, duplication, and intense competition of a decentralized standards war, and thus promotes orderly technical transitions. Participating firms can actively seek to influence standards toward their preferred specifications and hence effectively overcome the uncertainty arising from their R&D process as well as from incompatible or conflicting standards. This also resonates with the argument of Waguespack and Fleming (2009) that standards setting helps shift the burden of innovation from individual firms to the SSO level.

Market uncertainty. Secondly, developing technology standards can be vital for creating new market demand and reducing *market uncertainty* associated with transformational thus riskier technologies, since industry standards can greatly promote employee trust and customer confidence (Hudson and Orviska, 2013; Blind et al., 2017). The increased compatibility and interoperability resulting from standards development in ICT domains can especially facilitate the path to a larger consumer market across economic sectors. As early innovators, firms participating in developing emerging technologies can particularly benefit from scale and scope economies, as well as

efficiency gains to achieve product growth stemming from the early exposure to standards (David and Steinmueller, 1994; Blind and Mangelsdorf, 2016). Using data for UK manufacturing firms, Foucart and Li (2021) find empirical support for their theoretical prediction that technology standards can be used by firms (especially those further away from the technological frontier) as an “insurance” hedging against the risky process of developing new products. It follows that the effect of setting technology standards on future financial returns is expected to be more profound in markets with a high level of uncertainty. In a related study, Aggarwal et al. (2011) analyze standard-setting announcements in IT investments and find that market returns and market risk decrease, and idiosyncratic risk rises with the number of parties of standard-setting initiatives.

Information environment. Finally, as with most investment decisions, a firm’s *information environment* is likely to condition the extent to which the firm’s SSO participation exerts an influence on its perceived financial returns. Under asymmetric information, inefficiencies in the capital market can arise: outside investors may not easily observe the quality of technologies possessed by innovators (which may result in under-investment); at the same time, technology-intensive firms may be involved in riskier R&D projects at the expense of investor profits (which may lead to an agency problem). Managers thus have an incentive to obfuscate information in financial statements and hide adverse information. Disclosure of standard-setting initiatives by SSO member firms signals the quality of their technologies (Baron and Spulber, 2018), thus reducing the level of information asymmetry in R&D projects as a source of capital-market failure. The ongoing disclosure of SSO memberships and standards-developing activities can plausibly breed increased transparency in both operations and investments among member firms. As for technology contributors, the subsequent endorsement by SSOs significantly bolsters the value of selected technologies and that of the owner firms, further alleviating information asymmetry (Rysman and Simcoe, 2008; Waguespack and Fleming, 2009).

Based on these considerations, we thus postulate that participation in standards setting is likely to lead investors to perceive a reduced level of riskiness in member firms, materializing into a lower cost of equity. We argue that being SSO members is likely to bring about more reduction in equity cost for firms with higher innovation intensity, facing higher uncertainty or information asymmetry. In ensuing empirical analyses, we test the conditioning role of these three mechanisms.

3 Data and methods

3.1 Sample construction

We utilize several data sources to construct our main sample. We start by drawing accounting data from the Compustat-CRSP Merged database covering all U.S. listed firms. Then, we name-match all firms with information collected from the Searle Centre Database (SCDB) to identify if they are members of any SSOs over the period 1996-2014. The SCDB offers the most comprehensive and systematic data on the membership of over 190 SSOs that develop and/or promote technology standards in a range of ICT technology domains (for a detailed description of SCDB, see Baron and Spulber, 2018). For all matches, we manually check firm names and postcode information on the Internet. Since the SSOs and their standards covered in SCDB constitute the preponderance of ICT standardization, we consider the unmatched Compustat firms in our sample as non-members of SSOs in a given year.

As participation in setting ICT standards may not be relevant to all economic sectors, we ensure our research questions are meaningfully tested by carefully selecting the industries included in our sample. Excluding the financial and the public sectors, we select those (2-digit SIC) industries in which a minimum of 10% of firms have been SSO members at least once during the 1996-2014 period.³ Table 1 lists the 14 industries selected. Note that our sample includes all industries in the high-tech sectors (SIC codes 28, 35, 36, 37, 38 and 73) as in Brown et al. (2009). These six industries jointly account for over 82.38% of our sample.

[Insert Table 1]

We collect stock prices, returns, as well as the year of firms' initial public offering or trading from the CRSP database. Patent data is obtained from Orbis Intellectual Property (Orbis IP).

3.2 Implied cost of equity

³ While Chemicals and Applied Products (SIC 28) does not meet the 10% cut-off, it has the highest R&D intensity among all the industries. Moreover, as Acharya and Xu (2017) indicate that biotechnology industries rely heavily on external capital, it is of great interest to study the relationship between SSO participation and the cost of equity in this industry. Our results remain unaffected if we exclude this industry from our sample.

We empirically estimate the cost of equity implied by the firms' current market value and their future cash flows. This approach does not rely on noisy realized returns or on specific asset pricing models. Following recent studies (e.g., Hail and Leuz, 2009; Boubakri et al., 2012; Ortiz-Molina and Phillips, 2014; Dhaliwal et al., 2016; Pham, 2019), we construct our implied cost of equity measure based on four models: Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005). Broadly, Gebhardt et al. (2001) and Claus and Thomas (2001) employ the residual income valuation model, Easton (2004) is based on a modified price-earnings growth model, while Ohlson and Juettner-Nauroth (2005) implement an abnormal earnings growth valuation model.

A common caveat of the four models is their use of analysts' forecasts, which are available only for a subset of firms and which sometimes deviate much from future cash flows expectations. To address this issue, following Pham (2019), we use instead the forecasting model developed by Hou et al. (2012) to derive earnings forecasts. More specifically, to calculate the individual estimates in the four models we use the earnings forecasts obtained from the cross-sectional profitability model in Fama and French (2000, 2006). Detailed descriptions of the four models and the Hou et al. (2012) procedure are provided in the Appendix.⁴

We follow Hail and Leuz (2009) and construct our implied cost of equity measure (*ICE*) as the equal-weighted average of the four individual estimates. This approach has the additional benefit of mitigating the effects of measurement errors associated with any particular model (Dhaliwal et al., 2006). To maximize coverage, we require a firm to have at least one non-missing individual estimate to calculate our composite measure (Hou et al., 2012). Our results remain qualitatively unchanged when we require all four individual estimates to be non-missing, but the sample size drops considerably.

3.3 Empirical model

We analyze the effect of SSO membership on the implied cost of equity by estimating the baseline model below:

$$ICE_{i,t} = \alpha_i + \beta MEMBER_{i,t-1} + \gamma Controls_{i,t-1} + v_j + \mu_t + \epsilon_{i,t} \quad (1)$$

⁴ The Online Appendix B provides detailed explanations and results obtained with the Fama and French three-factor model (1992, 1993) and the CAPM model, two ex-ante cost of equity measures employed in earlier studies.

where $ICE_{i,t}$ is the “composite” implied cost of equity measure calculated for firm i in year t . $MEMBER_{i,t-1}$ is a binary variable that takes the value one if firm i is a member of any SSO in year $t-1$, zero otherwise. As usual, $\epsilon_{i,t}$ is the error term, while α_i , v_j , and μ_t stand for firm, industry and time specific effects, respectively.

Our study uses firms’ SSO memberships as recorded in the SCDB database to proxy for their participation in ICT standardization. While we use these terms interchangeably, it is worth noting that SSO membership is not necessarily synonymous with active contribution to standards development. This discrepancy can be explained by several factors. First, some SSOs do not set or develop any technology standards but only incorporate, promote, or disseminate standards that are developed elsewhere. Second, even within SSOs that develop new standards, the mode and extent of involvement of individual members in the standard-setting process varies markedly ranging from passive observation, meeting attendance, vote on standardization decisions, active technical contribution, election to leadership positions and so forth (Baron and Spulber, 2018). Third, as discussed earlier, the degree of a member firm’s engagement in standardization activities is likely to be driven by its business model, standardization strategy, motive for SSO membership and costs incurred, all of which may broadly correlate with whether the firm is a technology-centric developer or a product-centric implementer.

Our ensuing empirical analysis thus attempts to account for such treatment heterogeneity that is contingent on SSO- or firm-level characteristics. We first exploit variation in firm innovation intensity, and especially ownership of standard-essential patents to shed light on the disparity between developers, that frequently make technological contributions to standards under development, and implementers, that utilize developed standards to bring to market standard-compliant products or services. Furthermore, we construct additional attributes of SSOs to investigate whether the link between SSO membership and the implied cost of equity is dependent on the influential position of an SSO in the standardization network or the technology- versus market-centric position of the SSO.

$Controls_{i,t-1}$ is a set of variables known to influence the cost of equity. We first control for firm innovation ($PATAPP$), measured as the annual number of patent applications (eventually granted). Prior literature highlights the role of patents in signalling the quality of a firm’s R&D projects and thus mitigating the effect of uncertainty and information ambiguity on investors’ perceived risk of unsuccessful

research outcomes (Griliches, 1990; Hall et al., 2005; Czarnitzki and Toole, 2011; Hussinger and Pacher, 2019). As we control for patenting activity, the β coefficient on *MEMBER* should capture any additional informational effects of participating in SSOs on the firm's cost of equity. To check robustness of our patenting activity measure, we use, alternatively, the firms' patent stock (*PATSTK*) and forward citations (*CITATION*). *PATSTK* is calculated as (the natural logarithm of one plus) the current number of patent applications plus the patent stock in the previous year using the 15% depreciation rate (Hall et al., 2005); *CITATION* is (the natural logarithm of one plus) the total number of citations generated in subsequent years by all the patents the firm applied for in year $t-1$. As standard in the literature, we scale the number of citations received by each patent using the average number of citations received by all patents in the same technological class each year to correct for truncation bias. These estimates are presented in the Online Appendix Table OB1.⁵

In line with previous studies (e.g., Hail and Leuz, 2009; Boubakri et al., 2012; Fu et al., 2012; Ortiz-Molina and Phillips, 2014; Pham, 2019) on the implied cost of equity, we also control for firm size (*SIZE*) measured by total real assets (using 2010 as reference)⁶ and firm age as the number of years since the firm's initial public offering or first trading, both of which capture the information environment of the focal firm. *VOLATILITY* is the annual standard deviation of monthly stock returns. *MTB* is the market-to-book ratio. As low market-to-book firms earn higher *ex-post* returns (Fama and French, 1992), *MTB* is expected to be negatively associated with the cost of equity. Modigliani and Miller (1985) argue that the cost of equity increases as leverage increases. Therefore, we also control for the leverage ratio (*LEVERAGE*) calculated as long-term debts to total assets. The return on assets (*ROA*) helps capture the effect of the overall profitability on the cost of equity. Finally, we control for the forecast error (*FORECASTER*) calculated as earnings forecasts next year minus actual earnings, scaled by lagged total assets. It captures the potential effect of forecasting biases on the cost of equity estimates (Hail and Leuz, 2006).

⁵ In a separate exercise, we use the CRSP-linked granted patents data constructed by Kogan et al. (2017) made available at <https://iu.app.box.com/patents>. Following Guo et al. (2019), we exclude observations after 2006 to mitigate the truncation problem arising from the time gap between application and grant dates. Our results remain unaffected when we use the much shorter panel.

⁶ Using instead market capitalization (i.e., the average market equity value at the beginning and end of calendar year $t-1$) is inconsequential.

3.4 Descriptive statistics

Our final sample used in the estimations contains 32,824 firm-year observations for 3,350 listed U.S. firms spanning the period 1997-2015. We eliminate firms with fewer than three consecutive annual observations and winsorize the 1% tails of all continuous firm-level variables.

Table 2 presents a summary of the variables used in the empirical analysis. The mean value of the cost of equity in our sample is around 13.5%, similar to that reported in Hou et al. (2012). On average, 16.1% of the observations refer to SSO member firms and the average number of memberships is around 0.6 in our sample.⁷ In terms of firm numbers, 909 out of the 3,350 firms in our sample participate in at least one SSO. There is major variation in membership patterns among participants, with 448 firms participating in more than one SSO (max value 60). Simple t-test results ($t = 15.470$) confirm that the average implied cost of equity is 3.04 basis points lower for SSO members relative to non-member firms.

The breakdown of the summary statistics by industry (Panel B) reveals that the average implied cost of equity ranges from 9.9% in General Merchandise Stores (SIC 53) to as high as 15.2% in Textile Mill Products (SIC 22). As expected, the highest SSO participation rate (29.7%) is in Electronic and Other Electric Equipment (SIC 36), which is nearly twice as high as the average participation rate for the whole sample. The average SSO membership count (1.289) is also highest in this industry.

All the pairwise correlation coefficients presented in Panel C are small in magnitude and statistically significant at 5% level. Members of SSOs are associated with a lower implied cost of equity. The signs of the other coefficients are consistent with previous studies: the implied cost of equity is negatively related with firm size, the market-to-book ratio, returns on assets and age, and positively associated with stock return volatility, leverage and forecast error.

[Insert Table 2]

⁷ We carefully inspect data accuracy in the SCDB membership database. For instance, we ascertain that no firms are assigned membership of an SSO in the years following its closure. See Section 6.3 SSO closures.

4 Estimation results

4.1 Baseline models

Table 3 presents our fixed effects estimates of Equ.1 controlling for firm and time specific effects. Standard errors are clustered at the firm level and the corresponding t-statistics are reported in parentheses. In column (2) we control for time-invariant industry specific effects using the Hausman-Taylor estimator.⁸ In column (3) we employ the fixed effects estimator on Equ.1 augmented with industry-time interaction terms. As expected, SSO participation is associated with a lower cost of equity. Overall, we find a significantly negative estimated parameter of *MEMBER* suggesting a 0.6 basis point lower cost of equity for SSO member firms. Firms with a larger number of patent applications are associated with lower costs of equity. This result is in line with previous evidence regarding the positive effect of patenting on firms' market value by allowing firms to better appropriate economic rents from their invention and offering them IP protection to fend off competition (Hall et al., 2005; Belenzon and Pataconi, 2013).

[Insert Table 3]

Turning to the other control variables, we find that they exhibit the expected signs. Consistent with Boubakri et al. (2012), Fu et al. (2012), Chen et al. (2016) and Pham (2019), the market-to-book ratio (*MTB*) is negatively related to the implied cost of equity. A higher volatility in returns (*VOLATILITY*) is associated with a larger implied cost of equity as documented in Hail and Leuz (2009), Boubakri et al. (2012) and Boubaker et al. (2018). The positive association between leverage (*LEVERAGE*) and the implied cost of equity is consistent with Boubakri et al. (2012), Chen et al. (2016) and Boubaker et al. (2018). Larger and more profitable firms are able to raise external capital at a lower cost (Boubakri et al., 2012; Pham, 2019). Consistent with Boubakri et al. (2012), firm age (*AGE*) positively relates to the implied cost of equity. Finally, a larger forecast error (*FORECASTER*) correlates positively with the implied cost of equity (Hail and Leuz, 2009).

In columns (4), (5) and (6), we consider alternative measures of SSO participation. Exploiting time-varying membership information, we first exclude firms which are SSO members consistently throughout our sample period. Next, we disregard firms that never

⁸ All our explanatory variables are considered potentially correlated with α_i in Equ.1 in the Hausman-Taylor regression.

participate and focus on the first recorded SSO participation (*fMEMBER*). In the last column, we account for the total number of SSO memberships held by a firm in a given year (*MEMBERCOUNT*). The estimates presented indicate a consistently negative and statistically significant correlation between each measure of SSO participation and firms' implied cost of equity. Most notably, a firm's first-recorded participation in any SSO (i.e., first entry) is associated with a large reduction in its cost of equity. Besides, a firm with more different SSO memberships is also associated with a larger reduction in its equity financing costs, as the -0.011 estimated coefficient on ICE is statistically significant at the 1% level.

4.2 Possible mechanisms

Our consistent finding of a negative association between SSO participation and a firm's cost of equity is in line with our conjecture that the *de jure* standardization process mitigates technological and market uncertainty arising from the alternative *de facto* standards (that emerge from market-based competition). Participation in SSOs also helps boost firms' transparency in both operations and management, improving the information environment of member firms. To shed light on the specific channels underlying our key findings, in this section, we exploit heterogeneity among member firms in terms of their innovation intensity, market competition, uncertainty regarding future performance, and information transparency.

4.2.1 ICT industries

We now slice our sample into ICT and non-ICT industries as ICT-based firms have a higher exposure to technology standardization as well as technological and market uncertainty. In our sample, some 86.5% of the observations for SSO members belong to six high-tech ICT industries. Participation in ICT standardization can reduce technology varieties, increase modularity and interoperability and improve operation transparency. SSO participation is thus likely to exert a stronger influence on the cost of equity among ICT firms.

We first construct the ICT sample A by selecting the 4-digit SIC codes suggested by Shackelford and Jankowski (2016). This specific ICT industry definition used by the National Science Foundation is generally comparable to the one used by the Organization

for Economic Cooperation and Development (OECD). We construct also a broader ICT sample B comprising almost the entire high-tech sectors in the U.S. (SIC codes 28, 35, 36, 37, 38 and 73). Following Brown et al. (2009), we exclude the aerospace industry, a high-tech part of SIC 37 with very few firms which have most of their R&D funded by the government.⁹ Table 4 reports the estimates of Equ.1 when the ICT sector is singled out of the whole sample. The negative and highly significant relationship between SSO participation and the implied cost of equity persists regardless of the sample definition used in columns (1) and (3). Our results indicate that the overall negative relation between firms' SSO membership and their cost of equity seems to be mostly driven by the ICT industries as the estimated parameter is statistically indifferent from zero outside the ICT industries (columns (2) and (4)).¹⁰

[Insert Table 4]

4.2.2 Innovation intensity

Next, we explore to what extent the SSO participation and cost of equity relationship is contingent on firm-level heterogeneity in terms of innovation intensity. More innovation intensive firms are expected to have high levels of absorptive capacity (Cohen and Levinthal, 1990) which holds the key to appropriating knowledge spillovers and other learning benefits from participating in collaborative R&D that is coordinated by SSOs. At the same time, R&D-intensive firms, especially in ICT industries, can encounter higher uncertainty such as R&D investment failure or unexpectedly surging costs in innovation (Czarnitzki and Toole, 2011). We measure firm-level R&D intensity as R&D expenses over total sales.¹¹ We then set the *High (Low) RDI* dummy equal to one if the firm's R&D intensity is above (below) the industry-median in a given year, and zero otherwise.¹²

⁹ The ICT sample B defined at 3-digit SIC level comprises SIC 283 (Drugs), SIC 357 (Computer and Office Equipment), SIC 366 (Communications Equipment), SIC 367 (Electronic Components and Accessories), SIC 382 (Measuring and Controlling Devices), SIC 384 (Medical Instruments and Supplies) and SIC 737 (Computer and Data Processing Service). Relative to ICT sample A, ICT sample B includes the highly R&D-intensive fields within Chemicals and Applied Products industry (SIC 28).

¹⁰ We also estimate the model on the whole sample and interact all variables with ICT and non-ICT indicators. We find that the estimates for ICT members are statistically significant (coefficient: -0.008, t stat: -2.426 for sample A and coefficient: -0.007, t stat: -2.276 for ICT sample B) while those for non-ICT members are not.

¹¹ In a separate exercise, following Kim and Zhu (2018), we replace missing values for R&D expenses with zero, which is inconsequential for our results.

¹² We compute every industry-year median in this section at 3-digit SIC.

Given the attrition of R&D expenditure amounts reported in Compustat, we also use narrative R&D disclosure to separate firms into categories. Specifically, we collect the annual 10-K filings for all U.S. companies between 1996 to 2014 from the Software Repository for Accounting and Finance (SRAF) provided by Loughran and McDonald.¹³ To identify R&D-related disclosure, we utilize the word list provided by Merkley (2014), which contains narrative R&D keywords and phrases such as “research development” and “technology breakthrough”, and count the total number of R&D-related sentences in firms’ 10-K filings.¹⁴ We then set the *High (Low) RDdisclosure* dummy equal to one if the firm’s narrative R&D disclosure is above (below) the industry-year median, and zero otherwise.

To further understand treatment heterogeneity among firms with distinct business models, such as general inventors of patents, technology-centric contributors of standards and product-centric implementers, we first consider firms’ yearly patent applications. We set *HPT (LPT)* equal to one if the firm’s number of patent applications are above (below) the industry-year median, and zero otherwise. Second, we look further into firms’ patent portfolio and consider their holdings of standard-essential patents (SEPs). A patent can be considered an SEP when the patent technology is the only method of implementing a standard (Baron and Pohlmann, 2018). We identify SEP holder firms by mapping the 139,620 essential patents identified by Baron and Pohlmann (2018) to our dataset using company names and create *SEP* as a dummy variable equal to one if firm *i* has at least one declared SEP in year *t-1*. As for non-SEP holders, we use two additional indicator variables to distinguish between patent holders without SEPs (*NoSEP*) and non-patent holders (*NoPT*).¹⁵

The results presented in columns (1)-(2) of Table 5 suggest that more R&D intensive SSO members are associated with lower cost of equity, in line with our conjecture that participation in SSOs helps overcome uncertainty stemming from risky R&D projects by

¹³ The 10-K files from the EDGAR database in SRAF are cleaned and suitable for subsequent textual analysis. More information is provided at: <https://sraf.nd.edu/data/stage-one-10-x-parse-data/>

¹⁴ Similar results are obtained if we use the other two measures proposed by Merkley (2014): the amount of numerical R&D disclosure and forward-looking R&D disclosure.

¹⁵ Though SEP holding firms can be considered more technology-centric contributors, and the inclusion of a patent within a standard significantly increases its value (Rysman and Simcoe, 2008) and that declared SEPs contribute to better firm performance than do comparable control assets (Pohlmann et al., 2015), we have to note that a patent might not be technically essential but commercially essential for implementing a standards; besides, many patents are developed in the process of standard development but they are not included in standards or necessary for the implementation of the standards. Therefore, the SEP data can only partially capture a firm’s standards developing activities, while the disclosure of SEPs may have some impact on the market perception of a firm’s innovation quality.

shifting the burden of innovation from the firm to SSO level. When we separate members into inventors and implementers, we find that firms with high patenting activity are those associated with a reduced cost of equity (column (3)). As expected, this reduction is most marked among owners of declared SEPs whose patented technologies are incorporated in standards developed by SSOs (column (4)).¹⁶

4.2.3 Product-market uncertainty

Our conceptual framework also underlines that capital market's perceptions of the riskiness of SSO members may be conditional on the uncertainty these firms face in the product market. A firm's product-market uncertainty is primarily determined by the volatility in the aggregate market demand. For a given level of volatility in aggregate market demand, a firm's product-market uncertainty can also derive from sources such as the intensity of competition it faces in the market and any specific shocks that might hit its customer base. We thus proxy the effect of SSO membership on product market uncertainty with measures of product market competition and customer base concentration.

We start by calculating the commonly used Herfindahl-Hirschman Index (HHI) to measure product market concentration or competition, which is given by the sum of the firms' squared market shares:

$$HHI_{jt} = \sum_{i=1}^{N_j} ms_{ijt}^2,$$

where ms_{ijt} is the market share of firm i in (3-digit SIC level) industry j in year t . Following Hou and Robinson (2006), for each year t , we use the average value of the HHI index for the past three years, which helps alleviate potential data errors in our analysis. We then set *High (Low) Comp* equal to one if the industry HHI is below (above) the year-median, and zero otherwise.

¹⁶ We present the summary statistics and correlation matrix for the four innovation intensity measures in Appendix B. The four measures capture relatively different aspects of firm innovation. R&D intensity captures the input of a firm's innovation, while patent applications account for the output of the firm's R&D investment. R&D narrative disclosure capture both the input and output of firm innovation since we have word phases such as "R&D", "new patent", "applications pending", etc. Finally, as noted in footnote 15, SEPs partially capture a firm's standards developing activities in SSOs.

We then use information from the Compustat's segment files to calculate the degree of concentration of our sample firms' customer base. The SFAS 1997 regulations require suppliers to identify their customers accounting for at least 10% of revenues. These major customers are considered a significant concentration of risk. Following Dhaliwal et al. (2016), we measure supplier i 's customer concentration across its K major customers in year t as:

$$Customer\ HHI_{it} = \sum_{k=1}^K \left(\frac{sales_{ikt}}{sales_{it}} \right)^2,$$

where $sales_{ikt}$ is supplier i 's sales to major customer k and $sales_{it}$ is supplier i 's total sales in year t . A high *Customer HHI* value indicates supplier i has a concentrated customer base. Similar to Dhaliwal et al. (2016), we set the index equal to zero if a supplier does not disclose sales to any major customer and equal to one if a supplier depends on a single customer. We set *High (Low) CustConc* equal to one if the customer concentration index is above (below) the industry-year median, and zero otherwise.¹⁷

We report the results distinguishing among SSO members according to the degree of competition in their product market and the concentration of their customer base in columns (5)-(6) of Table 5, respectively. These estimates imply that SSO member firms operating in a more competitive market or having a more concentrated customer base are associated with lower cost of equity.

4.2.4 Information environment

To capture firms' information environment, we use three indicators: financial constraints, annual report readability and transparency. Financial constraints arise from frictions such as information asymmetry, making it difficult for firms to obtain all necessary outside financing. We use the KZ index suggested by Kaplan and Zingales (1997) to measure financial constraints.¹⁸ We set the *High (Low) FC* dummy variables equal to one if the firm' KZ index is above (below) the industry-year median, and zero otherwise.

Next, we follow the strand of literature which argues that more frequent and less complex disclosure can reduce information asymmetry. Garel et al. (2019) advocate that

¹⁷ Our results hold when we use instead the total share of the major customers or when the customer concentration index includes disclosed data for corporate customers accounting for less than 10% of the supplier's sales.

¹⁸ The KZ index is calculated as $-1.002 \times \text{cash flow} + 0.283 \times \text{Tobin Q} + 3.139 \times \text{leverage} - 39.368 \times \text{dividend} - 1.315 \times \text{cash holding}$. Higher index values indicate stronger financial constraints.

increased complexity and size of annual reports substantially increase information processing costs. Innovative firms, in turn, may have incentives to write complex financial reports to obfuscate adverse information (Kim et al., 2019) or innovative knowledge to competitors. The downside of higher opacity would be heightened financial market information asymmetry and a higher cost of equity. Following this strand of literature, we calculate the Fog index as:

$$Fog\ index = 0.4 * \left[\left(\frac{words}{sentences} \right) + 100 * \left(\frac{complex\ words}{words} \right) \right],$$

where $\frac{words}{sentences}$ is the average number of words per sentence and $\frac{complex\ words}{words}$ is the percentage of complex words, which contain three or more syllables. A higher Fog index value indicates less readable text.¹⁹ Similar to our approach for narrative R&D disclosure, we collect parsed annual 10-K filings for all U.S. companies from SRAF. We set the *High (Low) Fog* dummy equal to one if the firm's Fog index is above (below) the industry-year median, and zero otherwise.

Finally, in line with Leuz et al. (2003) and Zhong (2018), we employ earnings smoothing using accruals as a proxy for firms' transparency.²⁰ We set the *High (Low) Transparency* dummy equal to one if the firm's earnings smoothing ratio is below (above) the industry-year median, and zero otherwise. The estimation results distinguishing member firms according to their degree of information asymmetry are given in columns (7)-(9) in Table 5. We consistently find that SSO member firms with higher information asymmetry (less transparent information environment) are associated with a lower cost of equity.^{21, 22}

[Insert Table 5]

¹⁹ As in Kim et al. (2019), our identified list of complex words excludes multisyllabic words such as corporation, company and telecommunications, which are presumably easy to understand in the context of financial disclosures. Similar results are obtained with two common alternative readability measures: the Flesch Reading Ease Score and the Kincaid Index.

²⁰ Earnings smoothing using accruals is computed as the product of (-1) times the standard deviation of income before extraordinary items divided by the standard deviation of cash flows. The standard deviation is computed over the rolling window of a minimum of three and a maximum of five years. Higher values of the ratio indicate lower firm transparency. We obtain similar results with two alternative measures of firms' transparency, i.e., earnings smoothing based on the correlation between changes in accruals and operational cash flows, and the magnitude of total accruals.

²¹ We estimate all models presented in Table 5 on the sample restricted to ICT industries and note that these estimates have larger magnitudes relative to those in Table 5, consistent with our findings in Table 4.

²² We present the full model specification results in Appendix C.

5 SSO Heterogeneity

5.1 Network analysis - influential SSO membership

As SSOs vary in size and influence, we employ network analysis to examine if the effect of membership is contingent on how “*influential*” an SSO is. A network can be described by an $N \times N$ adjacency matrix A consisting of N unique “nodes”, which are connected through “edges”. In our case, these “nodes” refer to different SSOs, each of which is connected by co-participating firms. Each entry in the adjacency matrix A , denoted by a_{ij} , records the strength of the connection between nodes i and j (i.e., the number of co-memberships). To identify influential SSOs, we use the concept of network centrality, which captures the relative importance of a node or an edge in a graph. Following prior literature (Ahern and Harford, 2014; Kim and Zhu, 2018), we utilize the eigenvector centrality measure proposed by Bonacich (1987, 2007). More specifically, for each SSO we calculate

$$\lambda x_{it} = \sum_{j=1}^n a_{ijt} x_{jt}, i = 1, \dots, n,$$

where x_{it} is the eigenvector centrality of the SSO i in year t ; λ is the largest eigenvalue of the adjacency matrix and n is the number of vertices; a_{ijt} is equal to one if vertices i and j are connected by an edge in year t , and zero otherwise. This measure considers the node to be more central if it is connected to other central or well-connected nodes. Thus, each node’s centrality is the sum of the centrality values of other nodes that it connects. As such, the eigenvector measure captures the significance of an SSO’s network position in terms of facilitating knowledge exchange and promoting technology spillovers through connecting firms that simultaneously participate in multiple SSOs. Membership of SSOs that enjoy a more influential position may thus be perceived to further reduce a firm’s cost of equity.

To illustrate the characteristics of SSO networks in our sample, Figure 1 plots two simple networks. The SCDB database traces four SSOs in 1996, comprising 488 global participation records. Panel A provides the symmetric matrix for the year 1996 while Panel B illustrates how these four SSOs are connected. The network consists of four nodes that are connected through undirected weighted edges. The colour shade and number on each edge refer to the number of co-memberships - the attributes of the edge. Over time, more SSOs are established and increased firm participation is recorded,

leading to a more interconnected and complex network - see Panel C for the SSO network in 1998.

[Insert Figure 1]

The eigenvector centrality is taken from the eigenvector corresponding to the largest eigenvalue of the symmetric matrix. For the SSO network in 1996, the eigenvector centrality measure ranges from 0.983 for VESA, 0.173 for IMTC, 0.063 for ATSC to 0.019 for UWCC. We follow this methodology to obtain the centrality measure of each SSO in each year. Finally, we construct *iMEMBER* to indicate a firm's association with an influential SSO whose centrality is above the median value in a given year, and *iMEMBERCOUNT* to tally such influential SSO memberships. Similarly, *non-iMEMBER* and *non-iMEMBERCOUNT* refer to non-influential SSO participation. The estimates in Table 6 show that participation in (one or several) influential SSOs correlates negatively with the firm's cost of equity.²³

[Insert Table 6]

5.2 SSO specialization and categories

We further exploit heterogeneity among SSOs and identify five technological groups: *Electronics; Telecommunications. Audio & Video Engineering; Information Technology; Imaging Technology* and *Others*.²⁴ Figure 2 illustrates that most firm memberships over our sample period are in SSOs that specialize in *Information Technology* as well as *Telecommunications. Audio & Video Engineering*. It is important to note that one firm may be a member of several SSOs and one SSO may develop standards in different technological categories. To allow comparisons across categories, we identify the dominant SSO technological category for each firm in a given year and construct five corresponding indicators. Firm-years with multiple dominant categories are removed

²³ The four variables are measured in year $t-1$. Our results hold if we exclude permanent members before defining an influential SSO.

²⁴ Similar to Baron and Spulber (2018), we start by searching the internet archive of standards consortia provided by Andy Updegrave (<https://www.consortiuminfo.org>) for classification of SSOs in 2014, the last year of our sample. For the few SSOs in our dataset not listed on Consortiuminfo.org, we search their websites to identify the items they are working on and manually assign them to relevant technological categories. We define the five broad technological categories based on the International Classification for Standards (ICS) and classify SSO categories based on the ICS of their standards developed and promoted within.

from our sample for this analysis. The estimates in column (1) suggest that, overall, firms' participation in SSOs that develop standards in *Electronics* is associated with the largest reduction in their cost of equity capital relative to non-member firms. As for ICT firms, participation in SSOs that specialize in *Information Technology* is associated with the lowest cost of equity (column (2)). Instead of identifying the dominant technological group, column (3) uses the whole sample in estimation and separate firms SSO memberships into single versus multiple technological categories, where the latter can stem from participation in one or several SSOs. While multiple SSO memberships across technological categories seem to be important overall, SSO membership in a single technological domain matters especially in the ICT sector (column (4)). The latter result is not surprising as most observations in the *Single category* are in *Information Technology*, which is crucial for the ICT sector.

[Insert Figure 2 and Table 7]

We next follow the classification used in Baron et al. (2019) to distinguish SSOs into three types based on their prevailing functions: viz. standards developers, standards promoters and others.²⁵ Standards developers are more technology-centric SSOs that develop technology standards or technical specifications (e.g., Consumer Electronics Association/CEA and UPnP Forum) while standards promoters are more market-centric SSOs that promote standards developed by other organizations (e.g., Wi-Fi Alliance and Smart Card Alliance). Organizations that cannot be classified into either of the two groups above are defined as other SSOs (e.g., TM Forum and LonMark International). As one firm may participate in more than one SSO, we distinguish firms partaking in a single type of SSOs (*Developers Only*, *Promoters Only* and *Others Only*) from firms attending SSOs associated with “*Multiple Types*”. The latter are further split into firms participating in SSOs associated with two types (*Developers & Promoters*, *Developers & Others*, and *Promoters & Others*) and firms participating in SSOs associated with all three types (*Developers & Promoters & Others*). As revealed by Figure 3, most firms in our sample are members of standards-developing SSOs. Models in Table 8 estimate the correlation between firms' participation in varying SSO types and their cost of equity. Compared with memberships of the *Other* SSOs, memberships of both technology-

²⁵ Delcamp and Leiponen (2014) also distinguish between technically-oriented versus marketing-oriented consortia in the context of standards development in wireless telecommunications.

centric *Developer* SSOs and market-centric *Promoter* SSOs (full sample) are associated with statistically significantly lower cost of equity. In columns (3) and (4), participation in technology-centric *Developer* SSOs has more prominent effects for ICT firms.²⁶ Most notably, multiple memberships of various SSO types corresponds to the lowest cost of equity.

[Insert Figure 3 and Table 8]

6. Identification strategy

We have used linear regression analysis to establish robust correlation between SSO membership and the cost of equity. To the extent that a lower cost of equity may better equip firms with financial resources to participate in SSOs, our results may suffer from an endogeneity bias arising from reverse causality. Our analysis has dealt with this (albeit not perfectly) by including membership status at time $t-1$. Our identification strategy relies on a battery of fixed effects to control for unobserved but fixed omitted variables. One possible concern is that member and non-member firms are systematically different, implying that these firm-specific characteristics drive our results rather than their SSO membership. For instance, a firm may join SSOs only to signal its innovation performance to the capital markets. Alternatively, while the investors may be aware of the firm's successfully patented technologies, additional payoffs may arise from SSO participation should these patents be incorporated into future standards. In this section, we adopt two different identification strategies: we implement the probit instrumental variable model and exploit a plausibly exogenous variation in membership count caused by SSO closures to address the endogeneity concerns in this chapter.

6.1. Instrumental variables (2SLS)

A prominent motive for participation in standardization is to access technological opportunities arising from the diffusion of a standard in an industry. We assume that a firm's participation decision is influenced by SSO presence and linked technological opportunities in an industry as the standards gain market acceptance. To establish causality of firm SSO membership, we instrument it with the variable *SSO Availability*,

²⁶ Our results remain unchanged if we use ICT sample B defined in Section 4.2.1 in Tables 7 and 8.

which reflects the time-varying technological opportunities (across different domains) that are available to a firm as well as the extent of standardization within an industry. We start by assigning an SSO the industry codes (at the 3-digit SIC level) of all its member firms in year t . *SSO Availability* is calculated as the number of SSOs relevant to the focal firm (i.e., with exposure to the focal firm's industry) in year t . It is reasonable to assume that our IV plays a role in a firm's membership decision but is uncorrelated with the error term in the function of its implied cost of equity. We use the lagged variable in logarithmic form.

To operationalize our IV analysis, we follow the three-stage probit-2SLS procedure suggested by Angrist and Pischke (2008) and Adams et al. (2009) to deal with the binary nature of our endogenous variable (*MEMBER*). Specifically: (i) we first estimate a probit model of firms' SSO participation on our IV and other control variables; (ii) we use the predicted probability $\widehat{MEMBER}$ as an instrument in the first-stage of the 2SLS procedure; (iii) we follow with the second-stage 2SLS regression for the implied cost of equity on the control variables and the fitted values from the first-stage 2SLS. The advantage of this approach to the pseudo-IV procedure is that it does not require the binary response model of the first stage to be correctly specified.²⁷ Our results suggest a strong positive correlation between *SSO Availability* and SSO participation, given that greater availability of relevant SSOs increases the likelihood of firms' SSO participation. The final-stage 2SLS results confirm the negative relation between SSO participation and firms' implied cost of equity, as the -0.074 estimated coefficient on *MEMBER* is statistically significant at the 5% level. For brevity, we report these IV results in Table OC1 in the Online Appendix C.

6.2. Difference-in-Differences (DiD)

Our main identification strategy exploits the exogenous source of variation in firms' SSO membership count due to SSO closures in a difference-in-differences setting. SSOs may close for a variety of reasons, such as their initial agreed goals and objectives being fulfilled, their activities and technical specifications being transferred to other standards organizations, or a failure to achieve widespread adoption of their standards (e.g., losing

²⁷ In contrast, the pseudo-IV procedure, in which we directly regress the cost of equity on the predicted value of *MEMBER* and the other control variables, guarantees consistency only if the first stage is correctly specified.

a standards race).²⁸ Such process is often characterized by a complex interplay of technological, market, cultural and political factors alike. We can thus reasonably expect that the factors leading to the closure of SSOs are not driven by individual firms' standardization strategies, nor should they directly influence investors' perceptions of the riskiness of specific firms, hence their cost of equity.

Arguably, closures provide more reliable identification in firms' SSO membership count than does the emergence of new SSOs.²⁹ SSO creations are more likely when the industry transitions from obsolete to new technology standards; the standardization strategies of the founding members of the new SSOs drive new technology opportunities which can be anticipated to affect these firms' risk profiles.³⁰ It follows that SSO closures better respond to technology evolution and collective demand for standardization from heterogeneous firms across sectors and geographies, thus to some degree attenuating the correlation with characteristics of individual firms, including their standardization strategies.³¹

To perform our DiD analysis, based on information from Consortiuminfo.org and other Internet sources, we first identify eight SSO closures within our sample period (the year of closure is given in parentheses): Universal Wireless Communications Consortium/UWCC (2001), TV Anytime Forum (2005), FlexRay Consortium (2009), Liberty Alliance Project (2009), WiMedia Alliance (2010), OpenAjax Alliance (2013), International Imaging Industry Association/I3A (2013) and 3rd Generation Partnership Project 2/3GPP2 (2013).³² As the effect of SSO closure in year t on firms' membership count can be very quickly reflected in their stock prices, we focus on the change in the cost of equity between year $t-1$ and year $t+1$. To construct the group of treatment firms,

²⁸ For example, three competing SSOs – 3GPP, 3GPP2 and IEEE – worked on distinct systems as potential solutions for the fourth generation of broadband cellular network technology. The LTE system developed by 3GPP achieved widespread global adoption and hence 3GPP2 became dormant after 2013.

