University of Nottingham
UK | CHINA | MALAYSIA

research paper series

Globalisation, Productivity and Technology Programme

Research Paper 2020/29

Participation in setting technology standards and the implied cost of equity

Xin Deng, Cher Li and Simona Mateut

GEP

Participation in Setting Technology Standards and the Implied Cost of Equity

Xin Deng, Cher Li,* Simona Mateut

Nottingham University Business School

Abstract

This paper empirically investigates the financial market's reaction to firms' participation in developing standards coordinated by Standard Setting Organizations (SSOs). We present the first causal 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 participation in SSOs results in a significantly lower cost of equity for member firms, using exogenous variations from SSO closures and instrumental variables. This reduction is more pronounced for a firm's first SSO membership, in ICT firms, among members of most influential SSOs and in certain technology domains. We empirically document the contingent role of three potential mechanisms identified by our conceptual framework - technological uncertainty, market uncertainty and information environment – through which SSO membership can affect financial outcomes.

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

* Corresponding author. Nottingham University Business School, Jubilee Campus, Wollaton Road, Nottingham NG8 1BB, UK. Email: Cher.Li@nottingham.ac.uk

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, as well as promote 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, and so forth (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). The development of these standards 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] Our key research question focuses on how a firm's participation in developing open technology standards is perceived by its investors. More specifically, to what extent a firm's participation in SSOs impacts on equity holders' risk perception as reflected in the firm's cost of equity capital, i.e., the discount rate applied to the firm's expected future cash flows to determine its current stock prices. This discount rate is thus reminiscent of investors' perceptions of the firm's riskiness.

Our interest in the relationship between the cost of equity capital and participation in standards development is motivated by three reasons. First, a firm's cost of equity is of paramount importance to its investment and financing decisions (Shleifer and Vishny, 2003; Boubakri et al., 2012); and as such, it is inextricably linked to investors' risk perception. If the perceived riskiness of SSO member firms is different to that of non-members, we should expect their cost of capital to vary systematically with SSO

[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.

memberships. Second, the ICT industries have witnessed a surge in standard-setting activities as underlying technologies have evolved at fast pace and these industries are disproportionately dependent on external finance (Acharya and Xu, 2017). Hence, unpacking the causal links between the cost of equity and SSO participation holds the key to innovation financing particularly in some critical sectors of the economy. Third, despite the importance of standards setting for technological progress and its crucial implication for the financial management of the firms involved, 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.

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 participation in SSOs plays a significant role in lowering a member firm's implied cost of equity. Most notably, a firm's first-recorded participation in any SSO is associated with a 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 benefit from a statistically significant reduction in their cost of equity vis-à-vis their non-ICT counterparts.

To the best of our knowledge, this study presents a first analysis of the causal impact of SSO participation on firm-level financial returns in terms of cost of equity capital utilizing robust evidence from a large sample of firms and across scores of SSOs. Our identification strategy consists of several steps: propensity score matching, instrumental variables and a quasi-natural experiment based on SSO closures. Conditioning on observable characteristics, our matched sample analysis reveals a highly significant negative effect of participation in SSOs on a firm's implied cost of equity. We subsequently utilize two sources of exogenous variation to construct our instrumental variables which are plausibly linked to a firm's membership decision but uncorrelated with the error term in the model determining implied cost of equity. Our first IV is a peer imitation variable which captures any SSO participation activities of the focal firm's closest rivals identified using the product similarity scores constructed by Hoberg and Phillips (2010, 2016) from the text analysis of firms' product descriptions in 10-K reports.

Our second IV on SSO availability measures a firm's time-varying exposure to available SSOs which a firm could potentially become a member of in a given year across different domains. This IV analysis corroborates that our observed negative correlation between SSO membership and a firm's cost of equity has a causal interpretation. Our final step uses the closures of eight SSOs as external shocks that can directly affect a firm's membership count but are truly exogenous to firm-level activities. Our results from the difference-in-differences estimation are also able to show that the difference in the cost of equity between our treatment and control groups is highly statistically significant.

In a recent study, Blind et al. (2017) shed light on the enhancing role of formal standards on the innovation efficiency of firms in markets with high uncertainty. A critical and yet unaddressed issue is then the extent to which participation in developing standards improves firms' financial performance by mitigating technological and market uncertainty. We address this issue by developing a comprehensive conceptual framework with three potential channels whereby SSO memberships can affect firms' financial outcomes, namely by moderating technological uncertainty, market uncertainty, and information environment.

To capture the role of technological uncertainty, we use firm-level innovation intensity proxies such as R&D intensity, narrative R&D-related disclosure in firms' 10-K filings, patent applications and ownership of standard-essential patents (SEP). Our findings reveal that SSO members with above-industry average performance in the above characteristics invariably enjoy a significantly lower cost of equity, suggesting the effect of membership is most pronounced when technological uncertainty is high. In a similar vein, we find that SSO members facing higher levels of market uncertainty, in terms of product-market competition and customer-base concentration, also benefit from a reduction in their cost of equity. Finally, using novel measures for 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 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 can benefit from 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 central or 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).

We subsequently categorize SSOs in our sample by their technological specialization. Three largest categories in our sample are *Interoperability*, *Wireless and Mobile* and *Software*. Memberships in 17 (out of 19) SSO categories are associated with significantly lower cost of equity. Firms participating in SSOs that develop standards in *Network Centric and Grid Computing* are associated with the largest reduction in their cost of equity while the magnitude of this effect is broadly comparable among other categories. Additionally, we explore heterogeneity among SSOs by considering their technology-based versus market-based focus (Delcamp and Leiponen, 2014; Baron et al., 2019). Multiple memberships of various types are associated with lower cost of equity compared with memberships of SSOs of a single type. Participation in technology-centric SSOs has more prominent effects for ICT firms.

Our paper 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 impact evaluation. This paper also relates to the empirical literature on the determinants of the cost of equity. Recent studies have emphasized the role of 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. Our paper adds to this literature by highlighting an important yet neglected factor that is collaborative innovation as measured by the firms' participation in collectively developing emerging technology standards.

The remainder of the paper 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, 2020, 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 (see a detailed discussion in 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.

Consistent with this line of reasoning, our identification strategy utilizing instrumental variables is able to empirically verify that several motivations outlined above are indeed salient in determining the first stage of participation decision. More specifically, our probit model of membership decision illustrates that a firm's participation in SSOs is, inter alia, driven by its competitive strategy in terms of following and cooperating with main industry rivals in standards development as well as dynamically matching with the availability of SSOs (and thus emerging technological opportunities) which evolves

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

over time and across different technical fields. 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).

2.2 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 "infratechnology" 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, 2020).

Technological uncertainty. Firstly, participation in developing standards can minimize a firm's *technological uncertainty* and thus maximize its 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 *product-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 (2020) 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 facing higher technological- and market uncertainty, or information asymmetry. In ensuing empirical analyses, we test the 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) on firms' participation in technology standards and Standard Setting Organizations over the period 1996-2014 (see Baron and Spulber, 2018). For all matches, we manually check firm names and postcode information on the Internet. Since the SCDB records the full population of all members participating in a total of 191 SSOs across a range of ICT-based technology fields, we consider the unmatched Compustat firms as non-members in a given year.

