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Patents and the Performance of Voluntary Standard Setting Organizations

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Voluntary standard setting organizations (SSOs) are a common feature of systems industries, where firms supply inter-operable components for a shared technology platform. These institutions promote coordinated innovation by providing a forum for collective decision-making and a potential solution to the problem of fragmented and overlapping intellectual property rights. This paper examines the economic and technological significance of SSOs by analyzing the flow of citations to a sample of U.S. patents disclosed during the standard-setting process. Our main results show that the age distribution of SSO patent citations is shifted towards later years (relative to an average patent), and that citations increase substantially following standardization. These results suggest that SSOs identify promising technologies and influence their subsequent adoption.

Key words: standards; compatibility; platform; intellectual property; patents; cumulative innovation

1. Introduction

Many products and services are based on inter-operable yet independently supplied component technologies. In these markets, *coordination* is an important part of the innovation process. The book "Startup" (Kaplan, 1996 pg. 146) provides a vivid description of the problem:

> "All computer products are hopelessly interdependent. . . application designers exploit operating systems tailored to computers built around chips that implement protocols based on specifications developed in committees staffed by applications designers. Everyone in this evolving loop must guess which new technologies are most likely to provide a solid and enduring platform on which to build their own piece."

Recent work in strategy and economics has emphasized the role of "platform leaders" in promoting coordinated technical change (Bresnahan and Greenstein, 1999; Cusumano and Gawer, 2002). But when leadership is distributed among many firms, coordination becomes more complex, and major change is often orchestrated by voluntary standard setting organizations (SSOs).

SSOs work to create a *consensus* that can serve as a focal point for industry coordination or lead to a bandwagon process among adopters, thus lowering the risk of "forking" or a standards war. Some firms invest substantially in these efforts. In 2005 IBM spent an estimated $500 million — roughly 8.5 percent of its R&D budget — on standards development. Hewlett Packard and Sun Microsystems each participate in more than 150 SSOs.[1]

What do these companies get in return? It is often hard to say, since SSOs operate in diverse markets and their effect on standard variables, such as price or quantity, is usually ambiguous. While a large body of qualitative research describes how SSOs can facilitate technical coordination and mitigate hold-up problems by promoting "open" technology (e.g. Besen 1988, 1989, 1991; Weiss and Sirbu 1990; Hawkins 1995; Cargill 1997; Bolin 2002), there is no standard measure of SSO performance, and very little quantitative evidence on the impact of these institutions.

This paper uses patent citations as a window onto the role of SSOs in economic and technological change. Participants in the standard setting process are usually obliged to disclose relevant patents. By searching publicly available disclosure archives, we identify a sample of 724 U.S. patents disclosed to four major SSOs: the American National Standards Institute (ANSI), the Institute for Electrical and Electronic Engineers (IEEE), the Internet Engineering Task Force (IETF), and the International Telecommunications Union (ITU). We track the flow of citations to these patents and observe what happens following disclosure — which serves as a proxy for the creation of a new standard based on the patented technology. Thus, our method builds on a large literature that has established patent citations as a valid measure of economic and technological significance (Harhoff et al 1999; Jaffe and Trajtenberg 2004; Allison et al 2004; Hall, Jaffe and Trajtenberg 2005) to provide an initial measurement of the role of SSOs in the innovative process.

A first look at citation patterns reveals that SSO patents receive many more cites than other patents from the same technological field and application year, suggesting that they are more important or more valuable. We also use methods developed by Mehta, Rysman, and Simcoe

[1] The IBM figures are from Forbes magazine, as cited in Chiao, Lerner and Tirole (2007, footnote 1). The figures on HP and Sun are from Updegrove (2003).

(2007) to demonstrate a significant difference in the age distribution of citations to SSO patents. Specifically, these cites are less concentrated in the first few years after the patent issues, suggesting that SSO patents have a longer useful life. We consider two explanations for this pattern. The first explanation is a *selection effect*: SSOs identify or attract technologies that are more significant (or about to become so), and therefore more frequently cited. The second explanation is a *marginal effect*: by fostering consensus and creating an open standard, the SSO causes firms to begin using and citing a patented technology when they otherwise would not have, thus altering its citation profile.

In order to identify the marginal effect, we must estimate a counterfactual: what would have happened to a disclosed patent if the disclosure had never occurred? Obviously, we cannot observe this scenario, so we focus on a closely related comparison: how do citations differ before and after disclosure? In our statistical models, the impact of disclosure is identified by within-patent changes in citation frequency around the time of disclosure. We must be cautious in interpreting this comparison as identifying a causal effect. While we cannot sign the potential bias from measurement error or endogeneity of the disclosure date, we provide several robustness checks that suggest the validity of our results.

To summarize the results, we find that SSO patents' pre-disclosure citation rate is roughly double that of an average patent, while disclosure produces a 19 to 47 percent increase. The large difference in baseline citation rates suggests that SSOs perform well in selecting important technologies. If we are willing to place a causal interpretation on the disclosure effect, these results also imply that SSOs increase the significance of standardized technology through formal endorsement and other efforts to promote industry coordination. While it is difficult to attach a dollar value to citation counts, the estimates in Harhoff et al (1999) and Hall, Jaffe and Trajtenberg (2005) suggest that our results are economically meaningful.

These findings have both managerial and policy implications. While previous research on platform management has emphasized the trade-off between "opening" a platform to grow the market, and remaining "closed" to reduce competition or maintain control (e.g. Shapiro and Varian 1998;

Gawer and Henderson 2007), we focus on a complementary question: whether voluntary standards can increase the value of a technology by creating a consensus around particular design elements and providing a path to industry coordination. Our results suggest that they do. This does not imply that managers should rush to join every new SSO or technology consortium — the four that we study are widely viewed to be among the most influential. However, these findings provide some quantitative evidence on the benefits of SSO endorsement, which managers should weigh against the costs of participation and a commitment to openness.

Our results also help justify policy makers' interest in preventing abuse of the standard-setting process. For example, in 2005 the U.S. Federal Trade Commission (FTC) initiated an antitrust action against Rambus for failing to disclose relevant patents while participating in an SSO.[2] Arguments in the case centered on the distinction between selection and marginal effects — the FTC alleged that Rambus had acquired market power by fraudulently manipulating the standards process, and Rambus countered that it simply owned a superior technology, which would have been chosen by the SSO, even if its patents had been disclosed. Our findings suggest that SSOs can indeed have a significant impact on the value of a technology. Thus, concerns about manipulation of the standards process to engineer patent hold-up are legitimate, and efforts to enforce SSOs' private intellectual property rules (which encourage disclosure and widespread licensing) may actually stimulate innovation.

Related Literature and Outline

There is a relatively small theoretical literature on collaborative standards development. Farrell and Saloner (1988) model consensus standard setting as a war of attrition and compare its performance to a simplified "standards war." Farrell and Simcoe (2008) extend the war of attrition model to examine the welfare implications of different SSO policies, such as membership and licensing rules. Lerner and Tirole (2006) also consider the choice of SSO policies, but emphasize the fact that participants may be able to engage in "forum shopping" when there are multiple SSOs.[3] This

[2] *In the Matter of* Rambus Incorporated, FTC Docket Number 9302.

[3] Lerner, Tirole and Strojwas (2003) also examine the closely related institution of patent pools.

paper lends empirical support to an assumption shared by all of these models — that an SSO's formal endorsement increases demand for the standardized technology.

There is also a rapidly growing body of empirical work on SSOs. Bekkers et al (2002) document the role of intellectual property strategy in standard setting for wireless telecommunication. Simcoe (2006) examines the relationship between distributional conflicts and the duration of the IETF standard setting process. Chiao, Lerner and Tirole (2007) find evidence of a negative relationship between an SSO's "sponsor friendliness" and the concessions required of technology sponsors. While these papers focus on a single SSO, Leiponen (2006) suggests that in many cases standard setting occurs within a network of loosely affiliated organizations, and that a firm's position in that network can influence its effectiveness within a focal SSO. Tassey (2003) outlines the methods used by the National Institute of Standards and Technology (NIST) to evaluate the impact of government research programs, which are based on augmenting any available industry-specific data with surveys of industry participants to obtain the dollar impact of a given project. While the NIST approach provides an estimate that is in principal easy to interpret, our method is attractive in that it is inexpensive, objective, replicable and easy to compare across industries or over time.

Finally, this paper contributes to a stream of research on the impact of institutions on cumulative technological change. For example, using an approach broadly similar to ours, Furman and Stern (2006) exploit the longitudinal structure of citation data to examine the impact of biological research centers on citation patterns.

2. SSOs and Intellectual Property

The four SSOs examined in this paper are the American National Standards Institute (ANSI), the Institute of Electrical and Electronics Engineers (IEEE), the Internet Engineering Task Force (IETF), and the International Telecommunications Union - Telecommunication Standardization Sector (ITU-T, or often, ITU). Most of the patents disclosed to these four SSOs cover computing and communications technology (see Table A-1 in the appendix for a complete breakdown).

The ITU is based in Switzerland. It is the oldest of the four SSOs, with origins dating back to 1865, and its original mission was to promote international coordination among the various rapidly expanding domestic telephone networks. ITU members are either delegates from member nations, or representatives of large network operators or equipment vendors. The ITU's recent standard setting efforts have focused on such issues as numbering and addressing, traffic management, monitoring and accounting, and quality of service.