²⁹ We thank a reviewer for suggesting this point and highlighting the implied asymmetry between closures and creations of SSOs.

³⁰ For instance, the European Telecommunications Standards Institute (ETSI) partnered with other standards organizations to set up the 3rd Generation Partnership Project (3GPP) in 1998. New technical specifications had to be developed for faster 3G cellular networks as the 2G networks were overwhelmed. Therefore, the creation of the new 3GPP may be endogenously determined with the standardization strategies of its founding member firms (Leiponen, 2008).

³¹ Leiponen (2008) and Delcamp and Leiponen (2014) use mergers across SSOs for identification, which offers exogenous sources of variation that are analogous to our setting. Due to the limited number of merger events during our sample period, we are unable to isolate the effect of SSO mergers on firms' membership counts.

³² We utilize Wayback Machines to search the Internet archive for the official webpages of the SSOs before and after their closure to verify that each closure was finalized.

we first identify all members of the eight SSOs before their closure.³³ Firms in the treatment group are required to have non-missing cost of equity from year $t-1$ to year $t+1$ and non-missing matching variables in year $t-1$. Firms in the control group do not have a reduced SSO membership count due to the exogenous shock (because they were not members of the closing SSOs). For each treatment firm, we retain up to five closest control firms similar in terms of all variables in the baseline model (*PATAPP*, *SIZE*, *VOLATILITY*, *MTB*, *LEVERAGE*, *ROA*, *AGE*, *FORECASTER* and industry) in year $t-1$. We identify 185 unique pairs of treatment-control matches.³⁴

Panel A of Table 9 reports the univariate comparisons between the treatment and control firms' key variables. All the differences are insignificant, implying that all the meaningful observable differences between the treatment and the control groups before the event have been successfully removed. Panel B reports the difference-in-differences (DiD) analysis results. We compute the DiD estimator by calculating, for each firm, the difference in the cost of equity in year $t+1$ relative to year $t-1$. The average cost of equity difference for the treatment and control groups is reported in columns (1) and (2), respectively. We note a much smaller average change in the cost of equity for the treatment (-0.011) relative to that for the control (-0.022) group. Column (3) reports the DiD estimator: the difference in the differences for the treatment and control groups is statistically significant at the 1% level (with the standard error clustered at the event level).

To check the sensitivity of our DiD analysis to the construction of the matched control group, we adjust our matching technique by including additional variables drawn from two strands of literature. First, following studies on the cost of equity (e.g., Lui *et al.*, 2016), we match firms on *R&D intensity* (R&D expenses over sales), *SGAI* (the ratio of sales and general administrative costs to sales), *Financial slack* (current assets over total assets), *KZ* (financial constraints), as well as the performance indicators *sales growth* (*SG*) and *labour productivity* (*OIPE*, operating income over employee count). Second, we treat standardization as a strategic choice and follow the business strategy literature (e.g., Lim *et al.*, 2018) to match firms on capital intensity (*CAP*, measured as

³³ IEEE acquired I3A's CPIQ program and other assets in 2012. I3A disbanded in 2013. The new IEEE program has involved many of the corporate members that contributed to the original CPIQ program. As IEEE is included in our data, our treatment firms do not include those that became IEEE members after the merger and used to be I3A members before the merger.

³⁴ Using instead either 1-to-1 or 1-to-3 matching gives qualitatively similar results. Matching to fewer controls can help minimize bias at the cost of larger variance. Non-replacement keeps the variance low but at the cost of potential bias. Our algorithm imposes the common support restriction and a 0.0001 caliper.

the ratio of the net value of property, plant and equipment to total assets) and organizational stability (*TEMP*, the standard deviation in employment size). All additional data is collected from the Compustat-CRSP Merged Database.³⁵ Matching on a larger set of variables reduces the sample to 170 matched pairs. The estimates in Panels C and D of Table 9 are very similar to those reported above (although treated firms appear to be slightly larger than control firms).

[Insert Table 9]

7 Conclusion

In this study, we report novel evidence on the effect of SSO participation on the cost of equity capital. The implied cost of equity reflects the rate of return investors require, representing a crucial input in long-term investment decisions of businesses (Boubaker et al., 2018). A better understanding of how to mitigate risks in technology markets as perceived by investors has far-reaching managerial implications for business strategic and financial planning.

Against the backdrop of rapid technology development in recent years, firms strategically manage competing pressures to implement standardized common technologies and create competitive distinction in developing innovative products or services (Gnyawali and Park, 2011). Our research thus throws light on the debate surrounding the trade-off between cooperation in creating value by collaboratively developing open standards with other firms and the competition in capturing value to profit from innovation that is facilitated by common standards (see Waguespack and Fleming, 2009; Gnyawali and Park, 2011; Chiambaretto et al., 2019; Jones et al., 2020). Given the goals and potential pitfalls of participating in SSOs, this study offers a timely evaluation of whether the benefits of SSO membership outweigh its costs through the eyes of the investors.

Based on the analysis of 3,350 U.S. public firms and their memberships of 183 SSOs from 1996 to 2014, our results underscore significant financial returns to participation in SSOs especially for ICT firms. Our analysis takes into account the endogenous nature of a firm's membership decision. In particular, a firm's propensity to join one or multiple

³⁵ Additionally, we employ all these variables in a propensity score matching approach and report the results in the Online Appendix C.

SSOs may be related to unobservable time-varying effects on its cost of equity and thus our estimated impact of SSO membership may suffer from selection bias in the absence of random assignment (i.e., SSO member firms do not constitute a randomly selected group). Our analysis takes into account the endogenous nature of a firm's decision to participate in standard development. In particular, a firm's propensity to join one or multiple SSOs may be related to unobservable time-varying effects on its cost of equity, and thus our estimated impact of SSO membership may suffer from selection bias in the absence of random assignment (i.e., SSO member firms do not constitute a randomly selected group). Reverse causality may also arise, as firms with a lower cost of equity are better financially equipped to participate in SSOs. However, our main finding of the negative relationship between SSO membership and the implied cost of equity is robust to an instrumental variable model and a difference-in-differences approach. In particular, our quasi-natural experiment based on SSO closures utilizes an exogenous variation in membership count to identify the impact of membership. This identification strategy postulates that such variation in the supply of SSOs is not driven by the demand of individual firms stemming from their standardization strategies; if such an assumption were to hold, this part of our analysis should have a causal interpretation.

The negative relationship between SSO membership and the implied cost of equity is evident from the first ever SSO membership and is more prominent in markets with high levels of uncertainty arising from complex technologies, product competition and information asymmetry. More specifically, we find that firms that are more R&D or patenting-intensive or that own SEPs enjoy a discounted cost of equity. Additionally, SSO members operating in a more competitive market structure and/or having a more concentrated customer base enjoy a lower cost of equity. Timely standards development can accelerate firms' diversifying into new markets which can alleviate the financial distress facing firms in more competitive industries (Matutes and Regibeau, 1988; Hawkins et al., 2017). This also echoes Hou and Robinson (2006)'s observation that firms are more likely to conduct aggressive innovative activities and encounter a higher level of distress risk in more competitive markets. We find that SSO members with more significant financial constraints and/or information opacity tend to benefit more via their participation in developing technology standards.

Our study has several caveats. Based on the membership information from the SCDB data, our empirical measures of SSO participation are subject to a trade-off between the precision or depth of coverage and the need to incorporate SSO-,

technology- and firm-level heterogeneity to better understand the wider impact of ICT standardization. Prior studies have utilized various proxies to capture the degree of participation and effort involved; for instance, detailed written contributions made by firms to the development of new technical specifications within 3GPP committees (Leiponen, 2008; Baron and Gupta, 2018). In another single-SSO based study (in context of the Internet Engineering Task Force/IETF), Waguespack and Fleming (2009) consider several indicators of engagement including firms' gaining endorsement of their own standards, developing own technology, meeting attendance and taking leadership positions. However, such detailed participation records are only available from a handful of SSOs thus rendering the comparison or generalization across scores of SSOs impractical. Our unique setting allows a comprehensive assessment of the financial-market impact of SSO membership accounting for a firm's choice as to which and how many SSOs to join. Building on this line of inquiry, one fruitful avenue for future research thus lies in the use of more detailed contribution data or membership tier information to capture SSO participation more precisely.

As our analysis derives insight from relatively large, listed firms, our results may not be easily generalized to smaller firms characterised by higher degree of information asymmetry and lower propensity to participate in SSOs. Our conceptual framework postulates several mechanisms whereby standards setting can reduce technological and market uncertainty as well as information asymmetry. Nevertheless, our data limitations and identification strategy do not allow a full comparison of these possible channels or their causal transmission mechanisms.

Table 1 Industry composition in sample

SIC code	Description	Observations
22	Textile Mill Products	261
23	Apparel and Other Textile Products	584
26	Paper and Allied Products	574
27	Printing and Publishing	641
28	Chemicals and Applied Products	5,879
35	Industrial Machinery and Equipment	3,605
36	Electronic and Other Electric Equipment	5,006
37	Transportation Equipment	1,424
38	Instruments and Related Products	4,085
39	Miscellaneous Manufacturing Industries	564
48	Communications	1,625
53	General Merchandise Stores	405
73	Business Services	7,043
87	Engineering and Management Services	1,128
Total		32,824

Table 2 Descriptive statistics
Panel A. Summary statistics (full sample)

		Mean	Std.D	Std.Dw	Min	25%	50%	75%	Max
(1)	ICE	0.135	0.131	0.097	0.011	0.057	0.085	0.154	0.677
(2)	MEMBER	0.161	0.367	0.225	0.000	0.000	0.000	0.000	1.000
(3)	MEMERCOUNT	0.572	2.718	1.331	0.000	0.000	0.000	0.000	60.000
(4)	PATAPP	0.774	1.304	0.437	0.000	0.000	0.000	1.099	5.464
(5)	SIZE	5.660	2.027	0.535	1.798	4.147	5.504	7.020	10.966
(6)	VOLATILITY	-2.034	0.574	0.414	-3.326	-2.436	-2.043	-1.650	-0.565
(7)	MTB	0.915	0.869	0.592	-1.090	0.332	0.858	1.436	3.468
(8)	LEVERAGE	0.157	0.171	0.097	0.000	0.001	0.103	0.265	0.672
(9)	ROA	-0.062	0.268	0.167	-1.332	-0.084	0.028	0.076	0.266
(10)	AGE	2.464	0.876	0.407	0.693	1.792	2.485	3.135	4.344
(11)	FORECASTER	0.031	0.246	0.207	-0.660	-0.055	-0.007	0.065	1.233
Obs.	32,824								

Panel B. Summary statistics by industries

SIC code	(1) ICE	(2) MEMBER	(3) MEMBERCOUNT	(4) PATAPP	(5) SIZE	(6) VOLATILITY	(7) MTB	(8) LEVERAGE	(9) ROA	(10) AGE	(11) FORECASTER
22	0.152	0.080	0.115	0.287	6.167	-2.185	0.088	0.322	0.010	2.808	0.012
23	0.120	0.070	0.080	0.116	5.838	-2.139	0.487	0.193	0.039	2.609	-0.018
26	0.126	0.124	0.152	0.781	7.462	-2.428	0.617	0.330	0.027	2.870	0.009
27	0.132	0.101	0.114	0.206	6.202	-2.364	0.797	0.229	0.017	2.788	0.004
28	0.144	0.054	0.078	0.990	5.302	-1.955	1.251	0.154	-0.198	2.441	0.106
35	0.123	0.211	0.875	1.147	5.944	-2.064	0.791	0.154	-0.011	2.655	0.003
36	0.138	0.297	1.289	1.107	5.433	-1.933	0.719	0.130	-0.043	2.570	0.016
37	0.114	0.131	0.579	0.966	6.750	-2.268	0.726	0.219	0.034	2.884	-0.004
38	0.136	0.104	0.320	0.974	5.065	-2.068	0.908	0.126	-0.061	2.523	0.028
39	0.148	0.087	0.113	0.853	5.455	-2.078	0.604	0.208	0.013	2.599	-0.002
48	0.131	0.185	0.625	0.276	7.306	-2.208	0.826	0.319	-0.026	2.193	0.022
53	0.099	0.188	0.249	0.076	8.011	-2.327	0.627	0.214	0.052	2.799	-0.010
73	0.139	0.197	0.717	0.384	5.430	-1.946	1.044	0.113	-0.058	2.166	0.020
87	0.139	0.081	0.104	0.152	5.287	-2.083	0.902	0.140	-0.037	2.278	0.028

Refer to Table 1 for detailed industry description.

Panel C. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) ICE	1										
(2) MEMBER	-0.085*	1									
(3) MEMERCOUNT	-0.069*	0.481*	1								
(4) PATAPP	-0.191*	0.287*	0.320*	1							
(5) SIZE	-0.384*	0.288*	0.275*	0.401*	1						
(6) VOLATILITY	0.225*	-0.097*	-0.109*	-0.163*	-0.466*	1					
(7) MTB	-0.255*	0.035*	0.044*	0.164*	0.018*	0.030*	1				
(8) LEVERAGE	0.004	-0.035*	-0.022*	0.012*	0.331*	-0.114*	-0.006	1			
(9) ROA	-0.400*	0.082*	0.069*	0.101*	0.408*	-0.392*	-0.126*	0.075*	1		
(10) AGE	-0.054*	0.102*	0.118*	0.209*	0.335*	-0.391*	-0.098*	0.122*	0.247*	1	
(11) FORECASTER	0.289*	-0.052*	-0.036*	-0.036*	-0.167*	0.112*	0.090*	-0.051*	-0.230*	-0.077*	1

* p<0.05

Table 3 Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
				<i>Non-permanent member</i>	<i>First entry</i>	<i>MEMBERCOUNT</i>
<i>MEMBER</i>	-0.007*** (-3.012)	-0.007*** (-2.989)	-0.006*** (-2.670)	-0.007*** (-2.859)		
<i>fMEMBER</i>					-0.013*** (-3.326)	
<i>MEMBERCOUNT</i>						-0.011*** (-4.974)
<i>PATAPP</i>	-0.003** (-2.395)	-0.004*** (-3.224)	-0.003** (-2.380)	-0.003*** (-2.689)	-0.000 (-0.183)	-0.003** (-2.327)
<i>SIZE</i>	-0.027*** (-15.722)	-0.029*** (-16.820)	-0.029*** (-15.996)	-0.029*** (-15.712)	-0.028*** (-4.884)	-0.028*** (-15.879)
<i>VOLATILITY</i>	0.005** (2.407)	0.005** (2.572)	0.005** (2.481)	0.005** (2.511)	0.002 (0.327)	0.005** (2.344)
<i>MTB</i>	-0.044*** (-30.308)	-0.044*** (-30.645)	-0.044*** (-30.180)	-0.045*** (-30.139)	-0.028*** (-6.797)	-0.044*** (-30.272)
<i>LEVERAGE</i>	0.085*** (11.534)	0.087*** (11.843)	0.088*** (11.851)	0.091*** (11.857)	0.058*** (2.899)	0.089*** (11.888)
<i>ROA</i>	-0.130*** (-20.741)	-0.131*** (-20.817)	-0.129*** (-20.507)	-0.130*** (-20.371)	-0.135*** (-5.370)	-0.129*** (-20.579)
<i>AGE</i>	0.027*** (8.915)	0.022*** (9.463)	0.027*** (8.645)	0.027*** (8.334)	0.027*** (2.780)	0.027*** (8.580)
<i>FORECASTER</i>	0.086*** (15.797)	0.087*** (15.933)	0.085*** (15.849)	0.086*** (15.774)	0.115*** (5.440)	0.085*** (15.863)
<i>Constant</i>	0.223*** (21.190)	0.261*** (15.865)	0.185*** (7.405)	0.183*** (7.244)	0.244*** (6.276)	0.184*** (7.358)
Observations	32,824	32,824	32,824	31,694	4,138	32,824
<i>N</i> of firms	3,350	3,350	3,350	3,221	780	3,350
R-squared	0.264	-	0.276	0.280	0.257	0.276
Industry FE	-	YES	-	-	-	-
Year FE	YES	YES	-	-	-	-
Industry-Year FE	-	-	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variable is the composite implied cost of equity (ICE) based on the earnings per share forecasts derived from the HVZ model. In Columns 1-4, *MEMBER* takes the value one if the firm participates in at least one SSO in year *t*-1, zero otherwise. In Column 4, the sample excludes firms that always participate in an SSO. In Column 5, *fMEMBER* takes value one when the firm participates in an SSO for the first time during our sample period, zero otherwise. In Column 6, we replace the membership indicator with a membership count variable (*MEMBERCOUNT*). The control variables include: *PATAPP* measured as the natural logarithm of one plus the number of patents applied for in year *t*. Firm size (*SIZE*) as the natural logarithm of total real assets, the natural logarithm of the market-to-book ratio (*MTB*), the ratio of long-term debt to total assets (*LEVERAGE*), the return on assets (*ROA*), the natural logarithm of the annual standard deviation of the monthly stock returns (*VOLATILITY*), *AGE* as the logarithm of one plus the difference between the current year and the year of firms' initial public offering or first trading, and *FORECASTER* as earnings forecasts the next year minus actual earnings, scaled by lagged total assets. All variables (except *FORECASTER*) are measured at time *t*-1. In Column 2 we use the Hausman-Taylor estimator which allows inclusion of time-invariant industry effects. Columns 3-6 include industry-time interaction terms in the within groups model. **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

Table 4 ICT and non-ICT samples

	ICT sample A		ICT sample B	
	(1) <i>ICT</i>	(2) <i>Non-ICT</i>	(3) <i>ICT</i>	(4) <i>Non-ICT</i>
<i>MEMBER</i>	-0.009*** (-2.783)	-0.003 (-1.085)	-0.008** (-2.512)	-0.002 (-0.673)
<i>PATAPP</i>	-0.003 (-1.407)	-0.003* (-1.907)	-0.004*** (-2.822)	0.000 (0.043)
<i>SIZE</i>	-0.028*** (-10.883)	-0.029*** (-11.835)	-0.033*** (-15.279)	-0.022*** (-6.977)
<i>VOLATILITY</i>	0.005* (1.714)	0.005* (1.865)	0.004* (1.652)	0.005* (1.756)
<i>MTB</i>	-0.039*** (-17.307)	-0.047*** (-24.866)	-0.045*** (-24.322)	-0.039*** (-15.682)
<i>LEVERAGE</i>	0.064*** (5.379)	0.101*** (10.682)	0.078*** (8.521)	0.090*** (6.950)
<i>ROA</i>	-0.162*** (-16.509)	-0.109*** (-13.721)	-0.111*** (-16.461)	-0.204*** (-12.476)
<i>AGE</i>	0.027*** (5.648)	0.028*** (6.761)	0.027*** (6.228)	0.021*** (4.633)
<i>FORECASTER</i>	0.102*** (11.800)	0.074*** (11.120)	0.069*** (11.678)	0.150*** (11.205)
<i>Constant</i>	0.221*** (14.142)	0.162*** (5.029)	0.223*** (17.133)	0.220*** (10.939)
Observations	13,335	19,489	18,600	14,224
<i>N</i> of firms	1,426	1,929	1,949	1,405
R-squared	0.299	0.270	0.288	0.285
Industry-Year FE	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
Firm FE	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>

This table presents the estimated coefficients (t-statistics in parentheses) obtained from Equ. 1 on the sample split into ICT and non-ICT sectors. The dependent variable is the composite ICE measure. The ICT sample A covering both manufacturing and services includes 39 ICT sectors based on the 4-digit SIC codes in Shackelford and Jankowski (2016). The ICT sample B is based on Brown et al. (2009) and comprises the SIC codes 283, 357, 366, 367, 382, 384 and 737. The firm-level characteristics are defined in Table 3. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 5 Possible mechanisms

	Innovation intensity			Market uncertainty		Information environment			
	(1) <i>R&D intensity</i>	(2) <i>R&D disclosure</i>	(3) <i>Patent applications</i>	(4) <i>SEP holding</i>	(5) <i>Market competition</i>	(6) <i>Customer concentration</i>	(7) <i>Financial constraint</i>	(8) <i>10-K report readability</i>	(9) <i>Transparency</i>
<i>MEMBER # High RDI</i>	-0.008** (-2.493)								
<i>MEMBER # Low RDI</i>	-0.002 (-0.670)								
<i>MEMBER # High RDdisclosure</i>		-0.006** (-2.232)							
<i>MEMBER # Low RDdisclosure</i>		-0.004 (-1.220)							
<i>MEMBER # HPT</i>			-0.009*** (-3.164)						
<i>MEMBER # LPT</i>			-0.004 (-1.402)						
<i>MEMBER # SEP</i>				-0.015** (-2.319)					
<i>MEMBER # NoSEP</i>				-0.004 (-1.002)					
<i>MEMBER # NoPT</i>				-0.005 (-1.410)					
<i>MEMBER # High Comp</i>					-0.010*** (-2.823)				
<i>MEMBER # Low Comp</i>					-0.005 (-1.098)				
<i>MEMBER # High CustConce</i>						-0.008** (-2.048)			
<i>MEMBER # Low CustConce</i>						-0.006** (-2.168)			
<i>MEMBER # High FC</i>							-0.013*** (-3.671)		
<i>MEMBER # Low FC</i>							-0.002 (-0.722)		
<i>MEMBER # High Fog</i>								-0.006** (-2.308)	
<i>MEMBER # Low Fog</i>								-0.005 (-1.497)	
<i>MEMBER # High Transparency</i>									-0.005 (-1.620)
<i>MEMBER # Low Transparency</i>									-0.008*** (-2.625)
<i>Constant</i>	0.195*** (10.126)	0.224*** (19.160)	0.185*** (7.385)	0.182*** (7.238)	0.265*** (18.652)	0.186*** (7.439)	0.186*** (7.489)	0.224*** (19.238)	0.186*** (7.344)
Controls	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
Observations	24,499	29,992	32,824	32,824	32,824	32,824	31,077	29,992	28,404
<i>N</i> of firms	2,632	3,165	3,350	3,350	3,350	3,350	3,315	3,165	3,284
<i>R</i> -squared	0.277	0.271	0.276	0.276	0.276	0.276	0.280	0.271	0.275
Industry-Year FE	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
Firm FE	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>

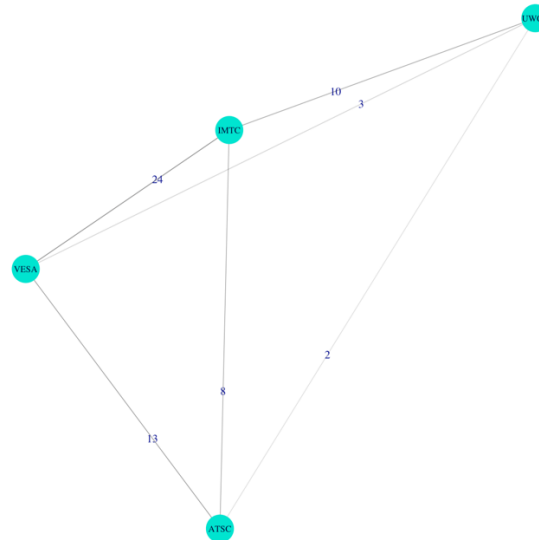
This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variable is the composite ICE measure. High (Low) RDI takes value one if the firm's R&D intensity, measured as R&D expenses over sales, is above (below) the industry-year median, zero otherwise. Using a text analysis approach, the narrative R&D disclosure is computed as the number of R&D-related sentences in firms' 10-K filings. High (Low) RDdisclosure takes value one if the firm's R&D disclosure is above (below) the industry-year median, zero otherwise. High (Low) HPT takes value one if the firm's number of patent applications are above (below) the industry-year median, zero otherwise. SEP takes value one if the firm holds at least one standard-essential patent (SEP), zero otherwise. The non-SEP holders are separated into patent (NoSEP) and no-patent holders (NoPT). Market competition is gauged by the Herfindahl-Hirschman Index (HHI) calculated at 3-digit SIC codes for each industry in each year. Following Hou and Robinson (2006), for each year t , we use the average value of the HHI index for the past three years. High (Low) Comp is set equal to one if the annual value is below (above) the year-median, zero otherwise. Customer concentration is measured for each supplier firm as the sum of the squared shares of its major corporate customers. High (Low) CustConce is set equal to one if the firm's customer concentration is above (below) the industry-year median, zero otherwise. Firm financial constraints are proxied by the Kaplan and Zingales index. High (Low) FC takes value one if the firm's KZ index is above (below) the industry-year median, zero otherwise. We measure the readability of firms' 10-K reports using the Fog index, where higher values indicate lower readability. High (Low) Fog is set equal to one if the firm's Fog index is above (below) the industry-year median, zero otherwise. Finally, we use the earnings smoothing ratio as a proxy for firms' transparency. High (Low) Transparency is equal to one if the firm's earnings smoothing ratio is below (above) the industry-year median. We compute each industry-year median at 3-digit SIC level. All dummy variables are measured at time $t-1$. Controls include all other firm-level characteristics included in Table 3. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure 1. Illustrative example of SSO networks:

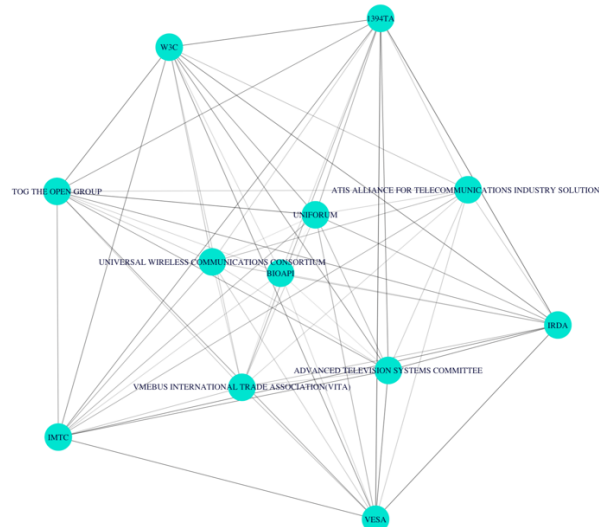
Panel A. Symmetric adjacency matrix example: SSOs in 1996

	ATSC	IMTC	UWCC	VESA
ATSC	54	8	2	13
IMTC	8	139	10	24
UWCC	2	10	21	3
VESA	13	24	3	274

Panel B. SSO network in 1996



Panel C. SSO network in 1998



Panel A is the adjacency matrix of the four recorded SSOs in 1996: Universal Wireless Communications Consortium (UWCC), Advanced Television Systems Committee (ATSC), the International Multimedia Telecommunications Consortium (IMTC) and Video Electronics Standards Association (VESA). Each entry in the symmetric adjacency matrix represents the number of co-memberships. Panel B plots the SSO network in 1996 shown in Panel A. The number on and the colour shade of each edge refer to the weight attributes of the edge. Panel C plots the SSO network in 1998.

Table 6 Influential SSO memberships – network analysis

	<i>iMEMBER</i>	<i>iMEMBERCOUNT</i>
	(1)	(2)
<i>iMEMBER</i>	-0.007*** (-2.840)	
<i>non-iMEMBER</i>	-0.004 (-0.967)	
<i>iMEMBERCOUNT</i>		-0.012*** (-5.067)
<i>non-iMEMBERCOUNT</i>		-0.008 (-1.627)
<i>PATAPP</i>	-0.003** (-2.371)	-0.003** (-2.316)
<i>SIZE</i>	-0.029*** (-16.004)	-0.028*** (-15.906)
<i>VOLATILITY</i>	0.005** (2.483)	0.005** (2.339)
<i>MTB</i>	-0.044*** (-30.186)	-0.044*** (-30.269)
<i>LEVERAGE</i>	0.088*** (11.855)	0.089*** (11.893)
<i>ROA</i>	-0.129*** (-20.509)	-0.129*** (-20.573)
<i>AGE</i>	0.027*** (8.644)	0.027*** (8.574)
<i>FORECASTER</i>	0.085*** (15.854)	0.085*** (15.862)
<i>Constant</i>	0.186*** (7.392)	0.184*** (7.352)
Observations	32,824	32,824
<i>N</i> of Firms	3,350	3,350
R-squared	0.276	0.276
Industry-Year FE	YES	YES
Firm FE	YES	YES

This table presents the fixed effects estimates (t-statistics in parentheses) obtained from Equ.1. The dependent variable is the composite ICE measure. We use a network centrality measure to define firm membership in an *influential* SSO. *iMEMBER* is an indicator of firm participation in at least one influential SSO, while *non-iMEMBER* indicates participation only in non-influential SSOs. *iMEMBERCOUNT* records the number of influential memberships, while *non-iMEMBERCOUNT* records membership counts for participation only in non-influential SSOs. All firm-level characteristics are defined in Table 3. *p < 0.1; **p < 0.05; ***p < 0.01.

Figure 2. Distribution of member firms across SSO technological categories

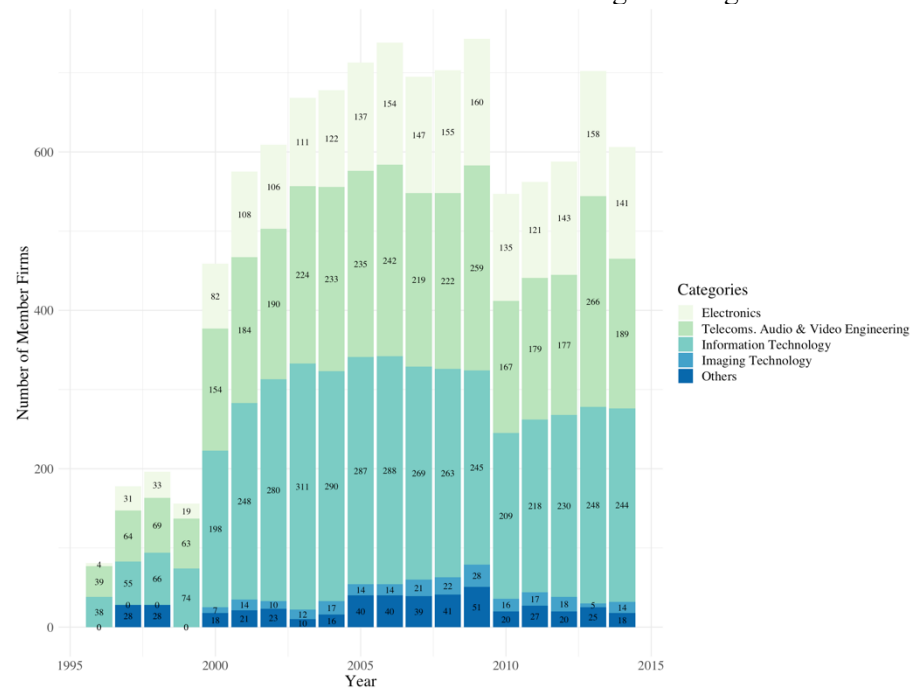


Table 7 Participation across specific SSO technological categories

	Dominant tech categories		Number tech categories	
	Full sample	ICT sample A	Full sample	ICT sample A
	(1)	(2)	(3)	(4)
<i>Electronics</i>	-0.012** (-2.198)	-0.013** (-1.984)		
<i>Telecoms. Audio & Video Engineering</i>	-0.009** (-2.166)	-0.013** (-2.228)		
<i>Information Technology</i>	-0.008*** (-2.610)	-0.019*** (-4.428)		
<i>Imaging Technology</i>	0.008 (0.241)	0.021 (0.680)		
<i>Others</i>	0.015 (1.242)	0.008 (0.484)		
<i>Single category</i>			-0.004 (-1.584)	-0.009** (-2.199)
<i>Multicategory - one SSO</i>			-0.002 (-0.505)	0.002 (0.359)
<i>Multicategory - multi SSOs</i>			-0.015*** (-4.103)	-0.022*** (-4.507)
<i>Constant</i>	0.182*** (7.133)	0.226*** (13.758)	0.185*** (7.365)	0.217*** (13.963)
<i>Controls</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
<i>Observations</i>	31,216	12,197	32,824	13,335
<i>N of Firms</i>	3,340	1,417	3,350	1,426
<i>R-squared</i>	0.279	0.307	0.276	0.301
<i>Industry-Year FE</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
<i>Firm FE</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variable is the composite ICE measure. In Columns 1-2, firms are assigned the dominant technological category associated with the SSOs they are members of. The five indicators (Electronics, Telecoms. Audio & Video Engineering, Information Technology, Imaging Technology and Others) are constructed based on the ICS classification of standards. In Columns 3-4, firm SSO memberships are separated according to association with one versus multiple technological categories, where the latter can be due to participation in one or several SSOs. Controls include all other firm-level characteristics included in Table 3. *p < 0.1; **p < 0.05; ***p < 0.01.

Figure 3. Distribution of member firms across SSO types

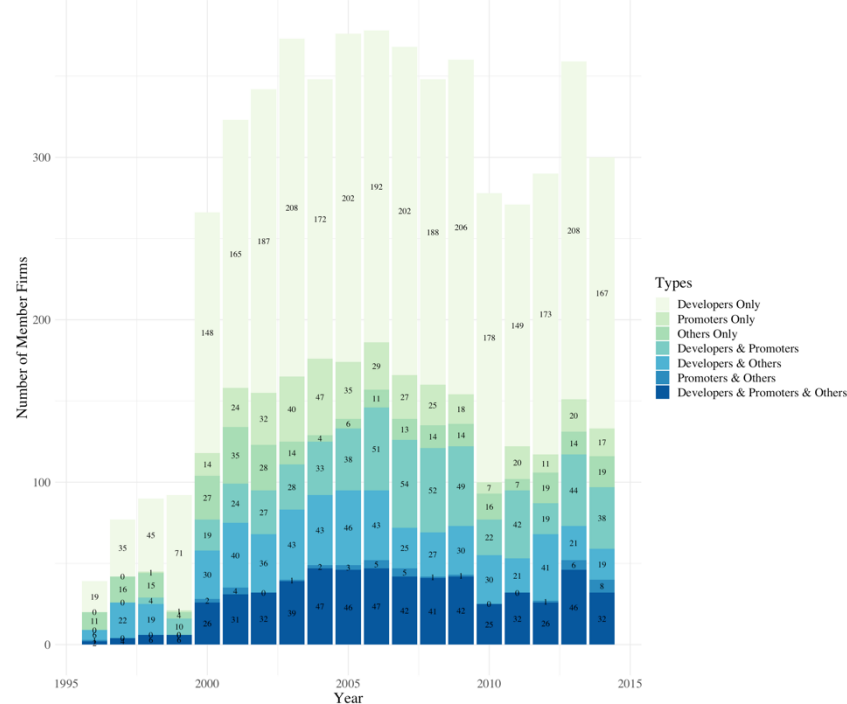


Table 8 Participation across specific SSO types

	Full sample		ICT sample A	
	(1)	(2)	(3)	(4)
<i>Developers Only</i>	-0.005* (-1.744)	-0.005* (-1.720)	-0.009** (-2.324)	-0.009** (-2.333)
<i>Promoters Only</i>	-0.008* (-1.875)	-0.008* (-1.938)	-0.003 (-0.602)	-0.004 (-0.619)
<i>Others Only</i>	-0.006 (-0.769)	-0.006 (-0.787)	-0.006 (-0.626)	-0.006 (-0.651)
<i>Multiple Types</i>	-0.013*** (-3.538)		-0.017*** (-3.557)	
<i>Developers & Promoters</i>		-0.012*** (-2.782)		-0.018*** (-3.011)
<i>Developers & Others</i>		-0.011** (-2.067)		-0.015** (-2.163)
<i>Promoters & Others</i>		-0.026*** (-2.655)		-0.014 (-1.400)
<i>Developers & Promoters & Others</i>		-0.016*** (-3.142)		-0.025*** (-3.947)
<i>Constant</i>	0.185*** (7.375)	0.185*** (7.371)	0.219*** (14.056)	0.219*** (14.075)
Controls	YES	YES	YES	YES
Observations	32,824	32,824	13,335	13,335
N of Firms	3,350	3,350	1,426	1,426
R-squared	0.276	0.276	0.300	0.300
Industry-Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variable is the composite ICE measure. The SSOs in our sample are classified as Developers, Promoters or Others based on their prevailing role in standards development. Developers Only, Promoters Only and Others Only are indicators (1/0) for firm participation in a single type of SSOs. Firm participation (1/0) in Multiple Types of SSOs is disaggregated into Developers & Promoters, Developers & Others, Promoters & Others, and Developers & Promoters & Others. Controls include all other firm-level characteristics included in Table 3. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 9 Difference-in-differences (DiD) test results

Panel A: Post-match difference

Variables	Treatment	Control	Differences	T-statistics
<i>PATAPP</i>	3.078	2.587	-0.491	-1.270
<i>SIZE</i>	8.736	8.369	-0.368	-1.060
<i>VOLATILITY</i>	-2.298	-2.257	0.041	0.491
<i>MTB</i>	0.942	0.871	-0.072	-0.460
<i>LEVERAGE</i>	0.176	0.213	0.037	1.239
<i>ROA</i>	0.005	0.009	0.004	0.111
<i>AGE</i>	2.961	2.861	-0.100	-0.693
<i>FORECASTER</i>	0.035	0.039	0.004	0.155

Panel B: DiD estimators

	Mean treatment difference (after-before) (1)	Mean control difference (after-before) (2)	Mean DiD (treat-control) (3)
<i>ICE</i>	-0.011	-0.022	0.010***
(standard error)	(0.004)	(0.004)	(0.001)

Panel C: Post-match difference with additional firm characteristics

Variables	Treatment	Control	Differences	T-statistics
<i>PATAPP</i>	3.058	2.387	-0.671	-1.647
<i>SIZE</i>	8.764	7.938	-0.826	-2.172**
<i>VOLATILITY</i>	-2.267	-2.175	0.092	1.088
<i>MTB</i>	0.849	0.830	-0.018	-0.123
<i>LEVERAGE</i>	0.170	0.165	-0.005	-0.158
<i>ROA</i>	0.003	-0.020	-0.023	-0.508
<i>AGE</i>	2.932	2.784	-0.148	-0.993
<i>FORECASTER</i>	0.042	0.070	0.027	0.969
<i>HHI</i>	0.099	0.111	0.012	1.146
<i>RDI</i>	0.144	0.159	0.015	0.353
<i>SGAI</i>	0.392	0.458	0.066	0.872
<i>Financial Slack</i>	0.511	0.525	0.014	0.538
<i>KZ</i>	-11.427	-9.039	2.388	0.941
<i>CAP</i>	0.138	0.130	-0.008	-0.442
<i>SG</i>	0.044	0.029	-0.015	-0.536
<i>OIPE</i>	0.101	0.075	-0.025	-1.269
<i>TEMP</i>	5.112	2.996	-2.117	-1.600

Panel D: DiD estimators

	Mean treatment difference (after-before) (1)	Mean control difference (after-before) (2)	Mean DiD (treat-control) (3)
<i>ICE</i>	-0.008	-0.017	0.009***
(standard error)	(0.004)	(0.003)	(0.002)

Appendix A

Measurement of the cost of equity

Our cost of equity measure (*ICE*) is calculated as the equal-weighted average of the estimates from four models. Formally, $ICE = average(R_{gls} + R_{ct} + R_{oj} + R_{es})$, where $R_{gls}, R_{ct}, R_{oj}, R_{es}$ are the cost of equity estimates obtained from the models of Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005), respectively. All four models use analysts' forecasts, which are available only for a subset of firms and sometimes deviate much from future cash flows expectations. To address this issue, we use instead the forecasting model developed by Hou et al. (2012) (HVZ model).

