Standard-Setting, IPR Policies and the Incentives to Innovate: Evidence from the IEEE Patent Policy Update

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Abstract

In this paper, I empirically study the effect of IEEE's IPR policy change in 2015 on standard-related innovation. First, I construct a novel dataset of companies that have declared at least one patent as essential for an IEEE standard (the treatment group), and I then collect a sample of firms active in the same industries and having similar characteristics but which have not declared a patent as essential to IEEE (the control group). Then, using a difference-in-differences approach, I provide causal evidence that the IEEE IPR policy change led to a reduction in standard related patenting among the firms affected by the change. My results show that patent policy revision at IEEE decreases the innovation effort of firms in standard-related technologies by 15.2%.

JEL Classification: O31, L15, O34, L44

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1 Introduction

Technology standards play a central role in the Information and Communication Technology (ICT) sector, where independently designed innovations depend on interoperability. Such a complex technological system requires that firms work together in order to guarantee interoperability of technologies, products, and services. Standard Development Organizations (SDOs) have played an important role in this context, allowing the development of standards through the collaboration of different stakeholders. Since the standard-setting process often involves diverse interests, a critical role of SDOs is to regulate the licensing of standard essential patents (SEPs), i.e. intellectual property rights on the technologies that are necessary for the implementation of the standard (Bekkers et al., 2014). To achieve an efficient process of the licensing of essential patents, SDOs need to ensure a balance between promoting the adoption of the standard in the downstream market and incentivizing the developers of key technologies to join and contribute to the standard development.

Despite the growing theoretical literature on technology standards and patents (Shapiro, 2000; Lerner and Tirole, 2015; Spulber, 2019), empirical evidence of the effect of the SDOs' patent policy on standardization is limited (Chiao et al., 2007; Bekkers et al., 2017). This paper develops and estimates a difference-in-differences model to understand how the SDOs' Intellectual Property Rights policy affects the innovative effort of firms in standard development. I exploit a large policy change that occurred in 2015 at the Institute of Electrical and Electronics Engineers (IEEE-SA), which arguably put pressure on the royalties that the holders of standard essential patents could charge to assess the impact of the IPR policy on standard-related innovation over time. This research contributes to the longstanding debate among policymakers, specialists, and SDOs on how technology standards and standard essential patents should be regulated.

The licensing rules for patents declared as essential have been at the center of cooperative standards development. Most SDOs require their members to commit to license SEPs under FRAND[1] terms. The objective of a FRAND commitment is to balance the incentives of diverse firms involved in standards development and facilitate a wide diffusion of the standards. Specifically, a FRAND commitment seeks to ensure that technology contributors can gain an appropriate return on their innovation, and on the other hand, to allow firms to have access to standards for a reasonable cost. FRAND clauses are designed to prevent the exploitation of the locked-in position, which firms may gain from the inclusion of their technologies into technology standards, and avoid potential underinvestment of standards' implementers due to this uncertainty on SEPs cost (Swanson and Baumol, 2005).[2]

Firms contributing to standardization can benefit from their involvement by taking the standard as input and selling the standardized product or by licensing the patents of the technologies included in the standard. This

[1]Fair Reasonable and Non-Discriminatory

[2]Repeated interaction in standard setting can alleviate the hold-up problem, as shown in Larouche and Schuett (2019). For a detailed discussion of patent hold-up problem in standardization see also Lemley and Shapiro (2006).

leads to the presence of two business models contributing to the standard development: pure upstream innovators, who solely benefit from the licensing of patents, and vertically integrated firms, whose revenues come from the licensing of patents and the sale of the end products. Firms with a different business model face different incentives in standardization.

Starting in the early 2000s, policymakers and standard specialists began to raise the concern that the FRAND commitment was intended but was not enough to prevent patent hold-up. In an attempt to mitigate the perceived risk, the IEEE-SA announced an update of its IPR policy in February 2015. Two main changes lie at the center of the policy revision: firms declaring to hold essential patents are recommended to base their royalties on the Smallest Salable Patent Practicing unit, and they are constrained in their right on taking injunctions against licensees of SEPs. Because the revision places strict limitations on the SEP holder's ability to enforce its patent rights against infringers and on its determination of the SEP royalty, it has been argued that it reduces the compensation SEP holder may obtain for its technological contributions to the standards (Sidak, 2016; Zingales and Kanevskaia, 2016; Contreras, 2019). Indeed, the policy update harms the innovation incentive of firms who rely on the SEP royalties to monetize their innovation, and ultimately it might affect their innovative effort in the standard development. As a consequence of the policy change, several firms started refusing to commit to licensing their SEPs under the new IEEE licensing rules.

To empirically estimate the effect of the policy change on firms' standard-related innovation effort, using data from the Searle Center Database, PATSTAT, and Compustat, I construct a novel dataset of companies that have declared at least one patent as essential for an IEEE standard (the treatment group). I then collect a sample of firms active in the same industries and having similar characteristics but which have not declared any essential patents to IEEE (the control group). Since firms can decide whether to declare a patent as essential, my sample is prone to a self-selection bias. Notably, firms can try to be involved in a standard development but can fail as well as they can decide to keep their innovation outside of the technology standard due to factors unobservable to the researcher. To control for this source of bias, I rely on a two-stage estimation procedure. In the first stage, I estimate a logit based propensity score equation, which assesses the probability of a firm declaring a patent as essential for a standard. To control for the high heterogeneity across firm-standard pairs, I use a measure of the technology similarity of firms and standards based on the corresponding portfolios. I use the estimated probabilities to compute the propensity scores for each firm-standard pair and define a comparable set of control firms. This methodology allows me to reduce the bias due to confounding covariates that can affect the allocation of firms in the treatment or control groups. Using a difference-in-differences approach, I then estimate the effect of the policy change on the patenting intensity of firms in the standard-related technology classes.

The results of the econometric analysis provide causal evidence that the IEEE IPR policy change led to a reduction in standard related patenting among the firms affected by the change. Notably, due to a more restrictive patent policy, essential patent holders file 15.2% patents less in the standard-related technology classes. As it can be assumed that members and stakeholders learned about the aim of the board to change the IPR policy before the policy update was publicly released, I test for an anticipation effect by firms holding essential patents. Excluding the two years before the policy change amplifies the effect by decreasing the firms' innovation effort by 21.1% (1.95 patents).

Different mechanisms can explain the decline in standard related patenting among SEP holders; firms could have reduced their R&D spending, or they could have started patenting less. To investigate how the patent policy change has driven the decrease in standard-related patents, I rely on two other specifications of the baseline model. First, I test for the effect of the policy revision on the overall number of patents filed by SEP holders. Second, I compare the magnitudes of the estimated effect with the inclusion and exclusion of R&D spending as an explanatory variable. My results suggest that the decrease in the absolute number of patents and the innovation expenditure are unlikely to be correlated with the decline in standard-related innovation. Besides, firms declare patents as essentials to multiple standards issued by several organizations, and technology standards in the ICT sector share multiple technology classes. Since I don't observe a decrease in the share of standard-related patents, my results suggest that firms are substituting away to other standard technologies issued by other organizations.

Since firms with divergent interests join standardization, I further investigate the heterogeneity of the effect across firms. The extent to which more restrictive patent policies affect the firms' standard-related innovation effort depends on how the IPR policy affects the monetary incentive firms face when they decide on the amount of innovation to invest in a standard, which in turn may depend on firm size. For instance, vertically integrated firms, typically large companies, can benefit from their participation in standardization through downstream sales, taking the standard as inputs. On the other hand, pure innovators, usually small and medium size firms, rely on the licensing of the patents protecting the technologies included in the standard to benefit from their involvement. To account for the effects of the IEEE policy update on firms facing different incentives, and since I cannot retrieve reliable information concerning the firms' business models, I follow the changes-in-changes methodology proposed by Athey and Imbens (2006) and test the impact of a more restrictive patent policy on firms depending on their size. I find a negative effect of the policy change for firms up to the 75th percentile, with a stronger effect for the mean ranks of the distribution. Conversely, I observe a positive effect for firms with a large patent portfolio (90th percentile). Since vertically integrated firms typically have big patents portfolio in my sample, my analysis suggests that the policy change positively affects large firms that benefit from the implementation of the standard, while it harms pure R&D firms who are more reliant on intellectual property rights to appropriate a return on innovation.

As robustness checks, I run alternative specifications of the baseline model. First, I use the number of patents filed in standard unaffected technology classes as the dependent variable of my baseline model. Second, I test for an effect on outcomes known not to be affected by the policy change, focusing on a time frame characterized by no policy change. Both specifications led to no effect of the policy change on the patents not related to standards and on the standard-related patents in years before the policy change took place.[3]

The paper proceeds as follows. Section 2 describes the IEEE organization, its standardization process, and the patent policy revision. Section 3 presents the data. Section 4 presents empirical evidence supporting my econometric model and documenting the innovation effort of firms in standards. In Section 5 I develop the estimation procedure and the identification strategy. The results of the empirical analysis are discussed in Section 6. Section 7 concludes.

2 Standard development organization

Formal technology standards are developed in standard development organizations (SDOs). An SDO is an institution actively involved in the development of technology standards by facilitating the coordination and collaboration of diverse participants. SDOs typically oversee and endorse the technology standards they develop. In some cases, a formal endorsement by standard setting organizations is required for standards developed by SDOs. Standard development organizations define the standard development procedure and they set the rules members must comply with to participate in the standardization process. These rules usually refer to the process and the majority required for standard approval, and how the licensing of standard essential patents is managed.

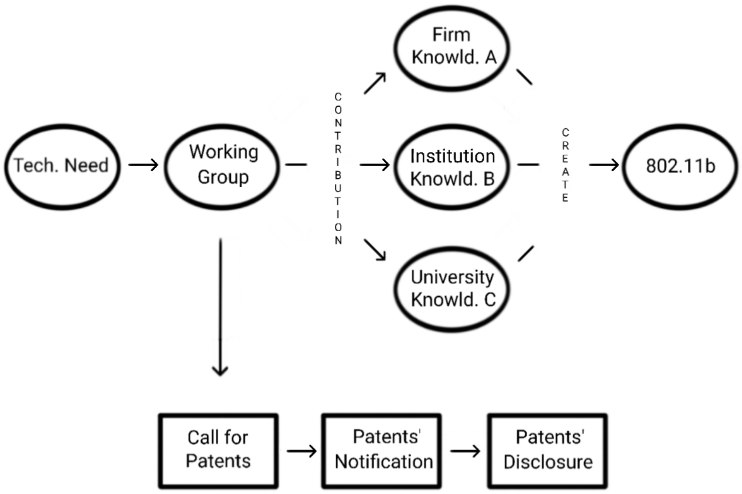
The Institute for Electrical and Electronics Engineers Standards Association (IEEE SA) is a globally recognized standard development organization of IEEE, not formally authorized by any government. While it was founded in the United States in 1890, it became global in its members and influence. IEEE SA focuses on developing technologies in electric, electronics, and telecommunication areas. Its most influential ICT standards are Ethernet, 802.11 wireless networking standard, and Firewire. Participation in the standard development is subject to a fee. IEEE SA members enjoy added benefits, including but not limited to the ability to hold working group positions, vote on standards, assume leadership positions in standards working groups and activities, and participate in elections for IEEE SA governing bodies. In any case, being a member does not require any obligation to contribute to the standard development; in fact, most of the members at IEEE SA do not bring any contribution to such development.[4]

Since technologies covered by intellectual property rights are often incorporated in standards, one of the most relevant sets of rules defined by SDOs is related to the licensing of standard essential patents. IEEE SA has developed two licensing rules to add to its governing bylaws; SEP holders must declare the ownership of patents that may be infringed by implementing a standard; holders of essential patents commit to accepting as com-

[3]Other robustness checks are described briefly in the Results section and presented in detail in the Appendix. Specifically, I use a two years lag of the explanatory variables. Moreover, I test the effect of the policy change using the interaction of the treatment variable with years as the explanatory variable.

[4]See IEEE SA Standard Association for more details on IEEE SA.

Figure 1
The Standardization Process



Source: Baron and Spulber (2015)

pensation for their patents a fair, reasonable, and non-discriminatory royalty (FRAND commitment). FRAND is meant to ensure both that implementers of the technology have access to the technology for a reasonable cost, and that patent holders receive adequate compensation for their innovation. Forcing contributing firms to comply with the FRAND commitment allows SDOs to avoid the patent hold-up problem. IEEE SA also allows blanket declaration, a generic statement through which a contributor declares to hold essential patents for a standard without specifying the patents' numbers.[5]

The process of developing standards at IEEE SA can be explained in four steps. I describe here the development process, as presented in Figure 1. The first step is the identification of a technological need. The technological need requires a new feature that must be developed in order to respond to the need and it usually gives place to a new standard. In the second step, the new need is allocated to a working group that is in charge of putting the idea into a concrete standard. All interested firms, agencies, and individuals can join the working group. When the working group has been established, the involved entities start providing possible technical solutions to the problem. The working committee selects the technologies and creates the standard. The last step involves the approval of the standard. The standard committee forms a balloting group containing individuals or entities interested in the standard. While any interested entity can comment on the standard draft, only votes by the members of the organization count toward approval. A standard is approved if 75% of eligible voting members express a positive vote. Concerning the declaration of standard essential patents, there is no specific timing compared to standardization; when the working group is set, at any time firms can declare to hold patents that are essential for the implementation of the standard.