The IEEE was founded in 1884 by several pioneers in the field of electrical engineering. Members include both individual engineers and companies interested in standards development. The IEEE's standard setting efforts cover a wide range of subjects, from electrical safety, to cryptography, to standards for semiconductor testing equipment. In recent years, the IEEE's most commercially significant work has revolved around the 802.11 specifications for wireless networking (i.e. "Wi-Fi").

ANSI was formed in 1918 to coordinate the ongoing standards development efforts of a number of different organizations, and continues to play a role in coordinating the activities of hundreds of different U.S. SSOs—primarily through an accreditation program focused on key dimensions of the standards development process.[4] While the IEEE is an ANSI accredited SSO, the majority of the patents in ANSI's disclosure records came from other standards developing organizations.[5] In fact, many of the ANSI disclosures are associated with the Telecommunications Industry Association, which has worked on technologies such as DSL (for data transmission over phone lines) and TDMA (a cellular telephony protocol).

The IETF creates protocols used to run the Internet. This organization grew out of an academic computer networking community that emerged during the 1970s, and did not resemble a formal SSO until the late 1980s (Mowery and Simcoe, 2002). Prominent IETF standards include the Internet's core transport protocols (TCP/IP and Ethernet), standards used to allocate network addresses (DHCP), and specifications used by popular applications such as e-mail or file transfer. Membership in the IETF is open to any interested individual, and much of the group's work takes place in online forums run by individual technical committees.

[4] ANSI also serves as the U.S. representative on the two major non-treaty international standards organizations, the International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC).

[5] The ANSI sample only contains disclosures that an accredited SSO *chooses* to forward to ANSI. This explains why there is little overlap in Table A-2, even though the IEEE is a member of ANSI. While this feature changes the interpretation of the ANSI sample, it is useful that it looks to largely independent sets of patents.

While these four SSOs differ in their technology focus, membership rules, and level of formality, their procedures for creating a new standard are quite similar. The process always begins with the recognition of some coordination problem, which leads to the formation of a technical committee. The committee's job is to analyze the problem and recommend a consensus solution. While voting rules differ across SSOs, "consensus" typically implies more than a simple majority, but less than unanimity. Once a consensus is reached, the SSO publishes the resulting specification as a standard. For an extended discussion of this process (which often takes several years) see, for example, Cargill (1997).

Intellectual property rights are an increasingly important part of the technology evaluation process at many SSOs. This growth partly reflects a well-documented surge in patenting—particularly for ICT industries—that began in the mid-1980s. It may also reflect changes in patenting strategy. Many firms would like to own IPR that is embedded in an industry standard. Patent owners frequently seek royalty payments for the use of their technology—even (or, perhaps, especially) when it is essential to the implementation of an industry standard.

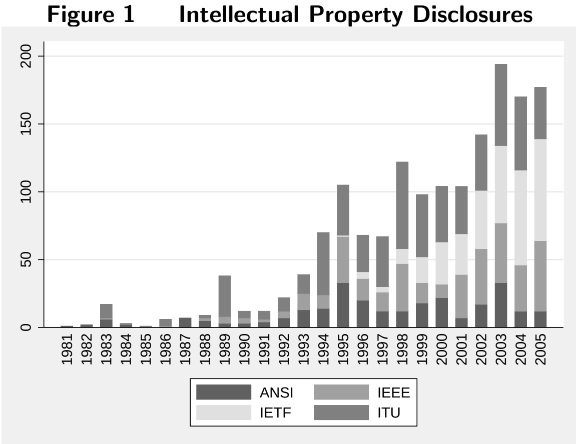
Lemley (2002) surveyed the formal intellectual property policies of thirty-six SSOs, and suggests that they have three basic parts: search, disclosure, and licensing rules. While only two of the groups in his study required members to conduct a full patent search, twenty-seven (including the four studied here) have rules stating that members should disclose any known property rights as soon as possible. Firms have good reasons to adhere. In particular, the FTC has taken action against firms that failed to disclose patents during the standard setting process and subsequently tried to license the protected technology.[6]

Our empirical work uses information collected from the publicly available IPR disclosure archives of ANSI, IEEE, IETF and the ITU. Figure 1 shows that the disclosure rate at these four SSOs

[6] See *Dell Computer* (FTC No. 931-0097) and *Rambus* (FTC Docket No. 9302). There is an extensive legal literature on the difficult problem presented by intellectual property in industry standards (see Farrell et al 2007, *inter alia*). On antitrust and standardization generally, see the American Bar Association *Handbook on the Antitrust Aspects of Standard Setting* (ABA 2003), or the FTC/DOJ Intellectual Property and Antitrust hearing transcripts and report (FTC 2002).

began to grow quite rapidly during the early 1990's.[7] This sustained growth reflects several factors: the surge in ICT patents; increased demand for standards (driven by diffusion of the Internet and wireless telecommunications); and a perceived strengthening of disclosure requirements, especially in the wake of FTC actions.

Figure 1 **Intellectual Property Disclosures**



For our purposes, the rise in IPR disclosure means that we have access to a publicly available list of patents associated with specific SSOs. Many features of these patents—such as the number of citations they receive—are easily compared across different industries and time periods. Thus, disclosed patents provide a unique window through which to examine the economic and technological significance of SSOs.

3. Data and Measurement

In this section, we discuss the contents of our data set and present some basic statistics. We then provide a brief discussion of how we interpret a patent citation in our research.

3.1. Data

At most SSOs, an IPR disclosure consists of a letter (or email) indicating that a company owns (or may own) intellectual property that is relevant to a proposed standard. We collected 1,664 disclosures filed between 1971 and 2006 at ANSI, IEEE, IETF or ITU. A close examination of these

[7] We define a disclosure as an announcement on a given date by a single firm that it potentially owns one or more pieces of intellectual property needed to implement a proposed standard. When a firm claims that a single patent covers two or more standards, each one counts as a separate disclosure. However, we only keep one copy of the patent in our data for analysis.

letters reveals substantial variation in practice—both within and between SSOs. Some disclosures contain detailed licensing terms and refer to specific patents, while others are simply general statements regarding a firm's willingness to offer a license. This variation in disclosure practices reflects differences in SSO participants, policies, and objectives, as well as evolving industry norms with respect to the entire issue of disclosure.[8]

Table 1 presents several summary statistics for our sample of IPR disclosures. The average disclosure listed between 1.2 and 2.5 pieces of intellectual property (i.e. a specific patent or pending application number). However, while some letters contained long lists of patents, a substantial fraction at each SSO simply made "blanket" licensing assurances, or referred to unpublished patent applications. Our analysis focuses on U.S. patents, which were listed in 20 to 30 percent of all disclosures.

Table 1 IPR Disclosure Summary Statistics

	IPR Disclosure Summary				Patent Counts	
	First Disclosure	Total Disclosures	Average Size†	Lists U.S. Patent††	U.S. Patents	Total Patents
ANSI	1971	278	2.04	0.33	194	222
IEEE	1983	390	2.48	0.31	425	588
IETF	1995	353	1.20	0.24	151	169
ITU	1983	643	1.99	0.22	337	532

†Size is a count of the patent or application numbers listed in the disclosure.
††Equals one if the disclosure provides one or more US patent numbers.

The last two columns in Table 1 show the total number of patents disclosed to each SSO. While the majority of these patents were issued in the U.S. a number of international patents were also disclosed. These international patents are often part of a "family" whose U.S. counterpart appears in the estimation sample. After removing duplicate observations[9], our review of the disclosure letters published by ANSI, IEEE, IETF and ITU yields a pooled sample of 724 U.S. patents.

[8] To provide a sense of this heterogeneity, we have reproduced two ANSI disclosure letters in the online appendix. Interested readers may also want to visit the public disclosure archives, such as the one located at www.ietf.org.

[9] Table A-2, which may be found in the Appendix, shows that there is a small amount of overlap created by patents disclosed to more than one SSO.

Before turning to a closer examination of these patents, we pause to note several limitations of the disclosure data. First, while it is trivial to link an IPR disclosure to an SSO, linking a disclosure to a particular standard is often quite difficult. As a result, we observe only disclosures—not whether the proposal became a standard, or whether the IPR was "essential" to the standard (i.e. whether a license would be needed to create a legal implementation). Consequently, our sample of patents will contain both "false positives" (non-essential patents or disclosures corresponding to a failed proposal) and "false negatives" (unlisted but essential patents referenced in a "blanket" disclosure or owned by non-participating firms).

Second, because we cannot link disclosures to standards, we do not observe when the SSO reaches a consensus or makes a formal endorsement. While these dates are potentially important, our analysis will focus on the disclosure date. The disclosure date is appealing as it represents the moment when a link between the patent and a proposed standard becomes public information. In practice, this tends to occur shortly before the emergence of a consensus. As noted above, participants that delay for too long may forfeit their property rights. At the same time, premature disclosure can be costly. For example, Chiao, Lerner and Tirole (2007) cite concerns that disclosure may reveal sensitive information about a firm's R&D strategy or spur efforts to "invent around" a particularly strong patent.[10] From a practical perspective, firms may save money by delaying a full patent search until the outlines of a final specification become clear, since there is often considerable uncertainty at the start of the standard-setting process.

Finally, it is unlikely that our sample of disclosed patents are broadly representative of the technology evaluated by these four SSOs. Rather, these patents are likely to be concentrated within several of the most commercially significant standard setting efforts. Nevertheless, we believe they provide a unique window into the technology evaluated by SSOs, and can be used to address important questions about SSO performance.