We present in detail the four methods used to obtain the cost of equity and the HVZ forecasting model. To maximize coverage, we require a firm to have at least one non-missing value of ICE estimates computed from the four models.

The Four Models for Estimating the Cost of Equity

Model 1: R_{gls} – Gebhardt et al. (2001)

The cost of equity is estimated from the following residual income valuation model:

$$P_t = B_t + \sum_{\tau=1}^{11} \frac{(FROE_{t+\tau} - R_{gls}) * B_{t+\tau-1}}{(1+R_{gls})^{t+\tau}} + \frac{(FROE_{t+12} - R_{gls}) * B_{t+11}}{R_{gls}(1+R_{gls})^{t+12}},$$

where

P_t = the end-of-June stock price for year t ;

$B_{t+\tau}$ = the book value per share for the estimation year, the clean surplus is applied

where $B_{t+\tau} = B_{t+\tau-1} + FEPS_{t+\tau} - DPS_{t+\tau}$;

$FROE_{t+\tau}$ = the earnings forecasts derived from the HVZ model (explained in the following) divided by book value in year $t + \tau - 1$;

$FEPS_{t+\tau} = FROE_{t+\tau} * B_{t+\tau-1}$;

$DPS_{t+\tau}$ = the dividend pay-out per share in year $t + \tau$. Following Gebhardt et al. (2001) and Claus and Thomas (2001), the current pay-out ratio is measured as dividends divided by income before extraordinary items for firms with positive current earnings or

dividends divided by 6% of total assets for firms with negative incomes before extraordinary items; missing values are then replaced with 50%.

The estimation of R_{gls} is based on a 12-year period. The linear interpolation is applied to let the five-year-ahead $FROE_{t+\tau}$ fade to the industry ROE median in year 12, while the industry ROE median is obtained from all ROEs within the same industry over the past 5 years and up to 10 years. The industry classification is based on the Fama-French 48 industry classification (Fama and French, 1997). We use a numerical approximation program to solve for R_{gls} within 0 and 100%, allowing for the right- and left-hand sides within a difference of \$0.001.

Model 2: R_{ct} – Claus and Thomas (2001)

Claus and Thomas (2001) calculate the cost of equity using the following model:

$$P_t = B_t + \sum_{\tau=1}^5 \frac{(FROE_{t+\tau} - R_{ct}) * B_{t+\tau-1}}{(1+R_{ct})^{t+\tau}} + \frac{(FROE_{t+5} - R_{ct})(1+g) * B_{t+4}}{(R_{ct} - g)(1+R_{ct})^{t+5}},$$

where

P_t = the end-of-June stock price for year t ;

$B_{t+\tau}$ = the book value per share for the estimation year;

$FROE_{t+\tau}$ = the earnings forecasts derived from the HVZ model (explained in the following) divided by book value in year $t + \tau - 1$;

g = the long-term rate equal to the contemporaneous risk-free rate in June (the yield on 10-year Treasury bonds) minus 3%.

We use a numerical approximation program to solve for R_{ct} within 0 and 100%, allowing for the right- and left-hand sides within a difference of \$0.001. We set the long-term growth rate as the upper bound of the equation.

Model 3: R_{oj} – Ohlson and Juettner-Nauroth (2005)

The third measure is based on an abnormal earnings growth valuation model from Ohlson and Juettner-Nauroth (2005) and modified by Gode and Mohanram (2003):

$$R_{oj} = A + \sqrt{A^2 + \frac{FEPS_{t+1}}{P_t} (g_2 - (\gamma - 1))},$$

where

$A = \frac{1}{2}((\gamma - 1) + \frac{DPS_{t+1}}{p_t})$ while $(\gamma - 1)$ is the contemporaneous risk-free rate minus 3%;
 $g_2 = 0.5 * (\frac{E_3 - E_2}{E_2} + \frac{E_5 - E_4}{E_4})$ where $E_n (n = 1, 2 \dots, 5)$ is the earnings forecasts from HVZ model; $FEPS_{t+\tau} = FROE_{t+\tau} * B_{t+\tau-1}$.

We require R_{oj} within 0 and 100%. The model also requires a positive change in forecasted earnings to yield a numerical solution.

Model 4: R_{es} – Easton (2004)

We finally estimate the cost of equity based on the modified price-earnings growth model in Easton (2004). We calculate the cost of equity by the following model:

$$P_t = \frac{FEPS_{t+1} + DPS_{t+1} * R_{es} - FEPS_{t+1}}{R_{es}^2},$$

where

P_t = the end-of-June stock price for the estimation year;

$FEPS_{t+\tau} = FROE_{t+\tau} * B_{t+\tau-1}$;

$DPS_{t+\tau}$ = the dividend pay-out per share in year $t + \tau$. Following Gebhardt et al. (2001) and Claus and Thomas (2001), the current pay-out ratio is measured as dividends divided by income before extraordinary items for firms with positive current earnings or dividends divided by 6% of total assets for firms with negative incomes before extraordinary items; missing values are then replaced with 50%.

We use a numerical approximation program to solve for R_{es} within 0 and 100%, allowing for the right- and left-hand sides within a difference of \$0.001. Note that the model requires positive change in forecasted earnings to yield a numerical solution.

The HVZ Forecasting Model

We employ the forecasting model developed by Hou et al. (2012) (HVZ model) to estimate earnings for year $t+1$ to year $t+5$. Specifically, we estimate the following pooled cross-sectional regression by using the past ten years of data to generate the earnings forecasts. The earnings and other level variables are winsorized each year at 1st and 99th

percentiles. To keep the survivorship bias to a minimum, only firms with non-missing values for independent variables in year t are included in estimation.

$$E_{i,t+\tau} = \alpha_0 + \alpha_1 * A_{i,t} + \alpha_2 * D_{i,t} + \alpha_3 * DD_{i,t} + \alpha_4 * E_{i,t} + \alpha_5 * NegE_{i,t} + \alpha_6 * AC_{i,t} + \varepsilon_{i,t+\tau},$$

where

$E_{t+\tau}$ = income before extraordinary items in year $t + \tau$;

$A_{i,t}$ = the total assets;

$D_{i,t}$ = the dividend pay-out;

$DD_{i,t}$ = dummy variable taking the value 1 for dividend pay-out larger than zero, 0 otherwise;

$NegE_{i,t}$ = dummy variable equal to 1 if firms have negative earnings, 0 otherwise;

$AC_{i,t}$ = accruals.

All explanatory variables are measured as of year t . Following Hou et al. (2012), we use the financial data of firms with fiscal-year end from April of year $t-1$ to March of year t in the estimation for year t to reduce look-ahead bias.

Appendix B

Table B1

Panel A Summary statistics of innovation intensity measures						
	Mean	Std.D	Std.Dw	25%	50%	75%
R&D intensity	0.184	0.243	0.091	0.026	0.086	0.204
R&D disclosure	2.848	0.844	0.332	2.303	2.944	3.497
Patent applications	0.848	1.085	0.424	0.000	0.000	1.609
SEPs	1.782	75.935	57.088	0.000	0.000	0.000

Panel B Correlation matrix				
	(1)	(2)	(3)	(4)
(1) R&D intensity	1			
(2) R&D disclosure	0.511*	1		
(3) Patent applications	0.028*	0.175*	1	
(4) SEPs	0.0004	0.024*	0.043*	1

* p<0.05

Appendix C

Table C1 Possible mechanisms (full specification)

	Innovation intensity			Market uncertainty		Information environment			
	(1) <i>R&D intensity</i>	(2) <i>R&D disclosure</i>	(3) <i>Patent applications</i>	(4) <i>SEP holding</i>	(5) <i>Market competition</i>	(6) <i>Customer concentration</i>	(7) <i>Financial constraint</i>	(8) <i>10-K report readability</i>	(9) <i>Transparency</i>
<i>High RDI</i>	-0.004 (-1.411)								
<i>MEMBER # High RDI</i>	-0.008** (-2.493)								
<i>MEMBER # Low RDI</i>	-0.002 (-0.670)								
<i>High RDdisclosure</i>		-0.001 (-0.270)							
<i>MEMBER # High RDdisclosure</i>		-0.006** (-2.232)							
<i>MEMBER # Low RDdisclosure</i>		-0.004 (-1.220)							
<i>HPT</i>			-0.001 (-0.309)						
<i>MEMBER # HPT</i>			-0.009*** (-3.164)						
<i>MEMBER # LPT</i>			-0.004 (-1.402)						
<i>NoPT</i>				0.004* (1.677)					
<i>MEMBER # SEP</i>				-0.015** (-2.319)					
<i>MEMBER # NoSEP</i>				-0.004 (-1.002)					
<i>MEMBER # NoPT</i>				-0.005 (-1.410)					
<i>Low Comp</i>					-0.083*** (-10.175)				
<i>MEMBER # High Comp</i>					-0.010*** (-2.823)				
<i>MEMBER # Low Comp</i>					-0.005 (-1.098)				
<i>High CustConce</i>						-0.001 (-0.391)			
<i>MEMBER # High CustConce</i>						-0.008** (-2.048)			
<i>MEMBER # Low CustConce</i>						-0.006** (-2.168)			
<i>High FC</i>							0.006*** (3.161)		
<i>MEMBER # High FC</i>							-0.013*** (-3.671)		
<i>MEMBER # Low FC</i>							-0.002 (-0.722)		
<i>High Fog</i>								-0.001 (-0.560)	
<i>MEMBER # High Fog</i>								-0.006** (-2.308)	
<i>MEMBER # Low Fog</i>								-0.005 (-1.497)	
<i>Low Transparency</i>									-0.000 (-0.089)
<i>MEMBER # High Transparency</i>									-0.005 (-1.620)
<i>MEMBER # Low Transparency</i>									-0.008*** (-2.625)
<i>Constant</i>	0.195*** (10.126)	0.224*** (19.160)	0.185*** (7.385)	0.182*** (7.238)	0.265*** (18.652)	0.186*** (7.439)	0.186*** (7.489)	0.224*** (19.238)	0.186*** (7.344)
<i>Controls</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
<i>Observations</i>	24,499	29,992	32,824	32,824	32,824	32,824	31,077	29,992	32,824
<i>N of firms</i>	2,632	3,165	3,350	3,350	3,350	3,350	3,315	3,165	3,350
<i>R-squared</i>	0.277	0.271	0.276	0.276	0.276	0.276	0.280	0.271	0.275
<i>Industry-Year FE</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
<i>Firm FE</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variable is the composite ICE measure. High (Low) RDI takes value one if the firm's R&D intensity, measured as R&D expenses over sales, is above (below) the industry-year median, zero otherwise. Using a text analysis approach, the narrative R&D disclosure is computed as the number of R&D-related sentences in firms' 10-K filings. High (Low) RDdisclosure takes value one if the firm's R&D disclosure is above (below) the industry-year median, zero otherwise. High (Low) HPT takes value one if the firm's number of patent applications are above (below) the industry-year median, zero otherwise. SEP takes value one if the firm holds at least one standard-essential patent (SEP), zero otherwise. The non-SEP holders are separated into patent (NoSEP) and no-patent holders (NoPT). Market competition is gauged by the Herfindahl-Hirschman Index (HHI) calculated at 3-digit SIC codes for each industry in each year. Following Hou and Robinson (2006), for each year t , we use the average value of the HHI index for the past three years. High (Low) Comp is set equal to one if the annual value is below (above) the year-median, zero otherwise. Customer concentration is measured for each supplier firm as the sum of the squared shares of its major corporate customers. High (Low) CustConce is set equal to one if the firm's customer concentration is above (below) the industry-year median, zero otherwise. Firm financial constraints are proxied by the Kaplan and Zingales index. High (Low) FC takes value one if the firm's KZ index is above (below) the industry-year median, zero otherwise. We measure the readability of firms' 10-K reports using the Fog index, where higher values indicate lower readability. High (Low) Fog is set equal to one if the firm's Fog index is above (below) the industry-year median, zero otherwise. Finally, we use the earnings smoothing ratio as a proxy for firms' transparency. High (Low) Transparency is equal to one if the firm's earnings smoothing ratio is below (above) the industry-year median. We compute each industry-year median at 3-digit SIC level. All dummy variables are measured at time $t-1$. Controls include all other firm-level characteristics included in Table 3. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Online Appendix A

1 Examples of News Reports related to SSO participation

1.1. Business Wire (2015, Aug 3). *AT&T, Comcast, Others Join TIA as it Strengthens Presence in Evolving Tech and Communications Industry.*

<https://www.businesswire.com/news/home/20150803006069/en/ATT-Comcast-Join-TIA-Strengthens-Presence-Evolving>

ARLINGTON, Va.--(BUSINESS WIRE) --The Telecommunications Industry Association (TIA), the leading association representing the manufacturers and suppliers of high-tech communications networks, today announced that the TIA Board of Directors has approved eight companies as new members, including the addition of AT&T and Comcast.

The companies joining TIA represent the complete communications value chain – from Internet and wireless service providers and solution services providers to the electronic equipment and component manufacturers. The new members announced today are: AASKI, AT&T (NYSE: T), Comcast Corporation (NASDAQ: CMCSA), Orchestra Technology, RideScout, Saft Batteries, TRX Systems, and VocalZoom.

“From a legendary global carrier to a dynamic new business that’s revolutionizing transportation, these are great companies that represent the diversity and impact of our members,” said TIA CEO Scott Belcher. “The range of TIA’s member companies offers a remarkable view of the ways in which technology and communications are ingrained in nearly every aspect of our economy and our society. And because of this, TIA is working to make certain that policymakers and the business community understand the vital role that network innovators and infrastructure play in advancing our economy, creating jobs and serving consumers.”

TIA offers its members a broad suite of benefits, including industry intelligence, events, public policy advocacy, networking opportunities, participation in standards-setting, and more. The organization is focused on delivering meaningful value for members and industry in a way that supports innovation, investment, economic growth and global competitiveness.

1.2 Business Wire (2017, Oct 25). *Selectron Technologies, Inc. Partners with PCI Security Standards Council to Improve Payment Data Security Worldwide.*

<https://www.businesswire.com/news/home/20171025005058/en/Selectron-Technologies-Partners-PCI-Security-Standards-Council>

PORTLAND, Ore.--(BUSINESS WIRE) --Selectron Technologies, a leading provider of interactive solutions for local government agencies and utilities, has joined the PCI Security Standards Council as a Participating Organization. Selectron Technologies will work with the Council to improve payment data security through ongoing development of PCI Security Standards, the Payment Card Industry Data Security Standard (PCI DSS), PIN Transaction Security (PTS), and the Payment Application Data Security Standard (PA-DSS).

PCI Security Standards require merchants and service providers that store, process or transmit customer payment card data to adhere to information security controls and processes ensuring data protection as a business-as-usual security posture. “By becoming a Participating Organization, Selectron Technologies demonstrates they are active in mitigating threats and improving security of the payment chain by driving security standards to higher levels of adoption and strength,” said Mauro Lance, Chief Operating Officer of the PCI Security Standards Council.

As a Participating Organization, Selectron Technologies adds its voice to standards setting processes and can recommend new initiatives for consideration, while engaging a community of over 800 organizations united to improve payment security worldwide.

“Serving the public sector for 25 years, we understand the unique challenges facing government agencies. Becoming a Participating Organization is the culmination of our investment to provide the most trusted solutions in the industry.” Todd Johnston, CEO/President Selectron Technologies

“We’ve developed our suite of solutions and architected our data center environment based on evolving industry payment standards. Participating in shaping these standards speaks to both our capabilities and our ongoing commitment to payment security.” Dan Porter, EVP Operations Selectron Technologies

2 Examples of Firm Disclosure of SSO Participation in their 10-K Annual Report

2.1 Company: ACI Worldwide. Inc.; Document: 2018 10-K Annual Report, p.6

We have two major types of third-party product partners: Technology Partners, industry leaders with whom we work closely and drive key industry trends and mandates, and Business Partners, with whom we embed the partners' technology in ACI products, host the partners' software in ACI's cloud as a part of our ACI On Demand ("AOD") offering, or jointly market solutions that include the products of the other company.

Technology partners help us add value to our solutions, stay abreast of current market conditions and industry developments such as standards. Technology partner organizations include Diebold, Inc. ("Diebold"), NCR Corporation ("NCR"), Wincor-Nixdorf, VISA, MasterCard, and SWIFT. In addition, ACI has membership in or participates in the relevant committees of a number of industry associations, such as the International Organization for Standardization ("ISO"), Accredited Standards Committee (ASC) X9, Financial Services, Interactive Financial eXchange Forum ("IFX"), nexo standards, International Payments Framework Association ("IPFA"), U.K. Cards Association, and the PCI Security Standards Council. These partnerships provide direction as it relates to the specifications that are used by the card schemes, and in some cases, manufacturers. These organizations typically look to ACI as a source of knowledge and experience to be shared in conjunction with creating and enhancing their standards. The benefit to ACI is in having the opportunity to influence these standards with concepts and ideas that will benefit the market, our customers, and ACI.

2.2 Company: ADTRAN. Inc. Document information: 2018 10-K Annual Report, p.8

Many communication requirements, processes and technologies are governed by Standards Development Organizations (SDOs). These SDOs consist of representatives from various manufacturers, service providers and testing laboratories working to establish specifications and compliance guidelines for emerging communications technologies. We are an active participant in several SDOs and have assisted with the development of worldwide standards in many technologies.

In 2018, we joined the Open Networking Foundation (ONF) as a strategic supply chain partner and advisory board member to help shape, design and integrate next generation access solutions within the growing, worldwide open networking ecosystem. These efforts focus on virtualization and disaggregation of access networks with interoperable components from various partners. Otherwise, our SDO activities are primarily in the area of broadband access. This includes involvement with the ITU Telecommunications sector (ITU-T), Alliance for Telecommunications Industry Standards (ATIS), European Telecommunications Standards Institute (ETSI), NICC (UK Interoperability Standards), and the Broadband Forum (BBF). We are involved in the evolution of optical access technologies, participating in activities in the ITU-T, Full-Service Access Network (FSAN), Institute of Electrical and Electronics Engineers (IEEE) and BBF on next-generation PON. We are also involved in standards development efforts related to maximizing the bandwidth potential of the copper pair to enable new applications. We continue to be involved with the industry wide interoperability, performance-testing, and system-level projects related to those standards in the BBF. We are also members of ATIS, MEF, Open Compute Project, Wi-Fi Alliance (WFA) and the ETSI Network Functions Virtualization Industry Specification Group (NFV-ISG).

Online Appendix B

1 Alternative cost of equity measures

We use two alternative ex-ante measures of the cost of equity employed in the literature (e.g., Fu et al., 2012; Ortiz-Molina and Phillips, 2014; Lui et al., 2016; Ahmed et al., 2018). Firstly, we use the Fama and French three-factor model (1992, 1993) to estimate the cost of equity (*FFCE*). This was the prevailing approach used in earlier studies but has been subject to recent criticism centering on its lack of precision (Fama and French, 1997; Pástor and Stambaugh, 2000). Secondly, we estimate the CAPM model to compute the cost of equity (*CAPMCE*). Data are collected from the Fama and French Data Library and the WRDS database. Details of the two estimation models are given below.

Fama and French three-factor model

The cost of equity in the Fama and French three-factor model is estimated from the model:

$$R_{i,t} - R_{f,t} = \alpha + \beta_{mrf}R_{mrf,t} + \beta_{smb}SMB_t + \beta_{hml}HML_t + \epsilon_t,$$

where $R_{i,t}$ is the stock returns of firm i in year t and $R_{f,t}$ is the risk-free rate in year t . $R_{mrf,t}$ denotes the market premium, while SMB_t and HML_t indicate risk premiums related to firm size and to the book-to-market ratio. The parameters α , β_{mrf} , β_{smb} and β_{hml} are estimated using 200 daily observations in the previous year. Following Ahmed et al. (2018), we compute the cost of equity for each firm-year as an annual risk premium given by:

$$FFCE = E(R_{i,t}) - R_{i,t} = \beta_{mrf}E(R_{mrf,t}) + \beta_{smb}E(SMB_t) + \beta_{hml}E(HML_t),$$

where we take the arithmetic mean of the three daily factors to compute $E(R_{mrf,t})$, $E(SMB_t)$ and $E(HML_t)$, and then annualize the calculated *FFCE* by multiplying 252.

The CAPM model

We estimate the CAPM model to compute the cost of equity (*CAPMCE*):

$$R_{i,t} - R_{f,t} = \alpha + \beta_{mrf}R_{mrf,t} + \epsilon_t,$$

where $R_{i,t}$ is the stock returns of firm i in year t and $R_{f,t}$ is the risk-free rate; $R_{mrf,t}$ indicates the market risk premium. The parameters α and β_{mrf} are estimated using (minimum 200) daily data in the past year for each firm-year observation. Value-weighted CRSP returns are considered the market return. *CAPMCE* is calculated similar to *FFCE*.

We match accounting data for all fiscal year ends in calendar year $t - 1$ with CRSP stock return data from July of year t to June of year $t + 1$. The minimum six months gap between fiscal year-end of accounting and membership data, and stock returns ensure that accounting and membership information are already incorporated into firms' stock returns.

The estimates for the Fama and French three-factor model and the CAPM model presented in columns (1) and (2) of Table OB1 suggest that the firms' participation in SSOs is negatively associated with their cost of equity. Both models are estimated on (minimum) 200 daily observations in the previous year. Using instead monthly data for the past-five years produces qualitatively similar results for both models.

2 Alternative innovation measures

To check robustness of our patenting activity measure, we now use alternatively, the firms' patent stock (*PATSTK*) and forward citations (*CITATION*). *PATSTK* is calculated as (the natural logarithm of one plus) the current number of patent applications plus the patent stock in the previous year using the 15% depreciation rate (Hall et al., 2005); *CITATION* is (the natural logarithm of one plus) the total number of citations generated in subsequent years by all the patents the firm applied for in year $t-1$. As standard in the literature, we scale the number of citations received by each patent using the average number of citations received by all patents in the same technological class each year to correct for truncation bias. These estimates are presented in columns (3) and (4) of Table OB1.

Table OB1 Alternative measures of the cost of equity and innovation

	Alternative COE measure		Alternative innovation measure	
	(1) <i>FFCE</i>	(2) <i>CAPMCE</i>	(3) <i>PATSK</i>	(4) <i>CITATION</i>
<i>MEMBER</i>	-0.009*** (-2.698)	-0.005** (-2.101)	-0.006** (-2.450)	-0.006*** (-2.579)
<i>PATAPP</i>	0.000 (0.241)	0.001 (0.545)		
<i>SIZE</i>	-0.008*** (-4.296)	-0.004** (-2.553)	-0.028*** (-15.759)	-0.029*** (-15.974)
<i>VOLATILITY</i>	0.008*** (3.158)	0.009*** (5.718)	0.005** (2.412)	0.005** (2.466)
<i>MTB</i>	-0.018*** (-10.768)	-0.011*** (-9.721)	-0.044*** (-30.145)	-0.044*** (-30.181)
<i>LEVERAGE</i>	0.027*** (3.075)	0.034*** (5.586)	0.089*** (11.898)	0.088*** (11.840)
<i>ROA</i>	-0.017** (-2.383)	-0.006* (-1.806)	-0.129*** (-20.517)	-0.129*** (-20.511)
<i>AGE</i>	-0.003 (-0.893)	0.007*** (2.659)	0.027*** (8.834)	0.027*** (8.639)
<i>FORECASTER</i>			0.085*** (15.847)	0.085*** (15.860)
<i>PATSTK</i>			-0.005*** (-3.512)	
<i>CITATION</i>				-0.002*** (-2.695)
<i>Constant</i>	0.269*** (6.265)	0.129*** (4.741)	0.184*** (7.507)	0.185*** (7.528)
Observations	34,533	34,533	32,824	32,824
<i>N</i> of firms	4,788	4,788	3,350	3,350
R-squared	0.506	0.745	0.276	0.276
Industry-Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variable is the cost of equity based on the Fama and French three-factor model using the past-year daily data in Column 1 and the cost of equity based on CAPM model using the past-year daily data in Column 2. The dependent variable in Columns 3 and 4 is the composite ICE measure. Columns 3 and 4 use alternative measures of firm innovation: the patent stock (PATSTK) is calculated as the current number of patent applications plus the patent stock last year with 15% depreciation rate; citations (CITATION) are measured as the natural logarithm of one plus the total number of citations that a firm receives in subsequent years on all the patents that it produces. All other firm-level characteristics are defined in Table 3. *p < 0.1; **p < 0.05; ***p < 0.01.

Online Appendix C

Identification strategy and additional tests

We discuss the results obtained with the probit instrumental variable model in Section 6.1; for brevity, we present the results in columns (1) to (3) of Table OC1.

In an additional sensitivity check, we match SSO members (treated group) to the nearest non-member firms (control group) on a range of characteristics observed in year $t-1$. To calculate the propensity scores, we estimate the logit model below:

$$Participation_{i,t} = f(X_{i,t-1} + Industry_j + Year_t),$$

where $Participation_{i,t}$ indicates (1/0) whether firm i participates in an SSO in year t . Matching is performed (without replacement) on all the previous controls, market competition (HHI index), 2-digit industry SIC codes, and time effects.³⁶ $X_{i,t-1}$ additionally includes variables discussed in the difference-in-differences analysis in Section 6.2. Our final matched sample contains 2,346 successful matches. We conduct balancing tests to assess the quality of the match. In Table OC1, we find no significant difference in means between the treated and the non-treated groups and the standardized biases are all less than 5% after matching. The fixed effects estimates on the matched sample are reported in column (4) of Table OC2. The results suggest that SSO participation reduces the firms' implied cost of equity by around 0.10 percentage points, which is an economically significant amount.

Finally, we report the results obtained from a treatment effect model in the last column of Table OC2. In contrast to the standard Heckman model employed to address self-selection, the treatment effect model uses the inverse Mills ratio (*MILLS*) and the endogenous indicator variable (*MEMBER*) as an independent regressor using the sample including both the self-selected and unselected groups (Acharya and Xu, 2017).³⁷ The negative SSO membership - cost of equity relationship continues to hold.

³⁶ To improve matching quality, our algorithm imposes the common support restriction and a 0.0001 caliper.

³⁷ We perform diagnostic analysis and verify the nonlinearity of the inverse Mills ratio, which is a requirement of the treatment effect model.

Table OC1 Matching method for SSO participation - Balancing tests

	Mean		% bias		t-test	
	Treated	Control	% bias	Reduction	t-value	p-value
<i>PATAPP</i>	1.151	1.123	1.8	97.0	0.66	0.510
<i>SIZE</i>	6.190	6.169	1.1	98.6	0.40	0.691
<i>VOLATILITY</i>	-2.049	-2.068	3.5	74.4	1.17	0.241
<i>MTB</i>	0.932	0.945	-1.6	88.0	-0.57	0.572
<i>LEVERAGE</i>	0.123	0.119	2.8	78.9	0.96	0.336
<i>ROA</i>	-0.020	-0.013	-3.6	74.1	-1.28	0.201
<i>AGE</i>	2.535	2.525	1.1	92.0	0.39	0.698
<i>FORECASTER</i>	-0.004	-0.009	2.4	51.3	0.90	0.37
<i>HHI</i>	0.164	0.164	-0.1	98.6	-0.04	0.965
<i>RDI</i>	0.153	0.149	1.5	29.3	0.52	0.601
<i>SGAI</i>	0.475	0.464	1.8	84.7	0.66	0.510
<i>Financial Slack</i>	0.600	0.600	0.1	99.4	0.02	0.986
<i>KZ</i>	-10.169	-10.632	2.2	71.7	0.75	0.45
<i>CAP</i>	0.153	0.151	1.6	94.0	0.56	0.577
<i>SG</i>	0.148	0.142	1.5	77.6	0.56	0.573
<i>OIPE</i>	0.025	0.027	-3.1	91.7	-1.15	0.251
<i>TEMP</i>	1.007	0.946	2.4	93.7	0.91	0.361

Table OC2 2SLS and PSM estimates

	IV			Matched sample	Mills ratio
	(1) <i>Probit</i>	(2) <i>1st stage 2SLS</i>	(3) <i>2nd stage 2SLS</i>	(4)	(5) <i>IMR</i>
<i>MEMBER</i>			-0.074** (-2.066)	-0.010** (-2.225)	-0.007*** (-2.854)
<i>MEMBER</i>		0.060*** (11.238)			
<i>SSO Availability</i>	0.646*** (14.474)				
<i>PATAPP</i>	0.206*** (5.559)	0.006 (1.531)	-0.002 (-1.445)	-0.002 (-0.703)	-0.003** (-2.332)
<i>SIZE</i>	0.614*** (15.023)	0.008* (1.690)	-0.026*** (-12.203)	-0.029*** (-5.742)	-0.031*** (-13.268)
<i>VOLATILITY</i>	0.121** (1.983)	-0.007* (-1.782)	0.004* (1.942)	0.001 (0.158)	0.005** (2.228)
<i>MTB</i>	0.112*** (2.976)	-0.005** (-2.020)	-0.044*** (-34.026)	-0.032*** (-8.181)	-0.043*** (-26.764)
<i>LEVERAGE</i>	-0.762*** (-3.176)	0.041** (2.563)	0.092*** (13.802)	0.069*** (3.848)	0.092*** (11.184)
<i>ROA</i>	-0.325*** (-2.988)	-0.019** (-2.114)	-0.126*** (-21.952)	-0.165*** (-7.630)	-0.120*** (-17.198)
<i>AGE</i>	-0.010 (-0.157)	-0.028*** (-2.998)	0.033*** (10.380)	0.021* (1.952)	0.034*** (7.774)
<i>FORECASTER</i>	-0.071 (-1.285)	0.003 (0.472)	0.079*** (16.968)	0.133*** (7.479)	0.079*** (12.839)
<i>MILLS</i>					-0.006** (-2.119)
<i>Constant</i>	-7.930*** (-12.021)			0.236*** (5.898)	0.204*** (7.279)
Observations	26,354	26,354	26,354	4,692	26,354
Log-likelihood	-5240.779				
Wald Chi2	865.05***				
Kleibergen-Paap LM statistic		126.78***			
Cragg-Donald F statistic		124.28***			
R-squared			0.242	0.307	0.266
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES

This table presents estimated coefficients (z-statistics or t-statistics in parentheses). The dependent variable is the composite ICE measure. Columns 1-3 report IV results obtained on the whole sample. Column 1 reports results from estimating a probit model of *MEMBER* on the instrumental variable (*SSO Availability*) and control variables. *SSO Availability* is the (natural logarithm of 1 plus) number of relevant SSOs, i.e., assigned with the same industry as the focal firm each year. An SSO is assigned all (3-digit SIC) industry codes of all its member firms each year. As *MEMBER* is measured in year t-1, *SSO Availability* and the other controls are measured in year t-2. The predicted probability, denoted *MEMBER*, is used as an instrument for *MEMBER* in the first-stage 2SLS regression in column 2. Column 3 reports the second-stage 2SLS results. Column 4 presents the fixed effects estimates for Equ.1 on the propensity score matched sample. Column 5 addresses the potential selection bias by including the inverse Mills ratio calculated from the probit model in column 1. All other firm-level characteristics are defined in Table 3. *p < 0.1; **p < 0.05; ***p < 0.01.

Chapter 2:
Analyst Coverage and Patent Value:
an Inverted-U Relationship

Analyst Coverage and Patent Value: an Inverted-U Relationship

Abstract

This chapter investigates the relationship between analyst coverage and patent value. Using the listed U.S. firms' data from 1990 to 2015, we find an inverted-U relationship between analyst coverage and firms' patent value, as well as between analyst coverage and innovation efficiency (measured as patent value over R&D capital). Our results are robust to considerations of the endogenous nature of firms' analyst coverage and other sample compositions and adjustments to variables. Additionally, we find that the curvilinear influence of analyst coverage is contingent on firm participation in industrial organizations with regard to innovation and technology (Standard Setting Organizations), and product market competition.

Keywords: analyst coverage; patent value; innovation efficiency

1 Introduction

Innovation productivity is an issue of significant interest to a wide range of stakeholders including company managers, investors and policymakers, as long-term growth in profits depends largely on firms' investment in innovation, particularly for innovative firms. Empirical evidence shows that there are various economic and financial variables affecting managerial incentives for investing in innovation (i.e., Aghion et al., 2013 and Fang et al., 2014). Reports by financial analysts have been highlighted in recent literature as important factors that affect firms' innovation incentives (He and Tian, 2013; Dai et al., 2015; Guo et al., 2019). Financial analysts, being the key ingredient of an equity market, not only provide firm information to the market, but also set external performance benchmarks (e.g., earnings forecasts) for the firms that they analyze. They help to reduce information asymmetries between firms and outside investors, and maintain investor recognition for the firms' stocks (Mola et al., 2013). Firms with reduced analyst coverage may suffer from a deterioration in bid-ask spreads and trading volume; the increased cost of financing can further reduce firms' investment (Derrien and Kecskes, 2013; Mola et al., 2013). Analysts also play the role of external monitors in the market. However, they may put excessive pressure on the firms' managers, as well as upon themselves. Managers must meet the short-term earnings targets set by analysts. This short-term pressure may exacerbate managerial myopia within firms and reduce a firm's level of investment, particularly in innovation (He and Tian, 2013; Guo et al., 2019). Analysts, however, must cope with peer pressures and provide objective analysis, while maintaining a good relationship with their clients (Yu, 2008).

The literature on the relationship between analyst coverage and innovation productivity is relatively limited. He and Tian (2013) find that firms covered by a larger number of analysts generate fewer patents, and the patents which are generated have a lower impact, measured by citations. Guo et al. (2013) focus on more detailed innovation strategies relative to analyst coverage. They find that firms covered by a larger number of analysts reduce their R&D expenses, but undertake acquisitions of more innovative firms and have increased investment in corporate venture capital. Overall, the current focus on the effects of analyst coverage on innovation is either innovative inputs or outputs, in terms of the technological value of innovation. One exception is found in the most recent paper by Zhong (2018). He uses analyst coverage as one of the transparency measures and finds that innovation efficiency, in terms of technological value of patents,

increases as transparency increases. However, traditional measures, such as patents and patent citations, are not ideal for measuring the value of innovation for shareholders. First, the number of patents is unable to capture the economic private value of innovation. Because it cannot reflect the influence and also the quality of innovation output; and it is also subject to the patent troll issue (Cohen et al., 2016). Firms may be able to produce a large number of patents, but subsequently fail to generate a higher marginal market value. Furthermore, patent citations reflect the intrinsic technological value of innovation rather than market value of inventions to shareholders. Citations also subject to truncation bias as it takes time for a patent to receive citations, and can also vary significantly with a patent's technology class and grant year (Seru, 2014). Therefore, this chapter overcomes these issues by leveraging on the recently developed method of evaluating patent quality by the market reactions to patent issuance announcements, and focuses on the relationship between analyst coverage and this market-perceived value of innovation to assess whether firms are able to generate patents with higher private economic value when subjected to the distortion of analyst coverage. Moreover, as innovation efficiency plays a vital role in firms' competitiveness (Zhong, 2018), we will further explore the relationship between analyst coverage and innovation efficiency, examining whether firms covered by a large number of analysts are able to generate more economically valuable innovation per R&D dollar.

Using the listed U.S. firms' data from 1990 to 2015, we find inverted-U relationships between analyst coverage and firms' patent value, and between analyst coverage and innovation efficiency. The private economic value of innovation increases under a certain level of analyst coverage. This is due to the fact that the coverage helps to mitigate the information asymmetry problem and imposes discipline on managers, restricting them from making wasteful investments. However, firms covered by too many analysts risk becoming myopic. Managers may be under too much pressure, posed by different analysts, to make value-enhancing, long-term innovation investment decisions. This results in a reduction in overall innovation value (He and Tian, 2013). Additionally, although firm transparency largely increases through analyst coverage, a significant amount of proprietary and strategic information is also revealed to competitors, which can further damage a firm's competitive advantages (Zhong, 2018). The loss of competitive strength over innovation can prevent firms from profiting from the originality of the innovation. In our case, our results are robust towards considerations of the endogenous nature of firms' analyst coverage and other sample compositions and

adjustments to variables. Instead of using all firms covered within our sample period, we conduct our analysis on samples of patenting firms, active innovative firms, and high-tech firms. We continue to find the inverted-U relationships between analyst coverage and firms' patent value, and analyst coverage and innovation efficiency across different sample compositions. Considering that the innovative process might take more than one year, we further test our analysis using different sample periods and lags of analyst coverage. The curvilinear influence of analyst coverage is unaffected. Furthermore, according to prior literature, we use expected coverage as the instrumental variable for coverage and conduct the two-stage least square (2SLS) analysis. We continue to find the significant inverted-U relationships between analyst coverage and firms' patent value, and between analyst coverage and innovation efficiency. Finally, we find that the curvilinear influence of analyst coverage on firms' patent value, and of analyst coverage on innovation efficiency is contingent on firm participation in industrial organizations, with regard to innovation and technology (Standard Setting Organization), and product market competition.

Our study contributes to the literature in two key ways. Firstly, we contribute to the literature on the market value of innovation. Since the private economic value of innovation is directly associated with a firm's market value and shareholder interest, it is important to consider all factors that may influence the true value of innovation. There are relatively few papers that link the private economic value of innovation to finance. A recent paper by Almeida et al. (2021) finds that firms with more cash generate fewer valuable patents, as a cash windfall may lead managers to engage in riskier projects that could destroy value. In this chapter, we additionally consider financial analysts, the key ingredient of an equity market, and find that analyst coverage has a curvilinear effect upon patent value. A certain level of analyst coverage increases a firm's patent value. However, as the number of analysts increases, the patent value is diminished. Secondly, our analysis contributes to the literature on the role of financial analysts in relation to innovation (Barth et al., 2001; He and Tian, 2013; Zhong, 2018; Guo et al., 2019). The current focus on the effects of analyst coverage on innovation is limited to the technological value of innovation. However, traditional measures, such as patent applications and citations, are not ideal for measuring the true value of innovation (Almeida et al., 2021). The perception of outside investors on the patented innovation can significantly influence the overall market value of a firm. Firms may carry out unnecessary R&D investment without carefully evaluating the profits and risks. The

investment is more likely to generate reduced innovation value or end in failure. Therefore, it is important to understand whether analyst coverage affects the actual market outcome of a firm's investment. Moreover, current studies focus on either innovative inputs or outputs when discussing the roles of analyst coverage on innovation. Firms may not invest in innovation efficiently when subjected to the distortion of analyst coverage. However, the issue of whether analyst coverage affects firm efficiency and generates innovation with high market value is unaddressed in the related literature. Our chapter further bridges this gap by computing innovation efficiency, using the market patent value. The measure of innovation efficiency in our study shows a firm's ability to generate a one-dollar market value per dollar of R&D investment.

The rest of the chapter is organized as follows. Section 2 reviews the related literature and develops our hypothesis. Section 3 describes our data and methodology. Section 4 presents our empirical results and robustness checks. Additional analysis on the effect of firm participation in industrial organizations (Standard Setting Organizations) and product market competition is given in Section 5. The final section concludes.