[5]For a detailed description of the SDO patent policy see (Baron and Spulber, 2015; Bekkers et al., 2017)

2.1 IEEE patent policy update

In 2015, IEEE SA adopted some controversial changes to its patent policy, following concerns of the policy community regarding any potential strategical use of SEPs by their holders.[6] Even though the policy amendments became effective after February 2015, they were the result of a process started two years before the update took place.[7] The organization did not publish the revision process until 2015, but it can be assumed that members and stakeholders learnt about the aim of the board to change the patent policy before the policy update was publicly released.

The revision includes two important changes.[8] First, any entity contributing to the standard development is strongly recommended to base its royalty for SEPs on the Smallest Salable Patent Practicing unit (SSPPU) and not on the value of the end product. It has been argued that a consequence of this obligation is to cut down the maximum royalty a firm can ask for its essential patents (Layne-Farrar et al., 2014; Llobet and Padilla, 2016).[9] Furthermore, even though the use of SSPPU as a baseline in defining the royalty rate is only a recommendation, the fact that other alternative methods are not recommended in the updated policy increases the likelihood that SSPPU will be the only methodology followed in the negotiation of essential patent licensing fees. Second, participants must agree to forgo their right to seek injunctions against licensees, except under limited circumstances. If the right for injunctions is absent for SEP holders, implementers face an incentive to infringe essential patents, as they know that at most they will eventually have to pay a reasonable fee (Contreras and Gilbert, 2015). Therefore the policy change weakened the bargaining position of firms holding essential patents.

The policy update has been highly controversial: both the amendments and the process that led to their adoption have been severely criticized. Firstly, following the policy update, several contributors to the technology standards at IEEE-SA refused to submit their Letter of Assurance, through which they commit to license their essential patents under the new licensing policy. Most of those firms are big players in the ICT industry such as Qualcomm, Alcatel-Lucent, Ericsson, General Electric, and Interdigital. Their motivations were based on the idea that the policy update would have changed the balance of power between the innovators and users of ICT technologies. Secondly, the revised policy was not drafted by all interested stakeholders. The process was dominated by major standard implementers, who defended their own interests that found a counterpart in certain policy changes. Standard-related technology developers, who should have been represented in the committee as a counterweight to equipment manufacturers and vendors, were involved in the process only at its final stages. It is very unlikely that their negative votes affected the policy revision outcome, as the selected committee members outnumbered them Zingales and Kanevskaia (2016).

[6] For a detailed explanation of the procedure of IEEE-SA 2015 patent policy update and the composition of the board of directors voting for the policy revision see subsection 8.1 of the Appendix.
[7] IEEE Website, News Releases Section, 2015, Patent Policy.
[8] For an exhaustive explanation of the IEEE-SA policy update, and its revisioning process see Zingales and Kanevskaia (2016)
[9] See Sidak (2014); Gautier and Petit (2019) for more details on the Smallest Salable Patent Practicing Unit.

However, in 2015, the US Antitrust division stated its support to the policy change at IEEE, underling the fact that clarity and certainty in the licensing negotiation of essential patents would have yielded to a net benefit for the society. Nonetheless, the Antitrust division published another business letter in 2020 through which it reversed its position with respect to the IEEE policy change. Specifically, in its 2015 letter, the division focused only on the potential risk of patent hold-up by SEP holders without accounting for the potential damage to standard participation and future innovation.[10]

Since the firms in my sample can also be members of IEEE, which would grant them the ability to contribute to the organization's activities and to be elected in governance bodies, they could potentially have influenced the policy revision. Thereby the exogeneity assumption of the policy change would be violated, and the results of the econometric models would be inconsistent. To verify whether the policy update that occurred in 2015 was endogenous to my sample of firms, I check for any possible affiliations of the members involved in the revision and voting process with the companies I focus on and for any membership subscription of my treatment firms. Focusing on the ad hoc committee members who were in charge of revising the organization's IPR policy, 50% of the committee was represented by individuals affiliated with private firms, and only 4 out of the 12 members were linked to firms in my treatment sample.[11] Regarding the Board of Directors, the IEEE body which is in charge of voting on the final approval of the policy update, and its composition in 2014, the larger share of the members were academics or professors not affiliated with any firms, individual companies employed nine members, and only three were associated with firms in my sample.[12] Lastly, looking at my treatment sample, 38 firms held a membership at IEEE before 2015[13] and 29 out of 38 are vertically integrated firms[14] Therefore, the 55% of firms in my sample were directly involved in the activities conducted by IEEE-SA and held a voting right when the policy revision started. And 42% of them were incentivized to support patent policies more user friendly.

3 Data

3.1 Data sources

My main datasource is the Searle Center Database (SCDB), a comprehensive and systematic database of technology standards documents and information about standard developing organizations.[15] The database contains information regarding the characteristics of more than 629,438 standard documents issued by 598 SDOs from 1985 to 2018. For my analysis, I focus on the set of standard documents related to the ICT sector issued by

[10]The DOJ 2020 Business Letter can be found at Business Letter Documentation.

[11]Details regarding the members appointed to the ad hoc committee to discuss and revise the patent policy can be found Here

[12]The members of the Board of Directors in 2013 can be found Here. Detail information regarding each member and its affiliations can be found at the IEEE Xplore website.

[13]The data regarding members at IEEE and the year of affiliation were collected from the Searle Center Database.

[14]To measure vertical integration, I rely on the list of licensors and licensees of a subset of patent pools, and I classify a firm as vertically integrated if it appears in both lists. For a detailed definition of the vertically integrated firms and the strategy pursued to classify the firms' business models, see the Empirical evidence section.

[15]See Baron and Spulber (2015) and Baron and Pohlmann (2018) for a detailed description of the database.

IEEE.[16] During this period, I observe 420 standard documents, their publication date, the version history and the identifier associated to each document.

The SCDB collects information at the standard document level, and it associates the same identifier to all standard documents being part of a common standard project. It is important to understand that there is not a common definition of the term technology standard: the word standard can refer to a technical specification, i.e. standard document[17], or it can refer to complex technology systems described by multiple standard documents (standard project). Moreover, standards change over time: the process of revising a standard to keep up with technology change can take different forms according to the standard organization.[18] I define technology standards as complex technology systems, sharing a common version history. Therefore, I use the information regarding standard documents identifiers and the version history in the Searle Center database in order to aggregate standard documents at the standard project level. Looking at a standard as the aggregation of complementary and substitute documents, it allows me to account for technology changes within a complex system over time. I obtain aggregate information for 182 technology standards. Since I am interested in the standard projects, I refer to standard projects as standards for this project.

Besides standards' information, the SCDB provides data about the declarations made by who holds the IP right over the technologies included in each standard (SEP holders): these data include the name of the companies making the declaration, the year of the declaration, the patent numbers declared in the letter of assurance, and the International patent classification (IPC) classes associated to each essential patent. I use these data to retrieve two types of information useful for my analysis: the set of firms contributing to the development of a standard, and the standard's patent portfolio.

I use the IPC classification of the set of essential patents declared to a standard in the entire period of observation in order to define the technology space (patent portfolio) of the standard.[19] Companies are allowed to make blanket disclosures at IEEE. In those cases, I cannot observe the list of essential patents and so the associated IPC classes. If a technology standard receives only blanket disclosures I am not able to infer the patent portfolio of that standard.[20] For the purpose of the analysis, I restrict the sample to technology standards with IPC classes information. I observe information about 29 technology standards issued by the organization.

[16] Since standardization rose during the beginning of the 21st century and most of the information regarding standards in the SCDB are collected in the years after 2000, I drop those observations before 2000 from my sample. Keeping only the observations after 2000 leads to minimal loss of data.

[17] "A standard is a document that provides requirements, specifications, guidelines or characteristics that can be used consistently to ensure that materials, products, processes, and services are fit for their purpose." International Organization for Standardization (ISO), Standard Definition.

[18] Baron and Pohlmann (2018) found that many organizations issue different versions for their standards, each version replacing the former one. Standard organizations can also issue new standard documents amending existing ones, in which case the previous version remains active.

[19] See the Empirical measure subsection for a detailed explanation of how I construct the patent portfolio of a standard.

[20] This problem is part of a broader missing value issue. Missing values of the IPC classes related to essential patents can be due to two different reasons: blanket disclosures and the lack of observation by the researcher.

I define any firm declaring to own an essential patent for a standard issued by IEEE as a contributor to the standard development. Firms declaring essential patents to IEEE are subject to the SDO's policy change, so they are the objects of interest. The SCDB contains information on the declarations made by 147 essential patent holders for the 29 standards in my sample: of these, 128 are firms, and the remaining part is composed of universities, national and international institutions, and governments. Since I am interested in the standard-related innovation at the firm level, I focus only on the 128 firms.

For the purpose of my analysis, I also add information about bibliographic data of patents filed by firms from the European Patent Office's PATSTAT database. PATSTAT contains data relating to more than 100 million patent documents, starting from the beginning of the twentieth century. I collect a set of patent statistical information regarding the patent's application date, the number of forwarding citations the patent receives, and the IPC technology codes assigned to the patent. Due to the delay between application and issuance dates, I count patents using the year of application. In this way, I follow more closely firms' R&D decisions over time. Moreover, given that each patent can be classified into more than one technology class, I count each patent related to a class as a separate patent. In other words, a patent is double-counted if it has been assigned to two different technology classes.[21] That is also true for standard documents associated with the same standard. Since standard documents linked to the same standard project share several technology classes, I double-count a patent if it has also been assigned to two different standard documents sharing a common technology class. This allows me to weigh patents by their importance for a given standard. For instance, if a patent is associated with a technology class related to several standard documents within the same standard, I count the patent as the number of times the technology class is reported in the standard documents.

I complete my analysis with data on firms' characteristics from the Compustat database. Specifically, I use the information on R&D spending, total revenue, and the number of employees for the companies in my sample between 2000 and 2018. All variables are known determinants of firms' patenting activity and thus may affect the number of patents filed by a firm in the set of standard-related IPC classes. Several studies also show how these variables are likely to affect the decision of firms to declare essential patents and thus to be involved in the standard development, as explained in the Methodology section.

I classify firms in the treatment group into four categories according to their size (in terms of number of employees): small firms have less than 315 employees during the entire period[22]; medium-size firms have more than 315 but less than 1,200 employees; large firms have more than 1,200 employees but less than 6,000; and very large firms have more than 6,000 employees. I also collect data about the 4-digit NAICS code and the country code of each firm, which is useful to define the control group for my analysis as explained in the following subsection. I restrict the analysis to firms who have data on Compustat for at least 3 consecutive years.

[21] In my sample, on average, patents are linked to 1.38 technology classes.
[22] The maximum number of employees per firm is lower than 315 (first quartile of the distribution) during the period 2000-2018.

To merge the datasets together, I rely on firm names and algorithms to match string variables.[23] Furthermore, I link the firm-level data to the specific standard information, based on the declaration made by the firms in the 15 years before the policy change. Finally, because of the effect I focus on occurs in 2015, I keep only the observations between 2011 to 2018. Thereby I limit the treated group to a sample of 29 standards issued by IEEE and 69 firms declaring at least one essential patent for this set of standards.

3.2 Control group

To construct a sample of firms comparable to the set of 69 firms holding at least one essential patent, I start by collecting data from Compustat of the firms active in the same 4-digit NAICS industries and countries as the 69 firms in the treatment group. I assume that firms active in the same industries as essential patent holders face the same opportunities to develop, and thus to declare, an essential technology for a standard as the treated companies. I then select only firms for which I have available accounting information for at least 3 consecutive years in the period of interest.

From these firms, I look for the ones who patented at least once in the period 2000-2018 in the set of technology classes related to the 29 IEEE technology standards and for which I have available data, following the same process as described in the Data sources subsection.[24] As highlighted in the subsection, the HAN dictionary covers more than 6 million names and matching errors may be met due to a large amount of data processed within the database. For this reason, taking also into account the size of the sample I obtain from the collection process of accounting data, I am not able to check all the names in the control group and thus I keep only firms for which I identify a match in names grouping from Compustat to the HAN database. Therefore I gather a sample of 1,862 firms filing around 1,200,000 patents.

After matching the firm's characteristics with the patent portfolio data, it leaves a sample of 878 control firms. I drop 2 firms as they are extremely large and they are not comparable with the treatment firms. I then connect the accounting and patents data for the control firms with standard information, taking into account the set of technology classes related to each standard. Notably, the firm is counted in the control group for a standard if it files at least a patent in one of the IPC classes related to that standard.

Lastly, for the purpose of applying the propensity score matching methodology I delete from my sample the observations related to declarations occurring in the years before 2001.[25] This leaves a sample of 27 standards.

[23]Specifically, I use the Harmonized Applicant Names (HAN) database developed by the OECD to retrieve the patent applications of each firm in the Worldwide Patent Statistical Database (PATSTAT). The OECD HAN database provides a grouping of patent applicants' names resulting from cleaning and matching of names. Through the database, a common identification number is assigned to each group of names and it is associated with a single company. First I determine the set of identifiers associated with my sample of 128 SEPs holders from the HAN database, and then I merge this information with the patent database to collect data on the firm's patent portfolio. As the HAN database includes more than 6 million identifiers and I rely on algorithms to match firms' names, I succeeded to match the applications identifiers for 110 firms out of the 128 declaring to own an essential patent.

[24]See footnote 23.

[25]For a detailed explanation see subsection 6.1

After merging firms data with the standard information, for both treated and control companies, I build up an unbalanced panel dataset of 27 technology standards issued by IEEE, 945 companies active in 25 NAICS sectors, 16,025 company-standard pairs observed over a period of 8 years (2011-2018). For each company-standard pair, I observe the number of filed patents by the specific company in the set of technology classes related to a standard per year and I include a dummy variable indicating whether the company declares to own an essential patent for the standard.