[10] They also suggest that there is "news" in an IPR disclosures—even when the patent has already been granted and published by the USPTO. In particular, many firms indicate that the volume of issued patents can make the problem of identifying relevant property rights akin to finding a needle in a haystack.

3.2. Descriptive statistics

We begin our evaluation of the SSO patents by linking them to the NBER U.S. patent data file (Hall, Jaffe and Trajtenberg 2001), which contains several important variables, including application and grant dates, assignee names, and citation counts.[11] Table 2 compares the sample of disclosed patents to a set of "control patents" with the same application year and primary technology class (nclass) as one or more SSO patents. The SSO patents contain more claims, receive more citations, and are more likely to be part of an international "family" of patent applications. They are also cited by patents from a broader set of technology classes, as indicated by the "generality" measure proposed in Henderson, Jaffe and Trajtenberg (1998).[12] Prior research has shown that these variables are positively correlated with a patent's economic value. Table 2 also shows that SSO patents are more likely to be assigned to a U.S. company, and reveals small differences between a "matched" control sample (where the one-to-one match is based on application-year and technology-class) and the set of all eligible controls.

While the control patents in Table 2 serve as a useful point of reference, it is unlikely that they are a valid set of "controls" in the sense that they are statistically indistinguishable from a pre-disclosure SSO patent. Our analysis uses the control patents to address macro changes to the patenting regime, and our main results are based largely on variation within the SSO sample. When we compare SSO patents to the control sample, it will be with an eye towards comparing SSO patents to "average" patents, rather than patents that are truly identical but for disclosure.

3.3. What is a citation?

In the remainder of the paper, our primary measure of economic and technological significance is based on forward-citations (i.e. cites that a focal patent receives from other patents). These citations identify relevant "prior art" for an invention, thus delimiting the scope of its claims.

[11] The NBER data have been updated through 2002 and are available on Bronwyn Hall's web site http://emlab.berkeley.edu/users/bhhall/bhdata.html. We are also grateful to Ajay Agrawal and Lee Fleming for providing us with data on the citations from patents granted between 2003 and 2006.

[12] This measure is $1-\sum_j^{n_i} s_{ij}^2$ where s_{ij} is the share of citations received by patent i from class j (out of n_i classes). In other words, it is one minus a Herfindahl index based on patent classes.

Table 2 SSO Patent Characteristics

	Pooled Sample			Individual SSOs			
	SSO	Matched Controls†	All Controls†	ANSI	IEEE	IETF	ITU
Total Claims	20.54	14.80	14.58	20.38	23.17	22.83	17.41
Total Cites	22.26	9.93	6.81	26.37	19.72	26.68	20.89
Cites/Year	2.36	1.16	0.92	2.41	2.19	3.14	2.18
Cites/Year/Claim	0.23	0.16	0.13	0.23	0.21	0.34	0.23
Generality	0.52	0.43	0.40	0.57	0.53	0.51	0.49
Int'l Family	0.42	0.33	0.31	0.37	0.39	0.29	0.56
Application Year	1992.7	1992.7	1993.9	1990.7	1993.6	1994.4	1992.0
Assignee Type							
US Company	0.67	0.57	0.56	0.73	0.70	0.71	0.57
Foreign Company	0.26	0.36	0.38	0.17	0.23	0.19	0.39
Other	0.07	0.07	0.06	0.10	0.07	0.11	0.04
Patents	724	724	185,357	131	267	101	225

†Control patents have the same application-year and primary 3-digit USPTO technology classification (nclass) as one or more of the SSO patents. The "matched" controls are a randomly selected one-to-one match (i.e. the joint distribution of application-year and technology-class is identical to the SSO sample).

Because of this legal issue, patent citations are carefully vetted by the inventor, the inventor's attorney and the USPTO. However, there are still questions about exactly what a citation implies, and what we can infer about economic processes from observing a patent citation.

One patent may obtain more citations than another for several reasons. To begin with, citations may indicate efforts to build upon or invent around a specific technology, suggesting that a cited patent has economic value. Harhoff et al (1999) document a positive relationship between citations and estimates of patent-value obtained from a survey of patent-holders. And Hall, Jaffe and Trajtenberg (2005) show that citation-weighted patent counts are more correlated with a firm's market value than un-weighted patent counts.

However, differences in economic value are not the only reason a patent may garner more citations. A patent that is well-publicized (e.g. through disclosure to an SSO) might capture more citations. And if disclosure indicates a willingness to license on "reasonable" terms, forward-citations may reflect follow-on innovations associated with a liberal licensing policy. Differences in the underlying technology could also influence citation rates. For example, patenting and citation patterns differ across industries. Even within industry classifications, there is likely to be heterogeneity.

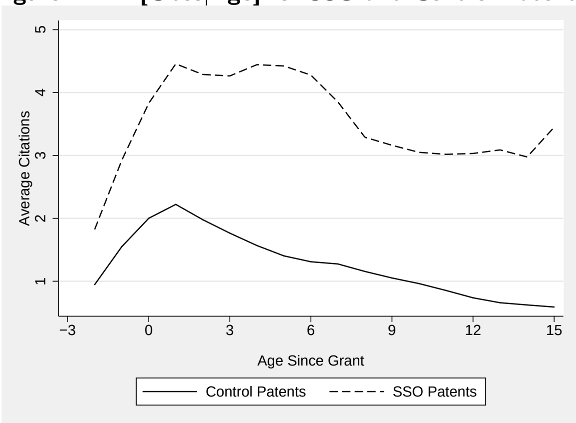
For instance, within computing and electronics, platform technologies (i.e. those "at risk" for standardization) might receive more citations because the nature of inter-operability makes them relevant in a larger number of complementary markets. It seems possible (but not obvious) that SSO endorsement can increase the "connectedness" of a patent without increasing its economic value.

Since patent citations may arise from multiple sources such as economic value, publicity, licensing practices, interconnectedness or other technological features, it is not obvious how to interpret them. In this paper, we hold two interpretations simultaneously. If a reader wants to treat our findings as purely descriptive, then citations are just a measure of how "interesting" a patent is, where interest can arise from any of these sources. However, those willing to interpret citations as a measure of economic value can use our results to infer the economic impact of SSOs. We provide several statistics in support of this interpretation, e.g by showing that results are similar across several control samples (including a group of "platform technologies") and examining self-citations, where issues of publicity should not play a role. However, definitively pinning down the meaning of a citation is beyond the scope of this paper, and we approach our conclusions cautiously with that thought in mind.

4. Citation Age Profiles

In this section, we examine the distribution of forward-citations to patents in the SSO and control samples, focusing on the citation age profile—i.e. the average citation rate conditional on the age of the cited patent. When comparing the age profile of SSO and control patents, we do not use any information about the timing of disclosure (which may occur at any point during the life of an SSO patent). Thus, we temporarily set aside the issue of selection versus marginal effects to focus on the question of whether and for how long SSO patents are especially significant. Figure 2 illustrates our two main findings. First, SSO patents are cited at roughly twice the rate of the controls. And second, SSO patents exhibit a different citation age-profile; specifically, a larger share of their cumulative cites arrive in later years.

Figure 2 E[Cites|Age] for SSO and Control Patents



In the remainder of this section, we estimate citation age profiles following an approach proposed in Mehta, Rysman and Simcoe (2007). This method uses a full set of application- and citing-year effects to control for various confounding factors — such as policy changes and funding issues at the USPTO, increases in citation propensity over time, and differences in the technological significance or "fertility" of various application-year cohorts. It is well known that one cannot identify a full set of patent-age, application-year and citing-year effects in a linear model because age equals citation year minus application year. Prior research on the age-profile of patent citations has relied on non-linear functional form restrictions to solve this problem. Mehta, Rysman and Simcoe suggest an alternative approach based on the assumption that the citation age process actually begins when a patent is granted (rather than its application-year) and present evidence in favor of this assumption for these data.[13] Intuitively, the age effects are identified by comparing the citation rate of patents from the same application-year cohort whose "age" differs as a result of variation in the length of the USPTO review process.

We estimate a set of citation age profiles using the following model, where C_{it} is the number of citations received by patent i in year t, α_y are fixed effects for application year y, α_t are fixed effects for citing year t (as measured by the application year of the citing patent), α_c are fixed effects for the three-digit USPTO technology classification, α_a^{CTRL} and α_a^{SSO} are the age effects for

[13] The age process is meant to capture a process of diffusion and obsolescence. Plausibly, that process does not begin until the information in a patent is publicly available, which is the grant date for U.S. patents. If the publication lag is exogenous, this re-definition of "age" identifies a model containing age, year and cohort effects.

the control patents and SSO patents at age a, ε_{it} is a patent-year error term that is uncorrelated with the fixed effects, and $f()$ is a Poisson process. Here, age is defined relative to the grant year g (i.e. $a = t - g$), so patents will receive citations at negative ages if the application-year of the citing patent is less than the grant-year of the cited patent.[14]

$$C_{it} = f(\alpha_y, \alpha_t, \alpha_c, \alpha_a^{CTRL}, \alpha_a^{SSO}, \varepsilon_{it}) \tag{1}$$

This specification is based on the assumption that application-year and citing-year effects are identical for the SSO and control patents, but the age profiles can be different.[15] While both the control sample and the SSO sample contribute to identifying the application-year and citing-year effects, the number of observations in the control sample dwarfs the number in the SSO sample. Conceptually, we are using the control sample to identify the application-year and citing-year effects, while estimating a separate age profile for each sample. Hence, the choice of the control sample has little effect of the shape of the SSO age profile.