As participation in developing 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.

[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.

[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

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.

---

[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.

3.3 Empirical model

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

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

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 participates in an 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.

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), $Controls_{i,t-1}$ is a set of variables known to influence the cost of equity: the market-to-book ratio (*MTB*); the leverage ratio (*LEVERAGE*) calculated as long-term debt to total assets; the return on assets (*ROA*); firm size (*SIZE*) is total real assets (using 2010 as reference);[5] the annual standard deviation of monthly stock returns (*VOLATILITY*). *AGE* is the number of years since the firm's initial public offering or first trading. *MTB, SIZE, VOLATILITY* and *AGE* are measured in natural logarithm. *FORECASTER* is calculated as earnings forecasts next year minus actual earnings, scaled by lagged total assets.

Importantly, we 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 market 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

---

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

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.[6]

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% 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.

---

[6] In a separate exercise, we use the CRSP-linked granted patents data downloaded from Noah Stoffman's website (https://iu.app.box.com/patents). Kogan et al. (2017) provide details on how the dataset is constructed. 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.

[7] We carefully inspect the SCDB membership database to ensure data accuracy. For instance, following the closure of an SSO during our sample period, we ascertain that none of its member firms show up as participating in that SSO in the years following its closure. See also Section 6.3.

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]

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. 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 Patacconi, 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 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 capital.

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 technological uncertainty, 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 US (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.[8] 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)).

[Insert Table 4]

4.2.2 Technological uncertainty

To proxy for technological uncertainty, we explore firm-level characteristics such as R&D intensity, narrative R&D disclosure, patent applications and holding standard-essential patents (SEP). To compute these indicators, we proceed as follows. According to Czarnitzki and Toole (2011), R&D-intensive firms, especially in ICT industries, encounter higher technological uncertainty. Operating in a fast-changing environment, these firms are more likely to encounter R&D investment failure or unexpectedly surging costs in innovations. We measure firm-level R&D intensity as R&D expenses over total sales.[9] 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.[10]

[8] 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).

[9] 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.

[10] 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 US companies between 1996 to 2014 from the Software Repository for Accounting and Finance (SRAF) provided by Loughran and McDonald.[11] 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.[12] 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 distinguish between inventors and implementers, we consider firms' yearly patent applications and their holdings of standard-essential patents (SEPs). 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. Finally, we pinpoint SEP holder firms by mapping the 139,620 essential patents identified by Baron and Pohlmann (2018) to our dataset using the company name (present in both databases), and create *SEP (NSEP)* as dummy variables equal to one if firm *i* has at least one (no) declared SEP in year *t-1*.

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 technological uncertainty stemming from risky R&D projects by shifting the burden of innovation from the firm to SSO level. Similarly, the estimated parameters in columns (3)-(4) highlight that SSO members that are SEP owners or patenting intensive enjoy a reduced cost of equity.

4.2.3 Product-market uncertainty

Our conceptual framework underlines also the role of the market environment in moderating the relationship between SSO membership and cost of equity. This analysis thus focuses on the factors associated with product market competition and customer base concentration.

---

[11] 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/

[12] 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.

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.

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:

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

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) CustConce* equal to one if the customer concentration index is above (below) the industry-year median, and zero otherwise.[13]

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.

[13] 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.

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.[14] 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 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:

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

where $\frac{words}{sentences}$ is the average number of words per sentences 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.[15] Similar to our approach for narrative R&D disclosure, we collect parsed annual 10-K filings for all US 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 Zhong (2018), we employ earnings smoothing using accruals as a proxy for firms' transparency. 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

[14] The KZ index is calculated as -1.002*cash flow + 0.283*Tobin Q + 2.139*leverage - 39.368*dividend - 1.315*cash holding. Higher index values indicate stronger financial constraints.

[15] As many multisyllabic words such as corporation, company and telecommunications are presumably easy to understand in the context of financial disclosures, we follow Kim et al. (2019) and remove such words from our identified complex words list. Our results hold when we employ other two commonly used readability measures: the Flesch Reading Ease Score and the Kincaid Index.

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.[16]

[Insert Table 5]

5 SSO Heterogeneity

5.1 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 $N*N$ 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

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

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.

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

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 two variables to indicate a firm's association with an influential SSO in a given year: viz. *iMEMBER* (*1/0*) denotes membership in an SSO whose centrality is above/below the median value, and *iMEMBERCOUNT* tallies the number of influential SSO participations. The estimates in Table 6 show that participation in (one or several) influential SSOs correlates negatively with the firm's cost of equity.[17]

[Insert Table 6]

5.2 SSO specialization and categories

We further exploit heterogeneity among SSOs and identify 19 categories based on the standards they are involved with, as suggested by Andy Updegrove.[18] The three largest technological categories are: *Interoperability*, *Wireless and Mobile*, and *Software,* accounting for 69.57%, 56.94%, 49.17% of total SSO memberships, respectively. Roughly one third of the members in our sample are associated

---

[17] Both variables are measured in year t-1. Our results hold if we exclude permanent members before defining an influential SSO.

[18] Following Baron and Spulber (2017), we search the internet archive of standards consortia provided by Andy Updegrove (https://www.consortiuminfo.org) for technological classification of SSOs in 2014, the last year of our sample. We search the websites of the SSOs in our dataset not listed on Consortiuminfo.org, identify the items they are working on and manually assign them into relevant technological categories.

with SSOs in *Hardware*, *Information Technology*, *Internet* and *Network*.[19] We capture membership in each of these SSO categories with 19 corresponding binary variables. The estimated coefficients and their significance are presented in Figure 2. The results suggest that, except for *Electronic Media* and *Othe*r categories, memberships are associated with lower cost of equity. Firms participating in SSOs that develop standards relating to *Network Centric and Grid Computing* are associated with the largest reduction in their cost of equity, followed by *security and cyber security* as well as *imaging* technologies.

[Insert Figure 2]

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.[20] 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 7 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-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.[21] Most notably, multiple memberships of various SSO types corresponds to the lowest cost of equity.

[19] One firm may attend several SSOs and one SSO may develop standards from different technological categories.

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

[21] Our results remain unchanged if we use ICT sample B defined in Section 4.2.1.

[Insert Figure 3 and Table 7]

6. Endogeneity concerns

We have used linear regression analysis to establish correlation between SSO membership and cost of equity. To the extent that lower cost of capital 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 by including membership status in time *t-1*. In this section, we address additional endogeneity concerns by employing several methods: viz., matching on observable characteristics, using instrumental variables, exploiting a plausibly exogenous shock to the membership count caused by SSO closures.

6.1 Matched sample analysis

We now use a matched sample analysis (Heckman et al., 1997, 1998; Rosenbaum and Rubin, 1983) to address the endogeneity concerns. Specifically, we create a control and a treatment group of firms similar in all characteristics except their participation in an SSO. Similarity between firms is based on estimated treatment probabilities, known as propensity scores. In other words, the two groups of firms have the same estimated likelihood of being SSO members based on a set of observable characteristics.