3.3 Empirical measures

Since some of the variables I use in my analysis are not observed, I need to construct empirical indicators. Specifically, I define the following measures:

Standard Contributors: I consider any firm declaring a patent as essential for a standard issued by IEEE as a contributor to the standard development. Because I focus on the innovation effort of firms in a standard project over the years, my unit of observation is at the firm-standard level.

Standard-related Innovation Effort: Since I cannot observe the share of R&D cost a SEP holder invests in the technological development of a standard, I use the number of patents filed by a company in the set of technology classes related to a standard as a proxy of the firm's innovation effort in the standard development. Specifically, I follow the methodology proposed by Baron et al. (2014), which builds upon patents that are declared essential for technological standards, and relies on the International Patent Classification codes assigned by the patent office's examiners to each SEP to define the technology space related to a standard. Even though essential patents represent the innovation at the firm level directly associated with a standard, they are a small share of patenting around standards (Bekkers et al., 2012).

As firms decide voluntarily to declare to own an essential patent to the standard organization, there might be some patents that are still relevant for a standard but that the firm decides not to declare as essential. Accounting only for essential patents as a measure of the innovation effort of firms in standards can lead to biased estimates in my analysis: firms for strategic reasons might have declared some patents as essential and have decided not to declare others, even though those patents might be technologically superior.

Furthermore, some of the patents filed by firms in the technology classes related to a standard might be commercially essential, i.e. patents not declared as essential but that cover methods of implementation that produce cost reductions or quality improvements for products using the standard as an input (Bekkers et al., 2012). In economic terms, a commercially essential patent has at least one substitutive technology, while an essential patent has no substitute. Both types of patented technologies, declared and commercially essential, are relevant in the evaluation of the innovative development of a standard.

It is also important to recognize that the date of the formal declaration is not necessarily linked with the standard development process (Spulber, 2019) and it can be highly strategic, likely to occur before the publication of a technical standard (Ganglmair and Tarantino, 2012; Bekkers et al., 2012).

So, while the number of essential patents would be a poor measure of the firm's innovation investment in a standard, the total number of patents filed in the standard-related technology classes provides a better description of the innovation investment of a firm in a standard over time. The dependent variable of my analysis can be defined as follow:

$$P_{ist} = \sum_{j \in J_s} P_{ijt} \tag{1}$$

where J_s is the set of technology classes defining standard s and P_{ijt} is the total number of patents filed by firm i in technology class j in time t.

Lastly, to also account for the quality of the firm's innovation effort in a technology standard, I weight the number of patents filed in the set of technology classes related to a standard by the number of forward citations each patent receives. The number of times a patent is cited by subsequent patents is commonly used in economic research as a proxy of the quality of a patent in terms of importance (forward citations) (Harhoff et al., 1997; Hall et al., 2000; Hall and Ziedonis, 2001; Sampat and Ziedonis, 2004).

Technology Similarity: I rely on patented technologies to measure technology similarity between firms and standards. Using PATSTAT data on filed patents, I construct a patent portfolio for each firm in my sample by accounting for the technological classes a firm file patents in, as defined by the International Patent Classification. As for the standard's patent portfolio, using the SCDB data on essential patents, I define the set of technology classes related to the standard's essential patents. I use the cosine similarity[26] as a measure of the technology similarity between a firm i and a standard s, defined as follow:

$$TECH_{i,s} = \frac{\vec{I_i} \cdot \vec{S_s}}{\|\vec{I_i}\| \|\vec{S_s}\|} = \frac{\sum\limits_{j \in J_{i,s}} \sum\limits_{t<2015} I_{ijt} S_{sjt}}{\sqrt{\sum\limits_{j \in J_i} \sum\limits_{t<2015} I_{ijt}} \sqrt{\sum\limits_{j \in J_s} \sum\limits_{t<2015} S_{sjt}}} \tag{2}$$

Where $\vec{I_i}$ and $\vec{S_s}$ are respectively the firm's and the standard's patent portfolio and J is the set of IPC classes in which firms patent and in which standards have essential patents. In order to construct the firm's and the standard's patent portfolio respectively, I consider the IPC classes a firm has filed patents in and a standard has patents declared as essential, and not how many patents are in each class. Specifically, using PATSTAT

[26] In order to construct the technology similarity between the firm's patent portfolio and the standard's one I start from the measure defined by Rosa (2019). Compared to my measure, in her paper, she defines the cosine similarity to assess the technological similarity of SEP holders.

data on filed patents, I construct a patent portfolio for each firm by counting the number of IPC classes a firm files in each technology class according to the International Patent Classification. I therefore define the vector $\vec{I_i} = (I_{i1}, I_{i2}, \ldots, I_{iJ})$, where I_{ij} is the technology class j where firm i has filed patents to. Consequently, using the SCDB data on essential patents, I also construct the patent portfolio of a standard taking into account the technology classes associated to each patent declared as essential to a standard. I thereby define the standard patent portfolio as a vector $\vec{S_s} = (S_{s1}, S_{s2}, \ldots, S_{sJ})$, where S_{sj} is the technology class j associated to the SEPs declared to standard s in the years before the declaration made by firm i. Since there can only be a non-negative amount of patents in any class, the cosine similarity will take values between 0 (no similarity, vectors are orthogonal) and 1 (completely equivalent, vectors have the same direction).

The advantage of the cosine similarity over the euclidean distance is that it does not depend on the size of the vectors but on their directions. Notably, it accounts for the IPC classes which compose the patent portfolio without accounting for the number of patents filed in each class. Mathematically, it measures the cosine of the angle of two vectors in a multi-dimensional space. This measure helps me to partially control the problem of blanket declarations. Since firms are allowed to declare to own essential patents without revealing any specific information about those patents, the size of the standard's patent portfolio, in terms of the number of essential patents per technology class, can be distorted. Because patents declared essential to a common standard share several technology classes, it is less likely that a technology class is not included in the composition of the patent portfolio of a standard, even if I observe blanket declarations. Therefore by using the cosine similarity instead of the euclidean distance to compute the technology similarity between a firm's and a standard's patent portfolio, the direction of the patent portfolio is unlikely to be affected by blanket disclosures.

3.4 Descriptive statistics

Table 1
Firms' Accounting Characteristics and Patent Portfolio Composition

	Treat pool	Control pool
Total number of firms	69	876
Firms' characteristics		
Average R&D expenditures per year (millions)	2,299.4	128.6
Average number of employees per year (thousands)	84.3	6.2
R&D/SALE (%)	11.5	38.7
Patent portfolio		
Average number of filed patents per firm per year	1,777.5	59.8
Average number of filed standard related patents per firm per year	642.6	10.8
Total number of standard related patents/total number of patents, average per firm (%)	40.1	33.9

Note: This table summarizes the characteristics of firms, and their patent portfolio characteristics per type of firm in 2011- 2018.

Table 1 summarizes firms' characteristics and portfolio composition of the treatment and the control group from 2009 to 2018. For instance, SEP holders on average have more than 81 thousand employees and invest around 2,299 USD million on R&D per year. The R&D investment represents the 11.5% of the total amount of revenue. In contrast, control firms are smaller in size, with 6.2 thousand employees, and they invest less in

R&D.[27] Besides, they invest more than the 38.7% of the total revenue in R&D. This data suggests that firms declaring patents as essential are big firms who invest a small share of their sales, compared to a set of firms active in the same industries as essential patent holders.

Concerning their patenting behavior, treated companies patent more, 1,777.5 patents per year, than control firms who patent 59.8 patents on average. Furthermore, the share of the innovation output of firms allocated to the standard development, in terms of patents, is around 40% of the total number of patents filed over the entire period of interest. This data suggests that SEP holders' innovation effort is mainly focused on standard-related technologies, compared to the set of control firms (33.9%). There are two likely explanations for these differences: firms that don't declare to hold any essential patent may be the ones that failed to transform their investments into innovation, and thus they result in patenting less compared to SEP holders and being less efficient. On the other hand, it might be that control firms invest a greater effort in the innovation development but decide to keep their innovation secret and benefit from staying outside of the standardization process.

The data suggests that strong differences exist between the treated and the control group, both in terms of firms' characteristics and patenting behavior.[28] To control for the high heterogeneity among firms and define a comparable control sample, I use the propensity score matching method, as I explain in the Methodology section.

Table 2
Summary Statistics of IEEE Standards

	2012	2014	2016	2018
Total number of standards	27	27	27	27
Standards' characteristics				
Number of SEP holders per standard	145.6	183.2	223.2	236.1
Number of disclosure made per standard	190.4	239.0	289.7	308.8
Number of standard related patents filed per standard	25,619.9	50,402.4	22,867.5	42,162.9
Number of essential patents declared per standard	3,520.4	4,377.6	5,382.3	5,695.4
Number of standard documents per standard	298.8	362.8	452.2	478.8
Age of the standard at the time of declaration (mean)	3.9	4.9	5.9	6.9
SEPs holders' characteristics				
Number of employees per SEP holder-standard pair (thousands)	28.3	32.2	49.9	48.6
R&D expenditures per SEP holder-standard pair (billions)	910.7	1,106.7	1,907.4	1,947.3

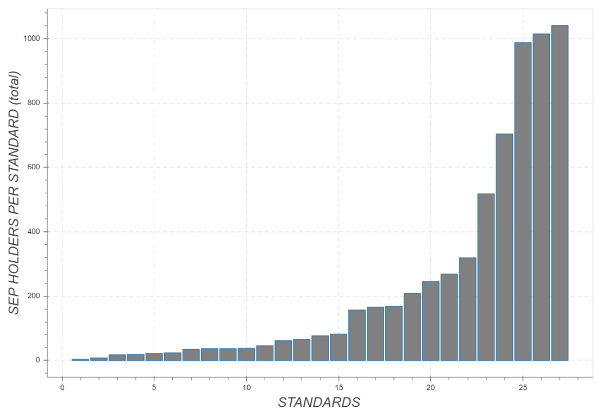
Note: This table summarizes the characteristics of standards issued by IEEE comparing the cumulative numbers in 2012 and 2014, before the policy update, to the cumulative numbers in 2016, and 2018. The data regarding the number of standard-related patents are calculated accounting only for the treatment firms in my sample. Standards' ages compute the mean age of standards in the years before and after the policy change.

Concerning technology standards, over the 27 standards in the sample, 24 technology standards are classified in the information technology field while 3 standards in telecommunications.[29] Table 2 reports the summary statistics of the 27 standards comparing the standards' characteristics before and after the policy update. Column (1) of Table 2 shows the average values of the standard's characteristics across my sample period. The variables reported in Table 2, except for the number of standard-related patents and the age of the standard,

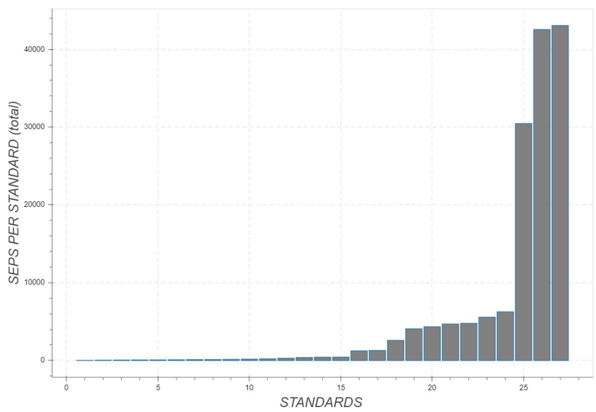
[27] The average R&D expenditures are around 128 USD million.

[28] Detailed summary statistics of the full sample are shown in Table 10 in the Appendix.

[29] In order to select the technology standards related to the ICT sector I follow the International Classification for Standards (ICS) developed by the ISO organization. Specifically, standards with an ICS code of 33 are classified in the Telecommunications field while standards with an ICS code of 35 are deployed for developing information technologies. See the ISO documentation for a detailed explanation at International Classification for Standards.



(a) Distribution of SEP Holders per Standards



(b) Distribution of Standard Essential Patents per Standards

Figure 2

These figures show the cumulative number of all SEP holders (left) and of standard-related patents (right) filed by SEP hodlers across the 27 standards in 2018. Data Source: Searle Center Database.

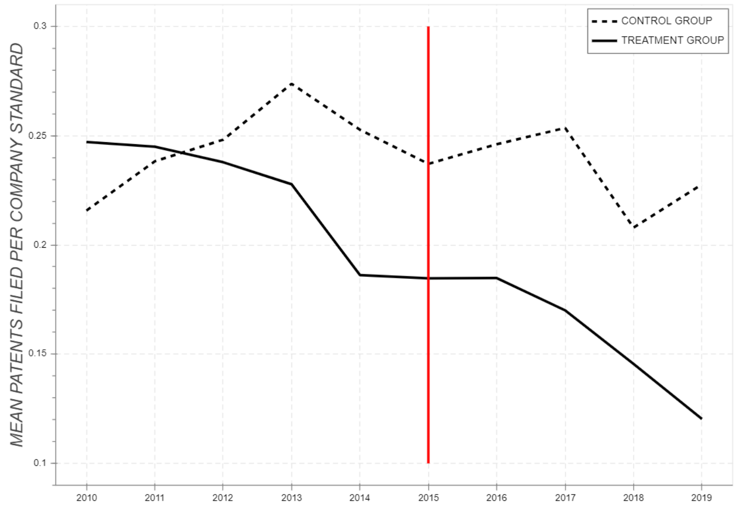
are computed accounting for the whole standard's history available in the Searle Center Database. Specifically, I calculate the cumulative values of the standard's characteristics from the first available year in the database to 2012 in Column (1), 2014 in Column (2), while Columns (3) and (4) report the cumulative values until 2016 and 2018, respectively. This allows me to provide representational information concerning each standard in the years before and after the policy change. On the other hand, since I cannot collect information regarding the patenting behavior for the population of SEP holders, the number of standard-related patents accounts only for the patents filed by the firms declaring SEPs in my sample in 2011-2018.