2 Literature review and hypothesis development

According to prior literature, the effect of analyst coverage on the private economic value of innovation remains unclear. On the one hand, analysts help to reduce information asymmetries and serve as external monitors to their client firms (Yu, 2008). If analysts help to convey accurate information to the market and facilitate firms in obtaining the true value of long-term investment, such as innovation, firm managers may be more willing to carry out value-enhancing innovation activities (He and Tian, 2013). Moreover, the increased transparency also helps managers to more accurately calibrate the returns on prospective R&D and to ensure that the R&D invested is used effectively, leading to higher innovation efficiency (Zhong et al., 2018). Finally, as firms are increasingly scrutinized by such external monitors, due to the disciplining effect, managers may be induced to cut wasteful investment, which can also eventually lead to a higher level of innovation efficiency (Guo et al., 2019). Given that financial analysts provide an improved information environment, which could possibly incentivize management to focus on long-term value-enhancing investment, and also pose certain scrutiny on a firm's investment, outside investors might react positively to its patent issuance events

as they have more information over the firm's investment and development, at the same time, knowing that the investment is of high quality and well-managed.

However, on the other hand, firms with more financial resources may not increase their level of innovation or innovate more effectively (Almeida et al., 2021). Previous literature has highlighted positive relationships between analyst coverage and firms' investment, analyst coverage and financing decisions, as well as between analyst coverage and liquidity (Irvine, 2003; Chang et al., 2006; Derrien and Kecskes, 2013). Since analyst coverage reduces the information asymmetries, which in turn, helps to maintain investor recognition for the firms' stocks, firms are able to increase investment with lower associated costs (Derrien and Kecskes, 2013; Mola et al., 2013). In this case, firms are more likely to have higher risk-taking incentives without carefully evaluating the innovation projects (Almeida et al., 2021). The failure of such investments will cause substantial loss to the firms (Levinthal and March, 1993). Moreover, increased analyst coverage might also reduce firms' competitiveness and dampen their performance as it not only increases the firms' transparency but also potentially reveal their proprietary strategic information to the market (Zhong, 2018). This form of knowledge leakage could further reduce the potential value of innovation (Bhattacharya and Ritter, 1983). Finally, excessive analyst coverage may counteract the benefits of the disciplining effect on managers. Managers are under too much pressure to reach the earnings goals set by each analyst. They may become more myopic and engage in less value-enhancing, long-term investment (He and Tian, 2013). In this case, as a firm's analyst coverage increase, outside investors might perceive less value of its innovation.

Examining both the positive and negative sides of analyst coverage, in this chapter, we hypothesize that analyst coverage has a curvilinear effect upon firms' private innovation value. Firms can experience an increase in the economic private value of innovation that results from a certain level of analyst coverage, since the information asymmetry problem is mitigated, and managers are restricted from carrying out unnecessary investment. However, as analyst coverage exceeds a certain level, the drawbacks of being covered by analysts begin to outweigh the benefits. Managers become overwhelmed by the short-term earnings targets set by different analysts and choose to forgo positive, value-enhancing R&D projects. Moreover, with a substantial amount of proprietary strategic information being revealed to market competitors, firms' competitiveness and performance might be dampened. High levels of analyst coverage

eventually lead to a decrease in the market-perceived value of innovation and a reduced level of innovation efficiency.

3 Data and methods

3.1 Data and sample composition

Our sample includes all listed U.S. firms for the period 1990 to 2015. We begin with all U.S. companies in the Compustat-CRSP merged database. Financial and utilities firms (standard industrial classification (SIC) codes between 6000 and 6799, and between 4900 and 4949) are excluded from the sample. We further require that firms are listed in Compustat for two years before including them in the sample in order to mitigate backfilling bias. For the remaining firms, we obtain financial analyst information from the Institutional Brokers Estimate Systems (I/B/E/S) database. Our sample period starts from 1990 to ensure the quality of I/B/E/S data (Yu, 2008). The granted patent data is collected from the U.S. Patent and Trademark Office (USPTO), obtained through Orbis Intellectual Property (hereafter Orbis IP). The Orbis IP historic data covers patent granted data up to 25th December 2018. Since we use the year of application to measure innovation, to adjust the truncation bias due to the application-grant lag, we use the data up to 2015, given that it normally takes three years for applied patents to be officially granted (Guo et al., 2019). We further collect firms' holding period returns and the returns of market portfolio data from the CRSP daily database for the calculation of the market value of patents.

3.2 The private economic value of patents

As discussed earlier, the number of patents may not capture the economic value of a firm's innovation and citations only reflect the technological value of a firm's inventions (Almeida et al., 2021). Hence, Kogan et al. (2017) propose a novel measure for computing the private economic value of innovation. They document that a firm's trading activity in the stock increases after the issue date of the patent, and their stock returns on patent grant days are more volatile. The measure of the private economic value of patents is then based on these stock market reactions to patent grants. This private value can differ significantly from the technological value, which is widely used and measured using forward patent citations in past studies. For example, Kogan et al. (2017) point out

that a patent with little scientific value can be used strategically by a firm and may be able to effectively restrict competition, which can eventually generate large private rents. Therefore, in this chapter, we follow Kogan et al. (2017) by calculating the economic value of patents, according to the stock market reactions to patent issuance events, and study whether analyst coverage affects the market value of innovation. Specifically, and in line with Kogan et al. (2017), we first choose a three-day announcement window after the patent grant date, $[t, t+2]$, to calculate the market return around patent issuance events. The three-day announcement return for newly granted patent i can be written as the sum of two parts:

$$r_i = p_i + \varepsilon_i, \quad (1)$$

where r_i is the firm's idiosyncratic returns, calculated as the firm's return, minus the market return. p_i is the value of patent i as a fraction of the firm's market capitalisation, while ε_i denotes the components that are unrelated to the newly granted patent i . Following Kogan et al. (2017), we assume that p_i follows a normal distribution with a truncated mean (0) and a variance of σ_p^2 , and ε_i follows a normal distribution with a mean 0 and a variance σ_ε^2 . Given these assumptions, the filtered value of p_i can then be calculated as a function of the idiosyncratic returns r_i :

$$E[p_i|r_i] = snr \times r_i + \sqrt{snr} \times \sigma_\varepsilon \times \frac{\phi(-\sqrt{snr} \times \frac{r_i}{\sigma_\varepsilon})}{1 - \Phi(-\sqrt{snr} \times \frac{r_i}{\sigma_\varepsilon})}, \quad (2)$$

where ϕ and Φ denote the standard normal probability density function and cumulative distribution function. snr is the signal-to-noise ratio:

$$snr = \frac{\sigma_p^2}{\sigma_p^2 + \sigma_\varepsilon^2}. \quad (3)$$

To calculate snr , we allow σ_ε and σ_p to vary across firms and time, while keeping snr constant across firms and time (Kogan et al., 2017). As for snr , we regress the log squared returns on a patent issue-day dummy variable I_{fd} ,

$$\log(r_{fd}^2) = \gamma I_{fd} + cZ_{fd} + v_{fd}, \quad (4)$$

where r_{fd} is the three-day idiosyncratic return of firm f starting from day d . I_{fd} is the binary variable that takes the value of one if the firm is granted at least one patent on day

d. Z_{fd} are the day-of-week fixed effect and year-firm fixed effect. The snr can then be recovered from: $snr = 1 - e^{-\gamma}$.³⁸ According to Eq. (3), after recovering snr , we finally need to estimate σ_ε . To uncover σ_ε , we first estimate the conditional volatility (σ_{ft}^2) of firm f at year t using the realised mean idiosyncratic squared return r_{ft}^2 . The σ_{ft}^2 is a mongrel of both σ_ε^2 and σ_p^2 as it is calculated over both announcement and non-announcement days. We calculate D_{ft} as the fraction of trading days that are patent announcement days. The σ_ε can then be estimated as: $\sigma_\varepsilon^2 = 3\sigma_{ft}^2(1 + 3D_{ft}(e^\gamma - 1))^{-1}$.

Finally, we estimate the market value of patent i , P_i , as a function of the product of the estimated stock return related to the patent issuance events and the market capitalisation (MC_i) of the firm that is granted patent i on the day prior to the announcement of the patent issuance:

$$P_i = (1 - sr)^{-1} \frac{1}{N_i} E[p_i | r_i] MC_i, \quad (5)$$

where sr is the unconditional patent application success rate³⁹ and N_i is the number of patents granted to the same firm on the same day as patent i . Following Almeida et al. (2021), the private economic value of patents ($Ptval$) is calculated as the sum of the market value of all patents applied for (and eventually granted) in the same year for each firm, scaled by the lagged assets.

3.3 Innovation efficiency

Firms may be unable to invest in innovation efficiently when subjected to the distortion of analyst coverage. The positive relationship between innovation efficiency, in terms of the technological value of innovation and firm transparency, has been established by Zhong et al. (2018). However, whether analyst coverage affects a firm's ability to efficiently generate innovation with a high market value is unaddressed in the literature. Therefore, in addition to our key focus on the economic value of firms' innovation ($Ptval$), we further compute innovation efficiency ($Pteff$) using the market patent value. More specifically, $Pteff$ is calculated as the sum of the market value of patents applied for in year t over the R&D capital. R&D capital is defined as the weighted average of R&D

³⁸ The fitted value of γ in our data is 0.0255226.

³⁹ Following Kogan et al. (2017), we set sr equal to 56% and adjust it by multiplying 2.27.

expenses over the last five years with an annual depreciation rate of 20% (Chan et al., 2001). According to Hirshleifer et al. (2013),⁴⁰ Gao and Chou (2015) and Zhong (2018), we estimate R&D capital for firm i in year t as:

$$R\&D\ Capital_{i,t} = R\&D_{i,t} + 0.8R\&D_{i,t-1} + 0.6R\&D_{i,t-2} + 0.4R\&D_{i,t-3} + 0.2R\&D_{i,t-4}. \quad (6)$$

We replace missing R&D expenses reported in Compustat with zero following prior studies (e.g., Gao and Chou, 2015). The innovation efficiency in this chapter represents a firm's ability to generate a one-dollar market value per dollar of R&D investment.

3.4 Analyst coverage

We measure analyst coverage as the number of analysts that issue earnings forecasts for a firm. The number of analysts each year is computed as the mean of a 12-monthly quantity of earnings forecasts that a firm receives annually from the I/B/E/S summary file. Following Chang et al. (2006), Hameed et al. (2015) and Guo et al. (2019), we replace firm-year observations with missing values in I/B/E/S with zero. Finally, our main independent variable, *Coverage*, is given by the natural logarithm of one plus the number of analysts calculated as above.⁴¹

3.5 Empirical model

To study the effect of analyst coverage on firms' patent values and on efficiency, we base our estimation on firm fixed effect regression. Our baseline empirical model is given below:

$$Ptval, Pteff_{i,t+1} = \alpha_i + \beta_1 Coverage_{i,t} + \beta_2 Coverage_{i,t}^2 + \gamma Controls_{i,t} + v_j + \mu_t + \epsilon_{i,t}, \quad (7)$$

⁴⁰ The measure of R&D capital is slightly different from that in Hirshleifer et al. (2013). The reason is that Hirshleifer et al. (2013) examine the stock market values of innovation and need the innovation information to be incorporated in stock returns. They thus construct the data using the grant date. We focus on the ability of firms to convert R&D to innovation. Measures in this chapter are more intuitive as the application year of patent counts and citations are used.

⁴¹ Considering the possibility that an analyst could make several forecasts within one month, following He and Tian (2013), we also calculate the total number of unique analysts that issue earnings forecasts for a firm by using the historical detail file of I/B/E/S. Our results remain unchanged.

where $Ptval$ is the private economic value of patents calculated in Section 3.2, following Kogan et al. (2017), while $Pteff$ measures innovation efficiency, computed as $Ptval$ over R&D capital. Both $Ptval$ and $Pteff$ are measured in year $t+1$. Considering that the innovative process may take more than one year, we also examine the effect of analyst coverage on $Ptval$ and $Pteff$ both two and three years ahead in a later section for the purposes of testing robustness. As usual, $\epsilon_{i,t}$ is the error term, while α_i , ν_j and μ_t stand for firm, industry, and time specific effects, respectively.

In line with previous literature (e.g., Almeida et al., 2021; He and Tian, 2013; Gao et al., 2015; Zhong, 2018), to disentangle the direct effect of analyst coverage on innovation productivity, $Controls_{i,t}$ is a set of variables known to influence firm innovation. Specifically, apart from controlling for firm size ($Size$) measured as the natural logarithm of sales,⁴² and firm age (Age) as the natural logarithm of one plus the number of years from the first year of stocks in CRSP, we include R&D expenditure ($R\&DS$), advertising expenses (ADS) and capital expenditure ($Capasset$) to control for the effect of a firm's operation and investment on its innovation (He and Tian, 2013). We further include $Profitability$ measured as the return on equity and $Tobin's Q$ to control for the potential effect of growth opportunities and profitability on innovation productivity. K/L is the assets-to-employees ratios, capturing the potential links between capital-intensity and the innovation performance of firms (Almeida et al., 2021). We further account for the effect of capital structure on innovation productivity by including leverage ratio ($Leverage$) measured as debts over the total assets, and internally generated cash ($Cash$) calculated as a firm's cash scaled by the total assets. We control for financial constraints measured using Kaplan and Zingales index ($KZ\ index$) as financially constrained firms may be more likely to generate innovation of higher quality (Almeida et al., 2021). Finally, as Aghion et al. (2013) identify a positive association between institutional ownership and innovation, we further control for $Instowner$ measured as the percentage of institutional ownership in a firm each year. The detailed definitions of all variables are given in Table 1.

[Insert Table 1]

3.6 Summary statistics

⁴² Our results remain unaffected if we control for size, measured as total employment.

Our sample consists of 26,926 firm-year observations of 2,674 U.S. listed firms. Following the existing literature, we eliminate firms with fewer than three consecutive annual observations and winsorize the 1% tails of all firm-level variables.

Table 2 provides the summary statistics of all variables used in our baseline analysis. The mean private economic value of patents (*Ptval*) in our sample is 0.096, indicating that, on average, the private market value of patents can account for almost 10% of a firm's total assets. Since the value created by innovation is nontrivial, it is important to identify possible control mechanisms that might have an impact on firms' innovation value, particularly for high-tech innovation-intensive firms. In our sample, the mean of the innovation efficiency (*Pteff*) is around 0.57. Given that innovation efficiency is computed as the economic value of patents over R&D capital over the past five years, on average, the private economic value of patents account for over half of the R&D investment made by a firm in the last five years. As for analyst coverage, our sample firms, on average, there are around seven analysts covering each firm, each year (*Coveragenum*). Other variables also exhibit similar magnitudes as reported in other papers (Almeida et al., 2021; He and Tian, 2013; Gao et al., 2015; Zhong, 2018; Guo et al., 2019). Finally, the small magnitudes of all pairwise correlation coefficients of our explanatory variables presented in Table 3 further indicate that the collinearity will not be an issue in our analysis.

[Insert Table 2 and Table 3]

4 Estimation results

4.1 Baseline models

Our baseline results are presented in Table 4. The dependent variable in columns (1)-(4) is the patent value (*Ptval*) and the innovation efficiency (*Pteff*) is the dependent variable in columns (5)-(8). In columns (1) and (5), we estimate the Eq. (7) with firm and year fixed effect, but without controlling for additional firm-specific factors. The estimates from this parsimonious model provide clear evidence that our hypothesised inverted-U relationship does exist between analyst coverage and firms' patent value, as well as between analyst coverage and innovation efficiency. Firms benefit from innovation value gains under a certain level of analyst coverage, given that *Coverage* loads positive and is statistically significant at the 1% level. However, beyond a certain

level of analyst coverage, patent value and innovation efficiency decrease, given that the coefficient of *Coverage_sq* is significantly negative.

In line with the existing literature, we further include variables on firm specifics that are commonly discussed in previous studies on firm innovation and innovation efficiency (He and Tian, 2013; Gao and Chou, 2015; Zhong, 2018; Guo et al., 2019). In columns (2) and (6), we first include *Size*, *Age*, *R&DS*, *ADS*, *Profitability*, *Leverage*, *Capasset*, *K/Z*, while in columns (3) and (7), we include *Tobin'Q*, *KZ index* and *Instowner* as additional controls for firms' characteristics. Finally, in columns (4) and (8), we further include the industry-year fixed effect, in which the industry is classified based on the Fama-French 17 industrial classification. Across all of the model specifications, we find consistent evidence that analyst coverage has a curvilinear effect on firms' patent value and innovation efficiency. In columns (4) and (8), the overall test for the presence of an inverted-U relationship is significantly below the 1% confidence interval (Lind and Mehlum, 2010). Figure 1 further illustrates the relationship between *Coverage* on *Ptval* and *Pteff*, and the optimal level of analyst coverage. As for the patent value, the optimal value of *Coverage* is 1.46 (3.3 in *Coveragenum*) under the specification of column (4), and 1.38 (3.0 in *Coveragenum*) for the innovation efficiency in column (8). Both optimal values are slightly below the sample median of *Coveragenum*. However, when the value of *Coverage* over 2.5 (12.2 in *Coveragenum*), we start to see a larger and quicker decrease in firms' innovation productivity (Figure 1). However, the analysis undertaken to find an optimal level of analyst coverage should be interpreted with caution, as it indicates general tendencies, rather than a precise effect or clear benchmarks.

Other control variables are then examined. The coefficients of controls exhibit signs in line with prior literature. Specifically, *Size* and *R&DS* are negatively related to innovation and innovation efficiency, as in He and Tian (2013), Gao and Chou (2015) and Guo et al., (2019). The *Age* loads positive, which is also in line with Gao and Chou (2015). Positive and significant coefficients of *Profitability* and *Capasset* are consistent with those in He and Tian (2013), Gao and Chou (2015) and Zhong (2018). *Leverage* and *K/L* are negatively related to patent value and innovation efficiency, as in He and Tian (2013) and Almeida et al. (2021). Institutional ownership is positively associated with innovation, as in He and Tian (2013) and Guo et al. (2019). We find that, although the magnitude is relatively trivial compared to that of other factors, financial constraint (*KZ index*) is significantly and positively associated with the patent value. The reason for this may be that financially constrained firms are more likely to have a lower tolerance

for failure, as the margin of error is relatively small (Almeida et al., 2021). Financial constraint actually plays a role in forcing firms to innovate more economically.

[Insert Table 4 and Figure 1]

4.2 Alternative samples of innovation-intensive firms

In this section, we consider different sample compositions to give more emphasis to innovation-intensive firms. In columns (1) and (2) of Table 5, we first exclude non-patenting firms from our sample and only examine firms with patents. We require firms to have applied for at least one patent during our sample period from 1990 to 2015. This results in 1,586 firms with 19,389 firm-year observations. Since our sample covers a substantial period of time, it is possible that the identified patenting firms have not applied for any further patents, or have only started to file patents in more recent years. Thus, following Gao et al. (2018), we further define active innovative firms in year t as those firms filing at least one patent over the 3-year period, from the year $t-2$ to year t . This final sample contains 14,820 firm-year observations of 1,342 firms. The estimates are presented in columns (3) and (4) of Table 5. Finally, as high-tech industries are highly relevant in the context of our study and firms within these industries are the key players in innovation, we further consider firms in high-tech industries in columns (5) and (6). Following Brown et al. (2009), the high-tech sample comprises SIC 283 (Drugs), SIC 357 (Computer and Office Equipment), SIC 366 (Communications Equipment), SIC 367 (Electronic Components and Accessories), SIC 382 (Measuring and Controlling Devices), SIC 384 (Medical Instruments and Supplies) and SIC 737 (Computer and Data Processing Service). Across the columns in Table 5, we consistently find an inverted-U relationship between analyst coverage and patent value, as well as between analyst coverage and innovation efficiency. Moreover, the effect of analyst coverage is relatively stronger for innovation-intensive firms, particularly in relation to active firms.

[Insert Table 5]

4.3 Lag effects on patent value and innovation efficiency

Considering that the innovative process may take more than one year (He and Tian, 2013), in this section, we further examine the effect of analyst coverage on $Ptval$ and $Pteff$,

both two and three years ahead. In columns (1) and (2) of Table 6, patent value (*Ptval*) and innovation efficiency (*Pteff*) are measured two years ahead, while in columns (3) and (4), *Ptval* and *Pteff* are three years ahead. We continue to find evidence of the curvilinear influence of analyst coverage on firms' patent value, and on innovation efficiency.

[Insert Table 6]

4.4 2SLS

Thus far, we have analyzed our baseline model using a fixed effect and all explanatory variables are taken from the years $t-1$, $t-2$ and $t-3$. The potential endogeneity problem may need to be addressed further. Endogeneity comes in the form of both omitted variables and reverse causality. For instance, in our case, firms can still be significantly distinct if they have different talent bases, which may substantially affect their innovation value and efficiency. Moreover, if firms participate in some form of industrial consortia related to innovation, and take part in R&D collaborations, their innovation efficiency may be further influenced. Additionally, analysts may also be in favour of innovation-efficient firms or firms with a high innovation value. Considering these potential endogeneity problems, and in line with the prior literature (Yu, 2008; He and Tian, 2013; Guo et al., 2019), we further apply expected coverage (*ExpCoverage*) as the instrumental variable for *Coverage*. This instrumental variable is considered to be exogenous because the number of analysts that a brokerage house employs depends on its performance, not on the characteristics of its client firms (Yu, 2008). In the context of our study, it is highly unlikely that covered firms' innovation value and efficiency will affect the number of analysts that a brokerage house employs. Therefore, following previous studies, we construct the instrumental variable as follows:

$$ExpCoverage_{(i,t,j)} = (Brokersize_{(t,j)} / Brokersize_{(0,j)}) * Coverage_{(i,0,j)}, \quad (8)$$

$$ExpCoverage_{(i,t)} = \sum_{j=1}^n ExpCoverage_{(i,t,j)}, \quad (9)$$

where $ExpCoverage_{(i,t,j)}$ is the expected coverage of firm i in year t from brokerage house j ; $Brokersize_{(t,j)}$ and $Brokersize_{(0,j)}$ are the number of analysts employed by

broker j in year t and in benchmark year 0. To generate the expected coverage for as many firm-year observations as possible, following Yu (2008), we use the year 2003 as the benchmark year, as it is the middle year of our sample. $Coverage_{(i,0,j)}$ is the number of analysts from broker j following firm i in benchmark year 0. We limit the maximum number of analysts sent to a firm by a broker to one, as a brokerage house rarely assigns more than one analyst to a particular firm (Yu, 2008). Finally, $ExpCoverage_{(i,t)}$ is the sum of the number of analysts from broker j in year t and refers to the total expected number of analysts for firm i in year t . We also follow the existing literature by dropping all observations in the benchmark year. Moreover, in order to calculate $ExpCoverage$, we also need the firm to be covered by at least one brokerage house in the benchmark year. In Table 7, we present the 2SLS estimation results, as we use $ExpCoverage_{(i,t)}$ to instrument our $Lncoverage_{i,t}$ in Eq. (7). Columns (1) and (2) give the first-stage estimates. $ExpCoverage$ is positively and significantly related to $Coverage$, indicating the strong relevance of the instrumental variable. Columns (3)-(4) present the estimates for the second stage, when the dependent variables are the patent value ($Ptval$) and the innovation efficiency ($Pteff$), respectively. The coefficient of $Coverage$ remains significantly positive, while its squared term ($Coverage_sq$) loads negative, demonstrating the existence of an inverted-U relationship between analyst coverage and firms' patent value, and between analyst coverage and innovation efficiency. We also conduct the same analysis for $Ptval$ and $Pteff$ two and three years ahead in columns (5)-(8). Our results remain unchanged.

[Insert Table 7]

5 Additional analysis

5.1 Participation in industrial organizations

In this section, we consider firm participation in industrial consortia related to innovation, as mentioned earlier. We assume that such strategic affiliations will affect firms' patent value and innovation efficiency, as well as the relationship between analyst coverage and innovation. The type of strategic affiliation we consider relevant in our study is participation in Standard Setting Organizations (SSOs). SSOs are largely self-governed institutions which coordinate the development of innovative technologies. Firms participating in SSOs collaborate to collectively define common rules, technical

specifications, and regulations for players in the market, and promote these as voluntary open standards in relevant industry fields (Simcoe, 2012). Participation in SSOs has its benefits and drawbacks. On the one hand, it helps to keep member firms' innovative activities on the right trajectory. Through meetings and discussions, firms can stay abreast of cutting-edge technologies. On the other hand, however, it is costly and time-consuming for firms to become involved in standards setting (Baron and Spulber, 2018). Information leakage is also inevitable. Participation in SSOs increases the likelihood of firms' proprietary knowledge being stolen by competitors, which may eventually lead to lower innovation value and efficiency.

From previous analysis, we find an inverted-U relationship between analyst coverage and patent value, as well as between analyst coverage and innovation efficiency. As the information asymmetries between investors and firms are reduced by analyst coverage, firms may be able to carry out more innovative activities at a lower cost. It is due to analyst coverage that the investment base is maintained and the cost of capital is reduced (Derrien and Kecskes, 2013; Mola et al., 2013). Furthermore, under a certain level of analyst coverage, the discipline effect helps to improve the resource allocation of firms, resulting in firms innovating more effectively and efficiently. Rysman and Simcoe (2008) show that SSOs are able to identify higher quality technologies and to subsequently influence their wider usage. Therefore, from this perspective, we can expect the negative relationship between analyst coverage and innovation value, and the relationship between analyst coverage and efficiency to be improved when firms choose to participate in SSOs. However, Zhong (2018) argues that the information leakages can reduce a firm's competitiveness, and greater transparency may eventually undercut innovation efficiency. Participation in SSOs increases the risk of unintentional knowledge leakage, misappropriation of intellectual property rights (IPRs), and technology lock-in, which could eventually lead to a reduction in a firm's innovation efficiency and private patent value. As firms covered by a large number of analysts are more exposed, relative to their competitors, they may be more likely to experience the substantial drawbacks of participation in SSOs.

In order to disentangle the causes of the relationship, we collect information on firms' participation in technological standardisation from the Searle Centre Database on Technology Standards and Standard Setting Organizations (see Baron and Spulber, 2018) (hereafter SCDB). This database contains comprehensive information on the institutional membership of 183 standards organizations. We use membership data associated with

U.S. firms across several industries over the period 1996 to 2014. We conduct name-matching to link the SCDB data to Compustat *gvkey* of all U.S. listed firms. We manually check the matches by comparing the names provided and postcode information online. Missing firm-year membership data is treated as zero, as we assume that the SCDB database records the names of all members of the 183 SSOs, i.e., firms without a record in a given year are considered to not be participating in any SSO that year. Finally, we create *SSO member*, a binary variable that takes the value of one if the firm participates in at least one SSO in year t , and zero otherwise. In Table 8, we interact this time-varying *SSO member* with *Coverage* and *Coverage_sq* in columns (1) and (2), as well as the instrumented *Coverage* and *Coverage_sq* in columns (3) and (4). As expected, firms with a certain level of analyst coverage benefit from SSO participation and obtain higher patent values and increased innovation efficiency. However, as analyst coverage increases, firms begin to suffer from a decrease in their patent value and level of innovation efficiency. Participation in SSOs makes firms more exposed to their competitors, leading to a further decrease in innovation quality. Figure 2 illustrates the average marginal effect of *Coverage* on patent value (*Ptval*) and innovation efficiency (*Pteff*). The plots relating to SSO member firms have a steeper slope, indicating that participation in SSOs reinforces the curvilinear influence of analyst coverage on firms' patent value and innovation efficiency.

[Insert Table 8 and Figure 2]

5.2 Product market competition

In this section, we further consider product market competition. Firms in competitive markets engage in increased levels of innovation in order to remain competitive (Hou and Robinson, 2006). Aghion et al. (2005) find an inverted-U shape relationship between competition and innovation, using panel data from the UK. Especially for “neck-and-neck” firms, as product market competition increases, they are encouraged to innovate more to retain a leading position among their rivals (Aghion et al., 2005). Under a certain level of analyst coverage, reduced information asymmetries and increased transparency help managers to better calibrate returns on R&D investments and to ensure that the R&D invested is directed to its best use (Yu, 2008; Zhong, 2018). Moreover, firms covered by a certain number of analysts may improve their behaviour and cut wasteful investment or resources relating to innovation, as analysts play the role of external monitors. We,

therefore, expect that firms which have a certain level of analyst coverage and are in a relatively competitive market can obtain a more significant increase in their patent value and level of innovation efficiency, as each unit increase in R&D investment, induced by competition, is more effectively monitored and directed to its best use. However, rapid imitation and catch-up by competitor firms are also more likely to happen in a relatively competitive market. The essence of the inverted-U relationship between competition and innovation is the endogeneity of the fraction of sectors with “neck-and-neck” firms (Aghion et al., 2005). As these firms are encouraged to innovate under competition, the industry will gradually change from the levelled state to the unlevelled one, where the Schumpeterian effect dominates. Hence, we see a downward innovation slope as competition increases further. Due to fierce imitation and successful catch-up by rivals, innovation increases at a much slower rate or even decreases. Although firms become more transparent as analyst coverage increases, they are also more likely to reveal their proprietary strategic information to competitors, resulting in faster imitation by market rivals (Zhong, 2018). Firms which have high analyst coverage and are in a relatively competitive market may face a potential reduction in their innovation value (Bhattacharya and Ritter, 1983). The information leakage also induces a reduction in firms’ competitiveness, which can further undercut innovation efficiency (Zhong, 2018), particularly within a competitive market. We, therefore, expect that firms which have a high level of analyst coverage and are in a relatively competitive market may suffer a greater decrease in their patent value and innovation efficiency.

We apply the measure of product fluidity, developed by Hoberg et al. (2014), to measure market competition.⁴³ Fluidity is based on the product description reported in a firm’s 10-K filings and defined as the similarity between a firm’s product description vocabulary and the change in the use of vocabulary of its rivals in the same industry. Fluidity captures the sensitivity of a firm’s products to the evolution of its rivals’ products, measuring the intensity of product market change around each firm. Firms with a high level of fluidity face a higher intensity of product market competition. To further examine how product market competition may affect the relationship between analyst coverage and firms’ patent value, and between analyst coverage and innovation efficiency, we also utilize the product similarity data created by Hoberg et al. (2014). This measure directly

⁴³ The Hoberg-Phillips Data Library is available at:
<https://hobergphillips.tuck.dartmouth.edu/industryconcen.htm>

captures the total pairwise similarity of the products of a firm. Product fluidity data from Hoberg-Phillips Data Library is available from 1997 to 2017 and similarity data is available from 1996 to 2017. We take product fluidity and similarity data as of year $t-1$ in our specification and further create two binary variables (*High fluidity* and *High similarity*) to conduct our analysis. *High fluidity* takes the value of one if a firm's product fluidity is higher than the industry-year median, and zero otherwise. *High similarity* is set as equal to one if a firm's product similarity is higher than the industry-year median, and otherwise zero. We classify an industry based on the Fama-French 17 industrial classification. In Table 9, we interact these two dummies (*High fluidity* and *High similarity*) with *Coverage* and *Coverage_sq* in columns (1) and (2) as well as the instrumented *Coverage* and *Coverage_sq* in columns (3) and (4) of both panels. The estimation results indicate that the curvilinear relationships between analyst coverage and patent value, and between analyst coverage and innovation efficiency are contingent on a firm's product market competition. In a relatively competitive market, firms can benefit from a certain level of analyst coverage. They are able to produce a higher innovation value and even to innovate more efficiently. However, as analyst coverage increases, firms subjected to relatively strong levels of competition start to experience a decrease in their patent value and level of innovation efficiency. Figure 2 further illustrates the average marginal effect of *Coverage* on *Ptval* and *Pteff*.⁴⁴ The slopes for firms in a relatively competitive industry are slightly steeper than those of firms in our original sample.

[Insert Table 9 and Figure 3]

6 Conclusion

Financial analyst reports have been highlighted by recent literature as an important factor affecting firms' innovation incentives (He and Tian, 2013; Dai et al., 2015; Guo et al., 2019). Financial analysts, being a key ingredient of equity markets, not only produce firm information to the market, but also set external performance benchmarks, such as earnings forecasts, to the firms that they cover. However, existing literature examining the impact of analyst coverage on innovation focuses either on the technological value

⁴⁴ The figures for product similarity are similar to those of product market fluidity. Thus, we refrain from plotting them again here.

of innovation or considers innovative inputs or outputs separately. Traditional measures, such as patents and patent citations, are not ideal for measuring the true value of innovation. It is important to understand the possible control mechanisms that may affect the private economic value of innovation, since it is directly associated with firms' market value and shareholders' interest. In this chapter, we bridge these gaps and study the relationship between analyst coverage and firms' patent value, and between analyst coverage and innovation efficiency. Measuring innovation efficiency inherently requires exploiting the information in both innovative inputs and outputs. Moreover, innovation efficiency in our study is computed using the market patent values as the innovative outputs. It can further represent a firm's ability to generate a one-dollar market value per dollar of R&D investment.

Using the listed U.S. firm data from 1990 to 2015, we find an inverted-U relationship between analyst coverage and firms' patent value, and between analyst coverage and innovation efficiency. Firms can benefit from innovation value gains under a certain level of analyst coverage, as it helps to reduce information asymmetries and restricts managers from conducting wasteful investment. However, high analyst coverage forces firms to become increasingly myopic. Managers overwhelmed by short-term earnings targets set by various analysts can be under too much pressure to engage in value-enhancing innovative activities. This eventually causes a reduction in innovation value (He and Tian, 2013). Additionally, although analyst coverage can largely increase firm transparency, excessive coverage may lead to a significant amount of strategic proprietary information being revealed to competitors. Knowledge leakage destroys a firm's competitive advantages and also a firm's ability to profit from the originality of the innovation, resulting in lower innovation efficiency (Zhong, 2018). Our results are robust towards considerations of the endogenous nature of firms' analyst coverage and other sample compositions and adjustments to variables. Finally, we find that the curvilinear influence of analyst coverage on firms' patent value, and its curvilinear influence on innovation efficiency are contingent on firms' participation in industrial organizations, with regard to innovation and technology (Standard Setting Organizations), and product market competition.

This study has several caveats. First, we focus on the role of financial analysts on the private value of innovation and study how analyst coverage affects shareholders' perceptions on granted innovation. A more holistic analysis might be needed for future research to look at both intrinsic value of innovation and its market-perceived value to

further disentangle the mechanisms through which analyst coverage affects a firm's innovation. Besides, instead of emphasizing the quality of innovation, financial analysts might also influence a firm's innovation search strategy such as the proportion of exploratory patents or highly cited patents. Finally, regarding the measure of patent quality, this chapter employs a recently well-developed measure of patent quality which is based on the market reactions to the announcement of the patent issuance. However, financial analyst might also influence a firm's decision on how much information a patent need to covey. In this case, more pertinent measures of patent quality using linguistic analysis such as the word count and the sophistication of words of patents, can be considered and further applied to studying the relationship between financial analysts and innovation quality. We leave these questions to future work.