To calculate the propensity scores, we estimate the logit model below:

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

where $Participation_{i,t}$ indicates (1/0) whether firm *i* participates in an SSO in year *t*. We match (without replacement) member firms to the nearest non-member firms on all the previous controls, market competition (HHI index), 2-digit industry SIC codes, and time effects.[22] To improve matching quality our algorithm imposes the common support restriction and a 0.0001 caliper (i.e., the maximum distance in the propensity scores for matched firms). Additional variables included in $X_{i,t-1}$ used in matching are mainly drawn from two strands of literature: one is related to innovation and cost of equity (e.g., Lui et al., 2016), while the other is on business strategy (e.g., Lim et al., 2017), as SSO

[22] One-to-one matching can help minimize bias at the cost of larger variance. Non-replacement helps keep the variance low but at the cost of potential bias.

participation can be seen as one of firms' strategic choices. Thus, following Lui et al. (2016), we match firms on characteristics such as: R&D intensity (R&D expenses over sales) to capture firms' managerial risk taking, *SGAI* (the ratio of sales and general administrative costs of sales), *Financial Slack* (current assets over total assets) as well as financial constraints (*KZ)* to capture the availability of financial resources enabling participating in SSOs, and two operating performance indicators sales growth (*SG*) and labour productivity (*OIPE*) measured as the operating income over the number of employees to gauge the firms' ability to innovate and decrypt technical knowledge, which may influence firms' participation choice. The non-financial variables above are employed also in the business strategy strand of literature: R&D intensity shows firms' tendency to search for new products and markets, while *SGAI* reflects firms' focus on exploiting and marketing new products. Following Lim et al. (2017), we match firms also on capital intensity (*CAP*), measured as the net property, plant and equipment to total assets, to reflect firms' technological efficiency, and on organizational stability (*TEMP*), given by the standard deviation of the total number of employees. This variable helps capture the difference of talent pools across firms. Employees of innovative firms normally have shorter tenure as their general skills grants them mobility across firms according to availability of projects (Lim et al., 2017). All additional data is collected from the Compustat-CRSP Merged database. [23]

Balancing tests assessing the quality of the match are presented in Table 8. For the 2,346 successful matches, there is no significant difference in means between the treated and the non-treated groups and the standardized biases are all less than 5% after matching.

[Insert Table 8]

Under the matching assumption, the only remaining difference between the two groups of firms is the actual SSO participation. Column (1) in Table 9 reports the fixed effects estimates on the matched sample. The highly significant coefficient associated with the *MEMBER* indicator confirms the negative relation between participation in SSOs and firms' implied cost of equity when we use a matched sample analysis. These estimates suggest that SSO participation reduces the firms' implied cost of equity by around 0.10 percentage points, which is an economically significant amount.

[23] In unreported alternative estimations, we control for these additional variables in our baseline models and find that our results for the membership-cost of equity relationship remain robust.

6.2 Instrumental variables

Here, we follow the 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, the procedure involves the following steps: (i) we first estimate a probit model of the firms' participation on instrumental variables and other control variables; (ii) we compute the predicted probability $\widehat{MEMBER}$, which we use 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.[24]

We identify two instruments – peer imitation and SSO availability – that are likely correlated with our endogenous binary variable *MEMBER* but not with the error term in the model determining the implied cost of equity, so as to satisfy the exclusion restrictions. To define peer imitation, we contrast firms and their competitors using measures of product similarity. We use the pairwise similarities constructed by Hoberg and Phillips (2010, 2016) from the text-based analysis of firms' annual 10-K product descriptions and identify the group of 5 firms with the most similar products to the focal firm. We generate the variable *Peer Imitation,* recording how many among these 5 competitors attend at least one SSO, to capture the imitation effect on a firm's propensity to join SSOs: a firm is likely to participate in standards development when it observes its closest rivals (with similar products) are doing so.

Our second instrument gauges the annual availability of SSOs across different operating domains. We start by assigning an SSO all (3-digit SIC) industry codes of all its member firms in a year *t*. The availability of SSOs in the focal firm's operating field (via both the establishment of new SSOs and increased firm membership within an operating field) can significantly affect a firm's participating choice. Our second instrument (*SSO Availability*) is the number of relevant SSOs (assigned with the same industry) for the focal firm in a year *t*. We use both *Peer Imitation* and *SSO Availability* in logarithmic form (using them in levels is inconsequential for our results).

[24] 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.

As firms' imitation and participation decisions are based on having observed the past actions of other firms and established SSOs, the probit model for the firm's participation in the first stage of our IV procedure includes the lagged values of both instruments. The probit estimates are reported in column (2) of Table 9. Both *Peer Imitation* and *SSO Availability* are positively and significantly related with the likelihood of being an SSO member. The higher the number of "nearest 5 firms" participating in an SSO, the more likely is the focal firm to join an SSO. Similarly, better availability of relevant SSOs increases the likelihood of firms' SSO participation. The second stage 2SLS results in column (4) confirm the negative relation between SSO participation and firms' implied cost of equity.

The negative SSO membership - cost of equity relationship holds also in the last column of Table 9, which reports the results obtained from a treatment effect model. 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).[25]

[Insert Table 9]

6.3 SSO closures

To address further sources of endogenous bias arising from unobserved confounding factors, our final identification strategy exploits exogenous sources of variation of SSO closures during our sample period. As a quasi-natural experiment, SSO closures can directly affect individual firms' membership counts but are exogenous to their cost of equity.[26] We identify 8 SSO closures within our sample period based on information from consortiuminfo.org and other internet sources (dissolving year in brackets): Universal Wireless Communications Consortium (UWCC) (2001), TV Anytime Forum (2005), FlexRay Consortium (2009), Liberty Alliance Project (2009), WiMedia Alliance (2010), OpenAjax

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

[26] Leiponen (2008) and Delcamp and Leiponen (2014) use mergers across SSOs for identification which offer exogenous sources of variation that are analogous to our setting. Due to limited number of merger events during our sample period, only SSO closures present a suitable source of variation.

Alliance (2012), International Imaging Industry Association (I3A) (2013), and 3rd Generation Partnership Project No.2 (3GPP2) (2013).[27]

As the effects of SSO closures on firms' membership counts 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* around the event year *t*. To construct a sample of treatment firms, we first identify all members of the 8 SSOs before their closure. 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*. We then construct a control group of firms that are matched to the treatment group on important observable characteristics one year prior to the events but that do not have reduced SSO membership count due to the exogenous shock (they were not members of the closing SSO). We require candidate control firms to be similar in terms of all key variables in the baseline model (*PATAPP, SIZE, VOLATILITY, MTB, LEVEAGE, ROA, AGE, FORECASTER* and industry) in the matching year *t-1*. For each treatment, we retain five closest control firms and end up with 150 unique pairs of treatment-control matches.[28]

Panel A of Table 10 reports the univariate comparisons between the treatment and control firms' key variables in our baseline model. 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 DiD analysis results. We compute the DiD estimators by first subtracting, for each firm, the cost of equity in year *t-1* from the cost of equity after the closure event in year *t+1*. The cost of equity difference is then averaged over the treatment / control group and reported in column (1) / (2). We note that the average change in the cost of equity for the treatment group (-0.011) is much smaller than the average change (-0.018) for the control group. Column (3) reports the DiD estimator: the difference in the differences for the treatment and control groups is statistically significant at 5% level (the standard error is clustered at the event level).