While the number of firms declaring standard essential patents increased by 28.9% after the policy change, the number of patents filed in the standard-related technology classes decreased by 19.5% on average. Besides, firms contributing to the standard development after the policy change are larger in size compared to SEPs holders who declared essential patents before 2015 and invested more in innovation. Lastly, standards in my sample keep growing and evolving: the number of documents composing a standard increased by 32% on average after 2014. The new standard documents issued in the years after the policy update can explain the increase in the number of SEPs holders and declarations in the same period.[30]

Based on the distribution of firms among standards, standards in the first quartile have, on average, no more than 35.5 firms declaring essential patents, while standards in the fourth quartile have 1,041 SEP holders, with an average number of SEP holders per standard around 236.1 firms.[31] Furthermore, the distribution of firms among standards is unbalanced towards a subset of big standards projects, as shown in Figure 2 left graph. The number of essential patents declared across standards also underlines the presence of a few big projects, as reported in Figure 2 right graph.[32] The distributions of the patents filed in the standard-related technology classes and essential patents across standards are highly skewed, with few standards holding most of the patents. Indeed, standards in the third and fourth quartiles of the distribution have, on average, 178,858 and

[30]See Table 11 in the Appendix for a comprehensive description of each standard.
[31]The data are computed on the cumulative numbers reported for each standard in 2018.
[32]The three major standards holding the larger share of SEPs are IEEE 802.16, IEEE 1394, and IEEE 802.11.

Figure 3
Normalized standard-related patents per firm-standard pair



374,329 patents filed in the standard-related technology classes and 4,616 and 43,057 essential patents, respectively. While standards in the first and second quartiles of the distribution have, on average, 23,331 and 49,234 standard-related patents and 126.5 and 438 SEPs declared, respectively. Accounting also for the number of technology classes per standard as a measure of the broadness of a standard project, it is straightforward that the sample is composed of a few broad standards and many minor projects. On average, there are around 13 technology classes related to a standard, with a maximum of 90 IPC classes.

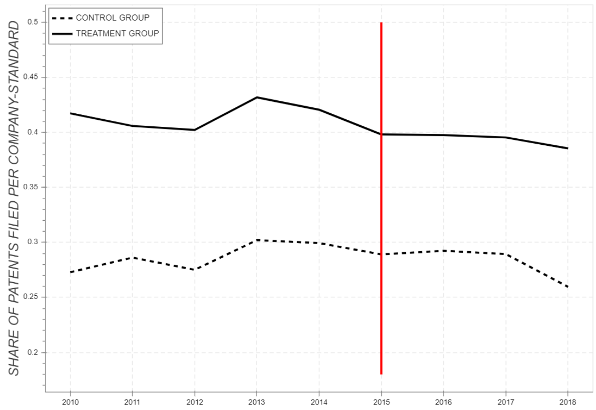
4 Empirical evidence

In this section, I present empirical evidence supporting my econometric model and documenting the innovation effort of firms in standards. I first report some descriptive results supporting the hypothesis that a decrease in the absolute number of patents and innovation expenditure are unlikely to be correlated with the decline of standard-related innovation. Secondly, I show that large firms in my sample are vertically integrated and hold big patent portfolios. Lastly, I show that my models' lag R&D structure assumption is descriptively adequate. I report some evidence showing no effect of lagged R&D on the number of patents filed by a firm.

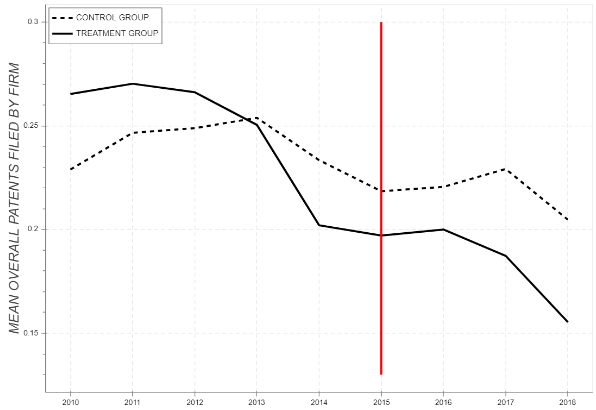
4.1 Patents and R&D expenditures

I start my analysis by plotting the trend of standard-related patents filed by treated and control firms in the period of interest. Figure 3 shows the average number of patents filed in the standard-related technology classes by the firms in my sample, normalized by the average number of patents filed in the pre-period by the firms.[33] The patents filed by SEP holders declined during the whole period of interest, with a higher rate from 2012. On the other hand, control firms increased their standard-related patenting until 2013 and again in 2016. The

[33] I normalize the number of standard patents filed by dividing by the average number of patents filed in the standard-related technology classes by all firms in the pre-period.



(a) Share of standard-related patents over total patents



(b) Normalized total patents

Figure 4

These figures show the share of standard-related patents over total patents (left) and the total number of patents (right) filed by treated and control firms before and after IEEE policy change.

reduction in filing patents in the standard's technology classes in 2014 and 2015 occurred at a lower rate compared to the one observed in the treatment group.

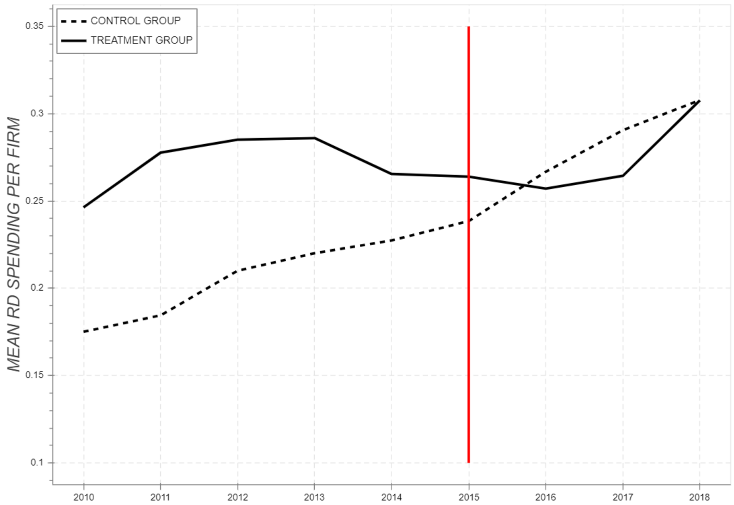
While the number of standard-related patents decreases after IEEE changes its patent policy, the share of patents filed in the standard-related technology classes stays constant throughout the period of interest, as shown in the left graph of Figure 4. Since ICT standards issued by different organizations are likely to share multiple technology classes, it might be that firms holding essential patents at IEEE moved to other organizations with more favorable policies after the IEEE policy revision. On the other hand, firms might have decreased the total number of filed patents and the standard-related patents, which would explain a constant share over time. As shown in the right graph of Figure 4, SEP holders started filing fewer patents after 2013 on average. Even if the number of patents also declined for firms in the control group after this year, it increased after the policy change with a relative pick in 2017. In order to test whether a decline in the standard innovation effort at IEEE is driven by a decrease in the overall amount of filed patents rather than by a substitution effect to other standard technologies, I test the effect of the policy update on the total number of patents. The regression output is presented in the Results section.

Moreover, the observed decrease in the standard-related patents after the policy was changed could have been driven by the firms' decline in R&D spending. I report the average R&D spending of treated and control firms over the years in Figure 5. Since firms in the treatment and control groups are highly heterogeneous in their innovation expenditures, as shown in Table 1, and to avoid comparing averages with a different number of observations, the data are normalized by the value of R&D expenditure in 2005. The Figure suggests that both treated and control firms did not decrease their R&D spending after the policy change occurred. Data also shows no effect of the policy change on the firm's R&D spending[34]. Hence, descriptive evidence supports the hypothesis that a decrease in standard-related innovation is not associated with a decline in the firm's innovation

[34]The results are shown in Table 9 in subsection 8.2 of the Appendix. The results also rule out an endogeneity problem regarding the correlation between the R&D spending and the variable $Post_t$ in my specification.

investment.

Figure 5
Normalized Average R&D Spending per firm and year



Data Source: Compustat

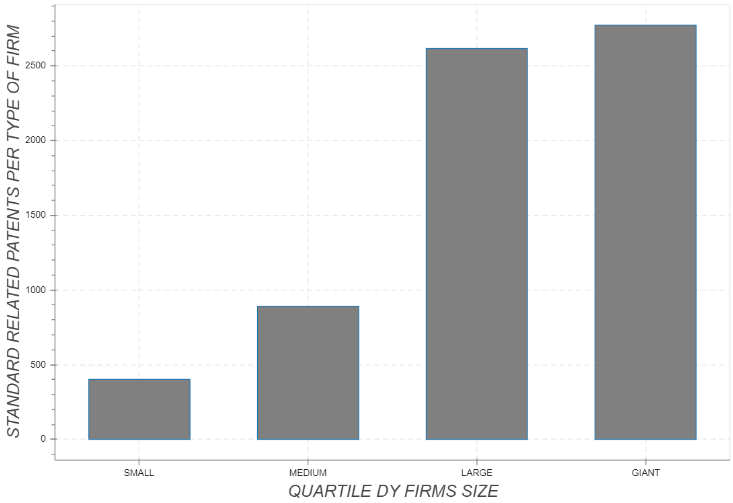
4.2 Vertically integrated firms

To show evidence documenting the relationship between the size of a firm, its business model, and its patent portfolio, I start by plotting the distribution of standard-related patents over firms according to their size. Figure 6 suggests that most of the patents are held by a set of few very large firms (fourth quartile of the distribution), while small and medium size firms hold a few shares of standard-related technologies protected by intellectual property rights.

To better understand whether firms in the third and fourth quartile of the distribution are also vertically integrated, I classify each firm in my treatment sample according to its business model. I rely on the list of licensors and licensees of a set of patent pools to identify the business model of the 69 firms in my sample. Starting from the idea that if a firm is both a licensor and licensee in a given patent pool is likely to both develop the technologies that are necessary for the implementation of the standard, and so it is the owner of standard essential patents and to use the standard for the production of downstream goods, I classify a firm as vertically integrated when it is present in both lists. From my data collection, I am able to retrieve information on 49 firms out of 69. Moreover, of those firms I have information on, 32 are coded as vertically integrated, while 17 as either licensor or licensee.[35]

[35] Since it is hard to determine the business model of firms, especially regarding firms that develop technologies for standards that can be implemented in a wide range of products, I follow this novel patent pool strategy to classify firms as vertically integrated with respect to standard projects. Nevertheless, this methodology presents several limitations. First, I cannot observe the complete set of licensors and licensees for all patent pools worldwide. But I can collect information on a subset of patent pools for which I have available data. Therefore, some firms classified only as licensors or licensees in my sample might be vertically integrated into other patent pools that are outside my sample. Besides, regarding the 20 firms for which I do not observe any information, it could be that those firms are vertically integrated but have decided to refrain from joining any patent pool to gain more bargaining power in cross-licensing negotiations.

Figure 6
Distribution of standard-related patents by size of firms



Note: The reported numbers of total patents are divided by 1000.

Figure 7
Vertically Integrated Firms and Patent Portfolios

Note: The reported numbers of total patents are divided by 1000.

Figure 7 plots the 69 treated firms by their size, in terms of the number of employees, and patent portfolio, according to their business model. Specifically, I classify firms into two types according to their business model: vertically integrated and not vertically integrated. I also assume that the companies that I have no information about are not vertically integrated. The Figure shows that vertically integrated firms are the ones bigger in size and with larger patent portfolios. Besides, comparing this Figure with Figure 6 and taking into account the individual firms included in each quartile, the data suggest that vertically integrated firms are also the ones holding the larger share of declared essential patents for standards.

4.3 Lagged R&D expenditures and patents

To test for possible lagged effects on the number of patents filed by a firm, I follow the methodology proposed by Hausman et al. (1984). It has been shown that if unobserved firm-specific effects exist, the residuals might all be of the same sign and thus indicating the presence of serial correlation. To overcome this problem, Hausman et al. (1984) developed a generalization of the Poisson regression model, which allows firms to have their own average propensity to patent by separately conditioning each firm's count distribution on the sum of its patents for the whole period. I, therefore, estimate the following Poisson probability specification:

$$pr(P_{it}|X_{it}, \upsilon_i) = \frac{e^{-e^{\beta X_{it}+\upsilon_i}}(e^{\beta X_{it}+\upsilon_i})^{P_{it}}}{P_{it}!} \tag{3}$$

where P_{it} is the number of patents filed by firm i in year t and υ_i is the firm-specific effect. In the vector X_{it}, I include the current R&D and three lagged values of R&D, and a time trend. I also control for industry effects to account for the propensity to patent in some specific industries compared to others by including a set of dummies for the 4-digit NAICS sectors. Lastly, I include firm-specific effects, as the estimates conditional on the sum of patents over all years, as in Hausman et al. (1984). As robustness checks, I perform two other econometric regressions: an OLS specification where the dependent variable is the log form of the number of patents filed and a random effect Poisson specification where the random effects are determined by $\alpha_i = e^{\upsilon_i}$, with α_i distributed independently as a gamma random variable with parameters γ and σ^2.