Table 1 Variable definitions

Variables	Definitions	Database
Dependent variables		
<i>Ptval</i>	Private economic value of patents following the calculation of Kogan et al. (2017)	Orbis IP and CRSP
<i>Pteff</i>	Ptval over R&D capital, where the R&D capital is defined as the weighted average of R&D expenses over the last five years with an annual depreciation rate of 20% (Chan et al., 2001)	Orbis IP and Compustat
Independent variable		
<i>Coverage</i>	Natural logarithm of one plus the arithmetic mean of the 12 monthly numbers of earning forecasts obtained from financial analysts	I/B/E/S
Control variables		
<i>Size</i>	Natural logarithm of sales (#12)	Compustat
<i>Age</i>	Natural logarithm of the number of years from the beginning year of stocks in CRSP	CRSP
<i>R&DS</i>	R&D expenses (#46) over sales (#12)	Compustat
<i>ADS</i>	Advertising expenses (#45) over sales (#12)	Compustat
<i>Profitability</i>	Operating income before depreciation (#13) divided by book value of total stockholders' equity (#216)	Compustat
<i>Leverage</i>	Book value of debt (#9 + #34) divided by book value of total assets (#6)	Compustat
<i>Capasset</i>	Capital expenditure (#128) divided by book value of total assets (#6)	Compustat
<i>K/L</i>	Total assets (#6) over the number of employees (#29)	Compustat
<i>Cash</i>	Cash (#1) at the end of fiscal year divided by book value of total assets (#6)	Compustat
<i>Tobin's Q</i>	Market value of equity (#199*#25) plus book value of assets (#6) minus book value of equity (#60) minus balance sheet deferred taxes (#74) (replace missing with zero), divided by book value of assets (#6)	Compustat
<i>KZ index</i>	Kaplan and Zingales index calculated as $-1.002 \cdot \text{cash flow} [(\#18 + \#14)/\#8] + 0.283 \cdot \text{Tobin's } Q + 3.139 \cdot \text{leverage} - 39.368 \cdot \text{dividends} [(\#21 + \#19)/\#8] - 1.315 \cdot \text{cash holdings} (\#1/\#8)$, where #8 is lagged	Compustat
<i>Instowner</i>	Average institutional ownership percent for a firm	Thomson Reuter 13F

Table 2 Summary on the full sample

VARIABLES	Mean	Std.D	Std.Dw	25%	50%	75%
<i>Prval</i>	0.096	0.295	0.200	0.000	0.000	0.043
<i>Pteff</i>	0.570	1.597	1.042	0.000	0.000	0.315
<i>Coveragenum</i>	7.400	7.350	3.061	2.000	4.833	10.333
<i>Coverage</i>	1.775	0.853	0.391	1.099	1.764	2.428
<i>Size</i>	5.691	2.236	0.648	4.230	5.647	7.197
<i>Age</i>	2.710	0.772	0.329	2.079	2.639	3.258
<i>R&DS</i>	0.564	2.572	1.572	0.018	0.061	0.161
<i>ADS</i>	0.010	0.028	0.013	0.000	0.000	0.006
<i>Profitability</i>	0.159	0.614	0.481	0.048	0.220	0.363
<i>Leverage</i>	0.173	0.182	0.109	0.005	0.130	0.278
<i>Capasset</i>	0.045	0.039	0.028	0.019	0.034	0.060
<i>K/L</i>	12.483	0.846	0.402	11.878	12.436	13.030
<i>Cash</i>	0.247	0.237	0.108	0.053	0.170	0.380
<i>Tobin'Q</i>	2.340	1.777	1.235	1.261	1.745	2.704
<i>KZ index</i>	-9.061	23.110	15.902	-7.734	-2.574	-0.216
<i>Instowner</i>	0.540	0.281	0.157	0.309	0.567	0.767
Observations	26,926					

Table 3 Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Coverage	1											
(2) Size	0.681*	1										
(3) Age	0.275*	0.536*	1									
(4) R&DS	-0.095*	-0.429*	-0.133*	1								
(5) ADS	0.084*	0.064*	-0.000	-0.021*	1							
(6) Profitability	0.218*	0.406*	0.220*	-0.271*	0.023*	1						
(7) Leverage	0.116*	0.264*	0.163*	-0.040*	0.040*	0.155*	1					
(8) Capasset	0.111*	0.106*	0.006	-0.083*	-0.023*	0.110*	0.045*	1				
(9) K/L	0.277*	0.005	-0.036*	0.220*	0.050*	-0.126*	-0.016*	-0.265*	1			
(10) Cash	-0.106*	-0.529*	-0.355*	0.387*	0.003	-0.327*	-0.341*	-0.233*	0.427*	1		
(11) Tobin'Q	0.040*	-0.257*	-0.190*	0.210*	0.050*	-0.087*	-0.139*	0.037*	0.121*	0.396*	1	
(12) KZ index	0.041*	0.202*	0.090*	-0.151*	-0.057*	0.082*	0.175*	0.223*	-0.323*	-0.424*	-0.185*	1
(13) Instowner	0.547*	0.530*	0.243*	-0.138*	-0.004	0.199*	0.073*	-0.042*	0.253*	-0.095*	-0.062*	0.017*

+ p<0.10, p<0.05

Table 4 Empirical results on the full sample

	Patent market value (<i>Ptval</i>)				Innovation efficiency (<i>Pteff</i>)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Coverage</i>	0.052** (2.272)	0.065*** (3.029)	0.058*** (2.767)	0.060*** (2.914)	0.243** (2.313)	0.289*** (2.908)	0.232** (2.377)	0.238*** (2.581)
<i>Coverage_sq</i>	-0.029*** (-3.332)	-0.020** (-2.526)	-0.021*** (-2.759)	-0.020*** (-2.703)	-0.102*** (-2.588)	-0.091** (-2.443)	-0.091** (-2.465)	-0.086** (-2.522)
<i>Size</i>		-0.059*** (-7.099)	-0.059*** (-7.100)	-0.061*** (-7.309)		-0.212*** (-5.952)	-0.222*** (-6.250)	-0.227*** (-6.217)
<i>Age</i>		0.015 (0.875)	0.027 (1.614)	0.038** (2.076)		0.353*** (3.529)	0.381*** (3.895)	0.379*** (3.647)
<i>R&DS</i>		-0.010*** (-4.502)	-0.010*** (-4.654)	-0.011*** (-4.814)		-0.042*** (-6.266)	-0.044*** (-6.688)	-0.046*** (-6.819)
<i>ADS</i>		-0.180 (-1.050)	-0.160 (-0.949)	-0.176 (-1.051)		0.124 (0.185)	0.152 (0.231)	-0.086 (-0.132)
<i>Profitability</i>		0.006* (1.769)	0.002 (0.519)	0.002 (0.498)		0.055*** (4.260)	0.040*** (3.290)	0.035*** (2.927)
<i>Leverage</i>		-0.035 (-1.362)	-0.018 (-0.724)	-0.019 (-0.774)		-0.256** (-2.429)	-0.188* (-1.800)	-0.204** (-1.980)
<i>Capasset</i>		0.443*** (4.336)	0.344*** (3.522)	0.298*** (3.191)		1.557*** (3.212)	1.181** (2.526)	1.033** (2.350)
<i>K/L</i>		-0.066*** (-6.584)	-0.050*** (-5.080)	-0.054*** (-5.666)		0.010 (0.245)	0.049 (1.097)	0.035 (0.818)
<i>Cash</i>		0.045 (1.551)	0.007 (0.257)	0.013 (0.458)		0.034 (0.304)	-0.116 (-1.035)	-0.085 (-0.799)
<i>Tobin'Q</i>			0.022*** (7.482)	0.022*** (7.367)			0.072*** (6.824)	0.069*** (6.594)
<i>KZ index</i>			0.000** (2.212)	0.000** (2.105)			0.001 (1.263)	0.001 (1.229)
<i>Instowner</i>			0.060*** (2.698)	0.061*** (2.778)			0.434*** (3.967)	0.408*** (3.889)
<i>Constant</i>	0.161*** (11.444)	1.109*** (8.684)	0.857*** (7.066)	0.953*** (6.679)	0.667*** (9.674)	0.661 (1.281)	0.053 (0.098)	0.018 (0.030)
Observations	26,926	26,926	26,926	26,926	26,926	26,926	26,926	26,926
Number of firms	2,674	2,674	2,674	2,674	2,674	2,674	2,674	2,674
R-squared	0.100	0.131	0.149	0.178	0.079	0.090	0.099	0.134
Industry FE	NO	NO	NO	YES	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variables patent value (*Ptval*) in Columns 1 to 4 and innovation efficiency (*Pteff*) in Columns 5 to 8. *Ptval* is measured as the total value of all patents applied (and eventually granted) in year *t* scaled by the lagged assets. *Pteff* is calculated as *Ptval* over R&D capital, while R&D capital is defined as the weighted average of R&D expenses over the last five years with an annual depreciation rate of 20%. *Coverage* is the natural logarithm of one plus the number of analysts. Firm size (*Size*) is the natural logarithm of sales; firm age (*Age*) is measured as the natural logarithm of one plus the number of year from the beginning year of stocks in CRSP; R&D intensity (*R&DS*) is measured as the firm's R&D expenses over sales; *ADS* is measured as advertising expenses scaled by sales; *Profitability* is measured as the return on equity; *Leverage* is calculated as debts over the total assets; *Capasset* is the capital expenditures scaled by the total assets; *K/L* is the assets-to-employees ratios, capturing the potential links between capital-intensity and the innovation performance of firms (Aghion et al., 2013; Almeida et al., 2013); *Cash* is firms' cash scaled by the total assets; *Tobin's Q* measures firm's growth opportunities; *KZ index* measures firms' financial constraint; *Instowner* is the percentage of institutional ownership in a firm each year. In Columns 1-3 and 5-7, we include year and firm fixed effects, while in Columns 4 and 8, industry-year fixed effect is further included. All explanatory variables are measured at time *t*-1. **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

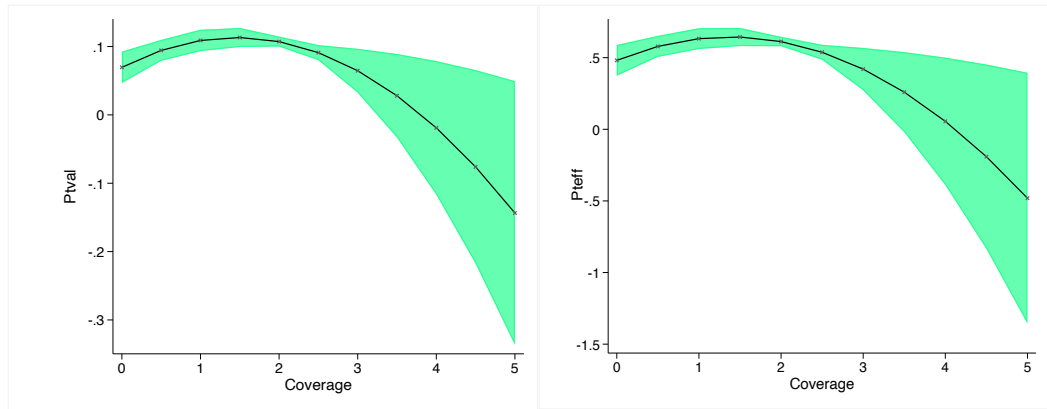


Figure 1. Predictive margins with 95% confidence interval

Table 5 Empirical results on different sample compositions

	Patenting firms		Actively innovative firms		High-tech firms	
	(1) <i>Ptval</i>	(2) <i>Pteff</i>	(3) <i>Ptval</i>	(4) <i>Pteff</i>	(5) <i>Ptval</i>	(6) <i>Pteff</i>
<i>Coverage</i>	0.088*** (2.838)	0.338** (2.412)	0.134*** (2.951)	0.480** (2.419)	0.115*** (2.989)	0.309*** (2.881)
<i>Coverage_sq</i>	-0.031*** (-2.783)	-0.125** (-2.506)	-0.046*** (-2.962)	-0.176*** (-2.638)	-0.041*** (-2.891)	-0.115*** (-2.788)
<i>Size</i>	-0.085*** (-7.235)	-0.322*** (-6.032)	-0.123*** (-7.299)	-0.438*** (-5.790)	-0.072*** (-5.644)	-0.187*** (-5.086)
<i>Age</i>	0.048* (1.949)	0.520*** (3.672)	0.048 (1.401)	0.582*** (3.089)	0.065 (1.621)	0.392*** (2.863)
<i>R&DS</i>	-0.013*** (-5.037)	-0.056*** (-6.757)	-0.019*** (-5.735)	-0.072*** (-6.783)	-0.005*** (-4.538)	-0.015*** (-5.907)
<i>ADS</i>	-0.202 (-0.833)	-0.035 (-0.037)	-0.323 (-0.790)	0.038 (0.024)	-0.262 (-0.968)	-0.352 (-0.481)
<i>Profitability</i>	0.004 (0.854)	0.055*** (3.356)	0.005 (0.688)	0.081*** (3.548)	0.005 (0.795)	0.027* (1.801)
<i>Leverage</i>	-0.020 (-0.590)	-0.256* (-1.729)	-0.014 (-0.295)	-0.283 (-1.370)	-0.039 (-0.923)	-0.144 (-1.297)
<i>Capasset</i>	0.405*** (2.903)	1.205* (1.786)	0.568*** (2.933)	1.441 (1.548)	0.337** (2.025)	1.310*** (2.587)
<i>K/L</i>	-0.080*** (-5.717)	0.030 (0.471)	-0.122*** (-5.763)	0.061 (0.627)	-0.086*** (-5.052)	0.033 (0.671)
<i>Cash</i>	0.011 (0.264)	-0.120 (-0.725)	0.026 (0.407)	-0.086 (-0.352)	0.027 (0.593)	-0.030 (-0.269)
<i>Tobin'Q</i>	0.031*** (7.189)	0.091*** (6.099)	0.045*** (7.423)	0.131*** (6.399)	0.023*** (5.749)	0.054*** (5.402)
<i>KZ index</i>	0.000 (1.637)	0.001 (0.998)	0.001* (1.943)	0.002 (1.530)	0.000 (0.588)	0.000 (0.244)
<i>Instowner</i>	0.091*** (2.870)	0.638*** (4.149)	0.132*** (2.811)	0.920*** (4.097)	0.087** (2.074)	0.313** (2.465)
<i>Constant</i>	1.364*** (7.468)	0.342 (0.401)	1.964*** (7.786)	0.300 (0.236)	1.537*** (6.984)	0.270 (0.406)
Observations	19,389	19,389	14,820	14,820	15,078	15,078
Number of firms	1,586	1,586	1,342	1,342	1,576	1,576
R-squared	0.209	0.162	0.253	0.198	0.188	0.183
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variables patent value (*Ptval*) in Columns 1,3 and 5 and innovation efficiency (*Pteff*) in Columns 2, 4 and 6. Patenting firms is defined as firms that have at least applied one patent during 1990 to 2015. Innovative firms in year t are identified as firms filing at least one patent over the 3-year period from the year $t-2$ to year t from 1990 to 2015. High-tech firms are from industries with 3-digit SIC codes 283, 357, 366, 367, 382, 284 and 737. All models include controls (defined in Table 1), industry, year and firm fixed effects. Explanatory variables are measured at time $t-1$. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6 Empirical results on lag effects

	Two-year ahead		Three-year ahead	
	(1) <i>Ptval</i>	(2) <i>Pteff</i>	(3) <i>Ptval</i>	(4) <i>Pteff</i>
<i>Coverage</i>	0.072*** (3.446)	0.292*** (3.020)	0.063*** (2.907)	0.267*** (2.611)
<i>Coverage_sq</i>	-0.025*** (-3.212)	-0.110*** (-3.054)	-0.024*** (-2.987)	-0.111*** (-2.955)
<i>Size</i>	-0.069*** (-7.628)	-0.282*** (-6.855)	-0.072*** (-7.228)	-0.304*** (-6.611)
<i>Age</i>	0.031* (1.908)	0.374*** (4.108)	0.025* (1.820)	0.335*** (4.419)
<i>R&DS</i>	-0.010*** (-4.835)	-0.051*** (-6.890)	-0.010*** (-4.886)	-0.048*** (-6.347)
<i>ADS</i>	-0.168 (-1.045)	-0.141 (-0.216)	-0.009 (-0.049)	-0.216 (-0.331)
<i>Profitability</i>	0.005 (1.405)	0.041*** (2.985)	0.006* (1.696)	0.057*** (3.683)
<i>Leverage</i>	-0.024 (-0.939)	-0.111 (-0.996)	-0.039 (-1.376)	-0.061 (-0.502)
<i>Capasset</i>	0.327*** (3.517)	0.980** (2.228)	0.254*** (3.118)	0.843** (1.988)
<i>K/L</i>	-0.054*** (-5.471)	-0.018 (-0.393)	-0.049*** (-4.546)	-0.063 (-1.299)
<i>Cash</i>	0.028 (0.968)	-0.046 (-0.397)	0.044 (1.601)	0.032 (0.255)
<i>Tobin'Q</i>	0.005** (2.007)	0.027*** (2.865)	-0.005** (-2.296)	-0.008 (-0.960)
<i>KZ index</i>	0.000* (1.802)	0.001 (0.974)	0.000 (1.146)	0.000 (0.218)
<i>Instowner</i>	0.080*** (3.286)	0.474*** (4.078)	0.096*** (3.624)	0.511*** (4.016)
<i>Constant</i>	1.005*** (6.958)	1.015* (1.722)	0.955*** (6.556)	1.853*** (2.953)
Observations	25,901	25,901	24,798	24,798
Number of firms	2,625	2,625	2,564	2,564
R-squared	0.168	0.138	0.170	0.144
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variables patent value (*Ptval*) in Columns 1 and 3 and innovation efficiency (*Pteff*) in Columns 2 and 4. All models include controls (defined in Table 1), industry, year and firm fixed effects. Explanatory variables are measured at time $t-1$. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7 Empirical results on 2SLS

	First stage		Second stage					
	(1)	(2)	year t+1		year t+2		year t+3	
			(3)	(4)	(5)	(6)	(7)	(8)
	<i>Coverage</i>	<i>Coverage_sq</i>	<i>Ptval</i>	<i>Pteff</i>	<i>Ptval</i>	<i>Pteff</i>	<i>Ptval</i>	<i>Pteff</i>
<i>ExpCoverage</i>	0.804*** (49.167)	0.780*** (14.421)						
<i>ExpCoverage</i>	-0.000 (-0.070)	0.617*** (40.454)						
<i>Coverage</i>			0.412*** (10.840)	1.969*** (11.428)	0.501*** (12.703)	2.509*** (13.172)	0.573*** (13.460)	2.736*** (13.296)
<i>Coverage_sq</i>			-0.118*** (-11.103)	-0.551*** (-11.319)	-0.145*** (-13.209)	-0.717*** (-13.481)	-0.168*** (-14.106)	-0.807*** (-14.195)
<i>Size</i>	0.086*** (17.902)	0.329*** (18.337)	-0.085*** (-10.766)	-0.353*** (-9.529)	-0.086*** (-10.527)	-0.386*** (-9.864)	-0.082*** (-9.409)	-0.345*** (-8.120)
<i>Age</i>	-0.011 (-1.093)	0.358*** (9.503)	0.093*** (6.569)	0.742*** (9.822)	0.086*** (6.397)	0.758*** (11.298)	0.083*** (7.001)	0.695*** (11.913)
<i>R&DS</i>	0.029*** (10.685)	0.100*** (11.011)	-0.026*** (-4.819)	-0.140*** (-9.870)	-0.023*** (-4.997)	-0.129*** (-9.443)	-0.020*** (-4.086)	-0.110*** (-7.012)
<i>ADS</i>	0.073 (0.540)	0.390 (0.760)	-0.230 (-1.233)	0.171 (0.210)	-0.196 (-1.108)	0.156 (0.186)	-0.225 (-1.121)	-0.927 (-0.992)
<i>Profitability</i>	-0.004 (-0.912)	-0.031* (-2.094)	-0.000 (-0.003)	0.045** (2.037)	0.008 (1.401)	0.047* (1.925)	0.002 (0.304)	0.060** (2.336)
<i>Leverage</i>	-0.050** (-3.059)	-0.242*** (-3.975)	-0.025 (-1.012)	-0.338*** (-3.310)	-0.013 (-0.524)	-0.073 (-0.681)	-0.015 (-0.572)	0.019 (0.157)
<i>Capasset</i>	0.435*** (6.195)	1.714*** (6.708)	0.585*** (5.084)	1.874*** (3.533)	0.661*** (5.740)	2.280*** (4.281)	0.607*** (5.537)	2.158*** (3.997)
<i>K/L</i>	0.021*** (3.383)	0.078*** (3.424)	-0.050*** (-5.506)	0.156*** (3.875)	-0.054*** (-5.845)	0.091** (2.158)	-0.054*** (-5.620)	0.016 (0.368)
<i>Cash</i>	0.076*** (4.152)	0.167* (2.543)	-0.007 (-0.238)	-0.272** (-2.459)	0.056** (1.986)	-0.140 (-1.193)	0.088*** (3.002)	0.026 (0.220)
<i>Tobin'Q</i>	-0.005** (-3.258)	-0.007 (-1.227)	0.035*** (10.778)	0.113*** (9.347)	0.012*** (4.114)	0.057*** (5.110)	-0.000 (-0.066)	0.003 (0.267)
<i>KZ index</i>	0.000 (0.618)	0.001 (1.865)	0.001*** (3.714)	0.003*** (4.723)	0.001*** (4.066)	0.004*** (4.974)	0.001** (2.489)	0.003*** (3.062)
<i>Instowner</i>	0.150*** (10.817)	0.437*** (8.634)	0.058*** (3.108)	0.432*** (4.825)	0.083*** (4.227)	0.524*** (5.327)	0.099*** (4.734)	0.581*** (5.466)
Observations	16,163	16,163	16,163	16,163	15,521	15,521	14,847	14,847
Number of firms	1,336	1,336	1,336	1,336	1,287	1,287	1,246	1,246
R-squared	-	-	0.200	0.157	0.180	0.150	0.166	0.146
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variables patent value (Ptval) in Columns 4, 5 and 7 and innovation efficiency (Pteff) in Columns 4, 6 and 8. Expected coverage (ExpCoverage) is the instrumental variable for Coverage. All models include controls (defined in Table 1), industry, year and firm fixed effects. Explanatory variables in Columns 3 and 4 are measured at time t-1; they are measured at time t-2 in Columns 5 and 6 and at time t-3 in Columns 7 and 8. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 8 Empirical results on additional analysis (industrial organization membership)

	Coverage instrumented			
	(1) <i>Ptval</i>	(2) <i>Pteff</i>	(3) <i>Ptval</i>	(4) <i>Pteff</i>
<i>Coverage</i>	0.008 (0.375)	-0.002 (-0.024)	0.240*** (6.110)	1.326*** (7.824)
<i>Coverage_sq</i>	-0.001 (-0.084)	0.016 (0.420)	-0.064*** (-5.716)	-0.342*** (-6.923)
<i>Coverage # SSO member</i>	0.088*** (3.683)	0.431*** (3.749)	0.140*** (6.341)	0.570*** (5.182)
<i>Coverage_sq # SSO member</i>	-0.045*** (-4.249)	-0.246*** (-4.767)	-0.065*** (-7.123)	-0.304*** (-6.770)
<i>Controls</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
Observations	21,550	21,550	13,695	13,695
Number of firms	2,478	2,478	1,329	1,329
R-squared	0.210	0.174	0.232	0.195
Industry FE	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
Year FE	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
Firm FE	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variables patent value (*Ptval*) in Columns 1 and 3, and innovation efficiency (*Pteff*) in Columns 2 and 4. SSO member is a binary variable that takes value one if a firm participates in at least one SSO in year *t*, and otherwise zero. All models include controls (defined in Table 1), industry, year and firm fixed effects. Explanatory variables are measured at time *t*-1. **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

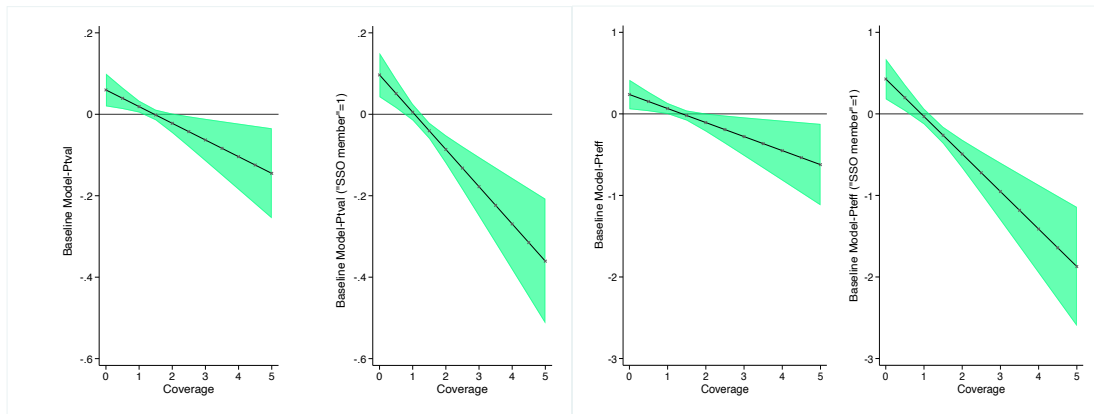


Figure 2 Average marginal effects of coverage with 95% confidence interval (industrial organization membership)

Table 9 Empirical results on additional analysis (product fluidity and similarity)

Panel A: Product fluidity				
	Coverage instrumented			
	(1)	(2)	(3)	(4)
	<i>Ptval</i>	<i>Pteff</i>	<i>Ptval</i>	<i>Pteff</i>
<i>Coverage</i>	0.019 (0.895)	0.144 (1.462)	0.206*** (5.105)	1.151*** (6.445)
<i>Coverage_sq</i>	-0.007 (-0.879)	-0.049 (-1.310)	-0.055*** (-4.915)	-0.310*** (-5.864)
<i>Coverage # High fluidity</i>	0.040*** (3.358)	0.124** (2.231)	0.065*** (5.105)	0.197*** (3.030)
<i>Coverage_sq # High fluidity</i>	-0.017*** (-3.146)	-0.057** (-2.171)	-0.028*** (-5.262)	-0.092*** (-3.232)
<i>Controls</i>	YES	YES	YES	YES
Observations	20,065	20,065	12,851	12,851
Number of firms	2,381	2,381	1,317	1,317
R-squared	0.190	0.144	0.218	0.170
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Panel B: Product similarity				
	(1)	(2)	(3)	(4)
	<i>Ptval</i>	<i>Pteff</i>	<i>Ptval</i>	<i>Pteff</i>
<i>Coverage</i>	0.018 (0.777)	0.074 (0.688)	0.275*** (6.879)	1.613*** (8.605)
<i>Coverage_sq</i>	-0.006 (-0.647)	-0.025 (-0.587)	-0.073*** (-6.638)	-0.443*** (-8.074)
<i>Coverage # High similarity</i>	0.045*** (2.651)	0.215*** (2.813)	0.086*** (5.337)	0.235*** (2.918)
<i>Coverage_sq # High similarity</i>	-0.020*** (-2.616)	-0.092*** (-2.631)	-0.038*** (-5.480)	-0.101*** (-2.914)
<i>Controls</i>	YES	YES	YES	YES
Observations	21,386	21,386	13,590	13,590
Number of firms	2,470	2,470	1,328	1,328
R-squared	0.198	0.155	0.217	0.171
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variables patent value (*Ptval*) in Columns 1, 3, 5 and 7 and innovation efficiency (*Pteff*) in Columns 2, 4, 6 and 8. High fluidity is a binary variable that takes value one if firms' product fluidity is higher than the industry-year median, and otherwise zero. High similarity takes value one if firms' product similarity is higher than the industry-year median, and otherwise zero. All models include controls (defined in Table 1), industry, year and firm fixed effects. Explanatory variables are measured at time $t-1$. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

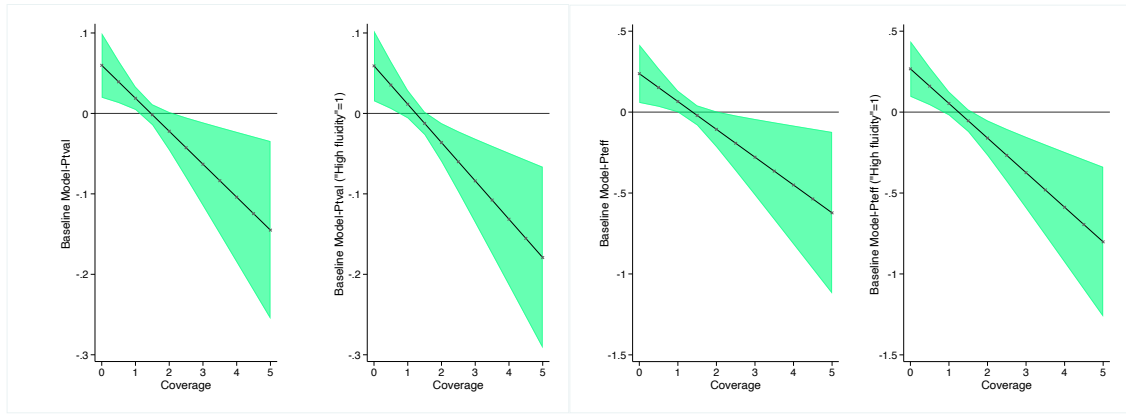


Figure 3 Average marginal effects of coverage with 95% confidence interval (product market competition)

Chapter 3:
**Narrative R&D Disclosure and Investment
Efficiency**

Narrative R&D Disclosure and Investment Efficiency

Abstract

This chapter examines the effects of narrative R&D disclosure on investment efficiency. Using the enactment of the Leahy-Smith America Invents Act of 2011 (AIA) as a quasi-natural shock on narrative R&D disclosure, we provide strong evidence that firms' narrative R&D disclosure improves investment efficiency by reducing underinvestment in innovation-intensive firms. We argue that these firms are able to issue more equity and are less likely to experience financial constraints in financing innovative projects, since narrative R&D disclosure reduces their cost of equity. In addition, we find that the positive effect of R&D disclosure on investment efficiency is more pronounced for firms with greater information asymmetry, poorer financial reporting quality, higher R&D intensity and more volatile cash flows.

Keywords: narrative R&D disclosure; investment efficiency; underinvestment

1 Introduction

Investment efficiency is one of the most fundamental and important factors that determine firm value and investor wealth. Under the conditions of a perfect capital market, optimal investment takes place when firms only finance projects with positive net present value (NPV) and return all surplus cash to their shareholders. However, due to the frictions of the real capital market, such as agency problems, information asymmetries, or other deficiencies relating to a firm's liquidity and financing status, firms may be led to make excessive investments, or, in other cases, insufficient investments. Deviations from the optimal investment level, either by over or under investing, negatively affect shareholders' rights (Biddle et al., 2009). Therefore, it is of pivotal importance in the corporate finance literature to understand the possible factors that may affect firms' investment efficiency.

According to the literature on the determinants of investment efficiency, various control mechanisms have been discussed with the aim of attenuating information asymmetries to enable improved supervision of firms' managerial activities (i.e., financial reporting quality (Biddle et al., 2009), corporate social responsibility (Benlemlih and Bitar, 2018), mandatory risk disclosure (Campbell et al., 2014 and Li et al., 2019)). However, whether firms' voluntary non-financial disclosure on firm-specific information affects their investment efficiency is rarely addressed in the existing literature, except for the recent study by Allman and Won (2021), which focuses on the effect of firms' environmental, social and governance (ESG) disclosure on investment efficiency. This chapter intends to extend this strand of literature on the impact of non-financial disclosure on investment by highlighting the role of firms' R&D-related disclosure. We focus on narrative R&D disclosure for two reasons. On the one hand, R&D is highly firm-specific and is positively associated with information asymmetries and uncertainty (Aboody and Lev, 2000; Chan et al., 2001). Managers have access to inside information, unavailable to the external stakeholders, regarding the specification and progress of a firm's R&D investments. Disclosing more narrative information on R&D investments, in addition to the R&D expenditure provided in financial statements, can help to reduce the level of information asymmetry between firms and investors. In fact, firms are disclosing more R&D information in their 10-K documents, in spite of the risk of knowledge leakage. In Figure 1, we plot the quantity and the percentage of firms' narrative R&D disclosure in their 10-K reports from 1996 to 2018. We can see that firms

disclose more R&D-related information over time, and also that the R&D information disclosed accounts for a larger proportion of the 10-K documents as a whole, despite a slight decrease around the time of the financial crisis in 2008. However, since R&D is a fundamental driver of firms' competitive advantages, there is also a trade-off to be made by management. They must decide how much information to disclose in order to minimize the information asymmetry, but at the same time, there is a need to control the contents and timing of the disclosures to protect proprietary knowledge from competitors.

Merkley (2014) provides novel evidence on the properties of narrative R&D disclosure in firms' 10-K filings and finds that managers increase R&D disclosure, in order to provide more information when a firm's earning performance is poor. The author also highlights that increased R&D disclosure is associated with lower levels of information asymmetry. Firms carry out negative NPV projects (overinvestment), or reject positive NPV projects (underinvestment) due to market imperfections, as well as information asymmetries and agency costs (Gomariz and Ballesta, 2014). Since narrative R&D disclosure reduces information asymmetries, particularly the uncertainty derived from risky R&D investments, we should expect an improvement in firms' investment efficiency. In this chapter, we employ the main measures of narrative R&D disclosure, constructed in Merkley (2014), and intend to strengthen the linkage between firms' voluntary narrative R&D disclosure and investment efficiency.

Using a substantial sample of 48,027 firm-year observations of 6,355 firms from the year 1996 to 2018 in the U.S., we provide strong evidence that firms' narrative R&D disclosure positively affects investment efficiency. Moreover, narrative R&D disclosure is positively related to underinvestment and negatively related to overinvestment. Narrative R&D disclosure reduces the information asymmetry between firms and investors (Merkley, 2014), leading to an improvement in investment efficiency. We find similar results when using R&D investment efficiency as a dependent variable. Our results are also robust to alternative measures of investment efficiency and narrative R&D disclosure. When considering the quality of narrative R&D disclosure, we find that firms with more positive and readable R&D disclosures experience a further increase in their investment efficiency.

To establish causality, we implement a quasi-natural experiment in the difference-in-differences (DiD) framework, by comparing the change in investment efficiency around the time of the enactment of the Leahy-Smith America Invents Act of 2011 (AIA) on March 16, 2013. The AIA can be considered to be the most significant patent law

reform in two generations and has modified the nearly 60-year-old patent system. It shifts the patent system from the first-to-invent (FTI) to first-to-file (FTF). This shift largely reduces managers' incentives to disclose firm-specific information. We find that the investment efficiency of innovation-intensive firms decreases after the enactment, compared to non-innovation-intensive firms. This finding is primarily driven by the negative relationship between narrative R&D disclosure and underinvestment.

We further focus on firms' patenting and external financing activities to examine firms' investment adjustment around the time of the enactment of the AIA. We first find an increase in patent applications immediately after the enactment for innovation-intensive firms. These firms also face diminishing patent quality. When considering firms' financing activities, we find innovation-intensive firms are less likely to issue new equity after the enactment, as the cost of equity increases due to the reduction in the narrative R&D disclosure to the market. The results are consistent when conducting propensity score matching to create treatment and control groups to explicitly control for the unknown differences between innovation-intensive and non-innovation-intensive firms. Finally, we find that the positive relationship between narrative R&D disclosure and investment efficiency is more pronounced for firms with greater information asymmetry, poorer financial reporting quality, higher R&D intensity and increased cash flow volatility.

Our study contributes to the literature in several ways. First, we contribute the literature on the determinants of investment efficiency, by highlighting an important, but neglected, factor – narrative R&D disclosure. The existing literature focuses, in the main, on the effects of financial reporting quality and mandatory risk disclosure on firms' investment efficiency. However, the effect of voluntary disclosure on firm-specific investment information is unexplored. This chapter bridges this gap by focusing on firms' voluntary disclosure on R&D-related information in their 10-K filings and finds that firms' narrative R&D disclosure improves investment efficiency. Second, we contribute to the literature on voluntary R&D disclosure. Due to the difficulties in capturing narrative R&D disclosure, early literature on R&D disclosure is limited to small samples of selected industries and short periods (e.g., Entwistle, 1999; Guo et al., 2004; Jones, 2007; Merkley, 2014). Merkley (2014) provides the first large-scale study of public firms' R&D disclosure and finds that firms modify narrative R&D disclosure according to their earnings performance. Our study further links narrative R&D disclosure to firms' actual

investments and highlights the role of R&D disclosure in determining firms' investment efficiency.

The rest of the chapter is organized as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the data and variable construction, and summarizes the variables employed in the analysis. Section 4 presents our empirical results from the baseline model, alternative measures of investment efficiency and narrative R&D disclosure, as well as presenting an additional analysis on narrative R&D disclosure tones and readability. Section 5 provides our DiD specification and results. Additional analysis on investment adjustment is discussed in Section 6. Section 7 conducts an analysis on possible mechanisms. The final section concludes.

2 Literature review and hypotheses development

2.1 Determinants of investment efficiency

In a perfect capital market, all projects with positive NPV should be financed and carried out. However, due to market imperfections, as well as information asymmetries and agency costs, firms carry out negative NPV projects (overinvestment) or reject positive NPV projects (underinvestment). According to agency theory, both overinvestment and underinvestment can be explained by the existence of asymmetric information among stakeholders (Gomariz and Ballesta, 2014). The asymmetric information affects firms' investment efficiency through information problems, such as moral hazard and adverse selection (Jensen and Meckling, 1976; Myers, 1977; Myers and Majluf, 1984). With regard to moral hazard, overinvestment problems can be a result of managerial empire building and the limited liability of shareholders. A lack of monitoring of managers from the market may lead to unnecessary investments that are used only for the purposes of maximizing personal interest. Under adverse selection, suppliers of capital may ration the capital or raise its costs when they consider themselves to be less informed, which will eventually lead to the rejection of some positive NPV projects, due to funding constraints for some firms (Biddle et al., 2009).

Literature on investment efficiency mainly focuses on the control mechanisms through which the information asymmetries and information risk can be attenuated. Various factors have been highlighted and studied in the extant literature. For example, Biddle et al. (2009) and Chen et al. (2011) identify a positive relationship between firms' financial reporting quality and investment efficiency using an extensive sample of

publicly traded U.S. companies and a sample of private firms from emerging markets, respectively. Benlemlih and Bitar (2018) find that corporate social responsibility is an important factor that positively affects investment efficiency. Campbell et al. (2014) and Li et al. (2019) find that risk disclosure in a firm's annual reports is positively associated with the firm's level of investment efficiency, while Chiu et al. (2019) focus on the impact of customers' risk factor disclosure in 10-K reports on their suppliers' investment efficiency. Durnev and Mangen (2020) further highlight a positive spillover effect of the MD&A disclosure of peer firms (changes in rivals' tone in the MD&A section) on the investment efficiency of the focal firms. Other factors such as earning management (e.g., Shen et al., 2015) and corporate governance (e.g., Chen and Chen, 2012) have also been discussed in the related literature.

2.2 Investment efficiency and narrative R&D disclosure

A line of research has been developed on the positive effects of firms' disclosure level on investment efficiency (e.g., Lai et al., 2014). A higher disclosure level allows investors to more effectively supervise firms' managerial behaviours and reduces the information asymmetries, and consequently, adverse selection and moral hazards, leading to an increase in investment efficiency. Recent studies have focused on firms' risk disclosure in their public documents (e.g., Campbell et al., 2014; Li et al., 2019; Durnev and Mangen, 2020). In this chapter, we focus on firms' disclosure of R&D-related information. An understanding of the role of this information disclosure is of pivotal importance, as R&D is highly firm-specific and is positively associated with information asymmetries and uncertainty. However, at the same time, R&D is the fundamental driver of firms' competitive advantages. In prior studies, Merkley (2014) provides evidence that managers increase R&D disclosure to improve firms' transparency, instead of strategically obfuscating or concealing information when the firm's earning performance is poor. He also finds that narrative R&D disclosure reduces firms' information asymmetry. As information asymmetries are mitigated, we should expect an improvement in firms' investment efficiency. Since R&D is associated with higher uncertainty and risks, disclosure of non-financial information could further assist in reducing information asymmetries (Cui et al., 2018), leading to a further increase in investment efficiency.

Narrative R&D disclosure may help to increase investment efficiency through the mitigation of overinvestment and underinvestment problems, by enabling better supervision by shareholders and by reducing external financing costs. On the one hand, with more investment information being disclosed, outside investors are more capable of tracking firms' managerial investment decisions and to supervise firms' investments more effectively. This helps to alleviate the moral hazard problems. An increased quantity of publicly disclosed information also makes it challenging for managers to make decisions for their own self-interest, further reducing the agency conflicts and leading to an improvement in firms' investment efficiency by mitigating firms' overinvestment. On the other hand, narrative R&D disclosure provides investors with additional information on firms' investment performance, which enables outside investors to better monitor the company and to limit managers' incentives and their ability to overstate a firm's financial performance. As a result, potential investors are less likely to price-protect themselves when purchasing shares. The resulting decrease in financial frictions decreases the cost of financing and helps to mitigate underinvestment problems. Thus, narrative R&D disclosure should be associated with higher investment efficiency. In addition, R&D disclosure should be positively related to underinvestment and negatively associated with overinvestment.

3 Data and methods

3.1 Data

We utilize several data sources to construct our main sample. We start by drawing accounting data from the Compustat-CRSP Merged database covering all the listed firms in the U.S. Firms' 10-K filings are collected from the Software Repository for Accounting and Finance (SRAF), provided by Loughran and McDonald.⁴⁵ Analyst data is collected from the Institutional Brokers' Estimate System (I/B/E/S), while the institutional ownership data is collected from the Thomson-Reuters Institutional Holdings. Quarterly operating cash flow data is collected from Compustat Quarterly. Stock market daily data is collected from CRSP. Finally, our patent data is obtained from Orbis Intellectual Property (Orbis IP).

⁴⁵ The 10-K files from the EDGAR database in SRAF are cleaned and suitable for subsequent textual analysis. More information is provided at: <https://sraf.nd.edu/data/stage-one-10-x-parse-data/>.

3.2 Proxy for investment efficiency

We measure investment efficiency as the deviation from the expected level of investment. According to Biddle et al. (2009), either underinvestment or overinvestment is the inefficiency of investment. Following prior studies (e.g., Biddle et al., 2009; Benlemlih and Bitar, 2018; Chiu et al., 2019; Durnev and Mangen, 2020), we estimate a firm-specific model of investment as a function of growth opportunities, measured as sales growth. The residual is then computed as a firm-specific proxy for deviations from the expected investment modelled in the following equation:

$$INVEST_{i,t+1} = \alpha_0 + \alpha_1 Sales\ Growth_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where $INVEST_{i,t+1}$ is the total investment in year $t + 1$, measured as the sum of R&D expense, capital expenditure, and acquisition expenditure minus cash receipts from the sale of property, plant, and equipment (PPE), all scaled by lagged total assets in year t ; $Sales\ Growth_{i,t}$ is the percentage change in sales from year $t - 1$ to year t . Following Chiu et al. (2019), we set the missing R&D expenditure to the yearly industry average, based on the 4-digit Standard Industrial Classification (SIC) code.⁴⁶ The equation is estimated for each industry-year, based on the Fama and French 48-industry classification for all industries with at least 20 observations in a given year. One of our main measures of investment inefficiency is then the absolute value of residuals estimated from Eq. (1) (Li et al., 2019; Durnev and Mangen, 2020). The absolute value of a residual captures the deviation in the firm's investment from the expected investment, based on sales growth. A lower absolute value of the residual suggests a reduced deviation from the expected investment. Following the prior studies (e.g., Durnev and Mangen, 2020; Rajkovic, 2020), we define investment efficiency (*InvEff*) as minus one times the absolute value of the residual; a high value of *InvEff* indicates higher efficiency. Furthermore, we divide the sample into under and over investment groups, where overinvestment (*OverInv*) is measured by positive residuals, and underinvestment (*UnderInv*), by negative residuals.

Thus far, we follow the literature on investment efficiency and consider both capital expenditures and non-capital expenditures that include R&D and acquisitions. As firms disclose higher levels of R&D-related information, we should also expect this type of disclosure on firm-specific information to have a direct effect on firms' R&D investment

⁴⁶ Our results remain unchanged if we drop the missing R&D expenditures, or replace them with zero.

efficiency. Therefore, we re-estimate residuals from the Eq. (1), where we only consider R&D expenditures on the left-hand side of the equation. $RDInvEff$ is then defined as minus one times the absolute value of the residual, while R&D overinvestment ($RDOverInv$) and R&D underinvestment ($RDUnderInv$) are measured by positive residuals and negative residuals, respectively.