We now repeat the DiD analysis on a different set of treatment-control matches. This time, we include all variables used in Section 6.1., which results in 114 matched unique pairs. We report these

[27] We utilize Wayback Machines to search the internet archive for the official webpages of the SSOs before and after their closure to ensure that each closure really takes place.

[28] Using instead either a 1-to-1 or 1-to-3 matching gives qualitative similar results.

estimates in Panels C and D of Table 10 and note that the DiD estimate for the cost of equity is 0.011 and significant at the 5% level, although treatment firms appear to be slightly larger than control firms.

[Insert Table 10]

7. Conclusion

In this study, we present the first causal evidence on the role 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 study 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, our 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 results are robust to considerations of the endogenous nature of firms' membership decision. We identify a causal and negative impact of SSO membership on firms' implied cost of equity using various strategies including propensity score matching, instrumental variables and a difference-in-differences estimation based on SSO closures.

The negative relationship between participation in SSOs and the implied cost of equity is evident from the first 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 some caveats. 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.

Acknowledgments

Cher Li gratefully acknowledges the support of the Economic and Social Research Council [ESRC grant ref. ES/T001771/1].

References

Acharya, V., Xu, Z. (2017). Financial dependence and innovation: The case of public versus private firms. *Journal of Financial Economics*, 124(2), 223-243.

Adams, R., Almeida, H., Ferreira, D. (2009). Understanding the relationship between founder–CEOs and firm performance. *Journal of Empirical Finance*, 16(1), 136-150.

Aggarwal, N., Dai, Q., Walden, E.A. (2011). The more, the merrier? How the number of partners in a standard-setting initiative affects shareholder's risk and return. *MIS Quarterly*, 445-462.

Ahern, K.R., Harford, J. (2014). The importance of industry links in merger waves. *The Journal of Finance*, 69(2), 527-576.

Ahmed, S., Judge, A., Mahmud, S.E. (2018). Does derivatives use reduce the cost of equity?, *International Review of Financial Analysis*, 60, 1-16.

Angrist, J.D., Pischke, J. S. (2008). Mostly harmless econometrics: An empiricist's companion. Princeton university press, 142-145.

Baron, J., Li, Q.C., Nasirov, S. (2019). Why do R&D-intensive firms participate in standards organizations? The role of patents and product-market position. *SSRN Electronic Journal*. Available at: https://ssrn.com/abstract=3287475.

Baron, J., Pohlmann, T. (2018). Mapping standards to patents using declarations of standard-essential patents. *Journal of Economics & Management Strategy*, 27(3), 504-534.

Baron, J., Spulber, D.F. (2018). Technology standards and standard setting organizations: Introduction to the Searle Center Database. *Journal of Economics Management Strategy*, 27(3), 462-503.

Belenzon, S., Patacconi, A. (2013). Innovation and firm value: An investigation of the changing role of patents, 1985–2007. *Research Policy*, 42(8), 1496-1510.

Besen, S.M., Farrell, J. (1994). Choosing how to compete: Strategies and tactics in standardization. *Journal of Economic Perspectives*, 8(2), 117–131.

Blind, K., Mangelsdorf, A. (2016). Motives to standardize: Empirical evidence from Germany. *Technovation*, 48, 13-24.

Blind, K., Petersen, S.S., Riillo, C.A.F. (2017). The impact of standards and regulation on innovation in uncertain markets. *Research Policy*, 46(1), 249–264.

Bonacich, P. (1987). Power and centrality: A family of measures. *American Journal of Sociology*, 92(5), 1170-1182.

—— (2007). Some unique properties of eigenvector centrality. *Social networks*, 29(4), 555-564.

Boubaker, S., Boubakri, N., Grira, J., Guizani, A. (2018). Sovereign wealth funds and equity pricing: Evidence from implied cost of equity of publicly traded targets. *Journal of Corporate Finance*, 53, 202-224.

Boubakri, N., Guedhami, O., Mishra, D., Saffar, W. (2012). Political connections and the cost of equity capital. *Journal of Corporate Finance*, 18(3), 541-559.

Brown, J.R., Fazzari, S. M., Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *The Journal of Finance*, 64(1), 151-185.

Chen, Z., Li, O.Z., Zou, H. (2016). Directors' and officers' liability insurance and the cost of equity. *Journal of Accounting and Economics*, 61(1), 100-120.

Chiambaretto, P., Bengtsson, M., Fernandez, A.S., Näsholm, M. H. (2019). Small and large firms' trade-off between benefits and risks when choosing a coopetitor for innovation. *Long Range Planning*.

Claus, J., Thomas, J. (2001). Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets. *The Journal of Finance*, 56(5), 1629-1666.

Czarnitzki, D., Toole, A.A. (2011). Patent protection, market uncertainty, and R&D investment, *Review of Economics and Statistics*, 93(1), 147–159.

David, P.A., Steinmueller, W.E. (1994). Economics of compatibility standards and competition in telecommunication networks. *Information Economics and Policy*, 6(3-4), 0-241.

Delcamp, H., Leiponen, A. (2014). Innovating standards through informal consortia: The case of wireless telecommunications. *International Journal of Industrial Organization*, 36, 36–47.

Dhaliwal, D., Judd, J.S., Serfling, M., Shaikh, S. (2016). Customer concentration risk and the cost of equity capital. *Journal of Accounting and Economics*, 61(1), 23-48.

Easton, P. (2004). PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital. *The Accounting Review*, 79, 73-95.

El Ghoul, S., Guedhami, O., Kwok, C.C., Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital?. *Journal of Banking & Finance*, 35(9), 2388-2406.

Fama, E.F., French, K.R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427-465.

—— (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56.

—— (1997). Industry costs of equity. *Journal of Financial Economics*, 43, 152-194.

—— (2000). Forecasting profitability and earnings. *Journal of Business*, 73, 161-175.

—— (2006). Profitability, investment and average returns. *Journal of Financial Economics*, 82, 491-518.

Farrell, J., Saloner, G. (1985). Standardization, compatibility, and innovation. *The RAND Journal of Economics*, 16(1), p. 70.

Fu, R., Kraft, A., Zhang, H. (2012). Financial reporting frequency, information asymmetry, and the cost of equity. *Journal of Accounting and Economics*, 54(2-3), 132-149.

Foucart, R., Li, Q.C. (2020). The Role of Technology Standards in Product Innovation: Theory and Evidence from UK Manufacturing Firms. In press. *Research Policy*. https://doi.org/10.1016/j.respol.2020.104157

Garel, A., Gilbert, A.B., Scott, A. (2019). Linguistic complexity and cost of equity capital, *SSRN Electronic Journal*.

Gebhardt, W., Lee, C., Swaminathan, B. (2001). Toward an implied cost of capital. *Journal of Accounting Research*, 39, 135-176.

Gnyawali, D.R., Park, B.J. (2011) Co-opetition between giants: Collaboration with competitors for technological innovation, *Research Policy*, 40(5), 650–663.

Gode, D., Mohanram, P. (2003). Inferring the cost of capital using the Ohlson–Juettner model. *Review of Accounting Studies*, 8(4), 399-431.

Griliches, Z. (1990) Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, 28(4), 1661-17.