Table 3
Estimates of the Patent Model

	OLS Cross-section	OLS Fixed Effects	OLS Random Effects	Poisson Cross-section	Poisson Fixed Effects	Poisson Random Effects
log $R\&D0$	-1.352	-1.352	-1.352	38.824**	1.633	1.600
	(4.570)	(8.340)	(9.050)	(11.454)	(15.850)	(15.840)
log $R\&D_1$	0.070	0.070**	0.070**	0.100	0.150***	0.150***
	(0.043)	(0.029)	(0.032)	(0.085)	(0.048)	(0.048)
log $R\&D_2$	0.039	0.039	0.039	0.099	0.002	0.002
	(0.039)	(0.034)	(0.037)	(0.069)	(0.049)	(0.049)
log $R\&D_3$	0.028	0.028	0.028	0.026	−0.154**	−0.154**
	(0.032)	(0.035)	(0.038)	(0.046)	(0.067)	(0.067)
Time	−0.026***	−0.026**	−0.026*	0.028	-0.017	-0.017
	(0.008)	(0.013)	(0.014)	(0.033)	(0.050)	(0.050)
Time*log R&D0	0.001	0.001	0.001	−0.019**	-0.001	-0.001
	(0.002)	(0.004)	(0.005)	(0.006)	(0.008)	(0.008)
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	No	No	Yes	No
Firm Random Effects	No	No	Yes	No	No	Yes
Number of observations	6,141	6,141	6,141	6,141	5,361	6,141
R-sq	0.90	0.37	0.90			
Log-likelihood				-37,1662	-133,807	-138,536

Note: The dependent variable is the log of total patents filed in the first 3 columns, while it is the level value of total patents in the last 3 columns. The method of estimation is the OLS for the first 3 columns, while it is the poisson for the last 3 columns. Standard errors are in parentheses and they are robust to heteroskedasticity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

The results of my econometric analysis are shown in Table 3. In line with my expectations, the current R&D and the two-year lagged R&D are not statistically significant across all specifications. In contrast, the lagged structure of R&D by one year is not statistically significant when I do not account for any firm-specific effects, but it turns statistically significant when I include either fixed or random effects in my regression. Moreover, the three-year lagged R&D spending coefficient is statistically significant only for the Poisson model with firms effects, but it reports a negative sign. Hence these results support the choice to exclude a lag R&D structure in my patent equation and to include only the one-year levels of R&D spending.

5 Methodology

To assess the implication of more restrictive patent policies on the standard-related innovation effort of companies contributing to a standard, I exploit the changes in the IEEE patent policy in 2015 using a panel dataset. I model a patent production function per firm in each standard. I then compare the change in the patenting intensity of firms that declared at least one patent as essential in the standard-related technology classes with a comparable set of firms. In order to identify the effect of the policy's restrictiveness on innovation at the firm level, I use a difference-in-differences approach (Card and Krueger, 1993; Heckman and Vytlacil, 2005; Imbens and Wooldridge, 2007; Athey and Imbens, 2021) and I construct an interaction term indicating whether a firm is affected by the policy change. This indicator is constructed based on the firm's ownership of an essential patent and the years after the policy change.

Since firms can decide which patents declare as essential by also submitting blanket declarations, there might be some patents that are still relevant for a standard but that the firm decides not to declare as essential. Therefore the number of SEPs declared does not represent the full standard-related effort exerted by a firm. To solve this source of bias, I measure the firm's innovation effort in the standard development as the number of patents filed in the standard-related technology classes..[36]

Even though I control for the selection bias due to the decision of which patents are declared as essential within a firm's patent portfolio, accounting for the total number of standard-related patents as my measure of the standard innovation at the firm level, I need to account for the self-selection of firms in the treatment and control group. Firms can decide whether to declare a patent as essential for a standard, so their decision to be in the treatment or control group might not be random. Indeed, firms declaring to own an essential patent are not necessarily the successful innovators: the developers of the most valuable technologies might decide to refrain from participating in the standard development to avoid unintended spillovers. On the other hand, firms contributing to the standard development might succeed in developing essential technologies, conditional on some specific firm's characteristics, and they might have more interest in patenting their innovation.

Besides strategic reasons, there is a structural explanation. The cost of participating in the standardization activities is a fixed cost, and small and medium firms can face several barriers before benefiting from standards.

[36] See the Empirical measures subsection for a detailed definition of the innovation effort of firms in standards.

On the one hand, as my control group is composed of firms active in the same industries and countries as SEP holders, they face the same opportunities to develop an essential technology for a standard as the firms in the treatment group. Therefore they might have voluntarily decided not to declare a patent as essential to the standard organization. On the other hand, firms in the treatment group might present some unobservable characteristics that are firm-specific and represent critical factors for developing essential technologies and their decision to participate in the standard development. While unobservable strategic factors can lead to a downwards bias problem in my econometric specification, the propensity to patent in standard-related technologies by treatment firms compared to control firms can bias the estimates of the effect upwards.

To solve the self-selection problem, I implement the propensity score matching (PSM) method (Rosenbaum and Rubin, 1984; Abadie and Imbens, 2006) to identify a comparable control group of competing firms that do not declare any essential patent but that have similar characteristics as SEP holders. The propensity score allows me to design and analyze a nonrandomized study since it mimics some of the particular characteristics of a randomized controlled trial, reducing or eliminating the selection bias. Nevertheless, I partially deal with the upwards bias that can arise in my econometric analysis by including in my specification firms fixed effects.

5.1 Patent equation

Since my interest is to understand how the SDO's patent policy affects the standard related patenting of firms contributing to a standard, I estimate a patent production function that relates the number of patents filed by a firm in the set of technology classes related to a standard with the patent policy regime in place in a given year (Hall and Ziedonis, 2001; Hausman et al., 1984). The equation I estimate is of the form:

$$ln(P_{ist}) = \delta_3 dT_{is} * Post_t + X'_{i,t-1}\beta_1 + S'_{s,t-1}\beta_2 + \gamma_i + \gamma_s + \tau_t + \epsilon_{ist} \quad (4)$$

where $ln(P_{ist})$ is the outcome, i.e. the logarithm of the number of patents filed by firm i in standard s in year t, dT_{is} is a dummy variable which captures possible differences between the treatment and the control group prior to the policy change, $Post_t$ is a dummy variable which equals one for years after the policy change, τ_t is a set of time fixed effects constant across firm-standard, γ are a set of time-invariant firm and standard unobserved fixed effects, and ϵ_{ist} is the iid idiosyncratic term. Other firm and standard characteristics are included in $X'_{i,t\text{-}1}$ and $S'_{s,t\text{-}1}$. The coefficient of interest, δ_3, multiplies the interaction term $dT_{is} * Post_t$, which is defined as a dummy variable that equals one for those observations in the treatment group for years after the policy changed.

In the vector $X'_{i,t\text{-}1}$ I include a firm's specific characteristics that are likely to affect the number of patents filed, in particular R&D spending and firm size. To account for the direct effect of R&D expenditures on the number of patents filed by a firm, and since it is reasonable to assume that the investment made in a given year generates some innovations in later years, I use one-year lag levels of R&D spending in my specification. Moreover, following the literature on R&D spending, which concludes that the lag R&D structure is very poorly identified because of the high within-firm correlation of R&D spending over time (Hausman et al., 1984), I abstract from adding a lag R&D structure in my specification.[37] Several studies have also documented economies of scale in generating patents, and others have highlighted a relationship between the size of the firm and its patent portfolio composition. For those reasons I include in the vector $X'_{i,t\text{-}1}$ the size of a firm, measured as the number of employees.

The policy change affects the return on innovation a firm can gain from licensing its essential patents, and thus it can affect directly or indirectly the R&D share invested in the standard development. Since I don't observe any decline in the total amount of R&D expenditure in the years after the policy change[38], and the effect of the policy change on R&D investment is not statistically significant[39], it is unlike that the IEEE patent policy revision has any direct effect on the investment decision of firms. Furthermore, because I cannot infer the share of spending allocated to each standard project, and since I focus on the total spending in innovation, it seems hard to assume that the policy change has a direct impact on the total R&D expenditure of firms, biasing the estimates upwards.

Finally, I control for industry and country effects, including a set of dummies for the 4-digit NAICS sector and the country where the firm is located. Firms in some industries are more likely to patent in specific technology classes because of the degree of importance of those classes for the industry, compared to others. Furthermore, the location of a specific firm might affect its propensity to patent for a standard because of the patent system in force or the accessibility to patent in a given country.[40]

In addition to account for the firm's characteristics in the patent regression, it is necessary to deal with the standard's specific characteristics that might affect the patenting activities of firms in the standard-related technology classes. The importance of a given standard for the ICT industry can affect the amount of related innovation the firm decides to develop. To measure the importance of a standard, I include the total number of declarations made and the total number of patents filed in the standard-related technology classes in the $S'_{s,t\text{-}1}$ vector. I further include the total number of firms declaring to own an essential patent as a measure of the attractiveness of the standard. As theoretical works on standards and essential patents have shown (Baron et al., 2014; Bekkers et al., 2017; Spulber, 2019), the number of SEP holders affects the licensing revenues a firm can gain from its essential patents. To account for immediate feedback of the dependent variable to the covariates, I lag all time-variant controls by one year. Lastly, I control for unobserved heterogeneity over years by absorbing a set of time fixed effects. Notably, I include standard age fixed effects, defined by the number of

[37] I run robustness checks to test for possible biases in timing. See Table 15 in the Appendix for the results. Moreover, I provide evidence regarding the timing of the lag R&D structure in subsection 4.3 of the Empirical evidence section.

[38] Figure 5 in subsection 4.1 shows the average R&D spending of firms over years. The data are normalized by the value of R&D expenditure in 2005.

[39] See subsection 8.2 of the Appendix for the results of the analysis testing the effect of the policy change on R&D spending.

[40] It should be noticed that the industry and the country's effects are wiped out by γ_i and γ_s in the econometric specification unless they change over time. Therefore I use industry and country effects only in the logit specification for matching.

years that elapsed since the publication of the first standard document to control for a natural decline of the technology standard due to its life cycles.[41]

The other regressors in equation (4) are included to control for shocks and unobserved heterogeneity. I use a set of firm and standard specific dummies which allow me to control for unobservable heterogeneity among standards and firms. As multiple technology classes are related to multiple standards, I need to control for unobservable determinants of the amount of the innovation effort a firm decides to invest in a standard, compared to a standard with a similar technology space.

The regressor of interest $dT_{is} * Post_t$, is an interaction of the years before and after the policy changed, $Post_t$, and the occurrence of the declaration of a firm for a standard, dT_{is}. Notice that the dT_{is} variable defines whether a firm is in the treatment or control group: specifically, a firm is included in the treatment group if it declares to own an essential patent for a standard issued by IEEE. While $Post_t$ is exogenous to the firm, dT_{is} is prone to a self-selection bias: the allocation of the firm in the control or treated group might depend on some strategic or structural factors intrinsic to the firm.

5.2 Identification and match propensity score method

To reduce the selection bias between the treatment and the control group, I define a binary outcome per type of firm (treated and control), in which dT_{is} takes the value of 1 if firm i declares to own an essential patent to standard s. dT_{is} takes the value of zero if firm i declares no essential patents to standard s. I then estimate a logit based propensity score equation, assessing the probability of a firm to participate in standardization. This methodology allows me to identify matching partners of treated and untreated firms, by balancing the firms' characteristics.

To define the matched group of control firms, I focus on the characteristics of a firm and its total patent portfolio in the year before it declares to own an essential patent to an IEEE standard. I then collect the same information for the control firms related to a given standard in the year before the declaration of treated firms. The probability of firm i declaring an essential patent in standard s is:

$$Pr(dT_{is} = 1|TECH, X, S) = \frac{\exp(\alpha_0 + \alpha_1 TECH_{is} + X_i'\alpha_2 + S_s'\alpha_3 + \upsilon_i + \upsilon_s)}{1 + \exp(\alpha_0 + \alpha_1 TECH_{is} + X_i'\alpha_2 + S_s'\alpha_3 + \upsilon_i + \upsilon_s)} \tag{5}$$

where α_0 is a constant, $TECH_{is}$ is the technology similarity between the firm and the standard patent portfolio, X_i' and S_s' are firms and standards characteristics. υ_i and υ_s capture the unobserved determinants of the firm's participation decision.

[41] Figure 11 in the Appendix shows the distribution of patents filed before and after the publication of a standard. As can be expected, the number of patents filed decreases as the standard becomes older; this information is coherent with the assumption of using the age of the standard in order to control for a natural decline in the number of patents filed in the standard-related technology classes. See the Methodology section for a detailed explanation.

The decision of a firm to contribute to the standard development depends on observable and unobservable factors. To partially control for the endogenous allocation of the innovation effort of firms across standards, I use a measure of the technology similarity between a firm's and a standard's patent portfolios $TECH_{is}$, as defined in the Data section. Since the technology classes overlap across standards, a patent can potentially be essential for multiple standards. Thus, a firm can decide which standards it wants to declare the patent to. Given two standards with a similar portfolios' composition as the firm, there might be intrinsic determinants that affect the firm's decision to declare a patent as essential to one standard and not to another, holding the patent portfolio of the firm constant. Accounting for the technology similarity of firm-standard pairs, it allows me to measure firm-standard specific factors which are unobserved to the econometrician but which are important drivers of the self-selection of the firm in the treatment or control group.

To solve some of the endogeneity concerns that may arise from comparing standards with different characteristics, I control for unobserved heterogeneity in standards by absorbing a set of fixed effects at a standard level. Notably, specific standards might be more attractive for a larger share of firms, given their importance for a specific sector. Besides, I include the number of declarations made for each standard in the years before a firm declare a patent as essential, the total number of essential patents declared, and the number of companies declaring essential patents in the vector S'_s, to control for observed heterogeneity across the standards in my sample.