3.3 Measurement of narrative R&D disclosure

We conduct text analysis on the R&D-related disclosure in firms' 10-K filings. To identify R&D-related disclosure, we utilize the word list provided by Merkley (2014), which contains narrative R&D keywords and phrases, such as “research development” and “technology breakthrough”. Our main measure of firms' narrative R&D disclosure ($RDSen$) is the natural logarithm of one plus the total number of sentences that contain at least one R&D-related word or phrase in firms' 10-K filings. For comparison purposes, we compute the total number of sentences in the 10-K reports ($TSent$) as a measure of the overall length of the reports. While the sentence count measures are intuitive and easy to construct, they represent a relatively crude disclosure proxy. Following Merkley (2014), in a later section, we utilize alternative proxies of narrative R&D disclosure capturing important nuances related to numerical and forward-looking R&D disclosure.

3.4 Empirical model

We analyze the effect of firms' narrative R&D disclosure on investment efficiency by estimating the baseline model below:

$$Y_{i,t} = \alpha_0 + \beta RDSen_{i,t-1} + \gamma Controls_{i,t-1} + v_j + \mu_t + \varepsilon_{i,t}, \quad (2)$$

where the dependent variable $Y_{i,t}$ stand for $InvEff$, $OverInv$ or $UnderInv$ in year t . Our variable of interest is the narrative R&D disclosure ($RDSen$) in year $t - 1$. As usual, v_j and μ_t stand for industry and time-specific effects, respectively, while $\varepsilon_{i,t}$ is the error term. We also conduct the analysis on R&D investment efficiency, where the dependent variables are $RDInvEff$, $RDOverInv$ and $RDUnderInv$.

In line with previous studies (e.g., Biddle et al., 2009; Chiu et al., 2019), $Controls_{i,t-1}$ is a set of variables known to influence firms' investment decisions, which

help mitigate correlated omitted variable concerns and to better isolate the association between narrative R&D disclosure and investment efficiency. Specifically, following Biddle et al. (2009) and Cheng et al. (2013), we first control for two variables that capture corporate governance mechanisms, namely, the percentage of a firm's shares held by institutional investment (*Instowner*) and the number of analysts following the firm (*Analyst*). Analyst coverage may affect a firm's investment behaviours by serving as a monitoring mechanism for management (Bae et al., 2017). Apart from firm size (*Size*) and age (*Age*), we also include the market to book ratio (*MB*) to control for firm growth opportunities (e.g., Baker et al., 2003). *StdCfo*, *StdSale* and *StdInvest* are cash flow-, sales- and investment- volatility included in our empirical model to control for business uncertainty, which might distort a firm's investment efficiency (e.g., Minton and Schrand, 1999; Liu and Wysocki, 2017). We further include *CfoSale* measured as operating cash flows relative to sales and *Slack* as the ratio of cash slack over PPE to control for liquidity. Inadequate liquidity constraints a firm's ability to undertake profitable investments. However, excess liquidity induces a firm to undertake wasteful and high-risk projects (Rajkovic, 2020). Dividend payout (*Dividend*), Altman's Z score (*Zscore*), leverage (*Leverage*), industry leverage (*Leverage_Ind*) and asset tangibility (*Tangibility*) are also included in our model to control for a firm's financial conditions and borrowing capability, since investment efficiency could decrease when fundraising is difficult and when internal resources are less available to finance new and profitable projects (Rajkovic, 2020). Besides, as operational cycles could also shape a firm's investment decision, following prior literature (e.g., Biddle et al., 2009), we also control for operating cycle (*OpCycle*), and loss (*Loss*). Finally, we include the length of the 10-K reports (*Tsent*) to further isolate the effect of narrative R&D disclosure on investment efficiency.⁴⁷ Detailed definitions of each variable are provided in Table 1.

[Insert Table 1]

3.5 Descriptive statistics

⁴⁷ We obtain similar results when we control additionally for the total number of words and the readability of the 10-K documents.

Our final sample consists of an unbalanced panel of more than forty-eight thousand observations of over six thousand firms for the period 1997-2019. To mitigate the effect of outliers, we winsorize all continuous firm-level variables at the 1st and 99th percentile.

Table 2 presents a summary of the main variables used in the empirical analysis. The mean value of investment efficiency in our sample is around -0.122, with a median of -0.083, while the mean (median) of R&D investment efficiency is -0.082 (-0.047). On average, firms in our sample have around 1,623 sentences per 10-K document (*Total_Sen*) and over 18 sentences that contain R&D-related words or phrases (*Total_RDSen*). Our sample firms possess significant growth opportunities, as indicated by the average market to book ratio (*MB*) of 2.06. Furthermore, around 34% of our sample firms experience a loss in their earnings in the preceding fiscal year (year *t-1*). Overall, the descriptive statistics for the sample firms are similar to those reported by previous research (e.g., Biddle et al., 2009; Gomariz and Ballesta, 2014; Benlemlih and Bitar, 2018).

Table 3 ranks the top 10 industries, based on the Fama and French 48 classification of industries by narrative R&D disclosure quantity. The industries included in this table are mainly technology and medical industries. Pharmaceutical firms provide the greatest quantity of R&D disclosure in their 10-K filings, followed by firms in the Medical Equipment industry. The overall list and ranking are similar to that created by Merkley (2014).

Finally, in Table 4, we examine the association between narrative R&D disclosure and investment efficiency, as well as R&D investment efficiency in a univariate setting. We classify a firm with high narrative R&D disclosure, if the average quantity of R&D disclosure of the firm is above the industry median, based on the Fama and French 48 classification. With reference to Table 4, the investment efficiency of firms in the high R&D disclosure group is, on average, approximately 30.19% higher than that of firms with low R&D disclosure, and the underinvestment (overinvestment) measure is 21.84% (52.24%).⁴⁸ In relation to R&D investment efficiency, firms with a high level of R&D disclosure gain, on average, an approximately 37.68% higher efficiency, compared to those with low levels of R&D disclosure.

[Insert Table 2, Table 3 and Table 4]

⁴⁸ $(-0.138 - (-0.106)) / (-0.106) = 0.3019$; $(-0.106 - (-0.087)) / (-0.087) = 0.2184$; $(0.204 - 0.134) / 0.134 = 0.5224$

4 Estimation results

4.1 Baseline models

Table 5 presents our baseline results. All models are estimated using the pooled time-series cross-sectional regression OLS, where the industry fixed effects are included, based on the Fama and French 48 industry classification and the standard errors are clustered at the firm and year level. In columns (1) and (2), the dependent variable is *InvEff*, measured as minus one times the absolute value of the residuals estimated from Eq. (1). In columns (3) and (4), the dependent variable is *UnderInv*, measured as the negative values of the estimated residuals, while in columns (5) and (6), it is *OverInv*, measured as the positive values of the residuals. The results from three parsimonious models in columns (1), (3) and (5) suggest that firms' narrative R&D disclosure is positively associated with investment efficiency and underinvestment, and negatively associated with overinvestment. In columns (2), (4) and (6), we further include all of the aforementioned control variables. The coefficient β across three models remains significant, despite being of smaller magnitudes. One percent increase in narrative R&D disclosure will result in an increase in investment efficiency by 0.14% standard deviation. Finally, the coefficients on the control variables are mostly in line with those reported in the prior studies (e.g., Biddle et al., 2009; Gomariz and Ballesta, 2014; Bae et al., 2017; Rajkovic, 2020). The coefficients are significantly positive for institutional ownership (*Instowner*), analyst coverage (*Analyst*), firm size (*Size*), Altman's Z score (*Zscore*), tangibility (*Tangibility*), leverage (*Leverage*), operating cycle (*OpCycle*) and loss (*Loss*), and significantly negative for market to book ratio (*MB*), investment volatility (*StdInvest*) and firm age (*Age*). We further conduct the analysis for R&D investment efficiency. The results are given in Table 6. Across columns, we find consistent results demonstrating that firms' narrative R&D disclosure is positively associated with investment efficiency and underinvestment in terms of R&D, and negatively associated with R&D overinvestment.⁴⁹

[Insert Table 5 and Table 6]

4.2 Alternative measures of investment efficiency

⁴⁹ We also run the fixed effect model for both investment efficiency and R&D investment efficiency. The results are presented in Table A1 in the Appendix. Our results remain unchanged.

In this section, we implement three alternative estimation models of investment efficiency as a robustness check. We first follow Chen et al. (2011), as the relationship between investment and revenue growth can differ between revenue decreases and revenue increases (e.g., Eberly, 1997; McNichols and Stubben, 2008; Chen et al., 2011). Chen et al. (2011) modify Biddle et al.'s (2009) model and allow for differential predictability for revenue decreases and revenue increases, by employing the following piecewise linear regression model:

$$INVEST_{i,t+1} = \alpha_0 + \alpha_1 Sales\ Growth_{i,t} + \alpha_2 NEG_{i,t} + \alpha_3 NEG_{i,t} * Sales\ Growth_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where $INVEST_{i,t+1}$ and $Sales\ Growth_{i,t}$ are calculated in the same way as is defined in Eq. (1); $NEG_{i,t}$ is the indicator variable, that takes the value of one for negative revenue growth, and zero otherwise. The equation is estimated for each industry-year, based on the Fama and French 48-industry classification for all industries with at least 20 observations in a given year. As in Section 4.1, we define investment efficiency as minus one times the absolute value of the residual estimated from this model, underinvestment as negative residuals, and overinvestment as positive residuals. The results are presented in columns (1)-(3) in Panel A of Table 7. For parsimony, we report only the coefficients of interest. The results provide robust evidence that firms' narrative R&D disclosure is positively associated with investment efficiency.

We further follow McNichols and Stubben (2008) and Bae et al. (2017) to estimate the investment efficiency from the following model:

$$INVEST_{i,t+1} = \alpha_0 + \alpha_1 Q_{i,t} Quartile2_{i,t} + \alpha_2 Q_{i,t} Quartile3_{i,t} + \alpha_3 Q_{i,t} Quartile4_{i,t} + \alpha_4 CF_{i,t} + \alpha_5 Growth_{i,t} + \alpha_6 INVEST_{i,t} + \varepsilon_{i,t}, \quad (4)$$

where $INVEST_{i,t+1}$ is the investment level as defined in Eq. (1). Q is Tobin's Q , while CF is cash flows, as calculated in McNichols and Stubben (2008); $Growth$ is the natural logarithm of total assets at the end of year $t - 1$, divided by total assets at the end of year $t - 2$. $Quartile2$, $Quartile3$ and $Quartile4$ are binary variables that take the value of one, if Q is in the second, third and fourth quartiles of its industry-year distribution (Fama and French 48-industry classification), and zero otherwise. Compared to the prior two models, this model further allows for the effects of asset growth, past investment, variation in the relationship between investment and Tobin's Q and prior-year investment.

We compute the firm-specific residuals by estimating the model separately for each industry and year. Columns (1)-(3) in Panel B provide the results for investment efficiency, underinvestment and overinvestment, respectively. We continue to find a positive relationship between narrative R&D disclosure and investment efficiency.

Finally, following Ward et al. (2020) and others (e.g., Li et al., 2019), we apply the model developed by Ricardson (2006) to estimate investment efficiency:

$$INVEST_{i,t+1} = \alpha_0 + \alpha_1 Growth_{i,t} + \alpha_2 Lev_{i,t} + \alpha_3 Cash_{i,t} + \alpha_4 Age_{i,t} + \alpha_5 Size_{i,t} + \alpha_6 Return_{i,t} + \alpha_7 INVEST_{i,t} + \varepsilon_{i,t}. \quad (5)$$

The model not only takes into account firms' growth opportunities, but also any financial constraints measured by leverage (*Lev*) and cash (*Cash*) and other firm characteristics measured by firm age (*Age*), the natural logarithm of firm total assets (*Size*), cumulative stock returns over the previous year (*Return*) and the lag of new investment (*INVEST*). We compute the firm-specific residuals by estimating the model separately for each industry and year. The results are presented in columns (1)-(3) in Panel C, where we still find robust evidence that firms' narrative R&D disclosure is positively associated with investment efficiency. We also conduct these analyses in columns (4)-(6) in Panel A, B and C on R&D investment efficiency. Our results remain unchanged.

[Insert Table 7]

4.3 Alternative measures of narrative R&D disclosure

Following Merkley (2014), we further implement two alternative measures of firms' narrative R&D disclosure: *RDNumSen* and *RDFwdSen*. *RDNumSen* is the natural logarithm of one plus the total amount of numerical narrative R&D disclosure. We treat an R&D sentence as numerical if it contains numerical information that is not in the form of a date, such as 31, Jan. *RDFwdSen* is the natural logarithm of one plus the total number of forward-looking narrative R&D disclosure. We consider a sentence as forward-looking if it contains "will", "could", "should", "expect", "anticipate", "plan", "hope", "believe", "can", "may", "might", "intend", "project", "forecast", "objective" or "goal". As presented in columns (1) in both Panels A and B of Table 8, the result that narrative R&D disclosure is positively associated with investment efficiency holds across different measures of R&D disclosure. For the two scenarios of investment inefficiency, the

coefficient estimates of *RDNumSen* and *RDFwdSen* remain significantly positive in underinvestment models in column (2) and significantly negative in column (3) in both panels. We further conduct this analysis on R&D investment efficiency in columns (4)-(6) and find similar results.

[Insert Table 8]

4.4 Tones and readability of narrative R&D disclosure

In this section, we further take into account the quality of firms' narrative R&D disclosure. The quality of disclosure may directly affect shareholders' perceptions of the disclosed information. For example, Rjiba et al. (2021) point out that complex textual reporting detracts from an investor's ability to process and interpret the reports, leading to higher costs of equity financing. Ertugrul et al. (2017) also finds that more complex reports and the use of an ambiguous tone both increase firms' borrowing costs. Despite the fact that firms may disclose information strategically, the market is still more confident about firms with more positive and readable reports. Tones and readability per se also convey certain information to the market about firm performance and managers' future expectations. Therefore, similar to Merkley (2014), we first measure the tone of each R&D disclosure sentence based on the frequency of positive and negative words using the word lists from Loughran and McDonald (2011).⁵⁰ The overall narrative R&D disclosure tone for each 10-K document is then measured as the number of positive sentences, less the number of negative sentences. We further construct a binary variable *Ptone*, that takes the value of one if a 10-K document contains more positive R&D sentences, and zero otherwise. To understand whether firms with more positive R&D disclosure can more significantly benefit from investment efficiency improvement, we interact *Ptone* dummy with our *RDSen*. The results are presented in columns (1) and (2) of Table 9 for both overall investment efficiency and R&D investment efficiency. We find that firms with more positive R&D disclosures benefit from a more significant increase in their level of investment efficiency.

Besides the affect which the tones of disclosure might have on how outside investors perceive the firm-specific information disclosed in the report, the readability of the R&D

⁵⁰ The word list can be found in Software Repository for Accounting and Finance (SRAF) and can be downloaded from the following link:
<https://sraf.nd.edu/textual-analysis/resources/#LM%20Sentiment%20Word%20Lists>.

information could also affect the way that the information is conveyed to the market. Therefore, following Merkley (2014), we measure the readability of narrative R&D disclosure using the Fog index, which is a readability measure, widely used in the related literature (e.g., Li, 2008).⁵¹ The less readable the text, the higher the index. By interacting the *Fog index* with *RDSen* in columns (3) and (4), we find evidence that firms with more readable narrative R&D disclosure benefit from increased investment efficiency.

[Insert Table 9]

5 Identification strategy

5.1 DiD specification

We have used a linear regression analysis to establish the correlation between firms' narrative R&D disclosure and investment efficiency. To the extent that firms with higher investment efficiency might be able, and more confident, to disclose information related to their R&D investments, our results may suffer from an endogeneity bias, arising from reverse causality. Our analysis has dealt with this by including narrative R&D disclosure in year $t-1$. In this section, we further address endogeneity concerns by employing a quasi-natural experiment in the difference-in-differences (DiD) framework.

The external policy shock comes from the enactment of the Leahy-Smith America Invents Act of 2011 (AIA) in 2013. The main change of the AIA is the shift from the first-to-invent (FTI) patent system to the first-to-file (FTF) system for all patent applications, filed on or after March 16, 2013. Under the original FTI system, patents were granted to the “first and true” inventors. However, under the new FTF system, patents are granted based on the filing date. Huang et al. (2020) find that the enactment of the AIA is associated with a greater decline in narrative R&D disclosure of innovation-intensive firms, relative to non-innovation-intensive firms. He points out that this shift in the patent system largely reduces the managers' incentives to disclose R&D-related information; this is because any revelations of IP-related information, before a firm is officially granted a patent, can accelerate the pace at which its competitors make similar patent applications. Moreover, the elimination of the requirement for “best mode” disclosure in the new patent system allows firms to disclose less innovation-related information. Firms are no longer required to disclose crucial information about the most

⁵¹ The Fog index is computed as: $0.4 * [(words/sentences) + 100 * (complex\ words/words)]$.

valuable and commercial form of the inventions, such as detailed invention description. Innovation-intensive firms are more likely to react to this change by also including less information regarding their commercialization of the innovation in the public corporate disclosure (Huang et al., 2020).

We implement the DiD approach by comparing the change in investment efficiency around the time of the enactment of the Leahy-Smith America Invents Act of 2011 (AIA) on March 16, 2013 of innovation-intensive firms (treatment firms) to the change in investment efficiency of non-innovation-intensive firms (control firms) using the following specification:

$$Y_{i,t} = \alpha_0 + \beta Treated_i \times Post_t + \beta_1 Treated_i + \beta_2 Post_t + \gamma Controls_{i,t-1} + v_j + \mu_t + \varepsilon_{i,t}, \quad (6)$$

where $Y_{i,t}$ equals *InvEff*, *OverInv* or *UnderInv* taken from year t ; $Post_t$ is an indicator variable that equals one for fiscal years subsequent to the enactment of the AIA in March 2013, and zero otherwise; $Treated_i$ is an indicator variable for innovation-intensive firms affected by the AIA; $Controls_{i,t-1}$ is a vector of time-varying control variables described in Section 3.4; $\varepsilon_{i,t}$ is the error term, while v_j and μ_t stand for industry and time specific effects, respectively. Following Huang et al. (2020), we include data for up to three years after (i.e., 2014, 2015 and 2016) and before (i.e., 2010, 2011 and 2012) the enactment of the AIA. We require each firm to have at least one valid observation in both the pre- and post-AIA periods. Similar to Huang et al. (2020), we follow Gao and Chou (2015) and code $Treated_i$ as one for firms that file at least one patent over the three-year period from the year $t-2$ to year t , and zero otherwise. This identification highlights the active innovation-intensive firms that can be affected by the enactment.

5.2 DiD results

The primary coefficient of interest in Eq. (6) is β on the interaction term ($Treated_i \times Post_t$), which measures the average change in investment efficiency of active innovation-intensive firms, relative to the average change of non-innovation-intensive firms. β captures the DiD estimate of the impact of the enactment of the AIA on investment efficiency. Table 10 provides formal evidence by presenting the estimates

of Eq. (6), where the standard errors are clustered by firm and year level.⁵² In Panel A, we focus on overall investment efficiency, while in Panel B, we consider R&D-related investment efficiency. Columns (1), (3) and (5) of both panels are estimated without any controls. Columns (2), (4) and (6) of both panels present the results of the full specification with all of our control variables. In columns (1) and (2), the dependent variable is investment efficiency (*InvEff*), measured as minus one times the absolute value of the residuals estimated from Eq. (1). The coefficient on the main variable of interest, $Treated_i \times Post_t$, is negative and significant at the 1% confidence level, suggesting that innovation-intensive firms, affected by the enactment of the AIA, experience a deterioration in their investment efficiency. In columns (3)-(6), we present the DiD estimates for underinvestment and overinvestment. The results further suggest that the negative relationship between narrative R&D disclosure and investment efficiency is primarily driven by the negative association between R&D disclosure and underinvestment, indicating that the increase in external financing costs is the main channel through which R&D disclosure affects investment efficiency. The enactment of the AIA reduces the amount of R&D-related information disclosed by firms, leading to higher information asymmetries between investors and firms. As R&D investments are relatively risky and uncertain, with less information, shareholders are unable to supervise the investments and track firms' managerial decisions. As a result, potential investors choose to price protect themselves when purchasing shares. This increase in external financing costs makes firms forgo profitable projects, further leading to underinvestment problems.

[Insert Table 10]

5.3 Propensity score matching method

We further examine the robustness of our main results using the propensity score matching (PSM) method to explicitly control for the unknown differences between our

⁵² To further account for unobserved and time-invariant firm-level heterogeneity, we also employ the FE model, based on the following specification to obtain the DiD estimate of the impact of the enactment:

$$Y_{i,t} = \alpha_0 + \beta Treated_i \times Post_t + \gamma Controls_{i,t-1} + \nu_j + \mu_t + \varepsilon_{i,t}, \quad (6a)$$

where $Y_{i,t}$ are investment efficiency (*InvEff*) and R&D investment efficiency (*RDInvEff*). The main effects of *Post* and *Treated* are not included in the equation, as they are subsumed by time and firm fixed effects, respectively. The results are presented in columns (1) and (2) of Table A3 in the Appendix. Our results remain unchanged.

treated firms (innovation-intensive firms) and control firms (non-innovation-intensive firms). The PSM approach helps to alleviate the concerns that our active innovative firms and non-innovation-intensive firms are not randomly conferred by constructing a control group with similar firm characteristics. Following He and Tian (2013) and Huang et al. (2020), we estimate the following logistic regression model on $Treated_{it}$, that takes the value of one for firms that file at least one patent over the three-year period from the year $t-2$ to year t , and zero otherwise:

$$\begin{aligned} Treated_{it} = & \beta_1 Analyst_{it} + \beta_2 Size_{it} + \beta_3 RDS_{it} + \beta_4 Age_{it} + \beta_5 ROA_{it} + \\ & + \beta_6 Tangibility_{it} + \beta_7 Leverage_{it} + \beta_8 Capx_{it} + \beta_9 TobinQ_{it} + \beta_{10} KZ_{it} + \\ & \beta_{11} HHI_{it} + \beta_{12} HHI2_{it} + \beta_{13} Instowner_{it} + \beta_{14} Illiquid_{it} + v_j + \mu_t + \varepsilon_{it}, \end{aligned} \quad (7)$$

where *Analyst*, *Size*, *Age*, *Tangibility*, *Leverage* and *Instowner* are measured as in Section 3.4. We further control for firms' R&D intensity (*RDS*), *ROA*, capital expenditure (*Capx*), Tobin's Q (*TobinQ*), Kaplan and Zingale index (*KZ*), Herfindahl index based on four-digit standard industrial classification (SIC) (*HHI*), squared term of Herfindahl index (*HHI2*) and illiquidity (*Illiquid*) in Eq. (7). Detailed definitions of each variable are given in Table 1. v_j and μ_t are industry (Fama and French 48 industry classification) and year fixed effects. We match each innovative firm to a control firm in the event year with replacement and a caliper of 0.0001. We also check the covariate balance between the control and treatment groups in pre- and post- match, and find that all mean differences between the two groups are statistically insignificant. The results are presented in Table A2 in the Appendix. Finally, we re-estimate the Eq. (6) using the PSM sample. The results are reported in Table 11 for investment efficiency in Panel A and R&D investment efficiency in Panel B. Overall, the results are consistent with the baseline test on the original sample in Table 10.^{53,54}

[Insert Table 11]

5.4 Trend analysis

⁵³ We also conduct the analysis using the FE model on the matched sample for investment efficiency (*InvEff*) and R&D investment efficiency (*RDInvEff*). The results are similar and presented in columns (3) and (4) of Table A3 in the Appendix.

⁵⁴ In a robustness check, we perform matching on a restricted set of variables and specify Eq. (7) as in Huang et al. (2020) : $Treated_{it} = \beta_1 Size_{it} + \beta_2 RDS_{it} + \beta_3 Age_{it} + \beta_4 ROA_{it} + \beta_5 Tangibility_{it} + \beta_6 Leverage_{it} + \beta_7 Capx_{it} + \beta_8 TobinQ_{it} + v_j + \mu_t + \varepsilon_{it}$. Our results remain unaffected.

The efficacy of the DiD approach in producing causal estimates relies on the assumption of parallel trends between treatment and control groups in the absence of the regulatory shock. To explore the timing of the changes in investment efficiency around the time of the enactment of the AIA, we first test the parallel trends assumption in the DiD design. Furthermore, we examine the persistence of the investment efficiency deterioration after the enactment. Parallel assumption states that, in the absence of the treatment shock, treated and control firms should exhibit parallel movements in their investment efficiency. To test this assumption, following the approach employed in prior studies (e.g., Huang et al. 2020), we augment our specification in Eq. (6) with three additional terms for indicator variables two years prior and during the enactment (*Time T-2*, *Time T-1* and *Time T*). The results are reported in Table 12. In columns (1)-(2), the dependent variable is investment efficiency (*InvEff*), while *UnderInv* in columns (3)-(4) and *OverInv* in columns (5)-(6). Results in column (1) show that none of $Treated \times Time\ T - 2$, $Treated \times Time\ T - 1$ and $Treated \times Time\ T$ are statistically significant, suggesting that innovation-intensive firms and non-innovation-intensive firms follow parallel trends, prior to the enactment of the AIA. We find similar results for underinvestment firms (column (3)).

To explore the persistence of the decline in investment efficiency following the enactment, we substitute the $Treated \times Post$ term with interaction terms for each of the three years after the regulation. The results in column (2) of Table 12 suggest that the decline the investment efficiency is persistent over time from the second year of the enactment, indicating a gradual adjustment of firms' investment activities after the shift to reduced disclosures. We find similar patterns for underinvesting firms in column (4). In columns (7)-(12), we conduct the analysis on R&D investment efficiency, where we continue to find evidence of the negative and lag effect of the enactment of the AIA on investment efficiency and underinvestment. Firms reduce narrative R&D disclosure from 2013 onwards. They then begin to experience higher information asymmetries and increased external financing costs. The cumulative increases in financing costs force firms to forgo positive NPV projects in later years (i.e., 2015, 2016).

We further illustrate our findings in Figure 2, by plotting the coefficients estimated in Table 12. From the figure, we can observe a clear decline in investment efficiency and underinvestment after the enactment of the AIA for both types of investment efficiency in Panels A and B. In Panel C, the enactment does increase the overinvestment, but the

effect is not statistically significant. Finally, we conduct the same analysis on the matched sample constructed in Section 5.3. The results are presented in Table 13 and illustrated in Figure 3. We find similar results and declining patterns for investment efficiency and underinvestment after the enactment.

[Insert Table 12 and Figure 2]

[Insert Table 13 and Figure 3]

6 Additional analysis on investment adjustment

6.1 Patenting activities

In this section, we study firms' patenting activities after the enactment of the AIA. Under the new act, the two choices remaining for inventors are to either file a patent before their idea is perfected, or to hope that no one discloses their idea before the completion of the inventions (Case, 2013). Firms disclose less valuable innovation-related information to prevent their competitors from filing patents using the revealed knowledge before them. However, at the same time, as a compensation, firms may file more patents to gain signalling benefits. They are also more likely to file more patents to protect themselves from any possible leakage of proprietary knowledge to avoid being undershot by other inventors with similar ideas. However, the quality of patents may be negatively affected by the new system, as firms are forced to file unperfected inventions in their haste to either protect their proprietary knowledge, or signal their innovations to provide additional information to the market as public R&D disclosure decreases.

To test our hypotheses, we follow the estimation model of Eq. (6), where $Y_{i,t}$ equals patent applications ($PtApp$) and patent value ($PtVal$). We measure patent applications ($PtApp$) as the natural logarithm of one plus the total number of patents applied for in year t , while the patent quality is computed using the measure designed by Kogan et al. (2017). This recently developed method evaluates patents through market reactions to patent grants.⁵⁵ Following Almeida et al. (2021), the private economic value of patents ($PtVal$) is calculated as the sum of the market value of all patents applied for in the same

⁵⁵ Forward citations are widely used as a measure of the quality of innovation output. However, they cannot reflect the real market value of inventions and are subject to truncation bias, as it takes time for a patent to receive citations. Citations can also vary significantly across different technology classes and years (Almeida et al., 2021). Therefore, in this chapter, we focus on the measure developed by Kogan et al. (2017) to measure the market value of firms' innovation output. Our results are robust if we use forward citations to measure patent quality.

year for each firm, scaled by the lagged assets. The results given in Table 14 suggest that innovation-intensive firms file more patents after the enactment of the AIA, as we expected, while the quality of patents deteriorates after the enactment, as shown in columns (5)-(8). The results are in line with the fact that there is diminishing patent quality and a surging increase in patent applications after the AIA documented by United States Patent and Trademark Office (USPTO). We further conduct trend analysis to better understand the timing of the changes in firms' patent applications and quality around the time of the enactment of the AIA. In columns (1)-(4) of Table 15, we find an immediate effect of the enactment on patent applications, as the coefficient of *Treated*Time T* loads significantly positive across samples. The results in columns (5)-(8) further suggest that the quality of patents diminishes from 2015 onwards, due to the fact that it usually takes two to three years for a patent to be finally granted.⁵⁶

[Insert Table 14 and Table 15]

6.2 External financing activities

In this analysis, we further investigate whether the enactment of the AIA affects firms' cost of equity and their sources of financing. We begin by looking at the association between narrative R&D disclosure and firms' cost of equity and two external financing measures. The cost of equity (*CoE*) is measured using the bid-ask spread, which is obtained as the annual median of monthly quoted spreads⁵⁷. We focus on two external financing activities in this analysis, which are equity issuance and debt issuance. Following Bakers et al. (2013), we measure new equity issuance (*NEquity*) as the ratio of external equity issues to the book assets at the beginning of the year, where the external equity issues are constructed as the change in book equity, minus the change in firms' retained earnings. New debt issuance (*NDebts*) is measured as debt issues over the start-of-year book assets, where the debt issues are the change in assets, minus the change in book equity. In column (1) of Table 16, we find that narrative R&D disclosure is negatively associated with firms' cost of equity. The result is in line with that of Huang et al. (2020). Narrative R&D disclosure reduces information asymmetries by providing more information on firm-specific investment to the market. Moreover, in columns (4)

⁵⁶ We also conduct the analysis in this section using the FE model and find similar results.

⁵⁷ We further follow Lang et al. (2012) to use the annual median of daily quoted spreads to obtain the bid-ask spread. Our results remain unaffected.

and (7), we find that firms with higher narrative R&D disclosure will issue more equity, but fewer debts. On the one hand, equity is preferable to debts in R&D investment for firms with higher narrative R&D disclosure. The uncertainty of R&D projects and the difficulties in quantifying intangible capitals as collateral make debt financing less attractive (Stiglitz, 1985; Hall and Lerner, 2010; Acharya and Xu, 2017). On the other hand, as the cost of accessing equity is reduced with R&D disclosure, firms become more willing to issue equity to finance their innovative projects, than they are debts.

To further identify the effect of the enactment of the AIA on firms' cost of equity and two external financing activities, we again follow the estimation model of Eq. (6), where $Y_{i,t}$ equals cost of equity (*CoE*), new equity issuance (*NEquity*) and new debt issuance (*NDebts*). The results given in Table 16 suggest that innovation-intensive firms encounter a higher cost of equity after the enactment of the AIA and issue less equity. We cannot find any significant effect of the policy change on firms' new debt issuance. Our previous results suggested that the enactment of the AIA reduces firms' incentives to disclose R&D-related information, which leads to more severe underinvestment problems due to the increased information asymmetries. Here, our results support this argument, and we find that firms reduce equity issuance after the shock. In this case, firms are more likely to experience financial constraints and have less money available to undertake any profitable project. Therefore, underinvestment problems may arise.

[Insert Table 16]

7 Possible mechanisms

In this section, we intend to explore the possible mechanisms under which firms' narrative R&D disclosure influences investment efficiency. We focus on three factors: information environment, R&D intensity and cash volatility.

7.1 Information environment

Merkley (2014) provides evidence that narrative R&D disclosure is negatively associated with information asymmetries. He finds that narrative R&D disclosure quantity is positively related to subsequent analyst following, higher accuracy and lower dispersion in analyst forecasts. As the information environment can be largely improved by R&D

disclosure, as we discussed in a previous section, we should expect increased investment efficiency of narrative R&D disclosing firms. Firms with a poorer information environment should benefit more from disclosing R&D-related information to the market. Thus, to further explore this channel of influence, we use two proxies for firms' information environment. First, we use the bid-ask spread constructed earlier as a proxy for information asymmetries. We set *High bid-ask* dummy equal to one, if the firm's annual bid-ask spread is above the industry-year median (Fama and French 48 industry classification), and zero otherwise. The results are presented in columns (1)-(2) of Table 17 for overall investment efficiency and R&D-related investment efficiency. As expected, the positive effect of narrative R&D disclosure is stronger for firms with higher information asymmetries.

Second, prior studies highlight the importance of financial reporting quality on firms' investment efficiency (e.g., Biddle et al., 2009, and Chen et al., 2011). It is well established in the existing literature that higher quality financial reporting enhances investment efficiency, by reducing information asymmetry (e.g., Leuz and Verrecchia, 2000; Bushman and Smith, 2001). Financial reporting information constitutes an important source of firm-specific information for investors and enables them to monitor managers (Biddle et al., 2009). High-quality financial reporting further enhances investors' ability to monitor firms' managerial decisions and reduces moral hazard. Narrative R&D disclosure also constitutes an important part of firm-specific information. Managers utilize narrative R&D disclosure to provide investors with additional information when firms' earning performance is poor (Merkley, 2014). Thus, we expect that firms with relatively poorer financial reporting quality to benefit more from disclosing R&D-related information.

Thus, to calculate financial reporting quality, we follow the measure used by Biddle et al. (2009). The accrual quality (*AQ*) is derived from Dechow and Dichev (2002) (DD hereafter) and McNichols (2002). Specifically, we estimate discretionary accruals based on the cross-sectional DD model, augmented with the fundamental variables from the modified Jones (1991) model:

$$TCA_{j,t} = \phi_{0,j} + \phi_{1,j}CFO_{j,t-1} + \phi_{2,j}CFO_{j,t} + \phi_{3,j}CFO_{j,t+1} + \phi_{4,j}\Delta Rev_{j,t} + \phi_{5,j}PPE_{j,t} + v_{j,t}, \quad (8)$$

where $TCA_{j,t}$ is the total current accruals of firm j in year t , measured as $\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$; $CFO_{j,t}$ is the cash flow from operations in year t , measured as $NIBE_{j,t} - TA_{j,t}$; $NIBE_{j,t}$ is firm j 's net income before extraordinary items in year t , while $TA_{j,t}$ is the total accruals computed as $\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPN_{j,t}$. $\Delta CA_{j,t}$ is the change in current assets from year $t - 1$ to year t ; $\Delta CL_{j,t}$ is the change in current liabilities from year $t - 1$ to year t ; $\Delta Cash_{j,t}$ is the change in cash from year $t - 1$ to year t ; $\Delta STDEBT_{j,t}$ is the change in debt in current liabilities from year $t - 1$ to year t , while $DEPN_{j,t}$ is firm j 's depreciation and amortization expense in year t . $\Delta Rev_{j,t}$ is the change in revenues between year $t - 1$ and year t ; and finally, $PPE_{j,t}$ is the gross value of PPE of firm j in year t . Following Biddle et al. (2009), we estimate the DD model cross-sectionally for each industry-year based on the Fama and French 48 industry classification. The AQ in year t is then defined as the standard deviation of the firm-level residuals from DD model during the years $t-5$ to $t-1$. As the AQ value increases, the financial reporting quality of the firm becomes poorer. We then set *Low FRQ* dummy equal to one if the firm's AQ is above the industry-year median (Fama and French 48 industry classification), and zero otherwise. As expected, in columns (3)-(4) of Table 17, the positive effect of narrative R&D disclosure is more pronounced for firms with poorer financial reporting quality.

7.2 R&D investment

R&D is highly firm-specific and is positively associated with information asymmetry and uncertainty (Aboody and Lev, 2000; Chan et al., 2001). Disclosing more information on R&D helps to reduce the information asymmetry between firms and investors and enables investors to track and monitor firms' R&D investment activities. We should, therefore, expect firms with higher R&D intensity to benefit more from narrative R&D disclosure. R&D intensity is measured as R&D expenditure over sales. *High RDI* is the dummy variable that takes value one if the firm's R&D intensity is above the industry-year median (Fama and French 48 industry classification), and zero otherwise. The results given in columns (5)-(6) of Table 17 show that the positive relationship between narrative R&D disclosure and investment efficiency is more pronounced for R&D intensive firms.

7.3 Cash flow volatility

When cash flows are volatile, firms are more likely to experience periods of internal cash flow shortage, which increases the need to access external capital markets (Hong et al., 2019). However, volatile cash flows may further increase information asymmetry, which makes access to external capital more costly. Therefore, firms with higher levels of cash flow volatility are more likely to reject or forgo profitable investment projects, due to funding constraints (Hong et al., 2019). However, firm-specific investment information provided through firms' narrative R&D investment, helps to resolve adverse selection and agency conflicts among shareholders, which, in turn, increases a firms' borrowing capacity and increases the optimal level of investment for the firm. Thus, we should expect the relationship between investment efficiency and firms' narrative R&D disclosure to be more pronounced for firms with higher levels of cash flow volatility. Following Hong et al. (2019), we measure cash flow volatility as the coefficient of variation in a firm's quarterly operating cash flow, estimated over the five-year period. The coefficient of variation is the standard deviation of operating cash flow, scaled by the absolute value of the mean over the same period. *High CashV* is then the binary variable, that takes the value of one if the firm's cash flow volatility is above the industry-year median (Fama and French 48 industry classification), and zero otherwise. The results presented in columns (7)-(8) of Table 17 for investment efficiency and R&D investment efficiency provide evidence that the positive relationship between narrative R&D disclosure and investment efficiency is more pronounced for firms with more volatile cash flows.

[Insert Table 17]

8 Conclusion

Prior research has already highlighted the positive relationship between firms' disclosure level and investment efficiency (e.g., Lai et al., 2014). More recent literature has begun to focus increasingly on specific contents of firms' public disclosure. For example, Campbell et al. (2014), Li et al. (2019) and Durnev and Mangan (2020) study the relationship between firms' mandatory risk disclosure in their public filings and investment efficiency. However, the effect of voluntary disclosure on firm-specific

investment information in firms' public documents on investment efficiency is rarely studied in the literature. In this chapter, we focus on the impact of firms' narrative R&D disclosure on investment efficiency, as R&D is highly firm-specific and is positively associated with information asymmetries and uncertainty. Using the substantial sample of 48,027 firm-year observations from 1997 to 2019, we provide strong evidence that firms' narrative R&D disclosure is positively related to their investment efficiency. Narrative R&D disclosure reduces information asymmetries between the firms and investors (Merkley, 2014), which helps to improve investment efficiency. Considering the two scenarios of investment inefficiency, we find that narrative R&D disclosure is positively related to underinvestment and negatively related to overinvestment. On the one hand, a larger quantity of disclosed information, particularly information on relatively uncertain R&D investments, enhances investors' ability to track and monitor firms' managerial decisions and activities, and, therefore, helps to eliminate any intentions of managers to over or under invest. As more information is provided to the market, it also becomes more challenging for managers to neglect stakeholders' rights and to make decisions for their own interest, leading to a further decrease in agency conflicts and an improvement in investment efficiency. On the other hand, additional information provided through narrative R&D disclosure makes potential investors less likely to price-protect themselves when making investments. The reduced financing costs further mitigate firms' underinvestment problems.