We limit the analysis to a period of about 15 years due to data availability. In particular, we have very few observations on "old" SSO patents, since the majority were either granted or disclosed near the end of the sample period.[16] There is also some truncation of our dependent variable near the end of the sample, since we do not observe citations made by patents with long pendency (i.e. application-to-grant) lags. To compensate, we limit our analysis to citing-patents with application-years prior to 2002 — even though we collected citations from patents granted through 2006. This

[14] For the assumption that age begins at grant date to be exactly correct, it must be that these citations are added by the patent examiner or turned up in a patent search as opposed to indicating an actual intellectual debt. Mehta, Rysman and Simcoe (2007) discuss this at length. In practice, we drop citations from ages below -2 from our data set.

[15] This additive specification also assumes that there is no "co-mingling" of the age, year and cohort effects (e.g. the age profiles are not changing over time). Mehta, Rysman and Simcoe (2007) provide evidence that the citation age-profile has remained relatively stable. We also experimented with interacting the citing-year and cohort effects and found that it made little difference.

[16] Figure A-1, which can be found in the Appendix, shows the application-year distribution for the SSO patents. While the truncation near the end of our sample might be an issue if the criteria for disclosure were changing rapidly during this time period, we find no evidence that this is the case. Table A-3, provides counts of the number of pre- and post-disclosure patent-year observations in our data set.

ensures that we only lose citations from patents with a pendency lag greater than five years, which is observed for 1.02 percent of the patents in the NBER data.

We estimate Equation (1) separately on the pooled sample and for each SSO. Table A-4 provides a complete set of age coefficients from these regressions. However, since it is difficult to evaluate hypotheses about the shape of the age distribution using these coefficients, we focus on summary statistics. In particular, we predict the number of citations conditional on age (setting the dummy variables for application year 1999 and citation year 1999 on and leaving all other application and citation years off) and use these values to compute a probability distribution. Then, we use the probability distribution to compute an “average citation age” for each group of patents. We compute standard errors for this statistic using the delta method, and test the hypothesis that the mean citation-age is equal in the SSO and control samples.

Table 3 presents estimates of the “average citation age” using both the unadjusted age distribution and the regression model. The average age is naturally higher when we use the regression procedure, since it corrects for the truncation problem inherent in observing many patents near the end of the sample period. The important point is that both methods indicate that SSO patents receive a significantly greater share of their citations in later years. This result is particularly striking in light of the market value regressions in Hall Jaffe, and Trajtenberg (2005) that indicate that “unexpected future citations” — which lead to a flatter age-profile — are more valuable than an average cite.

Figures 3 and 4 graph the citation probability distributions over ages -2 to 12 as computed from the regression results. Hall, Jaffe, and Trajtenberg (2001) draw similar graphs for a number of groups of patents and always find peaks in the 4th or 5th year after application. This is consistent with our control groups, which show peaks 1 to 2 years after the grant year. However, it contrasts with the SSO patents, whose age distributions are substantially flatter. In each graph, we can see that the SSO distribution is lower at low ages and higher at high ages, which implies that SSO patents have a higher mean and median citation age.

Table 3 Mean Citation Age

	Raw Data		Estimated PDF		
	Control	SSO	Control	SSO	Difference
Pooled Sample	2.50 (0.00)	4.26 (0.03)	4.16 (0.05)	4.97 (0.18)	0.81 (0.17)
Highly Cited	2.60 (0.00)	4.26 (0.03)	4.39 (0.06)	5.08 (0.18)	0.69 (0.18)
ANSI	3.11 (0.00)	5.94 (0.07)	4.47 (0.08)	5.40 (0.35)	0.93 (0.34)
IEEE	2.22 (0.00)	4.43 (0.05)	4.22 (0.08)	5.03 (0.34)	0.81 (0.33)
IETF	1.26 (0.00)	3.10 (0.05)	4.09 (0.11)	5.49 (0.29)	1.30 (0.26)
ITU	2.50 (0.00)	4.24 (0.04)	4.06 (0.08)	4.81 (0.24)	0.76 (0.23)

Mean citation ages for the Estimated PDF are an age-weighted average of fitted values from Equation (1). The standard errors in parentheses were calculated using the delta method, starting from a heteroskedasticity-consistent covariance matrix clustered on patents.

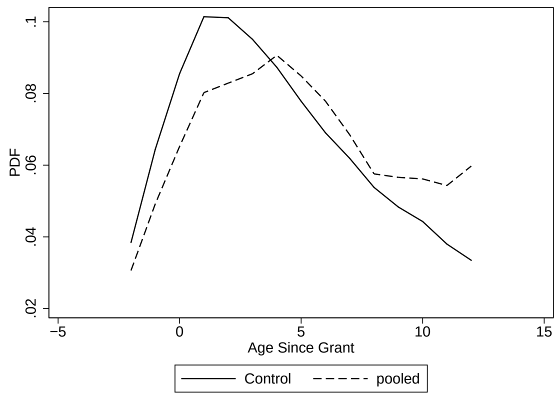


Figure 3 Estimated Citation Age Profile for the Pooled Sample

One concern with these results may be that the high average citation age in the SSO sample simply reflects greater overall importance. In other words, all highly cited patents might have a similar age profile. We checked this by comparing the SSO patents to a set of highly cited controls: patents in the top quartile of the cumulative cite distribution for a given grant-year technology-class cohort. (This definition results in a control sample whose average citation rate is slightly higher than the SSO patents.) The second row in Table 3 shows that with these controls, there is a small (roughly 15 percent) and statistically insignificant drop in the difference in mean citation age.

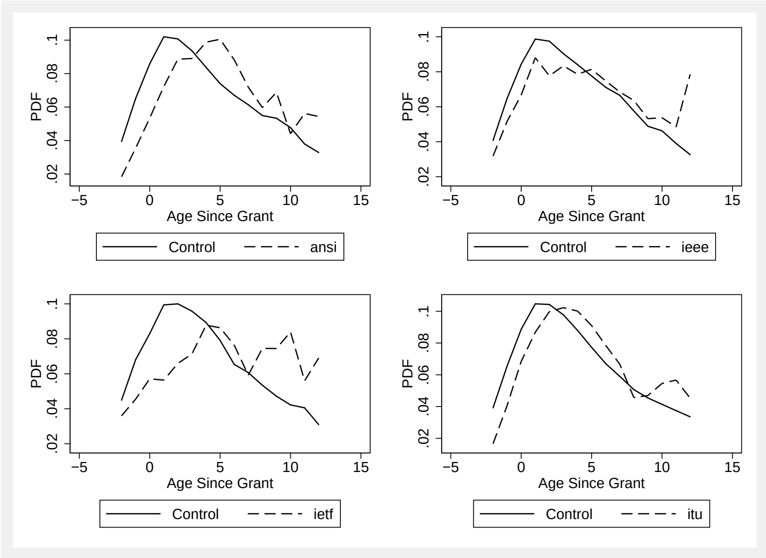


Figure 4 Estimated Citation Age Profile for Individual SSOs

Another potential concern is that differences between samples may reflect different distributions of application dates if the age profile is changing over time. However, Mehta, Rysman and Simcoe (2007) examined this issue and found that the overall age profile is quite stable.

Perhaps the flatter age profile is characteristic of all platform technologies (i.e. those "at risk" for standardization) and not just those disclosed to an SSO? There is no obvious way to identify such a control sample. However, as an attempt along these lines, we take the set of all patents that cite an IETF standard in their non-patent prior art, and compare them to both patents disclosed in the IETF standards process and the baseline controls. (The basic premise is that patents citing IETF standards are more likely to build upon or complement the Internet, making them plausible platform technologies.) We focus on the IETF primarily because its naming conventions make it particularly easy to locate relevant patents by searching for the string "RFCXXXX" in one or more non-patent prior art citations. In principle, we could extend this analysis to other SSOs by constructing a control sample based on patents that cite a disclosed patent. However, we are wary of using the same observations to construct the dependent variable and serve as the control group.

The non-patent prior-art cites provide a largely independent source of information for identifying controls.

Using the USPTO's Internet search engine, we identified 602 "platform technology" control patents. We then re-estimated Equation (1) using the original IETF patents (both SSO and controls) and the new set of platform technology patents. We continue to assume that technology-class, application-year and calendar effects (α_c,α_y,α_t) are constant across groups, but allow for three separate age profiles (α_a^{CTRL},α_a^{SSO},α_a^{PLTFM}). Because citations to IETF standards grew dramatically in the early 1990's, there is substantial right-censoring in the platform technology control sample. We therefore limit the analysis to observations between -2 and 9 years since grant.