Following the literature on standard participation (Layne-Farrar et al., 2014; Baron et al., 2015; Bekkers et al., 2017), the vector X'_i includes R&D expenditures, sales, and the total number of patents filed before declaration.[42] As mention above, firms might face some barriers to entry in the standard development due to high fixed costs. I therefore include the amount of sales to account for the size of the firm, controlling for the heterogeneity in profits across firms and their size. Furthermore, several studies suggest that a certain level of knowledge is required to benefit from contribution to standardization. However, high R&D performers are less likely to contribute to preventing disclosure of knowledge.[43] I also include the total number of patents filed by a firm in the years before the declaration occurs.

Furthermore, to control for the unobserved firms' determinants that can affect the firm's participation decision in the development of a standard, I use a set of firm fixed effects υ_i. For instance, pure innovators are more likely to contribute to some standards and not others compared to vertically integrated firms that might be willing to contribute to several standards. At the same time, firms might have decided to participate in standardization

[42]Blind and Thumm (2004) discuss the influence of a small sample of European firms' characteristics on the likelihood of joining formal standardization activities. They find that more intense the patent activity of firms is, the lower is the likelihood to join the standardization process.

[43]Blind and Mangelsdorf (2008) focus on service companies in Germany and confirm that company size, the export activities, and R&D expenditures are all important drivers of participation in standardization activities.R&D expenditures present an inverted U-shape relationship.

as they are the only successors in developing some standard-related technologies, conditional to unobserved (to the researcher) firm specific characteristics. The set of firm specific dummies allow me to partially control for the endogeneity issues due to the firms' and standards' unobserved heterogeneity.

6 Results

The following empirical analysis includes four subsections. In Section 6.1, I describe how I select a matched sample of comparable firms, analyzing the decision of firms to declare essential patents. In Section 6.2, I analyze how firms' standard-related innovation effort varies, given a change to more restrictive licensing requirements in IEEE patent policy. Lastly, Section 6.3 reports some robustness checks.

6.1 Propensity score matching and parallel trends assumption

Table 4
Firm's decision to declare essential technologies

	Logit 1 Year Lag	Logit 1 Year Lag	Logit 1 Year Lag
Technology similarity	4.049***	4.521***	4.083**
	(0.956)	(0.841)	(0.989)
$R\&D_1$	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)
$R\&D_1^2$	−0.006***	−0.006***	−0.005***
	(0.001)	(0.001)	(0.001)
Sales	0.007	0.008	0.001*
	(0.006)	(0.005)	(0.006)
Total Patents filed	0.474***	0.480***	0.507***
	(0.051)	(0.048)	(0.053)
SEP holders per standard		-0.019	-0.714
		(0.019)	(0.438)
Declarations per standard		-0.027	0.533
		(0.017)	(0.418)
Firm fixed effect	Yes	No	Yes
Standard fixed effect	Yes	No	Yes
Number of observations	33,595	33,595	33,595
Log Likelihood	-712.77	-728.05	-668.53

Note: The dependent variable is a binary outcome in which dT_{is} takes the value of 1 if firm i declares at least an essential patent for standard s during the period 2001-2014. The parameters are estimated by maximum likelihood. Standard errors are robust to arbitrary heteroskedacity and allow for serial correlation through clustering by firm-standard. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

To construct a control group of firms which have never declared any patent as essential to IEEE, but with comparable characteristics as firms which declare to hold SEPs, I first estimate the probability of the firm to declare standard essential patents to IEEE as a function of observed and unobserved characteristics. To construct the sample of matched firms, I rely on the firms' characteristics and patent portfolio in the year before the declaration by the treatment group. Since I have accounting information from 2000 I delete from my sample the firm-standard pairs for which I observe a declaration in the years before 2001. I therefore collect declaration data about 69 treatment firms and 27 standards in the 15 years before the policy was revised. I use the predicted values from the logit regression to identify a common support for the treatment and the comparison group. I then implement the Mahalanobis matching method to adjust for pre-treatment observable differences between the group of firms who declare at least a patent as essential to standards issued by IEEE and a group of untreated firms active in the same industries. I obtain a balanced sample of 56 treated firms and 50 control firms for 27 technology standards.

Table 4 shows the results of the logistic regression. The dependent variable is a binary outcome dT_{is} (Treat) which takes the value of 1 if firm i declares to hold an essential patent in standard s during the period 2001-2014. Results based on the baseline specification (1 year lagged values) are presented in column (3).[44] In accordance with my hypothesis, one of the variables capable of predicting firms' decision to contribute to the standard development is the technology similarity between the firms' and standards' patent portfolios. The more similar in terms of technology classes, the greater the likelihood that a firm will declare a patent as essential for a standard. Furthermore, in line with the findings of previous studies on participation in standards development, my results show that the size of the firm and R&D expenses are significant determinants of the choice of firms to contribute to standardization. Notably, there is an inverted-U shape relationship between the R&D expenses and the likelihood to declare an essential patent for a standard: this result supports the idea that, on one hand, high R&D performers are less likely to contribute to the development of a standard as they are more prone to keep their innovation out of standardization to avoid unintended spillovers. On the other hand, the results show that a minimum level of knowledge is required to be involved in the standard development. Aside from firms' characteristics, standards characteristics seem not to have a strong impact on the likelihood of firms to declare essential patents.[45]

Table 5
Summary Statistics Propensity Score matching: unmatched vs matched sample

	Treated	Control Unmatched	Control Matched	T-test Unmatched	T-test Matched
R&D Expenses (USD millions)	2,491.6	123.6	2,322.6	72.3*	0.7
Size (thousands of employees)	77.6	7.6	71.7	31.4*	0.7
Sales (USD millions)	31,156	2,845.3	27,358	36.2*	1.2
Total Patents filed	68,619	2,843.1	11,465	50.67*	7.0*

Note: This table summarizes the mean in variables, comparing the treated and the untreated samples in the pre-period 2001-2014. Respectively U (Unmatched) is for the full control sample and M (Matched) is for the matched sample. Total patents filed measures the aggregate number of patents filed before declaration to the SDO.

Table 5 reports the results of the propensity score matching. Specifically, it compares the moments of the treated, the full control and the match control sample. Overall, the matched sample of comparable firms presents similar characteristics of firms declaring essential patents.

The balance of firms' characteristics is important in order to partly deal with the issue of heterogeneity among firms. This high heterogeneity can be explained by several factors. First, SEP holders are a small subset of firms

[44]Column (1) of Table 3 includes only firms' characteristics as control variables. Instead, Column (2) presents the results of the baseline specification using 1-year lagged values, without including firm and standard fixed effects.

[45]See the Appendix for robustness checks. Table 12 shows the results of the logistic regression using 2 years lagged control variables.

in the population with specific confounding characteristics that affect the likelihood to succeed in developing essential technologies and to declare those technologies as essential. Moreover, how I construct the control group affect the heterogeneity between the treatment and control group: specifically, a firm is included in the control group of a standard if it files at least a patent in one of the technology classes related to the standard. Since standards can share several technology classes[46], a firm not declaring any patent as essential can be included in multiple control groups for several standards. This leads to an imbalance between the treatment and the full control group.

To claim the accuracy of the represented mechanisms below I show that the parallelization of trends assumption hold for the matched sample, which is in favor of my propensity score matching techniques and therefore supports my casual claims from the econometric results. Figure 8 compares the average number of patents filed per firm-standard pairs by treated and control firms normalized by the average patents filed in the pre-period, in logs. Focusing on the matched sample, the matched treatment and control groups follow a similar path before the policy change, and they diverge after 2013. SEP holders start decreasing the average number of patents filed in the standard-related technology classes two years before the policy changed, suggesting an anticipation effect of the policy revision by essential patent holders.[47] The similarity in the pre-trends between treated and control firms assesses the parallel trends assumption, crucial for the validity of the difference-in-differences estimates.

It has been argued that the parallel trends assumption is more plausible when treatment and control groups are similar in levels and not only in distribution. Because the two groups in my sample differ in levels and distribution ex-ante, I assume a log functional form of the variable of interest. First, this assumption implies that I consider the two groups evolving with the same percentage changes.[48] Moreover, this assumption is in line with my econometric specification since I test for the effect of the policy change on the logarithm of the number of filed patents in standard-related technology classes. Indeed, the matched sample performs well in making the magnitudes and distribution of the two groups more similar, thus increasing the validity of the parallel trends assumption. This result is also in favor of the propensity score methodology. Ryan et al. (2019) illustrate, via simulations, that matched difference-in-differences models do well at dealing with non-parallel trends in the context of health policy interventions.[49]

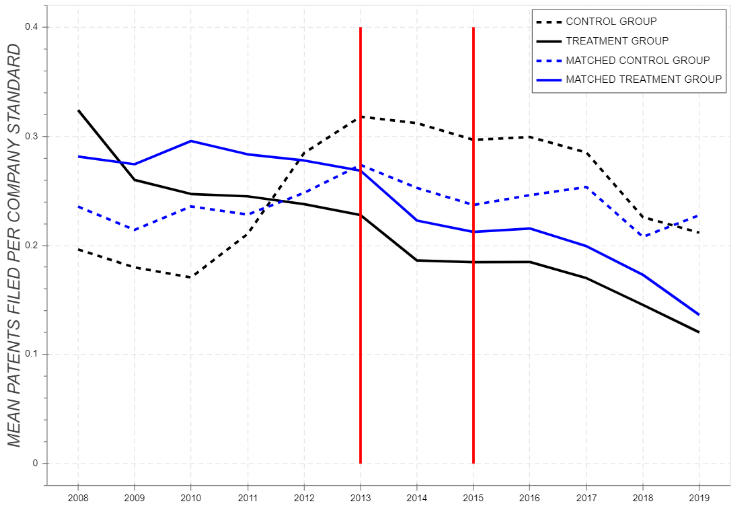
[46]This can be explained by the fact that all the standards in my sample are related to the ICT sector.

[47]IEEE Website, News Releases Section, 2015, Patent Policy Update. I also test for an anticipation effect of firms. The regression output is presented in the subsequent section.

[48]Even if the two groups differ in levels, as shown in Table 1, the treatment and the control group follow similar percentage changes over the years.

[49]For the validity of my parallel trends assumption I also performed a pre-treatment parallel trends test, by including a time trend variable and a interaction term of the treat and post variables with a time variable. To assess whether the linear trends are parallel prior to treatment, I then perform a Wald test. The results of the test are as follows: $F(1,93) = 0.11, Prob > F = 0.7452$. Therefore, the test results support the assumption that the linear trends in the outcome are parallel prior to treatment. However, Roth (2022) shows that pre-trend tests are often underpowered, and failure to reject parallel trends could mask important bias from non-parallel trends. He finds that the magnitude of violations of parallel trends against which there is a 50% and 80% power can be sizeable and often comparable in size to the estimated treatment effect.

Figure 8
Patents filed per firm-standard pairs before and after IEEE policy change



6.2 Difference in differences results

To test the empirical implication of more restrictive SDOs' patent policy on the innovation effort of firms in a standard, firstly I analyze the effect of IEEE policy change on firms' patenting activity in technology classes related to a set of 27 standards. As stated in the above sections, the dataset is a panel and the unit of analysis is the pair firm-standard per year.

The results of the estimations of the patent production function are shown in Table 6. Column 1 reports the results of the model based on the unmatched sample. The coefficient of the policy change is negative and highly significant, but the fit of the model is low, compared to the models based on the matched sample. This suggests a high unobserved heterogeneity between standards and firms which is not captured by the model. Indeed, I expect that firms self-select into the treatment and control group due to factors likely to be correlated with the company's choice of the declaration of essential patents. The issue of self-selection is particularly important in this specification since the control group consists of companies that could declare a patent as essential, but have chosen not to.

In my second model (Column 2) I try to address the self-selection problem by running the analysis on the matched sample of firms.[50] As expected, the propensity score methodology considerably reduces unobserved heterogeneity and strongly improves the fit of the model. Controlling for unobserved factors affecting the decision of a firm to contribute to standard development increases the magnitude of the effect of a change in the IEEE policy on standard-related innovation; comparing Column 1 and Column 2 in Table 6, the coefficients are slightly higher for the matched sample.[51] For changes in the IEEE policy, firms declaring patents as essential file on average 1.66 patents less in the standard related technology classes, which corresponds to 15.2% of the average patents filed by essential patent holders in the pre-period.[52]

[50]See Table 13 in the Appendix for different specifications of the baseline model.
[51]See Table 14 in the Appendix for the results on citation-weighted patents.
[52]The effect of the policy change on SEP holders is computed by comparing the estimates of the expected log of standard-related

Table 6
Effect of IEEE policy change on firm-standard innovation effort

	OLS Unmatched	OLS Matched	OLS Anticipation Effect
dT	0.156*	0.549***	0.444***
	(0.087)	(0.113)	(0.095)
Post	−0.032**	-0.005	-0.057
	(0.011)	(0.049)	(0.072)
dT*Post	−0.419***	−0.499***	−0.613***
	(0.039)	(0.058)	(0.062)
R&D expenditure	0.262***	0.192***	0.331***
	(0.007)	(0.032)	(0.026)
Size (Employees)	0.013***	0.219***	0.125***
	(0.004)	(0.033)	(0.020)
SEP holders per standard (Total)	0.099***	0.259**	0.072
	(0.031)	(0.115)	(0.092)
Declarations per standard (Total)	−0.079**	−0.252**	-0.044
	(0.030)	(0.115)	(0.087)
standard related patents (Total)	0.009	0.046	0.071**
	(0.006)	(0.028)	(0.025)
Constant	0.445***	1.462***	0.084
	(0.085)	(0.373)	(0.287)
Time fixed effect	Yes	Yes	Yes
Standard fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Number of observations	100,882	10,434	9,210
R-sq	0.36	0.87	0.86

Note: The dependent variable is the number of patents per firm-standard. The method of estimation is the fixed effect model. Standard errors are in parentheses and they allow for serial correlation through clustering by firm-standard. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

As shown in Figure 8, SEP holders started decreasing the number of patents filed in the standard-related technology classes two years before the policy changed, with a significant decline in 2014. To test for an anticipation effect of the policy change by firms holding essential patents, I compare the patenting activities of treated and control firms in standard-related technology classes in 2009-2012, excluding observations in the years 2013 and 2014 and the four years after the policy change.[53] Column 3 shows the results, taking into account the anticipation effect. As compared to the results in Column 2, the effect of the policy revision on the firms' innovation effort in standard technologies increases in magnitude. Excluding the two years before the policy change leads to a decrease in the innovation effort of firms by 21.1% (1.95 patents).