Our results are robust to R&D-related investment efficiency, alternative measures of investment efficiency and narrative R&D disclosure. As the quality of narrative R&D disclosure may affect how outside investors perceive the firm-specific information disclosed in the reports, we further compute the tones and readability of firms' R&D disclosure and find that firms with more positive and readable R&D disclosures experience a further increase in their investment efficiency. To address the endogeneity issue regarding causality, we employ a quasi-natural experiment in the difference-in-differences (DiD) framework by comparing the change in investment efficiency around the time of the enactment of the Leahy-Smith America Invents Act (AIA) on March 16, 2013. We find that the investment efficiency of innovation-intensive firms decreases after the enactment, compared to non-innovation-intensive firms. This finding is primarily driven by a negative relationship between narrative R&D disclosure and underinvestment and is consistent on the propensity score matched sample.

We further study firms' patenting and external financing activities around the time of the enactment of the AIA to better understand how firms adjust their investments after the reform. We find an increase in the quantity of patent applications immediately after the enactment for innovation-intensive firms, and diminishing patent quality. Moreover, our results suggest that these innovation-intensive firms are less likely to issue new equity after the enactment, as the cost of equity increases. The results are consistent when using the propensity score matched sample. Finally, we find that the positive relationship between narrative R&D disclosure and investment efficiency is more pronounced for firms with greater information asymmetry, poorer financial reporting quality, higher R&D intensity and higher cash flow volatility.

Our study also has some caveats. Our analysis focuses on firms' public 10-K filings. There may be other sources that firms use to convey firm-specific information to the market. Moreover, other firm-specific information disclosure, such as strategy, may also affect firms' investment decisions. Further study may be needed to address issues regarding various firm-specific information disclosures.

Table 1 Variable definitions

Variables	Definition	Database
Investment efficiency		
<i>InvEff</i>	The minus one times the absolute value of the residuals estimated from the cross-sectional regression from a firm-specific model of investment: $INVEST_{i,t+1} = \alpha_0 + \alpha_1 * Sales\ Growth_{i,t} + \varepsilon_{i,t}$ $INVEST_{i,t+1}$ is the total investment in year $t + 1$, measured as the sum of R&D expenses, capital expenditure, and acquisition expenditure minus cash receipts from the sale of property, plant, and equipment (PPE), all scaled by lagged total assets; $Sales\ Growth_{i,t}$ is the percentage change in sales from year $t - 1$ to year t	Compustat
<i>UnderInv</i>	The negative residuals estimated from the above model (Eq. (1))	Compustat
<i>OverInv</i>	The positive residuals estimated from the above model (Eq. (1))	Compustat
R&D investment efficiency		
<i>RDInvEff</i>	The minus one times the absolute value of the residuals estimated from the cross-sectional regression from a firm-specific model of investment: $INVEST_{i,t+1} = \alpha_0 + \alpha_1 * Sales\ Growth_{i,t} + \varepsilon_{i,t}$ $INVEST_{i,t+1}$ is the R&D investment in year $t + 1$ measured as R&D expenses scaled by lagged total assets; $Sales\ Growth_{i,t}$ is the percentage change in sales from year $t - 1$ to year t	Compustat
<i>RDUnderInv</i>	The negative residuals estimated from the above model (Eq. (1)) where $INVEST_{i,t+1}$ is R&D investment	Compustat
<i>RDOverInv</i>	The positive residuals estimated from the above model (Eq. (1)) where $INVEST_{i,t+1}$ is R&D investment	Compustat
Narrative R&D disclosure		
<i>RDSen</i>	The natural logarithm of one plus the number of R&D-related sentences in firms' 10-K filings	SRAF
<i>RDNumSen</i>	The natural logarithm of one plus the number of numerical R&D-related sentences in firms' 10-K filings	SRAF
<i>RDFwdSen</i>	The natural logarithm of one plus the number of forward-looking R&D-related sentences in firms' 10-K filings	SRAF
<i>Ptone</i>	An indicator variable that takes the value of one if a 10-K document contains more positive R&D sentences, and zero otherwise.	SRAF
<i>Fog index</i>	The readability of narrative R&D disclosure, computed as $0.4 * [(words/sentences) + 100 * (complex\ words/words)]$.	SRAF
Firm- and industry-specific variables		
<i>TSent</i>	The natural logarithm of the total number of sentences in firms' 10-K filings	SRAF
<i>Instowner</i>	The percentage of the firm' shares held by institutional investment. We set missing institutional ownership to zero	Thomson Reuter 13F
<i>Analyst</i>	The number of analysts following the firm. We set the number to zero if no analyst coverage reported by I/B/E/S.	I/B/E/S
<i>Size</i>	The natural logarithm of total assets	Compustat
<i>MB</i>	The sum of book value of debt and the market value of equity divided by total assets. The book value of debt is computed as the total assets minus the book value of equity	Compustat
<i>StdCfo</i>	The standard deviation of cash flow from operations deflated by lagged total assets over the past five years	Compustat
<i>StdSale</i>	The standard deviation of sales deflated by lagged total assets over the past five years	Compustat
<i>StdInvest</i>	The standard deviation of total investment scaled by lagged total assets ($INVEST$) over the past five years	Compustat
<i>Zscore</i>	Altman's Z-score, computed as $1.2 * (working\ capital / total\ assets) + 1.4 * (retained\ earnings / total\ assets) + 3.3 * (earnings\ before\ interest\ and\ taxes / total\ assets) + 0.6 * (market\ value\ of\ equity / total\ liabilities)$	Compustat

	+ 0.99 * (sales / total assets)	
<i>Tangibility</i>	The ratio of net PPE to total assets	Compustat
<i>Leverage</i>	The ratio of long-term debt to the sum of long-term debt and the market value of equity	Compustat
<i>Leverage_Ind</i>	The average of leverage (<i>LEVERAGE</i>) for firms in the same 4-digit SIC industry group	Compustat
<i>CfoSale</i>	Cash flow from operations divided by sales	Compustat
<i>Slack</i>	The ratio of cash to net PPE	Compustat
<i>Dividend</i>	An indicator variable that equals one if the firm paid dividends, and zero otherwise	Compustat
<i>Age</i>	The natural logarithm of the difference between the first year when the firm appears in CRSP and the current year	Compustat
<i>OpCycle</i>	The natural logarithm of receivables to sales plus inventory to cost of goods sold multiplied by 360	Compustat
<i>Loss</i>	An indicator variable that takes the value of one if income before extraordinary items is negative, and zero otherwise	Compustat

Additional matching variables

<i>RDI</i>	R&D expenses over sales	Compustat
<i>ROA</i>	Operating income before depreciation divided by book value of total stockholders' equity	Compustat
<i>TobinQ</i>	Market value of plus book value of assets minus book value of equity minus balance sheet deferred taxes (replace missing with zero), divided by book value of assets	Compustat
<i>Capx</i>	Capital expenditure divided by book value of total assets	Compustat
<i>KZ</i>	Kaplan and Zingales index calculated as $-1.002 * \text{cash flow} + 0.283 * \text{Tobin's Q} + 3.139 * \text{leverage} - 39.368 * \text{dividends} - 1.315 * \text{cash holdings}$	Compustat
<i>HHI</i>	Herfindahl index of four-digit standard industrial classification (SIC) industry j where firm i belongs	Compustat
<i>HHI2</i>	Squared term of <i>HHI</i>	Compustat
<i>Illiquid</i>	The annual average of Amihud (2002) illiquidity construct: $\text{Illiquidity}_t = \frac{ R_t }{DV\text{olume}_t}$, where R_t is the daily return and $DV\text{olume}_t$ is the daily dollar volume (in millions)	CRSP

Other variables in the analysis

<i>PtApp</i>	The natural logarithm of one plus the total number of patent applications	Orbis IP
<i>PtVal</i>	The sum of the market value of all patents applied scaled by the lagged assets, where the market value of patents is computed following Kogan et al. (2017)	Orbis IP
<i>CoE</i>	The bid-ask spread computed as the annual median of monthly quoted spreads	CRSP
<i>NEquity</i>	The ratio of external equity issues to the book assets at the beginning of the year, where the external equity is the change in book equity minus the change in retained earnings	Compustat
<i>NDebts</i>	The ratio of debt issues over the book assets at the beginning of the year, where the debt issues are the change in assets minus the change in book equity.	Compustat
<i>Low FRQ</i>	An indicator variable that takes the value of one if the firm's accrual quality (<i>AQ</i>) is above the industry-year median, and zero otherwise. <i>AQ</i> is computed following Dechow and Dichev (2002) and McNichols (2002)	Compustat
<i>High CashV</i>	An indicator variable that equals one if the firm's cash flow volatility is above the industry-year median, and zero otherwise. Cash flow volatility is measured as the standard deviation of quarterly operating cash flow over five years scaled by the absolute value of the mean over the same period	Compustat

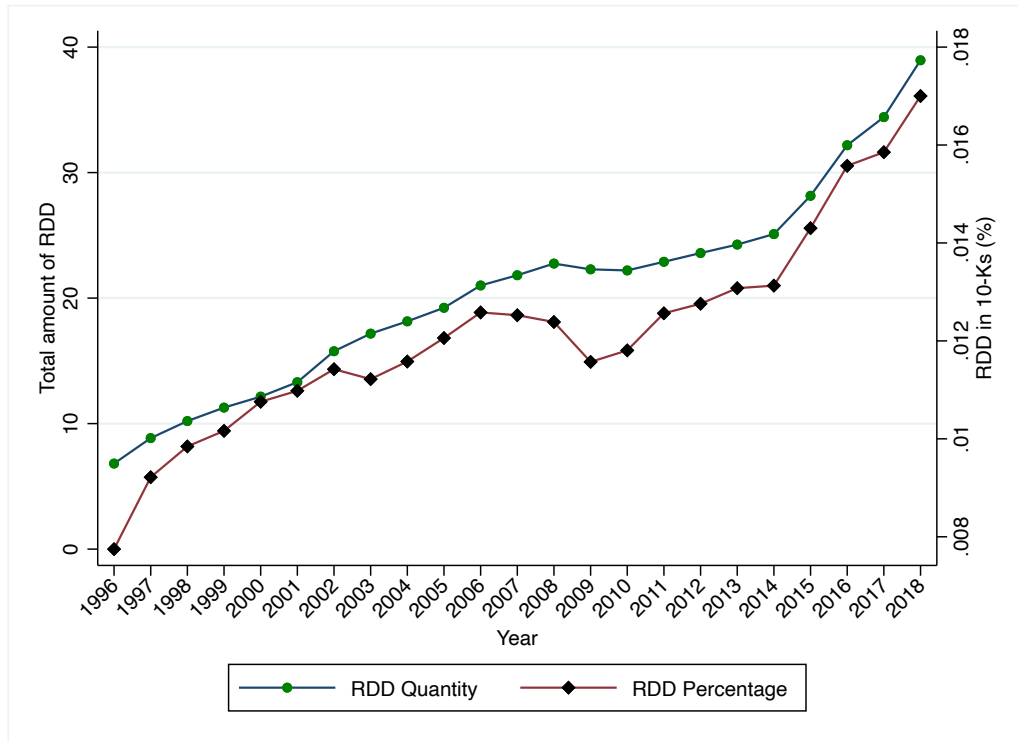


Figure 1. Narrative R&D disclosure by years (1996-2018)

Table 2 Summary statistics

	N	Mean	Std. D	Std. Dw.	Min	P25	Median	P75	Max
Investment efficiency									
(1) <i>InvEff</i>	48,027	-0.122	0.128	0.080	-0.725	-0.158	-0.083	-0.039	-0.002
(2) <i>UnderInv</i>	30,543	-0.097	0.077	0.047	-0.389	-0.133	-0.077	-0.040	-0.002
(3) <i>OverInv</i>	17,484	0.167	0.189	0.103	0.001	0.037	0.103	0.221	0.990
R&D investment efficiency									
(4) <i>RDInveff</i>	48,027	-0.082	0.106	0.055	-0.598	-0.108	-0.047	-0.013	-0.000
(5) <i>RDUnderInv</i>	33,003	-0.060	0.063	0.029	-0.289	-0.091	-0.039	-0.011	-0.000
(6) <i>RDOverInv</i>	15,024	0.129	0.158	0.075	0.000	0.022	0.069	0.167	0.789
Firm- and industry- specific factors									
(7) <i>Total_RDSen</i>	48,027	18.130	36.747	10.427	0.000	1.000	7.000	20.000	572.000
(8) <i>RDSen</i>	48,027	1.990	1.389	0.414	0.000	0.693	2.079	3.045	5.303
(9) <i>Total_Sen (K)</i>	48,027	1.623	0.973	0.690	0.001	0.994	1.445	2.003	29.091
(10) <i>TSent</i>	48,027	7.243	0.538	0.343	5.872	6.902	7.276	7.602	8.507
(11) <i>Instowner</i>	48,027	0.506	0.328	0.150	0.000	0.195	0.539	0.794	1.104
(12) <i>Analyst</i>	48,027	1.503	1.015	0.388	0.000	0.693	1.558	2.303	3.453
(13) <i>Size</i>	48,027	5.865	2.085	0.559	1.660	4.294	5.804	7.336	10.867
(14) <i>MB</i>	48,027	2.060	1.565	0.996	0.592	1.138	1.551	2.332	9.865
(15) <i>StdCfo</i>	48,027	0.085	0.092	0.051	0.006	0.032	0.056	0.100	0.592
(16) <i>StdSale</i>	48,027	0.268	0.285	0.174	0.011	0.095	0.179	0.330	1.767
(17) <i>StdInvest</i>	48,027	0.094	0.102	0.062	0.003	0.028	0.061	0.122	0.586
(18) <i>Zscore</i>	48,027	4.103	6.258	4.146	-15.516	1.732	3.227	5.306	35.493
(19) <i>Tangibility</i>	48,027	0.248	0.218	0.066	0.007	0.082	0.180	0.349	0.894
(20) <i>Leverage</i>	48,027	0.172	0.206	0.115	0.000	0.002	0.097	0.266	0.849
(21) <i>Leverage_Ind</i>	48,027	0.166	0.115	0.053	0.021	0.076	0.136	0.233	0.541
(22) <i>CfoSale</i>	48,027	-0.157	1.356	0.736	-11.181	0.011	0.072	0.141	0.626
(23) <i>Slack</i>	48,027	2.329	6.121	3.642	0.001	0.102	0.439	1.656	45.448
(24) <i>Dividend</i>	48,027	0.360	0.480	0.252	0.000	0.000	0.000	1.000	1.000
(25) <i>Age</i>	48,027	2.613	0.820	0.351	1.099	1.946	2.639	3.219	4.394
(26) <i>OpCycle</i>	48,027	4.652	0.776	0.330	2.045	4.265	4.740	5.142	6.436
(27) <i>Loss</i>	48,027	0.339	0.473	0.338	0.000	0.000	0.000	1.000	1.000

Table 3 Narrative R&D disclosure quantity (*RDSen*) by industry

Industry	N	Mean	Median	Std. Dev.
Pharmaceutical Products	3,722	98.294	70.000	87.538
Medical Equipment	2,357	28.022	23.000	22.679
Measuring and Control Equipment	1,441	23.656	20.000	17.154
Electronic Equipment	4,073	23.201	21.000	16.231
Computers	2,117	20.676	18.000	14.100
Electrical Equipment	1,090	14.815	10.000	14.725
Chemicals	1,344	14.737	9.000	19.556
Business Services	6,569	14.708	10.000	16.265
Automobile and Trucks	973	11.703	9.000	10.310
Machinery	2,435	11.581	9.000	10.103

Table 4 Univariate analysis

	High narrative R&D disclosure			Low narrative R&D disclosure			Differences	
	Mean	Median	N	Mean	Median	N	Mean	Median
Panel A: Investment efficiency								
(1) <i>InvEff</i>	-0.106	-0.072	23,755	-0.138	-0.096	24,272	0.032***	0.024***
(2) <i>UnderInv</i>	-0.087	-0.066	14,528	-0.106	-0.087	16,015	0.019***	0.021***
(3) <i>OverInv</i>	0.134	0.086	9,227	0.204	0.126	8,257	-0.070***	-0.040***
Panel B: R&D investment efficiency								
(1) <i>RDInveff</i>	-0.069	-0.038	23,755	-0.095	-0.058	24,272	0.026***	0.020***
(2) <i>RDUnderInv</i>	-0.051	-0.031	15,023	-0.068	-0.048	17,980	0.017***	0.017***
(3) <i>RDOverInv</i>	0.098	0.055	8,732	0.173	0.101	6,292	-0.075***	-0.046***

* p<0.1 ** p<0.05 *** p<0.01.

Table 5 Results of baseline model

	(1)	(2)	(3)	(4)	(5)	(6)
	Investment efficiency		Underinvestment		Overinvestment	
<i>RDSen</i>	0.019*** (31.873)	0.019*** (28.674)	0.010*** (24.239)	0.009*** (19.748)	-0.034*** (-25.464)	-0.028*** (-20.339)
<i>TSent</i>		-0.005*** (-4.168)		-0.002* (-1.751)		0.004 (1.373)
<i>Instowner</i>		0.023*** (11.058)		0.011*** (7.350)		-0.028*** (-5.728)
<i>Analyst</i>		0.006*** (6.121)		0.007*** (10.656)		-0.006*** (-2.600)
<i>Size</i>		0.006*** (11.326)		-0.005*** (-13.821)		-0.016*** (-12.399)
<i>MB</i>		-0.006*** (-12.128)		0.005*** (14.060)		0.008*** (9.135)
<i>StdCfo</i>		0.029*** (3.368)		0.016*** (2.658)		-0.077*** (-4.782)
<i>StdSale</i>		-0.002 (-0.737)		-0.012*** (-8.219)		-0.005 (-1.132)
<i>StdInvest</i>		-0.231*** (-26.573)		0.001 (0.220)		0.480*** (23.657)
<i>Zscore</i>		0.001*** (10.593)		-0.000*** (-3.344)		-0.001*** (-6.759)
<i>Tangibility</i>		0.017*** (4.331)		0.044*** (16.490)		-0.008 (-0.935)
<i>Leverage</i>		0.027*** (7.978)		-0.014*** (-6.707)		-0.050*** (-5.574)
<i>Leverage_Ind</i>		0.016*** (2.789)		0.018*** (4.578)		-0.016 (-1.063)
<i>CfoSale</i>		-0.000 (-0.072)		-0.003*** (-7.884)		0.000 (0.285)
<i>Slack</i>		-0.000 (-0.596)		-0.000* (-1.884)		0.000 (0.105)
<i>Dividend</i>		-0.003*** (-2.628)		-0.005*** (-6.013)		0.003 (0.916)
<i>Age</i>		-0.002*** (-3.516)		-0.002*** (-3.340)		-0.001 (-0.392)
<i>OpCycle</i>		0.003*** (3.695)		-0.005*** (-7.393)		-0.006*** (-3.267)
<i>Loss</i>		0.004*** (3.353)		-0.001 (-0.623)		-0.010*** (-3.329)
Constant	-0.209*** (-40.306)	-0.210*** (-19.415)	-0.158*** (-52.144)	-0.121*** (-16.564)	0.346*** (21.853)	0.356*** (13.509)
Observations	48,027	48,027	30,543	30,543	17,484	17,484
R-squared	0.286	0.347	0.437	0.468	0.321	0.424
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The industry fixed effects are included based on the Fama and French 48 industry classification and the standard errors are clustered at firm and year level. The dependent variables are investment efficiency (InvEff) in Columns (1) and (2), underinvestment (UnderInv) in Columns (3) and (4) and overinvestment (OverInv) in Columns (5) and (6). Narrative R&D disclosure (RDSen) is the natural logarithm of one plus the total number of sentences that contain at least one R&D-related word or phrase in firms' 10-K filings. In Columns (2), (4) and (6), the control variables include: the length of 10-K filings (TSent) measured as the natural logarithm of one plus the total number of sentences in the reports, institutional ownership (Instowner) measured as the percentage of the firm's shares held by institutional investment, the number of analyst following the firm (Analyst), firm size (Size), market to book ratio (MB), cash flow, sales and investment volatility (StdCfo, StdSale and StdInvest), Altman's Z score (Zscore), asset tangibility (Tangibility), leverage (Leverage), industry leverage (Leverage_Ind), operating cash flows relative to sales (CfoSale), cash slack relative to PPE (Slack), dividend payout (Dividend), firm age (Age), operating cycle (OpCycle), and loss in earnings (Loss). More detailed definitions of the variables are given in Table 1. All variables are measured at time t-1. * p<0.1 ** p<0.05 *** p<0.01.

Table 6 Results of baseline model on R&D investment efficiency

	(1)	(2)	(3)	(4)	(5)	(6)
	Investment efficiency		Underinvestment		Overinvestment	
<i>RDSen</i>	0.016*** (34.097)	0.015*** (29.974)	0.010*** (36.120)	0.009*** (28.854)	-0.030*** (-28.450)	-0.026*** (-21.394)
<i>TSent</i>		-0.003*** (-2.848)		-0.002*** (-3.121)		0.005* (1.878)
<i>Instowner</i>		0.021*** (13.460)		0.003*** (3.512)		-0.029*** (-6.699)
<i>Analyst</i>		0.004*** (5.644)		0.004*** (9.749)		-0.001 (-0.593)
<i>Size</i>		0.005*** (12.596)		-0.003*** (-12.812)		-0.016*** (-13.351)
<i>MB</i>		-0.006*** (-14.820)		0.003*** (10.442)		0.007*** (10.787)
<i>StdCfo</i>		0.021*** (2.947)		0.021*** (4.463)		-0.048*** (-3.804)
<i>StdSale</i>		0.000 (0.000)		-0.010*** (-10.725)		-0.007 (-1.599)
<i>StdInvest</i>		-0.170*** (-23.962)		0.006* (1.689)		0.348*** (20.772)
<i>Zscore</i>		0.001*** (12.910)		-0.000** (-2.108)		-0.001*** (-8.553)
<i>Tangibility</i>		-0.006** (-2.118)		-0.008*** (-5.090)		0.013 (1.452)
<i>Leverage</i>		0.024*** (9.202)		-0.001 (-0.533)		-0.039*** (-5.092)
<i>Leverage_Ind</i>		0.002 (0.413)		0.007*** (2.878)		-0.004 (-0.238)
<i>CfoSale</i>		0.001** (2.523)		-0.004*** (-9.461)		-0.001** (-2.054)
<i>Slack</i>		0.000** (2.130)		0.000*** (2.799)		-0.000* (-1.865)
<i>Dividend</i>		-0.003*** (-3.374)		-0.003*** (-5.221)		0.003 (1.074)
<i>Age</i>		-0.003*** (-4.931)		-0.001*** (-3.401)		-0.004*** (-2.591)
<i>OpCycle</i>		0.002*** (3.237)		-0.004*** (-8.450)		-0.006*** (-3.351)
<i>Loss</i>		0.002* (1.810)		0.004*** (6.685)		-0.003 (-1.390)
Constant	-0.139*** (-32.714)	-0.140*** (-16.225)	-0.100*** (-44.360)	-0.055*** (-11.482)	0.278*** (17.506)	0.281*** (11.411)
Observations	48,027	48,027	33,003	33,003	15,024	15,024
R-squared	0.378	0.437	0.614	0.634	0.379	0.478
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The industry fixed effects are included based on the Fama and French 48 industry classification and the standard errors are clustered at firm and year level. The dependent variables are R&D investment efficiency (RDInvEff) in Columns (1) and (2), R&D underinvestment (RDUnderInv) in Columns (3) and (4) and R&D overinvestment (RDOverInv) in Columns (5) and (6). The firm-level characteristics are defined in Table 5. * p<0.1 ** p<0.05 *** p<0.01.

Table 7 Results of alternative measures of investment efficiency

	Investment efficiency			R&D investment efficiency		
	(1) <i>InvEff</i>	(2) <i>UnderInv</i>	(3) <i>OverInv</i>	(4) <i>RDInvEff</i>	(5) <i>RDUnderInv</i>	(6) <i>RDOverInv</i>
Panel A: Chen et al. (2014)						
<i>RDSen</i>	0.018*** (27.105)	0.008*** (17.380)	-0.028*** (-20.250)	0.014*** (28.377)	0.008*** (24.847)	-0.025*** (-20.855)
Constant	-0.212*** (-19.599)	-0.117*** (-15.236)	0.352*** (13.767)	-0.146*** (-17.116)	-0.050*** (-9.706)	0.285*** (11.949)
Controls	YES	YES	YES	YES	YES	YES
Observations	47,932	30,070	17,862	47,932	32,490	15,442
R-squared	0.331	0.421	0.407	0.417	0.563	0.469
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Panel B: McNichols and Stubben (2008)						
<i>RDSen</i>	0.008*** (12.060)	0.002*** (3.082)	-0.016*** (-11.188)	0.005*** (12.992)	0.002*** (5.744)	-0.008*** (-11.787)
Constant	-0.111*** (-9.813)	-0.088*** (-8.637)	0.131*** (5.398)	-0.051*** (-8.260)	-0.031*** (-4.464)	0.075*** (6.746)
Controls	YES	YES	YES	YES	YES	YES
Observations	49,512	29,971	19,541	49,512	27,708	21,804
R-squared	0.167	0.220	0.149	0.291	0.321	0.280
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Panel C: Richardson (2006)						
<i>RDSen</i>	0.010*** (12.765)	0.003*** (4.200)	-0.016*** (-11.985)	0.005*** (13.203)	0.003*** (6.196)	-0.008*** (-12.397)
Constant	-0.132*** (-10.775)	-0.100*** (-7.977)	0.178*** (7.741)	-0.075*** (-10.718)	-0.059*** (-6.848)	0.092*** (8.169)
Controls	YES	YES	YES	YES	YES	YES
Observations	47,873	27,928	19,945	47,873	26,449	21,424
R-squared	0.198	0.248	0.183	0.303	0.322	0.303
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The industry fixed effects are included based on the Fama and French 48 industry classification and the standard errors are clustered at firm and year level. The dependent variables in Columns (1) and (4) are investment efficiency (*InvEff*) and R&D investment efficiency (*RDInvEff*), respectively. In Columns (2) and (5), the dependent variables are overall underinvestment (*UnderInv*) and R&D underinvestment (*RDUnderInv*), and in Columns (3) and (6), the dependent variables are overinvestment (*OverInv*) and R&D overinvestment (*RDOverInv*). In Panel A, investment efficiency (R&D investment efficiency) is estimated based on Chen et al. (2014)'s model (Eq. (3)). In Panel B, we apply the estimation model from McNichols and Stubben (2008) (Eq. (4)) to compute investment efficiency and R&D investment efficiency, while in Panel C, we use the model developed by Richardson (2006) (Eq. (5)). Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.

Table 8 Alternative measures of narrative R&D disclosure

	Investment efficiency			R&D Investment efficiency		
	(1) <i>InvEff</i>	(2) <i>UnderInv</i>	(3) <i>OverInv</i>	(4) <i>RDInvEff</i>	(5) <i>RDUnderInv</i>	(6) <i>RDOverInv</i>
Panel A: Numerical narrative R&D disclosure						
<i>RDNumSen</i>	0.022*** (30.617)	0.010*** (20.310)	-0.033*** (-20.964)	0.018*** (32.715)	0.011*** (31.392)	-0.028*** (-21.346)
Constant	-0.207*** (-19.119)	-0.120*** (-16.438)	0.355*** (13.465)	-0.137*** (-15.884)	-0.053*** (-10.928)	0.285*** (11.589)
Controls	YES	YES	YES	YES	YES	YES
Observations	48,027	30,543	17,484	48,027	33,003	15,024
R-squared	0.348	0.468	0.424	0.438	0.636	0.476
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Panel B: Forward-looking narrative R&D disclosure						
<i>RDFwdSen</i>	0.016*** (22.251)	0.011*** (23.215)	-0.022*** (-14.314)	0.012*** (22.431)	0.011*** (32.558)	-0.018*** (-13.540)
Constant	-0.209*** (-19.078)	-0.110*** (-15.055)	0.361*** (13.504)	-0.140*** (-15.979)	-0.045*** (-9.317)	0.290*** (11.568)
Controls	YES	YES	YES	YES	YES	YES
Observations	48,027	30,543	17,484	48,027	33,003	15,024
R-squared	0.341	0.471	0.416	0.431	0.637	0.466
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The industry fixed effects are included based on the Fama and French 48 industry classification and the standard errors are clustered at firm and year level. The dependent variables in Columns (1) and (4) are investment efficiency (*InvEff*) and R&D investment efficiency (*RDInvEff*), respectively. In Columns (2) and (5), the dependent variables are overall underinvestment (*UnderInv*) and R&D underinvestment (*RDUnderInv*), and in Columns (3) and (6), the dependent variables are overinvestment (*OverInv*) and R&D overinvestment (*RDOverInv*). In Panel A, the narrative R&D disclosure is measured as the natural logarithm of one plus the total amount of numerical narrative R&D disclosure (*RDNumSen*). A R&D sentence is treated as numerical if it contains numerical information that is not in the form of a date. In Panel B, we measure narrative R&D disclosure as the natural logarithm of one plus the total number of forward-looking sentences (*RDFwdSen*). A R&D sentence is considered forward-looking if it contains “will”, “could”, “should”, “expect”, “anticipate”, “plan”, “hope”, “believe”, “can”, “may”, “might”, “intend”, “project”, “forecast”, “objective” or “goal”. Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.

Table 9 Narrative R&D disclosure tone and readability

	R&D disclosure tone		R&D disclosure readability	
	(1)	(2)	(3)	(4)
	<i>InvEff</i>	<i>RDInvEff</i>	<i>InvEff</i>	<i>RDInvEff</i>
<i>RDSen</i>	0.017*** (23.621)	0.014*** (24.595)	0.029*** (18.639)	0.023*** (19.666)
<i>Ptone</i>	-0.005** (-2.339)	-0.002 (-0.984)		
<i>RDSen*Ptone</i>	0.004*** (4.147)	0.002*** (3.081)		
<i>Fog index</i>			0.000*** (3.946)	0.000*** (4.572)
<i>RDSen*Fog index</i>			-0.0004*** (-5.862)	-0.0003*** (-6.745)
Constant	-0.210*** (-19.255)	-0.141*** (-16.174)	-0.216*** (-18.048)	-0.146*** (-15.484)
Controls	YES	YES	YES	YES
Observations	48,027	48,027	39,342	39,342
R-squared	0.348	0.437	0.318	0.412
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The industry fixed effects are included based on the Fama and French 48 industry classification and the standard errors are clustered at firm and year level. The dependent variable in Columns (1) and (3) is investment efficiency (*InvEff*), while in Columns (2) and (4), the dependent variable is R&D investment efficiency (*RDInvEff*). *Ptone* is a binary variable that takes value one if a 10-K document contains more positive R&D-related sentences, zero otherwise. Fog index measures the readability of the firm' narrative R&D disclosure. Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.

Table 10 Results of difference-in-differences

	Investment efficiency		Underinvestment		Overinvestment	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Investment efficiency						
<i>Treated*Post</i>	-0.013*** (-3.815)	-0.012*** (-3.670)	-0.007*** (-2.957)	-0.008*** (-3.356)	0.006 (0.956)	0.004 (0.668)
<i>Post</i>	0.008** (2.241)	0.007* (1.893)	0.010*** (3.900)	0.011*** (4.419)	0.012* (1.757)	0.014** (2.242)
<i>Treated</i>	0.026*** (11.116)	0.015*** (6.426)	0.012*** (7.155)	0.013*** (7.650)	-0.029*** (-6.653)	-0.014*** (-3.271)
Controls	NO	YES	NO	YES	NO	YES
Observations	10,443	10,443	6,666	6,666	3,777	3,777
R-squared	0.285	0.336	0.476	0.520	0.242	0.331
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Panel B: R&D investment efficiency						
<i>Treated*Post</i>	-0.007*** (-3.684)	-0.007*** (-3.742)	-0.005*** (-3.306)	-0.005*** (-3.687)	0.007 (1.572)	0.006 (1.466)
<i>Post</i>	0.006*** (3.385)	0.006*** (3.307)	0.007*** (5.270)	0.008*** (5.935)	0.001 (0.113)	0.002 (0.559)
<i>Treated</i>	0.015*** (11.954)	0.009*** (7.364)	0.008*** (7.026)	0.008*** (8.057)	-0.025*** (-8.348)	-0.011*** (-4.004)
Controls	NO	YES	NO	YES	NO	YES
Observations	10,443	10,443	7,263	7,263	3,180	3,180
R-squared	0.499	0.530	0.685	0.721	0.356	0.461
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The standard errors are clustered at firm and year level. The industry based on the Fama and French 48 industry classification and year fixed effects are included. The dependent variable in Columns (1) and (2) is investment efficiency (InvEff) in Panel A and R&D investment efficiency (RDInvEff) in Panel B. In Columns (3) and (4), the dependent variable is underinvestment (UnderInv) in Panel A and R&D underinvestment (RDUnderInv) in Panel B. In Columns (5) and (6), the dependent variable is overinvestment (OverInv) in Panel A and R&D overinvestment (RDOverInv) in Panel B. Treated is an indicator variable for innovation-intensive firms, zero otherwise. Post is an indicator variable that equals to one for fiscal years subsequent to the enactment of the AIA in March 2013, zero otherwise. Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.

Table 11 Results of difference-in-differences on the matched sample

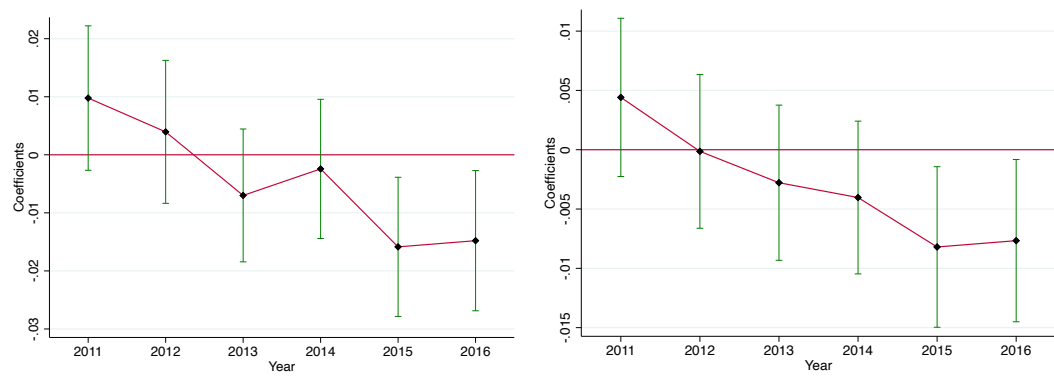
	Investment efficiency		Underinvestment		Overinvestment	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Investment efficiency						
<i>Treated*Post</i>	-0.016*** (-3.830)	-0.015*** (-3.641)	-0.010*** (-3.291)	-0.010*** (-3.507)	0.006 (0.712)	0.003 (0.420)
<i>Post</i>	0.009* (1.940)	0.007 (1.477)	0.012*** (3.705)	0.015*** (4.677)	0.021** (2.550)	0.025*** (2.986)
<i>Treated</i>	0.024*** (8.624)	0.018*** (6.507)	0.012*** (5.675)	0.011*** (5.781)	-0.027*** (-5.459)	-0.017*** (-3.577)
Controls	NO	YES	NO	YES	NO	YES
Observations	6,628	6,628	4,295	4,295	2,333	2,333
R-squared	0.274	0.323	0.471	0.516	0.232	0.319
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Panel B: R&D investment efficiency						
<i>Treated*Post</i>	-0.013*** (-4.190)	-0.011*** (-4.014)	-0.005*** (-2.703)	-0.005*** (-3.108)	0.005 (0.938)	0.004 (0.730)
<i>Post</i>	0.013*** (3.903)	0.011*** (3.638)	0.008*** (3.807)	0.009*** (4.888)	0.002 (0.392)	0.005 (0.901)
<i>Treated</i>	0.016*** (7.750)	0.011*** (5.525)	0.007*** (5.117)	0.008*** (6.284)	-0.019*** (-5.070)	-0.011*** (-3.202)
Controls	NO	YES	NO	YES	NO	YES
Observations	6,628	6,628	4,569	4,569	2,059	2,059
R-squared	0.400	0.457	0.667	0.708	0.371	0.474
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients on the PSM matched sample (t-statistics in parentheses). The standard errors are clustered at firm and year level. The industry based on the Fama and French 48 industry classification and year fixed effects are included. The dependent variable in Columns (1) and (2) is investment efficiency (InvEff) in Panel A and R&D investment efficiency (RDInvEff) in Panel B. In Columns (3) and (4), the dependent variable is underinvestment (UnderInv) in Panel A and R&D underinvestment (RDUnderInv) in Panel B. In Columns (5) and (6), the dependent variable is overinvestment (OverInv) in Panel A and R&D overinvestment (RDOverInv) in Panel B. Treated is an indicator variable for innovation-intensive firms, zero otherwise. Post is an indicator variable that equals to one for fiscal years subsequent to the enactment of the AIA in March 2013, zero otherwise. Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.