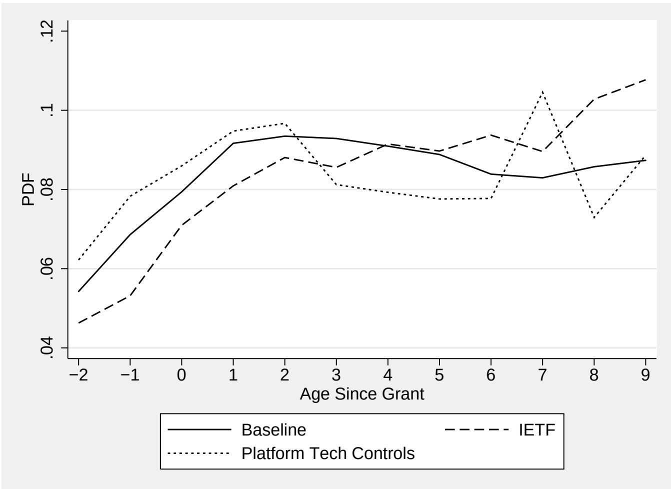


Figure 5 Age Profile Comparison: IETF, Baseline controls and Platform technologies

The main results of this analysis are illustrated in Figure 5. The age profile for the platform technology controls is quite similar to the baseline (technology class) control group, while the IETF patents continue to receive relatively more cites in later years. The average citation age (computed in the manner described above) is 3.61 for the platform technology controls, 3.74 for technology class controls and 4.16 for patents disclosed to the IETF. The difference between the IETF and the platform technology control patents is significant at a 90 percent level of confidence, and the difference between the IETF and the larger technology class control patents is significant at a

99.9 percent confidence level. Thus, we find no evidence that the SSO patents' unique citation age profile is a characteristic of all platform technologies.

5. The Impact of SSOs

The previous section showed that patents disclosed to SSOs are cited more often than an average patent and at later ages. While these findings suggest that SSO patents embody significant inventions, the age profile results have two plausible interpretations. Differences between the SSO and control patents could simply be a selection effect, whereby SSOs identify and endorse technologies that are more likely to exhibit a particular age profile. On the other hand, if the SSO's endorsement and consensus-building activities lead firms to adopt and build upon patented technology when they otherwise would not have, differences in the citation age profile will measure the marginal effect, i.e. the causal impact of the formal standards process. We address this question by studying the relationship between citation rates and the timing of disclosure. Our goal is to estimate the impact of disclosure on the forward citation rate.

To do so, we discard the control patents and use only those patents disclosed to an SSO — relying on variation in the timing of patent disclosures for identification. Specifically, we regress the citation count on a set of patent fixed effects, citing-year effects and a dummy for disclosure, using only SSO patents. In comparing this approach to that in the previous section, we can see them as two extremes in the spectrum of constructing control groups. In the previous section, we used a relatively broad set of controls. In this section, the "control sample" are patents that will be disclosed to an SSO in the future.

Using pre-disclosure SSO patents to estimate a counter-factual citation rate controls for a great many issues, including the inherent quality of the patent and the inter-connected nature of platform technologies. In particular, a causal interpretation of these results does not rest on the maintained assumption that patents are randomly selected for disclosure, but rather that an SSO patent's age at disclosure is exogenous to the citation process. While this assumption might still be violated, we believe that it would be hard to construct a superior control group outside of a randomized setting. Our main results show that the impact of an SSO endorsement is statistically significant and economically meaningful: disclosure generates a 19 to 47 percent increase in the citation rate.

Though we label the correlation between disclosure and citations the "marginal effect", we do not mean to overstate a causal interpretation of our results. If disclosure timing is correlated with some unobserved process that causes citations, we cannot interpret the coefficient on the disclosure dummy as causal. The sign of the associated bias is difficult to predict. For example, suppose there is a large causal effect but SSO members can predict which patents will be disclosed and begin to build upon or invent around them. In that case, SSO patents will start receiving citations before the disclosure date, and our method will understate the impact of the SSO. A similar bias could occur if patent examiners respond to disclosures by citing the SSO patents in pending applications filed prior to the announcement. On the other hand, patent disclosures may be correlated with time-varying unobservable events. If the usefulness of a patented idea becomes more apparent over time, SSOs may select for emerging technologies around the time period when they begin to receive a large number of citations. In this scenario, we would observe an increase in citations around the date of disclosure even if there is no "true" marginal impact. In what follows, we attempt to address this issue by studying pre-disclosure citation patterns. But regardless, these points caution us in interpreting the coefficient on disclosure in causal terms.

5.1. Marginal Effects in the SSO Sample

In this sub-section, we use variation in the timing of SSO patent disclosures to estimate the marginal effect. The advantage of using the disclosure year as a break point is that it is easily observed and likely to occur within a few years of standardization. As we argued above, firms that delay for too long risk losing their IPR, while disclosing too early has both practical and strategic costs.

Since we are no longer interested in separating the age, cohort and calendar effects, we rely on a more flexible specification that includes individual patent fixed-effects. Specifically, we estimate a fixed-effects Poisson model, where α_{it}^{Disc} is a post-disclosure dummy that captures the marginal effect; α_t are a set of citing-year effects; age_i^n are the non-linear terms from a fourth order polynomial in age-since-grant for patent i; and γ_i is a patent conditional fixed-effect.[17]

$$C_{it} = f(\alpha_{it}^{Disc}, \alpha_t, age_i^n, \gamma_i, \varepsilon_{it}) \tag{2}$$

While it is not possible to include a full set of age or cohort effects (since they are co-linear with the calendar and patent fixed-effects), we include the non-linear age terms to capture the hump-shaped age profile observed in Section 4 and earlier work.

By introducing patent-level fixed effects and dropping the control sample, this specification controls for any time-invariant technology characteristics and addresses concerns about the selection of SSO patents. In particular, α_{it}^{Disc} is estimated entirely off of within-patent variation in citation rates and between-patent variation in the timing of disclosure.[18] For example, if all SSO patents were disclosed at the same age, α_{it}^{Disc} would not be identified, since it would be co-linear with some combination of the patent and citing-year fixed-effects.

Table 4 presents our estimates of the disclosure effect. Each coefficient is a first-order approximation to the percentage change in the citation rate, though the figures discussed in the text are are based on the incidence rate ratio $\exp(\alpha^{Disc}) - 1$, which provides a somewhat better approximation for larger coefficients (e.g. above 0.3). Our main results are based on the pooled sample of SSO patents. Since we are working with relatively small numbers of patents, the pooled estimates will be less sensitive to outliers and timing issues than the individual SSOs. However, we include the individual SSO results for comparison.

The first row of Table 4 presents our baseline estimates, which use a simple post-disclosure dummy to estimate the marginal effect. The post-disclosure coefficient for the pooled sample indicates that disclosure is associated with a 19 percent increase in the citation rate. The individual SSO

[17] While the negative binomial model is widely used in similar settings, Wooldridge (1999) advocates for the fixed-effects Poisson, which provides a consistent estimate of the conditional mean function even when the dispersion is mis-specified. is consistent under quite general conditions. He also describes an estimator for the covariance matrix that is robust to both hetero-skedasticity and arbitrary serial correlation in the dependent variable. Code for computing these robust standard errors is available at http://www.rotman.utoronto.ca/timothy.simcoe/ and via the “ssc xtpqml” command in Stata.

[18] Table A-3 shows that there is significant variation in disclosure timing. In particular, there are more than 30 pre- and post-disclosure SSO patent observations at each age from 0 to 10 years after the grant date.

Table 4 Marginal Effects in the SSO Sample

DV = Cites_{it}	**Pooled**	ANSI	IEEE	IETF	ITU
	Model 1: Baseline				
PostDisclosure	0.177 (0.086)**	0.215 (0.139)	0.059 (0.097)	0.285 (0.113)**	0.175 (0.129)
Patents	621	128	251	97	218
Observations	5,337	1,317	1,962	686	2,046
	Model 2: Marginal Effect Starts at Disclosure_{-2}				
$\text{PostDisclosure}_{-2}$	0.221 (0.075)***	0.230 (0.184)	0.186 (0.090)**	0.328 (0.132)**	0.328 (0.133)**
Patents	621	128	251	97	218
Observations	5,337	1,317	1,962	686	2,046
	Model 3: Drop 2 year pre-disclosure window				
PostDisclosure	0.388 (0.128)***	0.257 (0.257)*	0.227 (0.128)*	0.659 (0.191)***	0.569 (0.242)**
Patents	571	120	227	90	204
Observations	4,339	1,084	1,562	582	1,700

* Significant at 10%; ** Significant at 5%; *** Significant at 1%. Robust standard errors in parentheses. Each column is based on the fixed-effect Poisson specification in Equation 2. Jointly significant age and citing-year effects are not reported. For pre- and post-disclosure SSO patent sample-sizes refer to Table A-3.

results show a positive and statistically significant disclosure effect at the IETF—corresponding to an increase of roughly 33 percent. The ANSI and ITU coefficients are comparable to the pooled effect, but statistically insignificant, and the IEEE effect is negligible.

The second and third panels in Table 4 consider models that use alternative definitions of disclosure. In Model 2, we artificially move the disclosure date forward by two years to look for evidence of a large pre-disclosure citation increase. In this specification, the pooled sample coefficient increases slightly, and there is an increase in the marginal effect at each of the individual SSOs. In particular, the post-disclosure coefficient becomes statistically significant for both IEEE and ITU. These results suggest variation in the amount of measurement error on our post-disclosure variable across the four SSOs in our sample. However, we find the relatively stable pooled sample results reassuring.

Model 3 returns to the standard definition of disclosure, but omits any observations that fall within a 2 year pre-disclosure window. Intuitively, this increases the likelihood that the baseline against which post-disclosure citation increases are measured precedes the start of the standard setting process. Not surprisingly, this also leads to an increase in the estimated marginal effects—in this case for the pooled sample, as well as all four individual SSOs. The pooled sample coefficient in this specification corresponds to a 47 percent increase in the baseline citation rate. While this is a substantial increase, it is not statistically different from the baseline estimate. In this specification, the marginal effect is positive and statistically significant at the 10-percent level or better for each of the individual SSOs.