Several mechanisms can explain the decrease in patenting by SEP holders. Specifically, a decline in R&D spending or in the overall amount of patents filed might explain how the policy change drives the decline in standard-related innovation. In order to investigate the mechanisms behind the policy revision that drove the decreasing number of standard-related patents filed after 2015, I run two other specifications of my model. The results are presented in Table 7. For testing the correlation between standard-related patents and innovation costs, I compare the effect of the policy change on the baseline specification (Columns 2 and 3 in Table 6) with the same specification, excluding the R&D spending as a covariate. Comparing the results, the coeffi-

patents in each combination of the dT and $Post$ variables. Moreover, since the values are in the log form, I transform the differences between expected values to percentages using the formula $100(e^x - 1)$ where x is the difference between $[log(Patents_{treated,post}) - log(Patents_{treated,pre})]$ and $[log(Patents_{control,post}) - log(Patents_{control,pre})]$.

[53] In this specification of the model, the period of interest is 2009-2012/2015-2018.

cients for the variable of interest are constant across the two models and not statistically different. Besides, the magnitude of the effect is slightly higher for the specification that excludes the R&D cost from the vector of regressors. This outcome, combined with an effect of the policy change on the R&D expenditures not statistically significant for the baseline specification[54], and an increase of the normalized average R&D spending by treated firms after 2015, as shown in Figure 5 in the Empirical evidence section, suggests that the decrease in the number of standard related patents is unlikely to be explained by a decline in the innovation investment of firms.

Table 7
Effect of IEEE policy change on outcomes

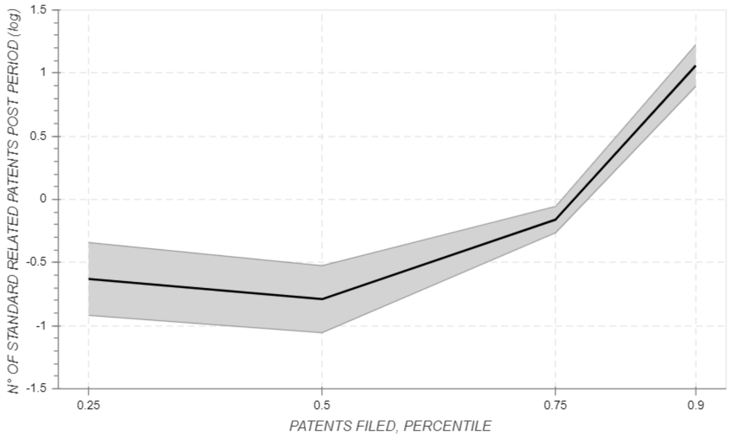
	OLS Matched	OLS Anticipation Effect	OLS Matched	OLS Anticipation Effect
Dependent Variable	Standard-related patents	Standard-related patents	Total patents	Total patents
dT	0.595***	0.446***	0.235**	0.193**
	(0.113)	(0.096)	(0.078)	(0.072)
Post	-0.016	−0.195**	−0.116**	−0.476***
	(0.048)	(0.072)	(0.035)	(0.055)
dT*Post	−0.542***	−0.629***	−0.306**	−0.388**
	(0.055)	(0.060)	(0.040)	(0.047)
R&D expenditure			0.314***	0.338***
			(0.022)	(0.019)
Size (Employees)	0.092**	0.151***	0.246***	0.147***
	(0.022)	(0.016)	(0.023)	(0.015)
SEP holders per standard (Total)	0.225**	0.077	0.164**	0.058
	(0.114)	(0.093)	(0.080)	(0.069)
Declarations per standard (Total)	−0.219*	-0.050	−0.168**	-0.052
	(0.113)	(0.087)	(0.079)	(0.066)
standard related patents (Total)	0.045*	0.080***	0.070***	0.099***
	(0.027)	(0.024)	(0.019)	(0.019)
Constant	2.823***	1.641***	2.206***	1.221***
	(0.331)	(0.255)	(0.259)	(0.217)
Time fixed effect	Yes	Yes	Yes	Yes
Standard fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Number of observations	10,434	9,210	7,630	7,705
R-sq	0.87	0.85	0.73	0.94

Note: The dependent variable in the first 2 columns is the number of patents per firm-standard. Dependent variable in the last 2 columns is the total number of patents per firm. The method of estimation is the fixed effect model. Standard errors are in parentheses and they allow for serial correlation through clustering by firm-standard. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

Furthermore, the decrease in the number of standard-related patents can be correlated with a decline in the total number of patents filed in the years after the policy revision. Even if I do not observe a decrease in measures that can affect the number of filed patents, such as R&D expenditures and sales, I observe a decline in the overall number of patents filed by firms in the post-period. Columns 3 and 4 in Table 7 report the results of the baseline model, using the total number of filed patents as the dependent variable. The policy change has a statistically significant effect for both the matched sample and when accounting for an anticipation effect. Besides, the effect is lower in magnitude compared to the same effect on standard-related patents. Since standard-related patents are included in the count of the overall amount of patents, the dependent variable is still affected by the policy change: this explains why I observe a statistically significant but weak effect of the policy change on total patents. These results suggest that the policy update has a weak effect on the total number of filed patents by SEP holders, and thus it is unlikely that the decrease in standard-related innovation

[54]The results are shown and discussed in Table 9 in subsection 8.2 of the Appendix.

Figure 9
Treatment Effect on the Treated



at IEEE is correlated to a decline in the absolute number of patents.

More restrictive patent policies have a statistically significant negative effect on standard-related innovation across the models.[55] The estimated effects are in line with other studies concerning SDOs' patent policies and the effects of changing patenting conditions. In her paper, Rosa shows that the restriction on patent licensing to royalty-free would have a big and negative effect on participation and effort decisions. The results of her analysis show a decrease of the 18% less of standardization effort by firms in the standardization process.[56] Hall and Ziedonis study the effect on the patenting behavior of semiconductor firms of the creation of the Court of Appeals for the Federal Circuit in 1982, which led to stronger patent rights: they show that the patenting intensity of firms increased at a rate of 10% per year after 1986 due to increased protection of patent rights.

Even though the fixed effects and the set of standard-specific control variables should deal in part with the issue of heterogeneity within treated firms, there might be reasons that are likely to be correlated to the firms' investment in a standard development but that are not captured by the models. For instance, pure R&D innovators are more likely to be negatively affected by patent policy changes concerning licensing requirements compared to vertically integrated firms, since they are more reliant on intellectual rights to gain the return on the developed innovation. Vertically integrated firms can instead face an incentive to increase their innovation effort in a standard due to a change to more restrictive rules (Bekkers et al., 2017; Spulber, 2019): a decrease in the price of the standard technologies can increase the demand for the patented technologies and thus of the final good by lowering its production costs. So, given the heterogeneity of the contributors involved in the standard development, the decisions made by the SDO can have a significant and divergent effect on the willingness to contribute by firms with different business models.

In order to partially investigate the heterogeneity of the effect of a more restrictive patent policy on the inno-

[55] For different specifications of the baseline model and additional robustness checks, see Table 13 to Table 15 in the Appendix.
[56] Note that her definition of contribution in a standard project is different: she uses the number of written contributions made by a firm to a standard as a proxy for firm effort. Furthermore, she focuses on wireless standards only.

vation effort of firms in a standard, I rely on the changes-in-changes methodology (Athey and Imbens, 2006). Athey and Imbens (2006) develop a non-linear difference-in-differences model which allows for heterogeneous changes over time and across groups in the effect of interest. Given the high heterogeneity of the incentives firms face to contribute to the standard development, it is likely that the policy change affects firms differently at different points in the distribution. The results are shown in Figure 9.[57] The effect is strong and negative for the mean ranks of the distribution (25th to 75th percentiles), but the coefficient of interest turns positive for the 90th percentile. Since vertically integrated firms usually build large patent portfolios, while R&D innovators are small firms which concentrate their innovation around few but valuable patents, the results of the analysis hint at a negative effect of the policy change on those firms that depend on the monetization of innovations, while it affects positively firms that usually use the technology standard as input and benefit from the selling of the end products.

Table 8
Effect of IEEE policy change on outcomes - Robustness check

	OLS Matched	OLS Anticipation Effect	OLS Matched
dT	0.477**	0.295**	-0.104
	(0.173)	(0.140)	(0.089)
Post	-0.119	-0.108	-0.036
	(0.081)	(0.098)	(0.057)
dT*Post	-0.107	-0.125	0.066
	(0.106)	(0.123)	(0.086)
R&D expenditure	0.294***	0.272***	0.305***
	(0.078)	(0.071)	(0.041)
Size (Employees)	0.159*	0.086	−0.028*
	(0.090)	(0.066)	(0.016)
SEP holders per standard (Total)			0.028
			(0.067)
Declarations per standard (Total)			-0.029
			(0.064)
standard related patents per standard (Total)	0.079**	0.061*	0.154**
	(0.036)	(0.034)	(0.078))
Constant	-0.182	0.179	1.206***
	(0.686)	(0.697)	(0.259)
Time fixed effect	Yes	Yes	Yes
Standard fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Number of observations	664	677	6,331
R-sq	0.62	0.69	0.86

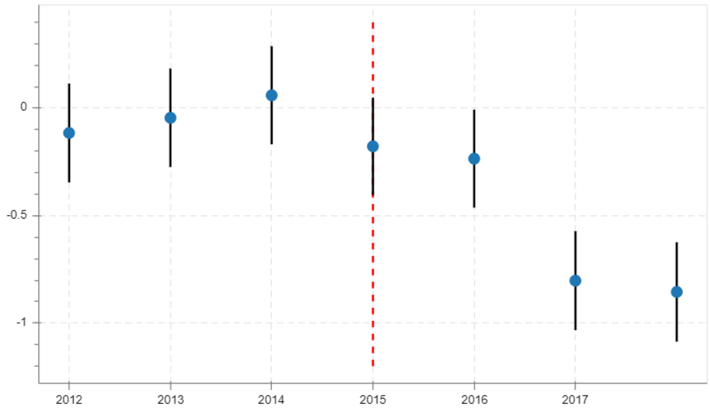
Note: The dependent variable in the first 2 columns is the number of unrelated patents. Dependent variable in the last column is the number of standard-related patents and the period of interest is 2006-2011. The method of estimation is the fixed effect model. Standard errors are in parentheses and they allow for serial correlation through clustering by firm-standard. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

6.3 Robustness

Table 8 reports the results of two other specifications I run to check for robustness of my main results. Firstly, I run a difference-in-differences model where the dependent variable is the number of patents filed in standard unaffected technology classes. The results are presented in Column 1 and 2. As expected, the coefficient is

[57]The results of the analysis are reported in Table 17 in the Appendix

Figure 10
Estimates of δ over time



not statistically significant for the matched sample, meaning that there is no effect of the policy change on the patents out of the standard technology classes. Besides, to test for an effect on outcomes that are known to be unaffected by the policy change, I run a different specification of the baseline model, taking into account the time frame 2006-2011 and a policy change that occurs in 2009.[58] I find no effect of the policy update, as shown in Column 3.

Other robustness checks are presented in the Appendix. Specifically, I use 2 years lagged covariates to check for possible bias in the timing between when the innovation costs occur and the application of the patents, and I interact the treatment dummy with years.[59] The first specification leads to similar results as the baseline model[60], while the second one reports not statistically significant coefficients for the years before the policy change.The time effect on the treatment group is reported in Figure 10. As expected the coefficients are not statistically significant in the pre-period and start being significant and decreasing in the years after the policy revision.[61]

7 Conclusion

SDOs have changed their patent policies over the years to prevent strategic behaviors by SEP holders. As the patent policies regarding SEPs became more restrictive, they focused more on users and implementers of the standard technologies. Since it is also important to understand how strengthened patent policies affect the innovation effort of innovators in the standards development, this paper contributes to the literature by

[58] As an additional robustness check, I tested for a policy effect on standard-related patents in 2007-2012 and a policy change in 2010. Again, the results led to a not statistically significant effect.

[59] The patent equation I estimate is of the form:

$$ln(P_{ist}) = \sum_{n=2011}^{2018} \delta_n dT_{is} * Year_n + X'_{i,t-1}\beta_1 + S'_{s,t-1}\beta_2 + \gamma_i + \gamma_s + \tau_t + \epsilon_{ist}$$

Where $Year_n$ is a dummy variable equals 1 for the year of interest

[60] The results of the econometric analysis are presented in Table 15 in the Appendix.

[61] The results of the econometric analysis are presented in Table 16 in the Appendix.

empirically analyzing the effect of IEEE patent policy revision on the number of patents filed by firms owing essential patents in the standard-related technology classes.