Guo, B., Pérez-Castrillo, D., Toldrà-Simats, A. (2019). Firms' innovation strategy under the shadow of analyst coverage. *Journal of Financial Economics*, 131(2), 456-483.

Hall, B.H., Jaffe, A., Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, 16-38.

Hail, L., Leuz, C. (2009). Cost of capital effects and changes in growth expectations around US cross-listings. *Journal of Financial Economics*, 93(3), 428-454.

Hawkins, R., Blind, K., Page, R. (Eds.). (2017). *Handbook of Innovation and Standards*. Edward Elgar Publishing.

Heckman, J.J., H. Ichimura, Todd, P.E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, 64, 605-654.

—— (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies*, 65, 261-294.

Hoberg, G., Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, 23(10), 3773-3811.

Hoberg, G., Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5), 1423-1465.

Hou, K., Van Dijk, M.A., Zhang, Y. (2012). The implied cost of capital: A new approach. *Journal of Accounting and Economics*, 53(3), 504-526.

Hou, K., Robinson, D. T. (2006). Industry concentration and average stock returns. *The Journal of Finance*, 61(4), 1927-1956.

Hudson, J., Orviska, M. (2013). Firms' adoption of international standards: one size fits all? *Journal of Policy Modelling*, 35(2), 289-306.

Hussinger, K., Pacher, S. (2019). Information ambiguity, patents and the market value of innovative assets, *Research Policy*, 48(3), 665–675.

Jones, S.L., Leiponen, A., Vasudeva, G. (2020). The evolution of cooperation in the face of conflict: Evidence from the innovation ecosystem for mobile telecom standards development, forthcoming in *Strategic Management Journal*.

Kaplan, S.N., Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics*, 112(1), 169-215.

Katz, M.L., Shapiro, C. (1994). Systems competition and network effects. *Journal of Economic Perspectives*, 8(2), 93-115.

Kim, C., Wang, K., Zhang, L. (2019). Readability of 10-K reports and stock price crash risk. *Contemporary accounting research*, 36(2), 1184-1216.

Kim, D.Y., Zhu, P. (2018). Supplier dependence and R&D intensity: The moderating role of network centrality and interconnectedness. *Journal of Operations Management*, 64, 7-18.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2), 665-712.

Leiponen, A.E. (2008). Competing through cooperation: The organization of standard setting in wireless telecommunications. *Management Science*, 54(11), 1904-1919.

Lerner, J., Tirole, J. (2006). A model of forum shopping. *American Economic Review*, 96(4), 1091–1113.

Lerner, J., Tirole, J. (2015). Standard-essential patents. *Journal of Political Economy*, 123(3), 547–586.

Lim, E. K., Chalmers, K., Hanlon, D. (2018). The influence of business strategy on annual report readability. *Journal of Accounting and Public Policy*, 37(1), 65-81.

Lui, A.K., Ngai, E.W., Lo, C.K. (2016). Disruptive information technology innovations and the cost of equity capital: The moderating effect of CEO incentives and institutional pressures. *Information Management*, 53(3), 345-354.

Matutes, C., Regibeau, P. (1988). “Mix and match”: Product compatibility without network externalities. *The RAND Journal of Economics*, 221-234.

Merkley, K.J. (2014). Narrative disclosure and earnings performance: Evidence from R&D disclosures. *The Accounting Review*, 89(2), 725-757.

Narayanan, V.K., Chen, T. (2012). Research on technology standards: Accomplishment and challenges. *Research Policy*. North-Holland, 41(8), 1375–1406.

Ohlson, J.A., Juettner-Nauroth, B.E. (2005). Expected EPS and EPS growth as determinants of value. *Review of Accounting Studies*, 10(2-3), 349-365.

Ortiz-Molina, H., Phillips, G.M. (2014). Real asset illiquidity and the cost of capital. *Journal of Financial and Quantitative Analysis*, 49(1), 1-32.

Pástor, Ľ., Stambaugh, R.F. (2000). Comparing asset pricing models: an investment perspective. *Journal of Financial Economics*, 56(3), 335-381.

Pham, A. (2019). Political risk and cost of equity: The mediating role of political connections. *Journal of Corporate Finance*, 56, 64-87.

Rosenbaum, P.R., Rubin, D.B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41-55.

Rysman, M., Simcoe, T. (2008). Patents and the performance of voluntary Standard-Setting Organizations. *Management Science*, 54(11), 1920–1934.

Simcoe, T. (2012). Standard Setting Committees: Consensus governance for shared technology platforms. *American Economic Review*, 102(1), 305–336.

Shackelford, B., Jankowski, J. (2016). Information and Communications Technology Industries Account for $133 Billion of Business R&D Performance in the United States. *National Science Foundation InfoBriefs*.

Shleifer, A., Vishny, R.W. (2003). Stock market driven acquisitions. *Journal of Financial Economics*, 70(3), 295-311.

Soh, P.H. (2010). Network patterns and competitive advantage before the emergence of a dominant design. *Strategic Management Journal*, 31, 438–461.

Swann, P. (2010). The economics of standardization: An update. Report for the UK Department of Business, Innovation and Skills, Tech. rep., BIS

Tassey, G. (2000). Standardization in technology-based markets. Research Policy, 29(4-5), 587-602.

Updegrove, A. (2006). Participating in standard setting organizations: Value propositions, roles and strategies. *Consortium Standards Bulletin*, 5(9).

Waguespack, D.M., Fleming, L. (2009). Scanning the commons? Evidence on the benefits to startups participating in open standards development. *Management Science*, 55(2), 210-223.

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

Panel B. Summary statistics by industries

SIC code	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
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

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

* $p<0.05$; Refer to Table 1 for detailed industry description.

Table 3 Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
				Non-permanent member	*First entry*	*MEMBERCOUNT*
MEMBER	-0.007***	-0.007***	-0.006***	-0.007***		
	(-3.012)	(-2.989)	(-2.670)	(-2.859)		
fMEMBER					-0.013***	
					(-3.326)	
MEMBERCOUNT						-0.011***
						(-4.974)
PATAPP	-0.003**	-0.004***	-0.003**	-0.003***	-0.000	-0.003**
	(-2.395)	(-3.224)	(-2.380)	(-2.689)	(-0.183)	(-2.327)
SIZE	-0.027***	-0.029***	-0.029***	-0.029***	-0.028***	-0.028***
	(-15.722)	(-16.820)	(-15.996)	(-15.712)	(-4.884)	(-15.879)
VOLATILITY	0.005**	0.005**	0.005**	0.005**	0.002	0.005**
	(2.407)	(2.572)	(2.481)	(2.511)	(0.327)	(2.344)
MTB	-0.044***	-0.044***	-0.044***	-0.045***	-0.028***	-0.044***
	(-30.308)	(-30.645)	(-30.180)	(-30.139)	(-6.797)	(-30.272)
LEVERAGE	0.085***	0.087***	0.088***	0.091***	0.058***	0.089***
	(11.534)	(11.843)	(11.851)	(11.857)	(2.899)	(11.888)
ROA	-0.130***	-0.131***	-0.129***	-0.130***	-0.135***	-0.129***
	(-20.741)	(-20.817)	(-20.507)	(-20.371)	(-5.370)	(-20.579)
AGE	0.027***	0.022***	0.027***	0.027***	0.027***	0.027***
	(8.915)	(9.463)	(8.645)	(8.334)	(2.780)	(8.580)
FORECASTER	0.086***	0.087***	0.085***	0.086***	0.115***	0.085***
	(15.797)	(15.933)	(15.849)	(15.774)	(5.440)	(15.863)
Constant	0.223***	0.261***	0.185***	0.183***	0.244***	0.184***
	(21.190)	(15.865)	(7.405)	(7.244)	(6.276)	(7.358)
Observations	32,824	32,824	32,824	31,694	4,138	32,824
N 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	*NO*	*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 variable is the composite implied cost of equity (ICE) based on the earnings per share forecasts derived from the HVZ model. In Columns 1 to 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 4 to 6 include industry-time interaction terms in the within groups model. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 4 ICT vs. non-ICT samples