Comparing the results of these three different models suggests that the marginal effect of disclosure on citation rates is somewhere between 19 and 47 percent. Some of this increase predates the actual disclosure letter. However, the results from Model 1 indicate that this effect continues for several years after disclosure occurs. (We present more evidence on the timing of the disclosure effect below.)

We performed a number of robustness checks and considered several alternative specifications for these results (see Appendix Table A-5). To examine whether the marginal effect is actually driven by "publicity effects" or increased awareness of the patent following disclosure — as opposed to increased economic or technological significance — we examined the impact of disclosure on self-citations. With self-citations, the citing and cited patent are owned by the same assignee, so it is harder to argue that this firm was simply unaware of the cited technology before disclosure. The self-citation analysis yields point estimates that are very similar to the marginal effects reported above, although none of them are statistically significant (in part because roughly half of the SSO patents receive no self-citations and are dropped from the regression).

We also estimated this model using OLS and a fixed-effects negative binomial specification. In both cases, the results are consistent with our earlier estimates. Finally, we interacted the post-disclosure variable with a dummy for whether the SSO patent was above the 75th percentile in terms of cumulative pre-disclosure citations (relative to other patents with the same grant year). In a Poisson specification, SSO patents below this threshold show a larger disclosure effect while the opposite holds true for an OLS regression. While this is not surprising, it suggests that our main results are not driven by a small set of patents at either end of the pre-disclosure cumulative citation distribution.

One drawback of a model with patent fixed-effects is that it precludes the estimation of a single time-invariant "SSO effect" which might provide a useful point of comparison for the marginal effects. To examine this additional benchmark, we re-introduce the full set of control patents and estimate a specification with technology-class, cohort and calendar effects, a single age profile for both SSO and control patents, and dummies for both an SSO and a disclosure effect. That is, we estimate Equation (1) with a single set of age coefficients, and dummy variable to capture the SSO and disclosure effects (see Appendix Table A-6 for results). While imposing a single age profile contradicts our results in Section 4, doing so allows for a direct comparison of the SSO coefficient and the disclosure coefficient (i.e. the selection effect and the marginal effect), which we find compelling.

The disclosure effect in this pooled cross-sectional specification is remarkably similar to the estimates produced by Equation (2): around 28 percent in the pooled sample. The selection effect is four times larger. Thus, 20 percent of the difference between the patents disclosed to an SSO and an average patent is due to disclosure, while 80 percent is a selection effect. Although we do not have strong prior beliefs about this statistic, these estimates strike us as quite reasonable.

5.2. Disclosure Timing and Citation Trends

We would like to interpret the post-disclosure parameter as a causal effect that measures the impact of an SSO's formal endorsement (and other consensus-building activities) on the economic and technological significance of a particular patent. However, this interpretation rests on the assumption that disclosure timing is exogenous. While it is not possible to test this assumption, we can look for supporting evidence in the pre-disclosure citation trends. We have already discussed several reasons why the marginal effect might pre-date a formal IPR disclosure, such as lags between the date when a committee learns about a patent and the formal disclosure letter. Nevertheless, the absence of a sustained increase in SSO patent citation rates — relative to an appropriate control sample — over the full pre-disclosure period would provide some evidence in favor of the causal interpretation.

In this sub-section we use a series of age-relative-to-disclosure dummies to more carefully discern how citation patterns change over time. This exercise requires the use of a control sample, since the age-relative-to-disclosure dummies are co-linear with the patent and citing-year effects (or the SSO effect in a cross-sectional model). Also, as this is a demanding task for our data set, we focus on an eleven year time-window centered on the disclosure year.

We estimate two models. The first regression uses the broad set of technology-class control patents, and adds a full set of age-relative-to-disclosure dummies to Equation (1), which already includes a separate set of age-relative-to-grant-year effects for both SSO and control patents. The second specification uses our sample of "highly-cited" controls (i.e. patents above the 75th percentile of the cumulative cite distribution within a technology-class grant-year cell) and replaces the disclosure dummy in Equation (2) with a set of age-relative-to-disclosure effects. While the cross-sectional specification will be more sensitive to patent-level heterogeneity and the composition of the SSO and control samples, the fixed-effects model assumes that the SSO and control patents share a common age-profile. In practice, the fixed-effects model produces similar results if we use the full set of control patents, since all un-cited patents are excluded from the estimation procedure.

Figure 6 graphs our estimates of the pre- and post-disclosure SSO patent citation-trajectory, along with a 95 percent confidence interval (the left-panel shows cross-sectional estimates, while the right panel displays fixed-effects results). In both models, the SSO patent citation rate declines relative to the controls from 5 until 2 years before disclosure, though the error bands show that we cannot reject the null hypothesis of no difference in the pre-disclosure trends. In other words, the SSO and control patents have a similar citation trajectory (conditional on age, citing-year, etc.) up that point. The point estimates show that SSO patents begin to experience an increase in citations two years before disclosure, and this trend lasts for a roughly five years, by which time the error bands show that our estimates are fairly imprecise.

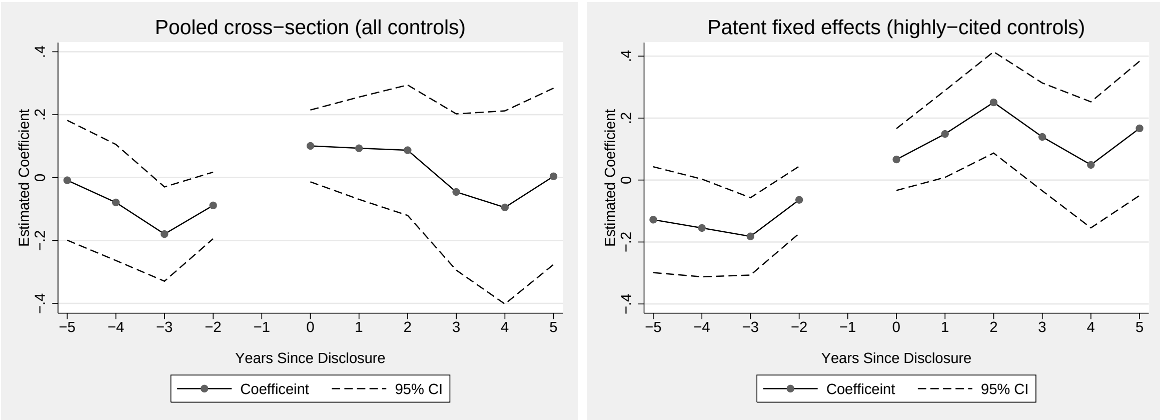


Figure 6 Pre and Post-disclosure SSO Effects

As we have already discussed, there are a number of potential explanations for the observed pre-disclosure "citation bump." In particular, it may provide evidence that SSO patent disclosures are correlated with a patent's unobserved time-varying technological significance. However, we are encouraged by the absence of a clear trend in the relative citation rate of the SSO patents from 5 until 2 years before disclosure. In particular, the data do not reject the hypothesis that the SSO and control patents have a parallel citation trajectory during that time period. (We also verified this claim by running models with a pre-disclosure time-trend for SSO patents, which was always statistically insignificant.) These results provide some support for the assumption that disclosure-timing is exogenous to the citation process. If this assumption is correct, pre-disclosure SSO patents will provide an unbiased estimate of the counterfactual citation rate, and it would be appropriate to place a causal interpretation on the estimated marginal effect.

Overall, we find that across several different SSOs and estimation methods, citation rates consistently increase by 19 to 47 percent following the disclosure of a patent to an SSO. We remain cautious about placing a strong causal interpretation on these results — primarily because it is impossible to test whether firms or SSOs can select patents based on time varying unobserved variables that are correlated with future citations. Nevertheless, lacking any truly exogenous events that push patents into SSO standards, our approach provides a reasonable starting point for identifying the causal impact of SSOs.

We conclude this section by noting that our focus on marginal effects does not imply that we find selection effects uninteresting. Rather, the existence of a significant marginal effect — which we interpret as evidence that SSOs' consensus-building efforts can have a significant impact — reinforces the importance of identifying the best possible technologies. The presence of substantial selection effects is therefore both reassuring and consistent with SSO claims regarding the role of "technical merit" in the evaluation process.

6. Conclusions

While the importance of SSOs has been widely discussed, there have been no attempts to systematically measure the effects of these institutions. This paper is the first to address this question using patent citations as a measure of SSO performance. Our approach leads immediately to the question of causality. Specifically, do SSOs' efforts to promote industry coordination confer an advantage on the standards they promote, or do these groups merely identify or attract important technologies?

We find substantial evidence that SSOs identify and endorse important technologies. In particular, patents disclosed in the standard setting process receive roughly twice as many citations as a set of controls from the same technology-class and application-year. We also find a significant increase in the citation rate of SSO patents following disclosure, which we use as a proxy for the arrival of a new standard. Citations after disclosure are 19 percent higher in our base specification. Even if one were to interpret these results entirely in terms of selection, they suggest that SSO's perform well in selecting important technologies. To the extent that the correlation of citations with disclosure represents a causal effect, the results show that SSO's contribute to the lasting significance of the technologies they endorse.