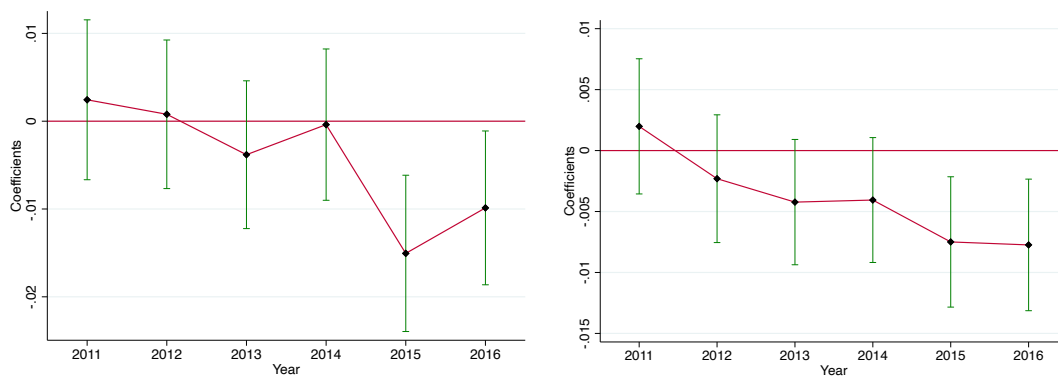
Table 12 Results of trend analysis

	Investment efficiency						R&D investment efficiency					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	<i>InvEff</i>		<i>UnderInv</i>		<i>OverInv</i>		<i>RDInvEff</i>		<i>RDUnderInv</i>		<i>RDOverInv</i>	
<i>Treated*Time T-2</i>	0.010 (1.539)	0.010 (1.539)	0.002 (0.527)	0.002 (0.525)	-0.008 (-0.713)	-0.008 (-0.714)	0.004 (1.297)	0.004 (1.297)	0.002 (0.702)	0.002 (0.702)	-0.009 (-1.222)	-0.009 (-1.222)
<i>Treated *Time T-1</i>	0.004 (0.628)	0.004 (0.629)	0.001 (0.181)	0.001 (0.182)	-0.005 (-0.413)	-0.005 (-0.416)	-0.000 (-0.042)	-0.000 (-0.041)	-0.002 (-0.864)	-0.002 (-0.863)	-0.007 (-0.997)	-0.007 (-0.997)
<i>Treated*Time T</i>	-0.007 (-1.201)	-0.007 (-1.199)	-0.004 (-0.889)	-0.004 (-0.889)	-0.002 (-0.185)	-0.002 (-0.190)	-0.003 (-0.834)	-0.003 (-0.833)	-0.004 (-1.614)	-0.004 (-1.613)	-0.007 (-0.980)	-0.007 (-0.980)
<i>Treated*Post</i>	-0.011** (-2.136)		-0.008** (-2.219)		0.001 (0.069)		-0.007** (-2.356)		-0.006*** (-2.812)		0.000 (0.001)	
<i>Treated*Time T+1</i>		-0.002 (-0.397)		-0.000 (-0.089)		-0.011 (-0.975)		-0.004 (-1.226)		-0.004 (-1.553)		-0.001 (-0.143)
<i>Treated*Time T+2</i>		-0.016*** (-2.593)		-0.015*** (-3.316)		0.001 (0.047)		-0.008** (-2.374)		-0.007*** (-2.749)		0.001 (0.197)
<i>Treated*Time T+3</i>		-0.015** (-2.401)		-0.010** (-2.209)		0.015 (1.241)		-0.008** (-2.197)		-0.008*** (-2.811)		-0.000 (-0.042)
Constant	-0.165*** (-6.716)	-0.166*** (-6.731)	-0.105*** (-6.399)	-0.105*** (-6.413)	0.187*** (4.679)	0.187*** (4.689)	-0.083*** (-6.647)	-0.083*** (-6.657)	-0.041*** (-4.607)	-0.041*** (-4.610)	0.116*** (4.159)	0.116*** (4.165)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,443	10,443	6,666	6,666	3,777	3,777	10,443	10,443	7,263	7,263	3,180	3,180
R-squared	0.336	0.337	0.521	0.521	0.331	0.332	0.530	0.530	0.721	0.722	0.461	0.461
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

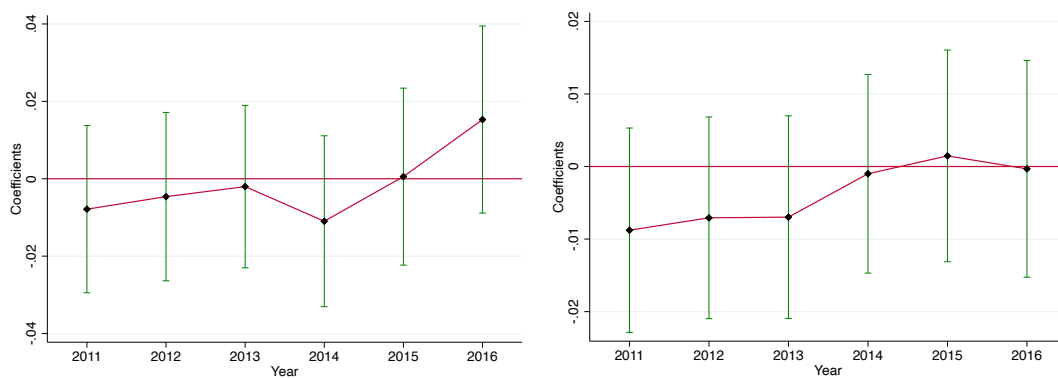
This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The industry fixed effects are included based on the Fama and French 48 industry classification and the standard errors are clustered at firm and year level. The dependent variables are investment efficiency (*InvEff*) in Columns (1) and (2), underinvestment (*UnderInv*) in Columns (3) and (4), and overinvestment (*OverInv*) in Columns (5) and (6). The dependent variables are R&D investment efficiency (*RDInvEff*) in Columns (7) and (8), R&D underinvestment (*RDUnderInv*) in Columns (9) and (10), and R&D overinvestment (*RDOverInv*) in Columns (11) and (12). Time T-2, Time T-1 and Time T are binary variables that take value one if the years are two and one year before and during the enactment of the AIA in 2013, zero otherwise. Time T+1, Time T+2 and Time T+3 are binary variables that are set equal to one if the years are one, two and three years after the enactment, zero otherwise. Post is an indicator variable that equals to one for fiscal years subsequent to the enactment of the AIA in March 2013, zero otherwise. Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.



Panel A: Investment efficiency (InvEff, left) and R&D investment efficiency (RDInvEff, right)



Panel B: Underinvestment (UnderInv, left) and R&D underinvestment (RDUnderInv, right)



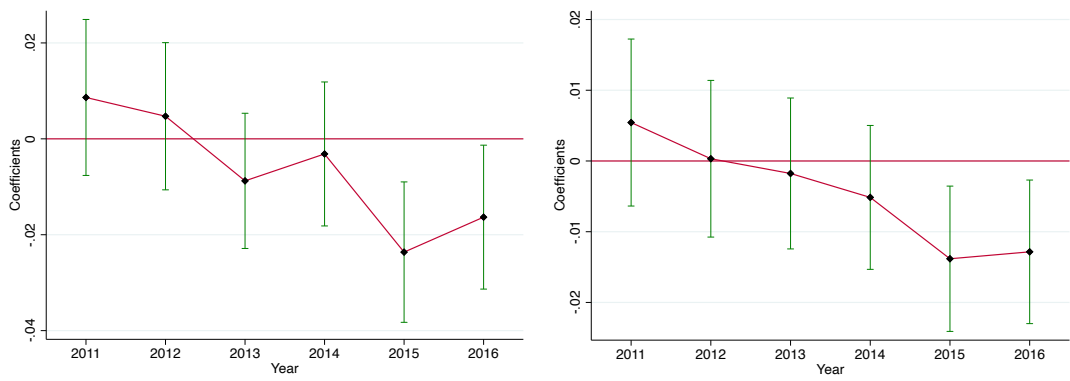
Panel C: Overinvestment (OverInv, left) and R&D overinvestment (RDOverInv, right)

Figure 2. Coefficients plots of trend analysis

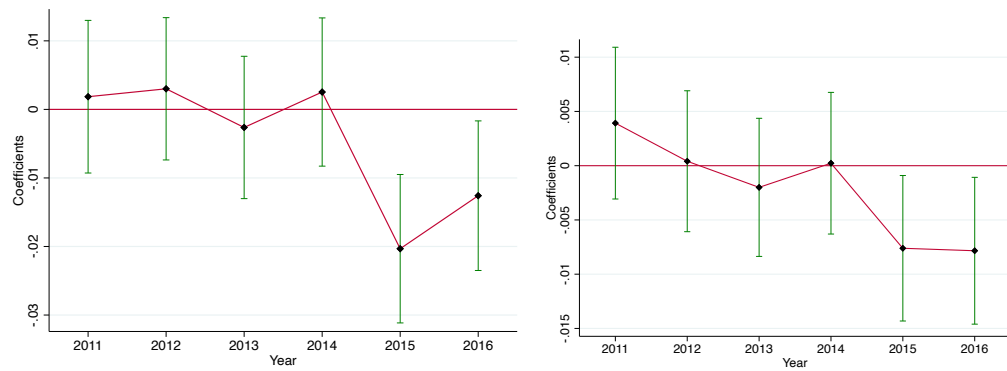
Table 13 Results of trend analysis on the matched sample

	Investment efficiency						R&D investment efficiency					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	<i>InvEff</i>		<i>UnderInv</i>		<i>OverInv</i>		<i>RDInvEff</i>		<i>RDUnderInv</i>		<i>RDOverInv</i>	
<i>Treated*Time T-2</i>	0.009 (1.040)	0.009 (1.040)	0.002 (0.329)	0.002 (0.326)	-0.004 (-0.319)	-0.004 (-0.318)	0.005 (0.902)	0.005 (0.903)	0.004 (1.099)	0.004 (1.100)	-0.000 (-0.003)	-0.000 (-0.003)
<i>Treated*Time T-1</i>	0.005 (0.601)	0.005 (0.602)	0.003 (0.567)	0.003 (0.568)	-0.005 (-0.385)	-0.005 (-0.385)	0.000 (0.055)	0.000 (0.056)	0.000 (0.123)	0.000 (0.124)	-0.007 (-0.743)	-0.007 (-0.743)
<i>Treated*Time T</i>	-0.009 (-1.220)	-0.009 (-1.219)	-0.003 (-0.497)	-0.003 (-0.498)	0.002 (0.176)	0.002 (0.176)	-0.002 (-0.325)	-0.002 (-0.324)	-0.002 (-0.617)	-0.002 (-0.615)	-0.010 (-1.085)	-0.010 (-1.085)
<i>Treated*Post</i>	-0.014** (-2.260)		-0.010** (-2.172)		0.001 (0.130)		-0.010** (-2.384)		-0.005* (-1.758)		-0.001 (-0.102)	
<i>Treated*Time T+1</i>		-0.003 (-0.412)		0.003 (0.460)		-0.007 (-0.544)		-0.005 (-0.992)		0.000 (0.069)		-0.000 (-0.005)
<i>Treated*Time T+2</i>		-0.024*** (-3.163)		-0.020*** (-3.680)		0.004 (0.275)		-0.014*** (-2.638)		-0.008** (-2.226)		0.000 (0.037)
<i>Treated*Time T+3</i>		-0.016** (-2.133)		-0.013** (-2.262)		0.009 (0.650)		-0.013** (-2.481)		-0.008** (-2.272)		-0.003 (-0.299)
Constant	-0.148*** (-4.717)	-0.149*** (-4.756)	-0.118*** (-5.635)	-0.119*** (-5.710)	0.171*** (3.585)	0.173*** (3.613)	-0.086*** (-3.825)	-0.087*** (-3.847)	-0.045*** (-3.479)	-0.046*** (-3.523)	0.179*** (4.545)	0.179*** (4.547)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,628	6,628	4,295	4,295	2,333	2,333	6,628	6,628	4,569	4,569	2,059	2,059
R-squared	0.323	0.324	0.516	0.518	0.319	0.320	0.457	0.457	0.708	0.709	0.475	0.475
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

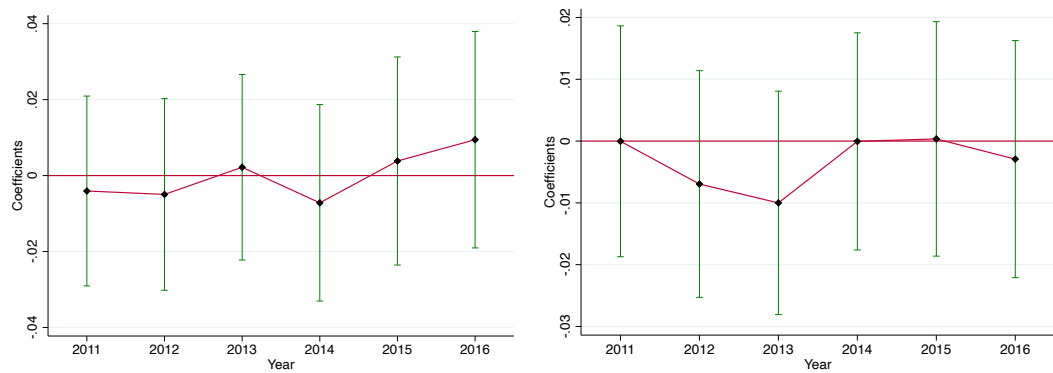
This table presents the pooled time-series cross-sectional regression OLS estimated coefficients on the PSM matched sample (t-statistics in parentheses). The industry fixed effects are included based on the Fama and French 48 industry classification and the standard errors are clustered at firm and year level. The dependent variables are investment efficiency (*InvEff*) in Columns (1) and (2), underinvestment (*UnderInv*) in Columns (3) and (4), and overinvestment (*OverInv*) in Columns (5) and (6). The dependent variables are R&D investment efficiency (*RDInvEff*) in Columns (7) and (8), R&D underinvestment (*RDUnderInv*) in Columns (9) and (10), and R&D overinvestment (*RDOverInv*) in Columns (11) and (12). Time T-2, Time T-1 and Time T are binary variables that take value one if the years are two and one year before and during the enactment of the AIA in 2013, zero otherwise. Time T+1, Time T+2 and Time T+3 are binary variables that are set equal to one if the years are one, two and three years after the enactment, zero otherwise. Post is an indicator variable that equals to one for fiscal years subsequent to the enactment of the AIA in March 2013, zero otherwise. Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.



Panel A: Investment efficiency (InvEff, left) and R&D investment efficiency (RDInvEff, right)



Panel B: Underinvestment (UnderInv, left) and R&D underinvestment (RDUnderInv, right)



Panel C: Overinvestment (OverInv, left) and R&D overinvestment (RDOverInv, right)

Figure 3. Coefficients plots of trend analysis on the matched sample

Table 14 Results of difference-in-differences on patent applications and quality

	Patent applications				Patent value			
	Unweighted sample		Matched sample		Unweighted sample		Matched sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Treated*Post</i>	0.188*** (3.127)	0.173*** (3.168)	0.219*** (3.397)	0.208*** (3.510)	-0.017*** (-2.835)	-0.021*** (-3.768)	-0.013*** (-3.262)	-0.014*** (-3.846)
<i>Treated</i>	2.090*** (49.887)	1.828*** (47.459)	1.823*** (40.880)	1.683*** (40.927)	0.103*** (24.724)	0.089*** (24.163)	0.069*** (24.130)	0.063*** (24.280)
<i>Post</i>	-0.068* (-1.740)	-0.114*** (-3.005)	-0.064 (-1.231)	-0.116** (-2.276)	-0.006* (-1.843)	-0.007** (-1.984)	-0.005* (-1.765)	-0.006** (-2.146)
Controls	<i>NO</i>	<i>YES</i>	<i>NO</i>	<i>YES</i>	<i>NO</i>	<i>YES</i>	<i>NO</i>	<i>YES</i>
Observations	10,443	10,443	6,628	6,628	10,443	10,443	6,628	6,628
R-squared	0.519	0.577	0.466	0.535	0.215	0.299	0.232	0.316
Industry FE	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
Year FE	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The standard errors are clustered at firm and year level. In Columns (1), (2), (5) and (6), we conduct the difference-in-differences analysis using the unweighted sample and on the PSM matched sample in Columns (3), (4), (7) and (8). The industry based on the Fama and French 48 industry classification and year fixed effects are included. The dependent variable in Columns (1)-(4) is patent applications (PtApp) and patent value (PtVal) in Columns (5)-(8). Patent applications (PtApp) are measured as the natural logarithm of one plus the total number of patents applied in year t , while the patent value (Ptval) is calculated as the sum of the market value of all patents applied in year t scaled by the lagged assets. The market value of each patent is computed following Kogan et al. (2017) based on the market reactions to patent grants. Treated is an indicator variable for innovation-intensive firms, zero otherwise. Post is an indicator variable that equals to one for fiscal years subsequent to the enactment of the AIA in March 2013, zero otherwise. Controls include all firm-level characteristics included in Table 5. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 15 Results of trend analysis on patent applications and quality

	Patent applications				Patent value			
	Unweighted sample		Matched sample		Unweighted sample		Matched sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Treated*Time T-2</i>	0.102 (0.965)	0.102 (0.965)	0.122 (1.072)	0.122 (1.072)	0.000 (0.031)	0.000 (0.032)	0.003 (0.446)	0.003 (0.446)
<i>Treated*Time T-1</i>	0.166 (1.572)	0.166 (1.574)	0.167 (1.465)	0.167 (1.466)	0.007 (0.629)	0.007 (0.630)	0.006 (0.731)	0.006 (0.731)
<i>Treated*Time T</i>	0.322*** (3.125)	0.322*** (3.127)	0.347*** (3.130)	0.347*** (3.131)	0.011 (0.949)	0.011 (0.950)	0.006 (0.753)	0.006 (0.754)
<i>Treated*Post</i>	0.326*** (3.829)		0.372*** (4.065)		-0.016* (-1.868)		-0.011* (-1.742)	
<i>Treated*Time T+1</i>		0.519*** (5.282)		0.611*** (5.814)		-0.001 (-0.096)		0.001 (0.148)
<i>Treated*Time T+2</i>		0.249** (2.380)		0.267** (2.350)		-0.019* (-1.790)		-0.013* (-1.761)
<i>Treated*Time T+3</i>		0.187* (1.773)		0.209* (1.847)		-0.032*** (-3.135)		-0.022*** (-3.178)
Control	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,443	10,443	6,628	6,628	10,443	10,443	6,628	6,628
R-squared	0.577	0.578	0.536	0.537	0.299	0.300	0.316	0.317
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The industry fixed effects are included based on the Fama and French 48 industry classification and the standard errors are clustered at firm and year level. In Columns (1), (2), (5) and (6), we conduct the difference-in-differences analysis using the unweighted sample and on the PSM matched sample in Columns (3), (4), (7) and (8). The dependent variable in Columns (1)-(4) is patent applications (PtApp) and patent value (PtVal) in Columns (5)-(8). Time T-2, Time T-1 and Time T are binary variables that take value one if the years are two and one year before and during the enactment of the AIA in 2013, zero otherwise. Time T+1, Time T+2 and Time T+3 are binary variables that are set equal to one if the years are one, two and three years after the enactment, zero otherwise. Post is an indicator variable that equals to one for fiscal years subsequent to the enactment of the AIA in March 2013, zero otherwise. Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.

Table 16 Narrative R&D disclosure and external financing

	Bid-ask spread			New equity issuance			New debt issuance		
	OLS	Unweighted	Matched	OLS	Unweighted	Matched	OLS	Unweighted	Matched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>RDSen</i>	-0.001*** (-9.863)			0.004*** (2.595)			-0.006*** (-5.072)		
<i>Treated*Post</i>		0.0004** (1.962)	0.0004** (2.009)		-0.017** (-2.279)	-0.021** (-2.471)		0.002 (0.260)	-0.009 (-1.127)
<i>Treated</i>		-0.000 (-0.855)	-0.001*** (-3.410)		0.014*** (2.656)	0.016*** (2.817)		-0.005 (-0.951)	0.003 (0.620)
<i>Post</i>		0.001** (2.191)	0.000 (1.308)		-0.011* (-1.670)	-0.011 (-1.315)		0.011* (1.831)	0.024*** (2.793)
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.075*** (31.343)	0.034*** (20.150)	0.033*** (16.387)	-0.073** (-2.575)	0.015 (0.261)	0.088 (1.143)	-0.006 (-0.218)	-0.089* (-1.685)	-0.070 (-0.872)
Observations	51,658	13,502	8,496	49,019	12,539	7,530	49,019	12,539	7,530
R-squared	0.518	0.503	0.516	0.339	0.375	0.377	0.056	0.047	0.051
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The standard errors are clustered at firm and year level. In Columns (1), (4) and (7), we conduct the analysis on the full sample. In Columns (2), (5) and (8), we conduct the difference-in-differences analysis using the unweighted sample and on the PSM matched sample in Columns (3), (6) and (9). The industry based on the Fama and French 48 industry classification and year fixed effects are included. The dependent variable in Columns (1)-(3) is the cost of equity (*CoE*) measured using the bid-ask spread obtained as the annual median of monthly quoted spreads. The dependent variable in Columns (4)-(6) is the new equity issuance (*NEquity*) measured as the ratio of external equity issues to the book assets at the beginning of the year, where the external equity issues are constructed as the change in book equity minus the change in retained earnings. The dependent variable in Columns (7)-(9) is the new debt issuance (*NDebts*) measured as debt issues over the start-of-year book assets, where the debt issues are the change in assets minus the change in book equity. Treated is an indicator variable for innovation-intensive firms, zero otherwise. Post is an indicator variable that equals to one for fiscal years subsequent to the enactment of the AIA in March 2013, zero otherwise. Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.

Table 17 Possible mechanisms

	Information asymmetry		Financial reporting quality		R&D intensity		Cash volatility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>InvEff</i>	<i>RDInvEff</i>	<i>InvEff</i>	<i>RDInvEff</i>	<i>InvEff</i>	<i>RDInvEff</i>	<i>InvEff</i>	<i>RDInvEff</i>
<i>RD_SEN</i>	0.015*** (21.968)	0.013*** (25.820)	0.015*** (19.949)	0.013*** (22.918)	0.010*** (14.858)	0.009*** (19.603)	0.017*** (23.180)	0.014*** (24.312)
<i>High bid-ask</i>	-0.013*** (-6.388)	-0.005*** (-3.550)						
<i>RD_SEN*High bid-ask</i>	0.008*** (10.302)	0.003*** (5.842)						
<i>Low FRQ</i>			-0.009*** (-4.749)	-0.003* (-1.863)				
<i>RD_SEN*Low FRQ</i>			0.005*** (6.424)	0.002*** (3.777)				
<i>High RDI</i>					-0.055*** (-25.955)	-0.045*** (-27.576)		
<i>RD_SEN*High RDI</i>					0.019*** (24.121)	0.014*** (21.700)		
<i>High CashV</i>							-0.008*** (-4.252)	-0.005*** (-3.420)
<i>RD_SEN*High CashV</i>							0.002*** (3.234)	0.002*** (3.196)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-0.204*** (-18.513)	-0.135*** (-13.354)	-0.195*** (-17.181)	-0.124*** (-11.989)	-0.188*** (-17.557)	-0.119*** (-14.049)	-0.207*** (-19.020)	-0.137*** (-15.905)
Observations	47,615	47,615	41,858	41,858	48,027	48,027	48,005	48,005
R-squared	0.345	0.434	0.358	0.454	0.359	0.449	0.348	0.437
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

This table presents the pooled time-series cross-sectional regression OLS estimated coefficients (t-statistics in parentheses). The industry fixed effects are included based on the Fama and French 48 industry classification and the standard errors are clustered at firm and year level. The dependent variable in Columns (1), (3), (5) and (7) is investment efficiency (*InvEff*), and R&D investment efficiency (*RDInvEff*) in Columns (2), (4), (6) and (8). High bid-ask takes value one if the firm's annual bid-ask spread is above the industry-median, zero otherwise. Financial reporting quality is measured using the accrual quality (AQ) derived from Dechow and Dichev (2002) and McNichols (2002) (Eq. (8)). Low FRQ is set equal to one if the firm's AQ is above the industry-year median, zero otherwise. High RDI takes value one if the firm's R&D intensity, measured as R&D expenses over sales, is above the industry-year median, zero otherwise. Following Hong et al. (2019), we measure cash flow volatility as the coefficient of variation in a firm's quarterly operating cash flow scaled by the absolute value of the mean over the same period. High CashV is then set equal to one if the firm's cash flow volatility is above the industry-year median, zero otherwise. We compute each industry-year median at the Fama and French 48 industry classification. All dummy variables are measured at time t-1. Controls include all firm-level characteristics included in Table 5. * p<0.1 ** p<0.05 *** p<0.01.

Appendix

Table A1 Results of baseline model with firm fixed effects

	Investment Efficiency			R&D investment Efficiency		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RDSen</i>	0.005*** (3.842)			0.004*** (3.883)		
<i>RDNumSen</i>		0.005*** (3.989)			0.004*** (4.218)	
<i>RDFwdSen</i>			0.003** (2.382)			0.002** (2.026)
<i>TSent</i>	-0.002 (-1.506)	-0.002 (-1.257)	-0.001 (-1.076)	-0.002** (-2.212)	-0.002** (-1.964)	-0.001 (-1.634)
<i>Instowner</i>	0.002 (0.429)	0.002 (0.423)	0.002 (0.454)	0.003 (1.060)	0.003 (1.052)	0.003 (1.087)
<i>Analyst</i>	-0.001 (-0.834)	-0.001 (-0.835)	-0.001 (-0.804)	0.000 (0.154)	0.000 (0.149)	0.000 (0.195)
<i>Size</i>	0.017*** (9.411)	0.017*** (9.491)	0.018*** (9.457)	0.014*** (8.404)	0.014*** (8.475)	0.014*** (8.461)
<i>MB</i>	-0.005*** (-6.317)	-0.005*** (-6.284)	-0.005*** (-6.306)	-0.005*** (-7.447)	-0.005*** (-7.417)	-0.005*** (-7.431)
<i>StdCfo</i>	-0.001 (-0.046)	-0.001 (-0.042)	-0.001 (-0.087)	0.011 (1.071)	0.011 (1.076)	0.010 (1.035)
<i>StdSale</i>	-0.001 (-0.322)	-0.001 (-0.346)	-0.001 (-0.364)	0.001 (0.306)	0.001 (0.284)	0.001 (0.254)
<i>StdInvest</i>	-0.017 (-1.242)	-0.017 (-1.261)	-0.017 (-1.252)	-0.039*** (-3.778)	-0.040*** (-3.801)	-0.039*** (-3.777)
<i>Zscore</i>	0.001*** (3.677)	0.001*** (3.681)	0.001*** (3.685)	0.001*** (5.859)	0.001*** (5.859)	0.001*** (5.863)
<i>Tangibility</i>	0.020* (1.943)	0.019* (1.922)	0.019* (1.911)	0.006 (0.710)	0.005 (0.691)	0.005 (0.676)
<i>Leverage</i>	0.014*** (2.612)	0.014*** (2.616)	0.014*** (2.568)	-0.005 (-1.284)	-0.005 (-1.275)	-0.005 (-1.320)
<i>Leverage_Ind</i>	0.019* (1.916)	0.019* (1.914)	0.019* (1.867)	0.007 (0.971)	0.007 (0.969)	0.006 (0.911)
<i>CfoSale</i>	0.000 (0.340)	0.000 (0.321)	0.000 (0.316)	0.001 (1.080)	0.001 (1.064)	0.001 (1.052)
<i>Slack</i>	0.000 (0.685)	0.000 (0.700)	0.000 (0.645)	0.000* (1.754)	0.000* (1.769)	0.000* (1.717)
<i>Dividend</i>	-0.003 (-1.318)	-0.003 (-1.358)	-0.003 (-1.351)	-0.002 (-1.111)	-0.002 (-1.152)	-0.002 (-1.153)
<i>Age</i>	0.001 (0.505)	0.001 (0.446)	0.001 (0.518)	-0.000 (-0.120)	-0.000 (-0.176)	-0.000 (-0.117)
<i>OpCycle</i>	0.004* (1.878)	0.003* (1.856)	0.004* (1.892)	0.002 (1.079)	0.002 (1.058)	0.002 (1.087)
<i>Loss</i>	0.001 (1.155)	0.002 (1.190)	0.002 (1.229)	0.001 (0.817)	0.001 (0.852)	0.001 (0.914)
Constant	-0.251*** (-15.606)	-0.250*** (-15.571)	-0.250*** (-15.470)	-0.162*** (-12.828)	-0.161*** (-12.799)	-0.161*** (-12.766)
Observations	48,027	48,027	48,027	48,027	48,027	48,027
R-squared	0.207	0.207	0.207	0.308	0.308	0.307
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (robust t-statistics in parentheses). The firm-level characteristics are defined in Table 5. *

p<0.1 ** p<0.05 *** p<0.01.

Table A2 Pre- and post-match mean differences

	Pre-Match			Post-Match		
	Treated	Control	T-Diff	Treated	Control	T-Diff
<i>Analyst</i>	2.167	1.673	21.130***	1.952	1.959	-0.200
<i>Size</i>	7.129	6.394	15.090***	6.741	6.769	-0.370
<i>RDS</i>	0.302	0.375	-1.970**	0.307	0.262	0.960
<i>Age</i>	3.038	2.829	11.970***	2.929	2.917	0.420
<i>ROA</i>	0.091	0.091	-0.130***	0.085	0.090	-0.830
<i>Tangibility</i>	0.177	0.267	-17.160***	0.199	0.206	-0.940
<i>Leverage</i>	0.182	0.215	-6.790***	0.188	0.188	0.020
<i>Capx</i>	0.038	0.052	-11.130***	0.042	0.043	-0.630
<i>TobinQ</i>	2.302	1.846	13.600***	2.042	2.086	-0.840
<i>KZ</i>	-11.545	-9.599	-3.020***	-10.540	-11.329	0.770
<i>HHI</i>	0.285	0.279	1.160	0.282	0.279	0.320
<i>HHI2</i>	0.126	0.122	1.020	0.123	0.123	-0.070
<i>Instowner</i>	0.698	0.572	15.560***	0.653	0.648	0.430
<i>Illiquid</i>	0.593	2.077	-7.120***	0.898	1.064	-0.620
Observations	2,504	5,069	-	915	915	-

* p<0.1 ** p<0.05 *** p<0.01

Table A3 Results of difference-in-differences (FE model)

	Original sample		Matched sample	
	(1) <i>InvEff</i>	(2) <i>RDInvEff</i>	(3) <i>InvEff</i>	(4) <i>RDInvEff</i>
<i>Treated*Post</i>	-0.008*** (-2.746)	-0.003** (-2.497)	-0.012*** (-3.425)	-0.009*** (-4.352)
Constants	-0.189*** (-5.262)	-0.078*** (-5.470)	-0.212*** (-4.574)	-0.121*** (-4.648)
Controls	YES	YES	YES	YES
Observations	10,443	10,443	6,628	6,628
R-squared	0.097	0.122	0.068	0.103
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

This table presents the fixed effects estimated coefficients (robust t-statistics in parentheses) for Eq. (6a). The industry based on the Fama and French 48 industry classification and year fixed effects are included. In Columns (1) and (2), we use the original sample used in Table 10, while in Columns (3) and (4), we conduct the analysis on the PSM matched sample as in Table 11. The dependent variable in Columns (1) and (3) is investment efficiency (*InvEff*), and R&D investment efficiency (*RDInvEff*) in Columns (2) and (4). *Treated* is an indicator variable for innovation-intensive firms, zero otherwise. *Post* is an indicator variable that equals to one for fiscal years subsequent to the enactment of the AIA in March 2013, zero otherwise. Controls include all firm-level characteristics included in Table 5. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Conclusion

The thesis focuses on bridging the corporate finance and economics of innovation literature and addresses three independent but related issues. From the outset, the thesis studies the role of business involvement in the development of technology standards. The research throws light on the trade-off between developing open standards collaboratively or creating competitive distinction in developing innovative products or services. Understanding of how engagement with standard setting affects investors' perceptions of a firm's riskiness has far-reaching implications for corporate strategic and financial planning.

Using the sample of 3,350 U.S. public firms and their memberships of 183 SSOs from 1996 to 2014, we document a significantly lower cost of equity for SSO participants. This finding resonates with evidence documented by Aggarwal et al. (2011) in their study of the nexus between financial risks and IT standard-setting initiatives. Using an event-study approach, those authors show that a larger standardization group decreases the risk-adjusted abnormal return and the market risk of individual firms (i.e., beta) while increasing their idiosyncratic risk (i.e., variance of returns). Our results further document that this negative correlation between SSO membership and the implied cost of equity is most pronounced when a firm joins an SSO for the first time. And the relationship is contingent on three mechanisms - innovation intensity, market uncertainty and information environment. The analysis also takes into account the endogenous nature of a firm's decision to participate in standard development. Our main finding of the negative relationship between SSO membership and the implied cost of equity is robust to an instrumental variable model and a difference-in-differences approach, which is based on SSO closures as an exogenous variation in membership count to identify the impact of membership. This identification strategy postulates that such variation in the supply of SSOs is not driven by the demand of individual firms stemming from their standardization strategies; if such an assumption were to hold, this part of our analysis should have a causal interpretation.

Chapter 1 makes several empirical contributions. First of all, to the best of our knowledge, we present the first comprehensive analysis of the relationship between SSO membership and firms' cost of equity capital by utilizing robust evidence from a large sample of firms as well as an extensive range of SSOs that operate across diverse

technology domains. Our novel evidence highlights that SSO participation can have a causal impact on a firm's cost of equity financing. Robust evidence surrounding this relationship holds the key to a better understanding of the innovation financing issues in some of the most dynamic and important industries of the economy. Second, our study contributes to the burgeoning literature on the economic and strategic implications of business organizations' involvement in standardization (e.g., Simcoe et al., 2009; Waguespack and Fleming, 2009; Aggarwal et al., 2011). We focus on the financial impact and document that the capital markets respond positively to a firm's participation in SSOs. We empirically unpack three channels through which SSO might affect the cost of equity: reductions in uncertainty stemming from both technological innovation and the product market; and the signalling effect of SSO participation mitigating information asymmetry. Finally, our paper contributes to the stream of the literature focusing on innovation- and technology-related factors that affect a firm's cost of equity. Lui et al. (2016), for instance, find that U.S. listed firms which adopted (disruptive) innovations in information technology are associated with a lower cost of equity. Our paper reveals that a firm's cost of equity capital can also be reduced through collaborative innovation, in the form of participation in the collective development of open technology standards.

Admittedly, our study has several caveats. First, as we drew membership information from the SCDB, our empirical measures of SSO participation are subject to a trade-off between the precision or depth of coverage and the need to incorporate SSO-, technology- and firm-level heterogeneity to better understand the wider impact of technology standardization. Prior studies of a single SSO have utilized various proxies to capture the degree of participation and effort employed by participants (e.g., Leiponen, 2008; Baron and Gupta, 2018; Waguespack and Fleming, 2009). However, such detailed participation records are available from only a handful of SSOs, which makes comparison and generalization across a representative sample of SSOs impractical. More advanced algorithms can be developed to identify firms' involvement in standards development for future research. Second, our analysis derives insight from listed firms. It would be interesting to assess whether the cost of capital of small and unlisted firms, arguably affected by higher information asymmetry, is also affected by their engagement with technology standardization.

Chapter 2 and Chapter 3 have a closer look at the issues regarding the role of information environment on firms' investment efficiency. More specifically, Chapter 2 sheds light on the role of financial analysts in firms' innovation productivity, while

Chapter 3 studies the impact of firms' voluntary disclosure of R&D-related information on their overall investment efficiency. Considering the nonnegligible role of financial analysts in the capital market, Chapter 2 utilizes the sample of the listed U.S. firm data from 1990 to 2015 and finds an inverted-U relationship between analyst coverage and firms' patent value, and between analyst coverage and innovation efficiency. The curvilinear results indicate that firms can benefit from innovation value gains under a certain level of analyst coverage; high analyst coverage causes a reduction in innovation value and further results in lower innovation efficiency. Our results are robust using different sample compositions, sample periods and lags of analyst coverage. The endogeneity concerns are further mitigated using the 2SLS analysis, where we compute the expected coverage as the instrumental variable. Finally, we find that the curvilinear relationships between analyst coverage and firms' patent value, and between analyst coverage and innovation efficiency are contingent on firms' participation in industrial organizations, with regard to innovation and technology (Standards Setting Organizations), and product market competition.

In this chapter, we contribute to the literature in three broad aspects. First, we contribute to the literature on the determinants of market value of innovation and the innovation productivity. Few papers link the private economic value of innovation to finance. Almeida et al. (2021) document that a cash windfall can be a key factor influencing patent value. In this paper, we take into account the role of a key ingredient of the capital market, financial analysts, and find that analyst coverage has a curvilinear effect upon patent value. A certain level of analyst coverage increases a firm's patent value. However, as the number of analysts increases, the patent value is diminished. The private economic value of innovation is directly associated with a firm's market value and shareholder interest. Therefore, it is of great importance to study factors that may influence the true value of innovation. Second, our analysis contributes to the literature on the role of financial analysts, especially bridging it and corporate innovation (Barth et al., 2001; He and Tian, 2013; Zhong, 2018; Guo et al., 2019). The existing literature solely looks at the technological value of innovation that mostly rely on the traditional measures such as patent applications and citations, which are not ideal for capturing the true value of innovation (Almeida et al., 2021). It is necessary to understand whether analyst coverage affects the actual market outcome of a firm's investment. Firms may carry out unnecessary R&D investment without carefully evaluating the profits and risks, resulting in reduced innovation value or even failure. Besides, the perception of outside

investors on the patented innovation can significantly influence the overall market value of a firm. Finally, firms may not invest in innovation efficiently when subjected to the distortion of analyst coverage. Existing studies focus on either innovative inputs or outputs when discussing the role of analyst coverage on innovation. The issue on whether analyst coverage affects the extent to which a firm is able to produce high-value patents efficiently is rarely addressed. Our paper further bridges this gap by documenting a curvilinear relationship between analyst coverage and innovation efficiency (a firm's ability to generate a one-dollar market value per dollar of R&D investment).

Chapter 2 focuses on the perceived value of innovation. For the further research, it would be interesting to compare the impact of analyst coverage on the intrinsic value of inventions and on the market-perceived value. Another limit of this study is the sole focus on the outcome value and efficiency of innovation. Financial analysts might also affect firms' innovation strategies, e.g., explanatory vs. exploratory innovations. They might further influence firms' decisions on how much information a patent need to convey. More advanced measures of patent quality through linguistic analysis can be applied to look at, for instance, word count and sophistication of words of patents. We leave these questions to the future study.

Finally, in Chapter 3, we underscore the role of firms' voluntary disclosure on R&D-related information in their investment efficiency. Apart from looking at firms' involvement in standards development and external analyst coverage as indicators of their information environment, the final chapter is motivated by the fact that R&D is firm-specific and positively associated with uncertainty and asymmetric information. As narrative R&D disclosure reduces information asymmetries between the firms and investors (Merkley, 2014), it should help improve investment efficiency. The analysis is conducted using the substantial sample of 48,027 firm-year observations from 1997 to 2019. Our results provide strong evidence that firms' narrative R&D disclosure is positively related to their investment efficiency. Regarding the two scenarios of investment inefficiency, we find that narrative R&D disclosure is positively related to underinvestment and negatively associated with overinvestment. That is, both forms of inefficiency are ameliorated. Our results are robust to R&D-related investment efficiency, alternative measures of investment efficiency and narrative R&D disclosure. To address causality in this chapter, we employ a quasi-natural experiment in the difference-in-differences (DiD) framework by comparing the change in investment efficiency around the time of the enactment of the Leahy-Smith America Invents Act (AIA) on March 16,

2013. We find that the investment efficiency of innovation-intensive firms decreases after the enactment, compared to non-innovation-intensive firms. This finding is primarily driven by a negative relationship between narrative R&D disclosure and underinvestment. Our finding is robust to controlling for firm fixed effects and employing the DiD analysis on a propensity score matched sample. Additionally, we study firms' patenting and external financing activities around the time of the enactment of the AIA to unveil two channels through which firms adjust their investments after the reform. We find an increase in the quantity of patent applications immediately after the enactment for innovation-intensive firms and lower patent quality. We also find that innovation-intensive firms are less likely to issue new equity after the enactment, as the cost of equity increases. Finally, considering possible contingent factors, we find that the effect of narrative R&D disclosure on investment efficiency is more pronounced for firms with higher R&D intensity and greater information asymmetry (higher cost of equity, poorer financial reporting quality, and higher cash flow volatility).

This study contributes to the literature on investment efficiency in several ways. It adds to works focusing on the effects of firms' disclosure level. Our study stresses the role of firm-specific discretionary disclosure as we link narrative R&D disclosure to firms' investment efficiency. Besides, our paper complements studies on voluntary R&D disclosure, which have generally been limited to small samples of selected industries and short time periods. For instance, Entwistle (1999) relies on interviews supplemented with annual reports disclosure to explore associations between six disclosure environment factors and the amount of R&D disclosure for 113 Canadian listed firms. Guo et al. (2004) examine the extent of product-related information (including patent protection and product development stage) disclosed in the prospectuses of 49 biotech firms which had their initial public offerings during 1995 to 1997. In a cross-sectional analysis, Jones (2007) investigates the determinants of voluntary R&D disclosures made by 119 firms in four R&D-intensive industries: chemicals and pharmaceuticals (SIC 28), machinery and computer hardware (SIC 35), electrical and electronics (SIC 36), and scientific instruments (SIC 38). Our paper analyses voluntary textual releases in the U.S. listed firms' 10-K filings and finds that R&D disclosure improves investment efficiency. It adds to the first large-scale study of public firms' R&D disclosure by Merkley (2014), which finds that firms adjust their narrative R&D disclosure according to their earnings performance to convey contextual information about their firms to market participants.

The study also has some limitations. Our analysis focuses on firms' public 10-K filings. There may be other sources that firms use to convey firm-specific information to the market. Moreover, other firm-specific information disclosure, such as strategy, may also affect firms' investment decisions. Further study may be needed to address issues regarding various firm-specific information disclosure.

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