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

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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	R&D intensity	*R&D disclosure*	*Patent applications*	*SEP holding*	*Market Competition*	*Customer Concentration*	*Financial constraint*	*10-K report readability*	*Transparency*
MEMBER # High RDI	-0.009***								
	(-2.939)								
MEMBER # Low RDI	-0.001								
	(-0.297)								
MEMBER # High RDdisclosure		-0.007**							
		(-2.349)							
MEMBER # Low RDdisclosure		-0.004							
		(-1.182)							
MEMBER # HPT			-0.009***						
			(-3.240)						
MEMBER # LPT			-0.004						
			(-1.383)						
MEMBER # SEP				-0.014**					
				(-2.165)					
MEMBER # NSEP				-0.006***					
				(-2.664)					
MEMBER # High Comp					-0.007**				
					(-2.454)				
MEMBER # Low Comp					-0.005				
					(-1.580)				
MEMBER # High CustConce						-0.008**			
						(-2.322)			
MEMBER # Low CustConce						-0.006**			
						(-2.128)			
MEMBER # High FC							-0.010***		
							(-3.038)		
MEMBER # Low FC							-0.004		
							(-1.449)		
MEMBER # High Fog								-0.006**	
								(-2.503)	
MEMBER # Low Fog								-0.004	
								(-1.428)	
MEMBER # High Transparency									-0.005
									(-1.625)
MEMBER # Low Transparency									-0.008***
									(-2.711)
Constant	0.193***	0.224***	0.185***	0.185***	0.185***	0.185***	0.189***	0.224***	0.186***
	(10.077)	(19.199)	(7.383)	(7.406)	(7.400)	(7.407)	(7.643)	(19.247)	(7.401)
Controls	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	24,499	29,992	32,824	32,824	32,824	32,824	31,077	29,992	32,824
N of firms	2,632	3,165	3,350	3,350	3,350	3,350	3,315	3,165	3,350
R-squared	0.277	0.271	0.276	0.276	0.276	0.276	0.280	0.271	0.276
Industry FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Firm FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

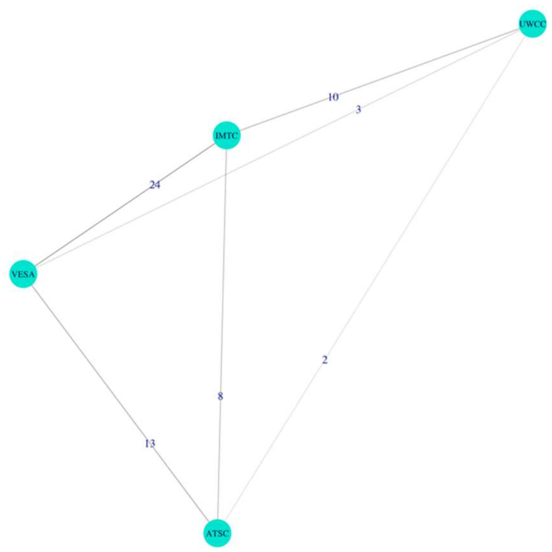
This table presents the fixed effects estimated coefficients (t-statistics in parentheses). The dependent variable is the composite ICE measure. High (Low) RDI takes value one if the firm's R&D intensity, measured as R&D expenses over sales, is above (below) the industry-year median, zero otherwise. 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 (NSEP) takes value one if the firm holds at least one (no) standard-essential patents (SEPs), zero otherwise. 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 earning 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:

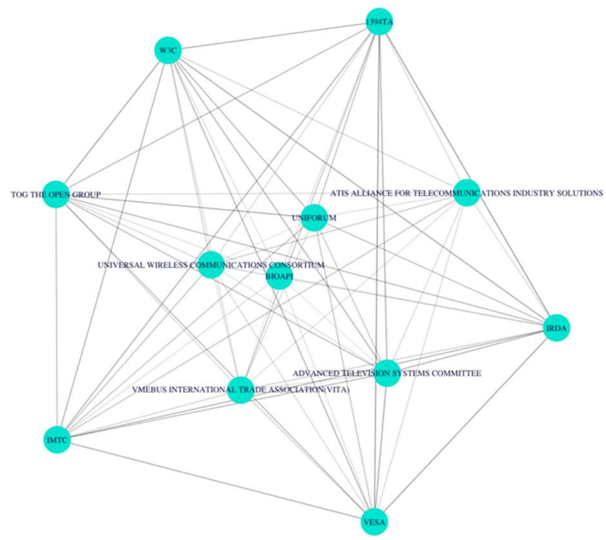
Panel A. Symmetric adjacency matrix example: SSOs in 1996

	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



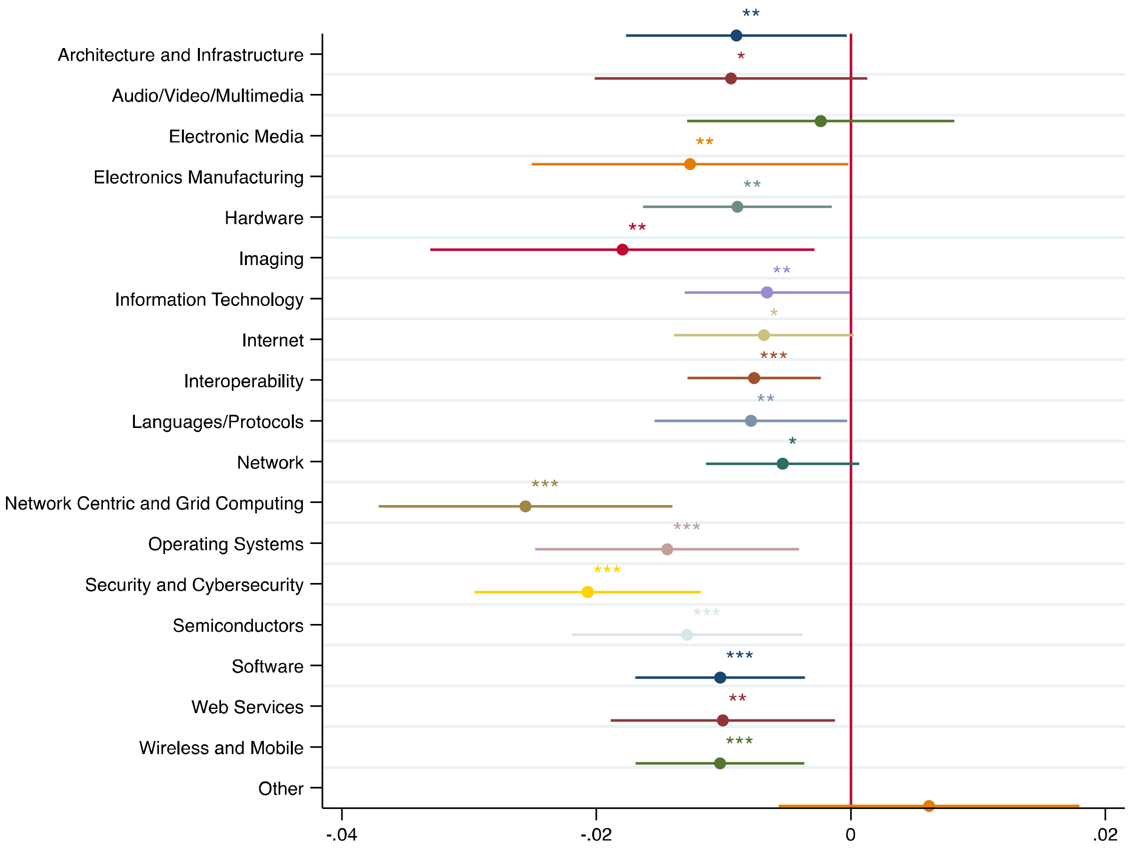
Panel A is the adjacency matrix of the four recorded SSOs in 1996: Universal Wireless Communications Consortium (UWCC), Advanced Television Systems Committee (ATSC), the International Multimedia Telecommunications Consortium (IMTC) and Video Electronics Standards Association (VESA). Each entry in the 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