These findings have significant managerial implications, particularly within the information and communications technology sector, where SSOs frequently define the parameters that enable new products to operate within existing platforms. For the consumers of voluntary consensus standards, our findings are largely reassuring: large selection effects suggest these four SSOs are discriminating in the technology evaluation process, and significant marginal effects indicate success in promoting industry coordination. For technology sponsors who question whether SSO participation is a wise investment of time and resources, our results suggest that the answer can be yes — particularly if we interpret the marginal effect as a causal relationship between SSO endorsement and subsequent technology adoption. But these benefits do not come free. To secure an SSO endorsement, firms typically give up some rights in their proprietary technology. Thus, our citation-based evidence provides some insight into the trade-off between co-operating to create value and competing to capture it. However, this evidence is just one part of a larger cost benefit calculation that may also incorporate competitive factors, coalition building and parallel efforts to establish a standard in the marketplace.

Our principal findings are also relevant to current policy debates regarding intellectual property and compatibility standards. In particular, any evidence that SSO endorsement can add value to a patented technology helps to justify recent policy initiatives aimed at promoting clarity and preventing manipulation of the standards process. Standards implementers should take a keen interest in these policies, which may help limit their exposure to "hold up" by other members of an SSO. However, we should acknowledge that it is hard to draw clear welfare implications from our current results. The impact of IPR on industry standards and cumulative technical progress will depend on SSO rules and participants' willingness to abide by them, as well as related public policy.

More generally, our findings raise a variety of questions for future research. For example, with data from a larger sample of SSOs, one might examine how selection and marginal effects vary with changes in SSO policies, procedures or membership. Our methods for estimating the citation age profile might be used to compare SSO patents to a control sample based on *de facto* industry standards. And to the extent that our findings link SSO endorsement to the economic value of a technology, our results raise a variety of interesting questions about competition within and between SSOs.

Finally, though we have focused on compatibility standards, our analysis may offer some insights into the broader topic of industry self-regulation. In particular, non-government organizations increasingly use SSOs such as the Forest Sustainability Council or Fair Trade Labeling Organizations International to create voluntary codes of corporate conduct. These efforts rely on the consensus process, and raise questions about agenda selection versus marginal effects that are very similar to those examined here. However, much work remains to determine whether and how much compatibility standard setting can teach us about standardization in these other domains. In particular, there is a clear need for theories that illustrate how the post-SSO process of market or political competition influences SSO participation, agenda formation and standards selection, and how these forces vary when standards promote quality or social responsibility as opposed to product inter-operability.

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References

Allison, J., M. Lemley, K. Moore, R Trunkey. 2004. Valuable patents. *The Georgetown Law Journal* **92** 435–478.

Besen, S. M., J. Farrell. 1991. The role of the ITU in standardization - pre-eminence, impotence or rubber stamp. *Telecommunications Policy* **15**(4) 311–321.

Besen, S. M., Leland Johnson. 1988. Compatibility standards, competition and innovation in the broadcasting industry. *RAND Study R-3453-NSF* .

Besen, S. M., G. Saloner. 1989. The economics of telecommunications standards. R. Crandall, K. Flamm, eds., *Changing the Rules: Technological Change, International Competition, and Regulation in Telecommunications*. Brookings, Washington, 177–220.

Bolin, S., ed. 2002. *Standards Edge: The Golden Mean*. Bolin Communications, Ann Arbor.

Bresnahan, T. F., S. Greenstein. 1999. Technological competition and the structure of the computer industry. *Journal of Industrial Economics* **47**(1) 1–40.

Cargill, Carl F. 1997. *Open Systems Standardization : A Business Approach*. Prentice Hall PTR, Upper Saddle River, NJ.

Chiao, B., J. Lerner, J. Tirole. 2007. The rules of standard setting organizations: An empirical analysis. *RAND Journal of Economics* **38**(4) 905–930.

Cusumano, M. A., A. Gawer. 2002. The elements of platform leadership. *MIT Sloan Management Review* **43**(3) 51.

Farrell, J., G. Saloner. 1988. Coordination through committees and markets. *Rand Journal of Economics* **19**(2) 235–252.

Farrell, J., T. Simcoe. 2006. Choosing the rules for formal standardization. *Unpublished manuscript* .

Furman, J., S. Stern. 2006. Climbing atop the shoulders of giants: The impact of institutions on cumulative research. *Unpublished manuscript* .

Gawer, A., R. Henderson. 2007. Platform owner entry and innovation in complementary markets: Evidence from Intel. *Journal of Economics and Management Strategy* **16**(1) 1–34.

Hall, B. H., A. Jaffe, M. Trajtenberg. 2001. The NBER patent citations data file: Lessons, insights and methodological tools. *NBER Working Paper No. 8498* .

Hall, B. H., A. Jaffe, M. Trajtenberg. 2005. Market value and patent citations. *Rand Journal of Economics* **36**(1) 16–38.

Harhoff, D., F. Narin, F. M. Scherer, K. Vopel. 1999. Citation frequency and the value of patented inventions. *Review of Economics and Statistics* **81**(3) 511–515.

Hawkins, R., R. Mansell, J. Skea. 1995. *Standards, Innovation and Competitiveness : The Politics and Economics of Standards in Natural and Technical Environments*. Edward Elgar, Hants England ; Brookfield, Vt., US.

Henderson, R., A. B. Jaffe, M. Trajtenberg. 1998. Universities as a source of commercial technology: A detailed analysis of university patenting, 1965-1988. *Review of Economics and Statistics* **80**(1) 119–127.

Jaffe, A., M. Trajtenberg. 2004. *Patents, Citations and Innovations: A Window on the Knowledge Economy*. MIT Press, Cambridge.

Kaplan, J. 1996. *Startup : A Silicon Valley Adventure*. Penguin Books, New York.

Leiponen, A. 2006. Competing through cooperation: Standard setting in wireless telecommunications. *Unpublished manuscript* .

Lemley, M. 2002. Intellectual property rights and standard setting organizations. *California Law Review* **90** 1889–1981.

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

Lerner, J., J. Tirole, M. Strojwas. 2003. Cooperative marketing agreements between competitors: Evidence from patent pools. *NBER Working Paper No. 9680* .

Mehta, A., M. Rysman, T. Simcoe. 2006. Identifying the age profile of patent citations. *http://ssrn.com/abstract=892457* .

Mowery, D. C., T. Simcoe. 2002. Is the internet a us invention? - an economic and technological history of computer networking. *Research Policy* **31**(8-9) 1369–1387.

Shapiro, Carl, Hal R. Varian. 1998. *Information Rules : A Strategic Guide to the Network Economy*. Harvard Business School Press, Boston, Mass.

Simcoe, T. 2006. Standard setting committees. *http://ssrn.com/abstract=899595* .

Updegrove, Andrew. 2003. Survey: Major standards players tell how they evaluate standard setting organizations. *Consortium Standards Bulletin* **2**(7) http://www.consortiuminfo.org/bulletins/jun03.php.

Weiss, M., M. Sirbu. 1990. Technological choice in voluntary standards committees: An empirical analysis. *Economics of Innovation and New Technology* **1** 111–134.

Wooldridge, J. 1999. Distribution-free estimation of some nonlinear panel data models. *Journal of Econometrics* **90**(1) 77–97.

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Appendix 1 : Supporting Tables & Figures

Table A-1 Technology Classification of SSO Patents†

	ANSI	IEEE	IETF	ITU	Totals
Computers & Communications	41	135	30	83	289
Computer Hardware & Software	56	95	65	80	296
Information Storage	10	7	2	0	19
Misc. Electrical	1	1	0	46	48
All Others	23	27	4	16	71
Total	131	267	101	225	724

†Based on subcategory classifications in the NBER U.S. patent database.

Table A-2 SSO Patent Overlap

	ANSI	IEEE	IETF	ITU
ANSI patents	131	5	7	19
IEEE patents	5	267	10	1
IETF patents	7	10	101	5
ITU patents	19	1	5	225
Total patents	162	283	123	247

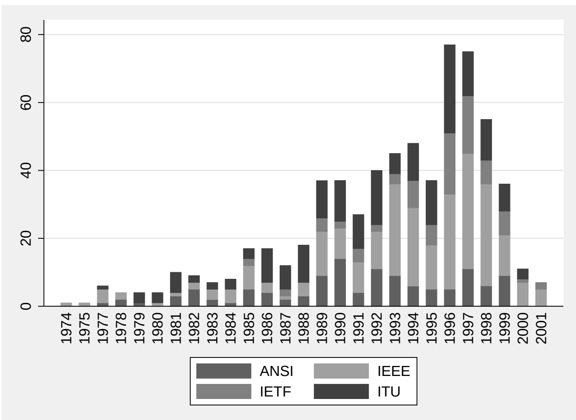

Figure A-1 SSO Patent Application Years

Table A-3 SSO Patent Observations by Age* (Pre & Post Disclosure)

	Pooled Sample			ANSI		IEEE		IETF		ITU	
	Pre	Post	Disclosed†	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Age -2	516	1	4	94	0	220	0	89	0	177	1
Age -1	631	5	56	124	0	260	2	101	0	218	3
Age 0	533	60	90	113	12	211	22	87	6	191	22
Age 1	395	142	58	73	39	166	40	64	18	144	55
Age 2	300	181	43	52	56	122	57	49	17	122	63
Age 3	231	193	20	40	60	94	64	41	13	94	71
Age 4	186	189	23	33	60	76	61	32	11	76	72
Age 5	150	196	14	28	63	62	61	25	12	60	75
Age 6	122	181	14	26	60	48	54	21	11	50	72
Age 7	98	162	14	23	57	36	43	17	8	42	66
Age 8	76	146	15	21	48	24	41	14	6	34	60
Age 9	54	135	11	15	43	16	40	13	3	25	54
Age 10	38	120	6	11	37	7	42	10	2	22	45
Age 11	29	97	9	10	28	6	30	5	5	16	43
Age 12	15	83	5	5	29	5	24	4	5	8	35
Age 13	8	72	1	4	25	3	23	4	4	3	30
Age 14	6	61	1	4	24	2	21	4	1	2	23
Age 15	4	46	1	3	19	1	16	1	0	2	16
Age 16	3	38	1	1	18	0	14	1	0	2	12
Age 17	2	29	0	0	15	0	9	1	0	2	11
Age 18	1	20	0	0	8	0	8	1	0	1	7
Age 19	1	15	0	0	7	0	7	0	0	1	4
Age 20	1	12	0	0	7	0	6	0	0	1	2
Totals	3,400	2,184	386	680	715	1,359	685	584	122	1,293	842

* Age measured relative to grant-year of the disclosed patent.
† This column reports the number of SSO patents disclosed at a given age.