	Influential SSO membership	
	(1)	(2)
	iMEMBER	*iMEMBERCOUNT*
iMEMBER	-0.007***	
	(-2.759)	
iMEMBERCOUNT		-0.012***
		(-4.930)
PATAPP	-0.003**	-0.003**
	(-2.377)	(-2.323)
SIZE	-0.029***	-0.028***
	(-16.050)	(-15.968)
VOLATILITY	0.005**	0.005**
	(2.491)	(2.359)
MTB	-0.044***	-0.044***
	(-30.188)	(-30.266)
LEVERAGE	0.088***	0.089***
	(11.854)	(11.890)
ROA	-0.129***	-0.129***
	(-20.501)	(-20.560)
AGE	0.027***	0.027***
	(8.650)	(8.586)
FORECASTER	0.085***	0.085***
	(15.856)	(15.865)
Constant	0.186***	0.185***
	(7.393)	(7.350)
Observations	32,824	32,824
N of Firms	3,350	3,350
R-squared	0.276	0.276
Industry FE	*YES*	*YES*
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 measures to define firm membership in an *influential* SSO. *iMEMBER* is an indicator of firm participation in at least one influential SSO, while iMEMBERCOUNT records the number of influential memberships. All firm-level characteristics are defined in Table 3. *p < 0.1; **p < 0.05; ***p < 0.01.

Figure 2. Estimated coefficients across SSO technological categories (95%)



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

Figure 3. Distribution of member firms across SSO types

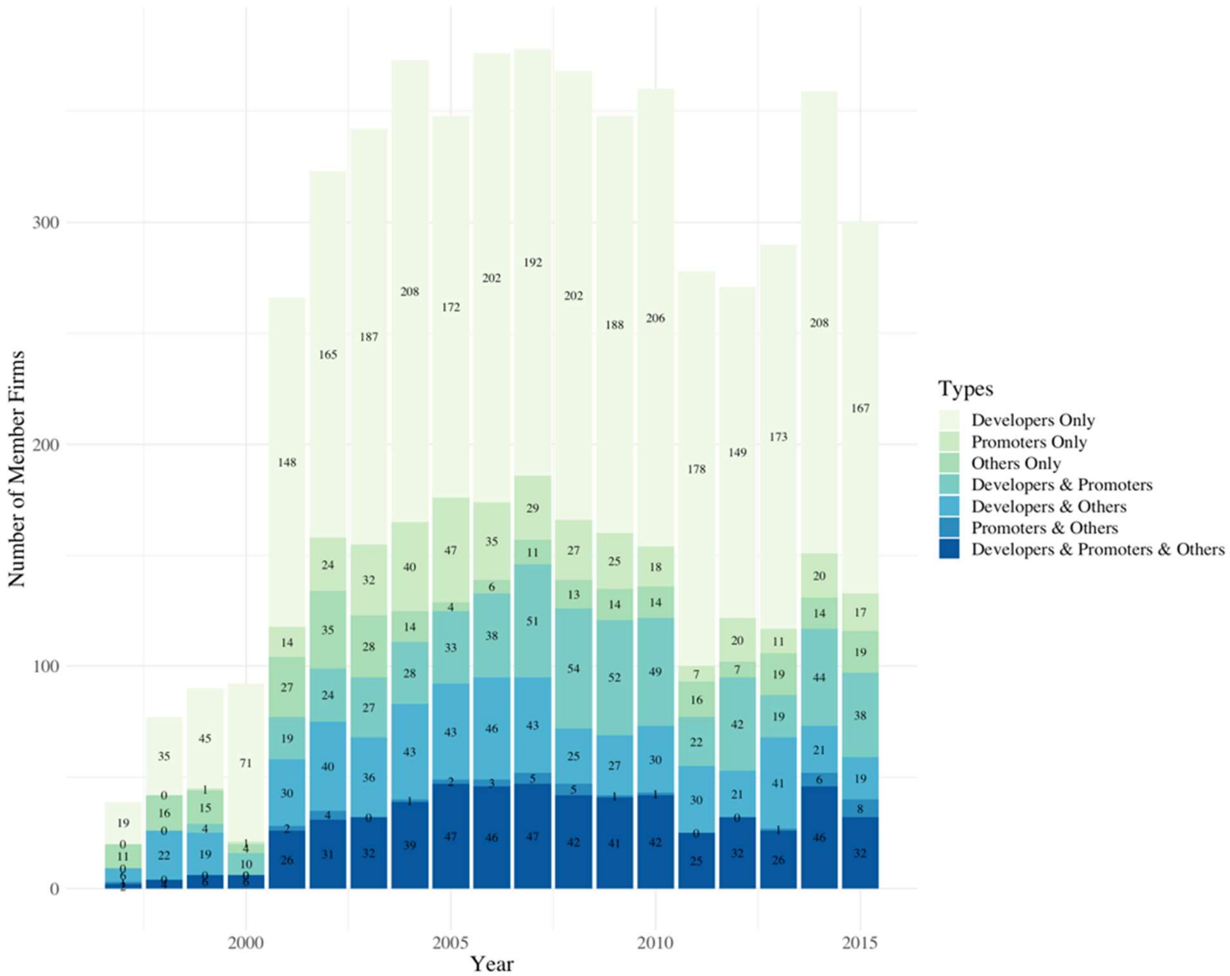


Table 7 Participation across specific SSO types

	Full Sample		ICT Sample	
	(1)	(2)	(3)	(4)
Developers Only	-0.005*	-0.005*	-0.009**	-0.009**
	(-1.744)	(-1.720)	(-2.324)	(-2.333)
Promoters Only	-0.008*	-0.008*	-0.003	-0.004
	(-1.875)	(-1.938)	(-0.602)	(-0.619)
Others Only	-0.006	-0.006	-0.006	-0.006
	(-0.769)	(-0.787)	(-0.626)	(-0.651)
Multiple Types	-0.013***		-0.017***	
	(-3.538)		(-3.557)	
Developers & Promoter		-0.012***		-0.018***
		(-2.782)		(-3.011)
Developers & Others		-0.011**		-0.015**
		(-2.067)		(-2.163)
Promoters & Others		-0.026***		-0.014
		(-2.655)		(-1.400)
Developers & Promoters & Others		-0.016***		-0.025***
		(-3.142)		(-3.947)
Constant	0.185***	0.185***	0.219***	0.219***
	(7.375)	(7.371)	(14.056)	(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 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 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 SSO. The Multiple Types indicator (1/0) for firm participation in multiple types of SSOs is further disaggregated into the binary variables Developers & Promoters, Developers & Others, Promoters & Others, and Developers & Promoters & Others, revealing firm participation in SSOs associated with the respective types. Controls include all other firm-level characteristics included in Table 3. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 8 Matching method for SSO participation - Balancing tests

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

Table 9 Addressing endogeneity concerns - PSM and 2SLS estimates

	Matched sample		2SLS		Mills ratio
	(1)	(2) *Probit*	(3) *1st stage*	(4) *2nd stage*	(5) *IMR*
MEMBER	-0.010**			-0.063**	-0.006***
	(-2.225)			(-2.087)	(-2.600)
$\widehat{MEMBER}$			0.071***		
			(12.801)		
Peer Imitation		0.271***			
		(4.673)			
SSO Availability		0.582***			
		(12.713)			
PATAPP	-0.002	0.192***	0.004	-0.002*	-0.003**
	(-0.703)	(5.200)	(1.054)	(-1.733)	(-2.369)
SIZE	-0.029***	0.588***	0.004	-0.026***	-0.031***
	(-5.742)	(14.398)	(0.798)	(-12.920)	(-13.112)
VOLATILITY	0.001	0.092	-0.005	0.005**	0.005**
	(0.158)	(1.531)	(-1.210)	(2.435)	(2.525)
MTB	-0.032***	0.102***	-0.005**	-0.043***	-0.043***
	(-8.181)	(2.719)	(-2.019)	(-33.481)	(-26.084)
LEVERAGE	0.069***	-0.661***	0.045***	0.090***	0.091***
	(3.848)	(-2.739)	(2.805)	(13.557)	(10.874)
ROA	-0.165***	-0.312***	-0.015	-0.125***	-0.119***
	(-7.630)	(-2.917)	(-1.644)	(-21.919)	(-17.083)
AGE	0.021*	-0.013	-0.030***	0.032***	0.033***
	(1.952)	(-0.201)	(-3.154)	(10.069)	(7.369)
FORECASTER	0.133***	-0.055	0.005	0.081***	0.081***
	(7.479)	(-0.952)	(0.845)	(17.271)	(13.239)
MILLS					-0.006**
					(-2.185)
Constant	0.236***	-7.534***			0.200***
	(5.898)	(-11.552)			(7.166)
Observations	4,692	25,127	25,127	25,127	25,127
Log-likelihood		-5074.249			
Wald Chi2		869.70***			
Kleibergen-Paap LM statistic			163.14***		
Cragg-Donald F statistic			164.12***		
R-squared	0.307			0.250	0.268
Industry FE	*YES*	*YES*	*YES*	*YES*	*YES*
Year FE	*YES*	*YES*	*YES*	*YES*	*YES*
Firm FE	*YES*	*YES*	*YES*	*YES*	*YES*

This table presents the results addressing endogeneity concerns (z-statistics or t-statistics in parentheses). The dependent variable is the composite ICE measure. Column 1 presents the fixed effects estimates for Equ.1 on the propensity score matched sample. Columns 2-5 report IV results obtained on the whole sample. Column 2 reports results from estimating a probit model of MEMBER on two instruments (*Peer Imitation* and *SSO Availability*) and all previous control variables. *Peer Imitation* records (natural logarithm of one plus) how many among the focal firm's 5 closest rivals are SSO members. We use the pairwise similarities constructed by Hoberg and Phillips (2010, 2016) based on firms' product descriptions in their 10-K reports to identify a firm's nearest 5 rivals (firms with the most similar products to the focal firm). *SSO Availability* is the (natural logarithm of one 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, the two instruments and the other controls are measured in year t-2 in the probit model in Column 2 and the predicted probability (denoted $\widehat{MEMBER}$) is used as an instrument for MEMBER in the first-stage regression (Column 3). Column 4 reports the second-stage results. Column 5 addresses the potential selection bias by including the inverse Mills ratio calculated from the probit model in Column 2. All other firm-level characteristics are defined in Table 3. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 10 Difference-in-differences (DiD) test results

Panel A: Post-match difference

Variables	Treatment	Control	Differences	T-statistics
PATAPP	3.182	2.646	-0.535	-1.584
SIZE	8.841	8.408	-0.433	-1.423
VOLATILITY	-2.336	-2.378	-0.042	-0.542
MTB	0.955	0.979	0.024	0.201
LEVERAGE	0.171	0.178	0.007	0.268
ROA	0.014	0.021	0.007	0.207
AGE	2.958	2.937	-0.022	-0.163
FORECASTER	0.026	0.019	-0.007	-0.147

Panel B: DiD estimators

	Mean treatment difference (after-before) (1)	Mean Control difference (after-before) (2)	Mean DiD (treat-control) (3)
ICE	-0.011	-0.018	0.007**
(standard error)	(0.004)	(0.003)	(0.003)

Panel C: Post-match difference with additional firm characteristics

Variables	Treatment	Control	Differences	T-statistics
PATAPP	3.088	2.626	-0.462	-1.229
SIZE	8.680	7.933	-0.747	-2.149**
VOLATILITY	-2.222	-2.285	-0.062	-0.684
MTB	0.759	0.821	0.061	0.434
LEVERAGE	0.173	0.157	-0.015	-0.491
ROA	0.012	0.013	0.000	0.009
AGE	2.921	2.829	-0.092	-0.611
FORECASTER	0.044	0.017	-0.027	-0.425
HHI	0.101	0.110	0.009	0.573
RDI	0.145	0.125	-0.020	-0.985
SGAI	0.364	0.359	-0.005	-0.130
Financial Slack	0.511	0.529	0.018	0.460
KZ	-10.538	-10.131	0.407	0.095
CAP	0.152	0.140	-0.011	-0.458
SG	0.033	0.068	0.035	0.715
OIPE	0.102	0.077	-0.025	-1.408
TEMP	4.374	3.180	-1.194	-0.811

Panel D: DiD estimators

	Mean treatment difference (after-before) (1)	Mean Control difference (after-before) (2)	Mean DiD (treat-control) (3)
ICE	-0.010	-0.021	0.011**
(standard error)	(0.004)	(0.003)	(0.004)

Appendix

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:

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

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:

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

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 $E_n (n = 1,2 \ldots,5)$ 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.