Table A-4 Age Effects for SSO and Control Patents

	Pooled Sample		ANSI		IEEE		IETF		ITU	
	SSO	Control	SSO	Control	SSO	Control	SSO	Control	SSO	Control
Age -2	0.649		0.174		0.575		1.068		-0.032	
Age -1	1.124	0.517	0.821	0.526	1.059	0.463	1.302	0.415	0.863	0.514
Age 0	1.406	0.800	1.230	0.833	1.315	0.727	1.530	0.613	1.384	0.816
Age 1	1.613	0.970	1.544	1.019	1.592	1.884	1.517	0.794	1.621	1.982
Age 2	1.645	0.967	1.760	1.018	1.467	1.871	1.674	0.799	1.761	1.978
Age 3	1.676	0.906	1.783	0.965	1.538	1.795	1.752	0.756	1.785	1.913
Age 4	1.735	0.820	1.909	0.872	1.479	1.723	1.959	0.687	1.765	0.808
Age 5	1.669	0.706	1.939	0.767	1.514	0.643	1.943	0.565	1.669	0.678
Age 6	1.583	0.586	1.817	0.693	1.429	0.556	1.821	0.375	1.521	0.536
Age 7	1.454	0.476	1.622	0.649	1.340	0.489	1.567	0.300	1.358	0.409
Age 8	1.281	0.336	1.463	0.568	1.267	0.345	1.796	0.173	0.979	0.257
Age 9	1.264	0.229	1.632	0.513	1.088	0.180	1.795	0.048	1.008	0.147
Age 10	1.256	0.142	1.201	0.419	1.099	0.125	1.915	-0.062	1.158	0.055
Age 11	1.223	-0.011	1.460	0.224	0.995	-0.044	1.510	-0.102	1.195	-0.045
Age 12	1.318	-0.137	1.449	0.067	1.478	-0.223	1.719	-0.372	0.971	-0.155
Observations	1,278,584		622,636		605,514		249,633		639,841	

Regressions based on Equation (1), including a full set of unreported application- and citing-year effects.

Table A-5 Robustness & Specification Checks

DV = Cites_{it}	**Pooled Sample**	ANSI	IEEE	IETF	ITU
	DV = Self-Citations				
PostDisclosure	0.237 (0.151)	0.326 (0.257)	0.268 (0.314)	-0.130 (0.329)	0.257 (0.227)
Patent Fixed Effects	Y	Y	Y	Y	Y
Citing-year & age controls	Y	Y	Y	Y	Y
Patents	321	79	121	54	105
Observations	3,064	882	1,000	387	1,089
	Ordinary Least Squares				
PostDisclosure	0.915 (0.248)***	1.752 (0.514)***	0.151 (0.425)	2.986 (1.039)***	0.877 (0.404)**
Patent Fixed Effects	Y	Y	Y	Y	Y
Citing-year & age controls	Y	Y	Y	Y	Y
Patents	649	131	267	101	225
Observations	5,445	1,339	2,000	699	2,092
	Fixed Effects Negative Binomial				
PostDisclosure	0.352 (0.043)***	0.470 (0.098)***	0.344 (0.069)***	0.295 (0.095)***	0.367 (0.076)***
Patent Fixed Effects	Y	Y	Y	Y	Y
Citing-year & age controls	Y	Y	Y	Y	Y
Patents	621	128	251	97	218
Observations	5,337	1,317	1,962	686	2,046
	Pre-Disclosure Cites & Marginal Effects (Pooled Sample)				
Specification	Poisson	OLS			
PostDisc * Above Cutoff†	0.096 (0.089)	1.832 (0.290)***			
PostDisc * Below Cutoff	0.748 (0.142)***	-0.299 (0.320)			
Patent Fixed Effects	Y	Y			
Citing-year & age controls	Y	Y			
Patents	621	639			
Observations	5,337	5,445			

* Significant at 10%; ** Significant at 5%; *** Significant at 1%. Robust standard errors in parentheses. Each column is based on the fixed-effect Poisson specification in Equation 2. Age coefficients and citing-year effects not reported. For pre- and post-disclosure SSO patent sample-sizes refer to Table A-3. †Cutoff is the seventy-fifth percentile of the pre-disclosure cumulative cite distribution within a grant-year cohort.

Table A-6 Pooled Cross-sectional Estimates of Selection and Marginal Effects

DV = Cites_{it}	**Pooled**	ANSI	IEEE	IETF	ITU
	Baseline Model: Age, Year, Cohort & Technology-class Effects				
SSO Patent	0.713 (0.051)***	0.521 (0.115)***	0.712 (0.081)***	1.100 (0.088)***	0.663 (0.091)***
PostDisclosure	0.247 (0.078)***	0.561 (0.171)***	0.175 (0.123)	0.129 (0.186)	0.308 (0.114)**
Observations	1,318,816	460,036	623,606	251,997	654,054
	Saturated Model: Age-Year, Cohort & Technology-class Effects				
SSO Patent	0.710 (0.031)***	0.524 (0.066)***	0.710 (0.048)***	1.067 (0.085)***	0.661 (0.053)***
PostDisclosure	0.250 (0.053)***	0.545 (0.096)***	0.187 (0.076)**	0.170 (0.102)*	0.307 (0.092)***
Observations	1,318,807	460,036	623,606	251,979	653,993
	Selection Effect Time-trend				
SSO Patent	0.680 (0.111)***	0.781 (0.152)***	0.505 (0.231)**	1.165 (0.180)***	0.949 (0.187)***
SSO * (DiscYear-2000)	-0.012 (0.020)	0.028 (0.026)	-0.074 (0.037)**	0.090 (0.084)	0.048 (0.032)
PostDisclosure	0.233 (0.078)***	0.457 (0.176)***	0.055 (0.147)	0.266 (0.106)**	0.252 (0.111)**
Observations	1,317,205	459,844	623,606	251,580	653,488

* Significant at 10%; ** Significant at 5%; *** Significant at 1%. Robust standard errors (clustered on patents) in parentheses. Each column is based on the Poisson QML specification in Equation **??**. Application-year, citing-year, age, and technology-class fixed-effects not reported. For SSO patent sample-sizes refer to Table A-3.

Appendix 2 : Sample Disclosure Letters

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PL 242

UNISYS

VIA FACSIMILE (202) 663-7554
CONFIRMATION BY REGULAR MAIL

December 12, 1995

RECEIVED

DEC 15 1995

ABA ST...

Ms. Cynthia Fuller
ASC X9 Secretariat
American Bankers Association
1120 Connecticut Avenue, N.W.
Washington, DC 20036

Re: United States Patent 4,107,653

Dear Ms. Fuller:

This is to advise you that Unisys Corporation is willing to grant to any requesting party a non-exclusive license under the claims of Unisys U.S. Patent No. 4,107,653, the infringement of which is recommended to properly make, use or sell Magnetic Signal Level Measuring Instruments used for the manufacture and/or calibration of secondary reference documents which are used to carry the signal level reference for the calibration of production signal level measuring equipment as referenced in ANS X9.27 - 1995, when approved and published. Please forward a copy of this letter to ANSI for their use. .

Each grant will be under separate agreement, at a royalty rate of one percent (1%) applied to the net selling price or fair market value of the equipment sold. Also, each requesting party must be willing to grant Unisys Corporation an option to a license of the same scope on similar terms, conditions and charges under the requesting party's patents.

Upon adoption of the ANSI standard, parties who wish a license should contact my office.

Sincerely,

Mark T. Starr

Mark T. Starr

MTS/cdt

Heather Benko

From: smontgomery@tiaonline.org
Sent: Wednesday, January 12, 2005 4:18 PM
To: hbenko@ansi.org
Cc: smontgomery@tiaonline.org
Subject: IPR/Patent Holder Statement

Document Information

Reference Doc. No.	PN-3-3972-UGRV.SF1 (refer to Project Number, Standards Proposal Number or title--one form per document. Note, may fill one statement for a document with multi-parts.)
Publication ID	TIA-733-A [SF1]
Document Title	Software Distribution for TIA-733-A - High Rate Speech Service Option17 for Wideband Spread Spectrum"

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