My results show a negative relationship between the number of patents filed by SEP holders in the standard-related technology classes and the degree of restrictiveness of IEEE patent policy. SEP holders reduce, on average, their innovation effort in standards by 15.2% after the policy revision. To investigate how the policy change drives the decline in standard-related patents, I test for the effect of the policy change on other factors that might be correlated with the innovation effort of firms in standards. Specifically, the decrease in the overall amount of filed patents or in the innovation expenses at the firm level can explain the lower number of patents filed in standard technology classes. After testing for other factors, my results suggest that the decrease in the absolute number of patents and R&D costs are unlikely to be drivers of the decline of the innovation effort of SEP holders in technology standards.

This research sheds some new light on how SDOs' patent policies affect the firms' incentive to innovate in standard development. Several issues are left for future research. First, not only has IEEE changed its policy, but other SDOs have updated their licensing requirements through the years. In order to better understand the relationship between standard developers and patent policies' requirements, further research should focus on extending the model to several policy changes at different points in time.

Besides, firms declare essential patents to multiple standards issued by several organizations, and technology standards in the ICT sector share multiple technology classes. The decrease in the number of patents filed by SEP holders in the technology classes related to standards issued by IEEE might have been balanced by a reallocation of the firms' investments in standards issued by other organizations, implying a consequent increase in the standards-related innovation. Even if I observe a decrease in the total number of patents filed by firms after the policy change, the share of patents filed in the standard-related technology classes remains constant over the entire period of interest. This evidence suggests that firms might substitute away to other technology standards issued by other standard development organizations.

Lastly, firms face different incentives to invest in standards according to their type of business (pure R&D innovators and vertically integrated firms), and they declare multiple patents to multiple standards in other SDOs. Modeling the movement of firms among technology standards can shed more light on the strategic behavior of firms, their incentive to invest and patent innovations in technology standards, and how to promote competition via SDOs' patent policies.

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8 Appendix

8.1 Governance and procedure of IEEE's policy revision

Being a specialized organizational unit of the Institute for Electrical and Electronics Engineers, the IEEE-SA has its own governance system and a high degree of authority over matters related to standardization. The IEEE-SA is governed by its own Board of Governors (BOG) that establishes the association's policies and delivers financial oversight of the association's activities to the IEEE's highest hierarchical authority, the Board of Directors. A maximum of 15 BOG members is elected every two years by IEEE voting members who also hold membership of the IEEE-SA.

Each year, the BOG appoints the Standards Board (SASB) amongst the voting members of both IEEE-SA and IEEE. The SASB plays an important role in the processes of development and approval of IEEE draft standards, and divides its activities between different SASB standing committees. For instance, the Patent Committee (PatCom) reviews standard-setting processes with regard to the use of patented technologies. PatCom is also responsible for defining the Institute's IPR Policy, although its contributions take the form of non-binding recommendations to the SASB. Modifications in the IEEE-SA's bylaws (including in the IPR Policy) involve participation of the other committee of SASB, namely the Procedures Committee (ProCom), also appointed by the SASB. However, the engagement of the ProCom in the processes of alteration the IEEE-SA's bylaws is not mandatory.[62]

In order to discuss possible amendments of its patent policy, an ad hoc committee was appointed by the PatCom during a meeting in March 2013. This committee consisted of seven 2013 PatCom members, an upcoming 2014–2015 PatCom member an upcoming 2014–2015 PatCom non-voting member, one IEEE staff member and two non-voting members of the 2016 BOG.[63] In the next two years, the members of the ad hoc committee worked on the development of the policy update. The policy's amendments were drafted by a subcommittee of the ad hoc committee within 15 months following the meeting of March 2013. Since neither the minutes the ad hoc committee's meetings, nor those of the subcommittee were publicly available, the course of the discussions and the rationale behind the decisions taken at those meetings remain unknown.

After the ad hoc's approval, the draft was opened for an online public review and commenting. In total, four drafts were available for the public review, 680 comments were made and 547 of them were responded to by the ad hoc. The forth and the last version incorporated some of the suggested modifications, and was approved by the PatCom in June 2014 in a process of simple majority voting, with favourable vote from three individuals who were also members of the Ad Hoc committee. The negative votes came from the two individuals who were not part of the committee. The draft was subsequently submitted for consideration of the SASB, which discussed

[62] See the IEEE-SA Operations Manual and the IEEE-SA Bylaws for detailed information about the structure and governance of IEEE-SA.

[63] PatCom Meeting Minutes

the proposed policy update in its open session held in August 2014. After accepting the PatCom report in paper balloting, the SASB forwarded the draft to the BOG for approval, which took place in December 2014. Subsequently, a final approval was sought and obtained from the Board of Directors at a meeting in February 2015.

8.2 R&D expenditures and patent policies

Since the patent policy endorsed by the organization can affect the firms' decision of the amount of the innovation investment to develop standard-related technologies by affecting their return on innovation, the R&D spending in my specification can be correlated with the variable $Post_t$, capturing the policy change. In order to test for an endogeneity problem in my specification, I run a regression testing the correlation between the policy change and the total R&D spending of SEP holders. The results are reported in Table 9.

Table 9
Effect of IEEE policy change on firms R&D expenditure

	OLS Matched	OLS Matched	OLS Matched	OLS Matched	OLS Matched
dT	-0.064	-0.042	-0.074	-0.076	-0.069^{*}
	(0.093)	(0.040)	(0.089)	(0.089)	(0.041)
Post	0.220^{***}	-0.018^{*}	0.246^{***}	0.260^{***}	-0.032^{*}
	(0.046)	(0.009)	(0.039)	(0.041)	(0.019)
dT*Post	-0.294^{***}	0.012	-0.293^{***}	-0.294^{***}	0.012
	(0.064)	(0.021)	(0.046)	(0.046)	(0.021)
Total patents filed		0.084^{***}			0.085^{***}
		(0.006)			(0.006)
Size (Employees)		0.462^{***}			0.459^{***}
		(0.011)			(0.011)
Average R&D expenditure of SEP holders				0.144	0.238^{***}
				(0.102)	(0.047)
Average Size of SEP holders				-0.053	-0.104^{**}
				(0.084)	(0.038)
SEP holders per standard (Total)			0.194^{**}	0.177^{*}	0.092^{**}
			(0.091)	(0.092)	(0.042)
Declarations per standard (Total)			-0.182^{**}	-0.166^{*}	-0.089^{**}
			(0.091)	(0.091)	(0.042)
standard related patents (Total)			0.012	-0.003	-0.024^{**}
			(0.022)	(0.025)	(0.011)
Time Fixed Effect	No	No	Yes	Yes	Yes
Standard Fixed Effect	No	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	Yes	Yes	Yes	Yes
Number of observations	7,802	7,630	7,801	7,801	7,630
R-sq	0.01	0.97	0.87	0.87	0.97

Note: The dependent variable is the R&D expenditure. The method of estimation is the fixed effect model. Standard errors are in parentheses and they allow for serial correlation through clustering by firm-standard. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

For the baseline specification (Column 5, Table 10), the interaction term is not statistically significant, suggesting that the endogeneity problem is not a concern for my research. Furthermore, for statistically significant coefficients (Columns 1, 3, and 4), the magnitude of the effect is weak. Since I cannot disentangle the share of R&D cost allocated to standards, and thus the standard-related innovation costs are included in the total amount of R&D expenses, it is reasonable to observe a weak effect of the policy change on R&D.

8.3 Tables and Graphs

Table 10
Summary Statistics of the variables in the time period 2009-2018

	Data source	Mean	SD	Min	Max
Patents filed in standard-related classes	PATSTAT	34.9	331.8	0	14,291.0
Patents filed total	PATSTAT	187.1	1,088.0	0	19,934
Lag1 R&D Expenses (USD billions)	Compustat	282.1	1,100.1	0	14,863.9
Lag1 Firm Size (thousands)	Compustat	12.4	44.7	0	726.8
Lag1 Sales (USD billions)	Compustat	4,598.9	17,835.1	0	253,347.3
Treat (dT)	SCDB	0.07	0.26	0	1
Standard Age (at the time of declaration)	SCDB	4.6	3.7	0.25	14.3
Broadness of standard (Total number of IPC classes per standard)	SCDB	13.1	10.2	1	90
Essential patent holders	SCDB	0.5	0.7	0	2.9
Standard documents	SCDB	1.1	1.7	0	7.2
Standard related patents filed per standard (Total)	5,780.0	6,315.7	9.2	18,716.5	
Essential patents	SCDB	6.3	10.3	0	38.7
Declarations	SCDB	0.6	0.7	0.0	3.0
Number of employees per SEP holder-standard pair (thousands)	49.5	25.6	27.9	155.8	
R&D expenditures per SEP holder-standard pair (billions)	1,783.3	550.6	701.7	3,078.1	

Table 11
Summary Statistics of the Technology Standards

	SEPs holders (Total)	Disclosures	standard related Patents (Total)	Essential Patents (Total)	Age(max)	Employees (mean)	R&D Expenditure (mean)
IEEE 1394	57.0	154.0	312,838.0	2336.0	23.0	164.8	4,589.1
IEEE 1588	8.0	8.0	801.0	144.0	16.0	154.2	5,557.5
IEEE 1619.1	8.0	8.0	78,282.0	40.0	11.0	311.6	4,116.6
IEEE 802.11	69.0	69.0	425,738.0	2544.0	21.0	94.9	2,792.9
IEEE 802.11a	31.0	31.0	72,630.0	750.0	19.0	126.8	2,890.4
IEEE 802.11aa	14.0	14.0	36,110.0	18.0	6.0	59.6	4,838.3
IEEE 802.11ac	108.0	110.0	432,600.0	645.0	5.0	80.5	3,673.8
IEEE 802.11g	32.0	32.0	36,676.0	728.0	15.0	58.7	1,403.4
IEEE 802.11n	74.0	76.0	368,669.0	664.0	9.0	96.0	2,9992.1
IEEE 802.11r	20.0	20.0	52,206.0	44.0	10.0	76.3	4,330.9
IEEE 802.11s	48.0	48.0	225,185.0	128.0	7.0	97.3	3,134.9
IEEE 802.11u	22.0	22.0	64,318.0	64.0	7.0	57.8	3,497.8
IEEE 802.11w	14.0	14.0	45,159.0	28.0	9.0	73.9	6,156.2
IEEE 802.15.3	16.0	16.0	30,122.0	180.0	15.0	81.5	2,586.3
IEEE 802.15.4	16.0	16.0	15,119.0	110.0	15.0	61.2	4,619.4
IEEE 802.15.6	24.0	26.0	60,006.0	46.0	6.0	55.8	3,006.8
IEEE 802.16	86.0	90.0	391,570.0	5026.0	17.0	96.7	3,999.9
IEEE 802.16a	22.0	22.0	7,277.0	100.0	15.0	63.8	2,339.9
IEEE 802.16e	42.0	42.0	403,288.0	696.0	13.0	92.8	2,685.5
IEEE 802.17	16.0	16.0	49,331.0	136.0	14.0	86.9	5,256.4
IEEE 802.1Q	62.0	72.0	88,856.0	1116.0	20.0	100.7	2,667.4
IEEE 802.1ah	12.0	12.0	29,227.0	76.0	10.0	124.9	3,328.6
IEEE 802.1aq	10.0	10.0	8,098.0	42.0	6.0	59.3	2,690.5
IEEE 802.2	24.0	24.0	169,774.0	444.0	33.0	83.2	3,249.7
IEEE 802.21	32.0	34.0	151,167.0	318.0	10.0	94.6	4,072.9
IEEE 802.22	36.0	36.0	142,298.0	276.0	7.0	89.9	3,399.6
IEEE 802.3	38.0	38.0	195.0	826.0	33.0	128.4	2,419.3

Table 12
Firms decision to declare essential technologies - 2 Years Lag Variables

	Logit	Logit	Logit
Technology similarity	4.187***	4.612***	4.229***
	(0.963)	(0.451)	(0.972)
$R\&D_1$	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)
$R\&D_1^2$	−0.006***	−0.006***	−0.005***
	(0.001)	(0.001)	(0.001)
Sales	0.007	-0.008	0.001*
	(0.005)	(0.005)	(0.006)
Total Patents filed	0.468***	0.474***	0.498***
	(0.051)	(0.048)	(0.053)
SEP holders per standard (Total)		-0.20	−0.716*
		(0.019)	(0.434)
Declarations per standard (Total)		-0.027	0.534
		(0.017)	(0.416)
Firm fixed effect	Yes	No	Yes
Standard fixed effect	Yes	No	Yes
Number of observations	31,769	31,769	31,769
Log Likelihood	-710.04	-725.39	-664.79

Note: The dependent variable is a binary outcome in which dT_{is} takes the value off 1 if firm i declares at least an essential patent for standard s during the period 2001-2014. The parameters are estimated by maximum likelihood. Standard errors are robust to arbitrary heteroskedacity and allow for serial correlation through clustering by firm-standard. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

Table 13
Effect of IEEE policy change on firm-standard innovation effort - Full specification

	OLS Matched	OLS Matched	OLS Matched	OLS Matched	OLS Matched
dT	0.582***	0.554***	0.577***	0.717***	0.549***
	(0.112)	(0.112)	(0.113)	(0.084)	(0.113)
Post	-0.031	-0.018	-0.020	−0.190***	-0.005
	(0.047)	(0.049)	(0.048)	(0.020)	(0.049)
dT*Post	−0.567***	−0.496***	−0.571***	−0.482***	−0.499***
	(0.054)	(0.058)	(0.054)	(0.042)	(0.058)
R&D expenditure		0.195***		0.276***	0.192***
		(0.032)		(0.021)	(0.032)
Size (Employees)		0.218***		0.183***	0.219***
		(0.033)		(0.021)	(0.033)
SEP holders per standard (Total)			0.209*	0.102	0.259**
			(0.112)	(0.067)	(0.115)
Declarations per standard (Total)			−0.205*	-0.078	−0.252**
			(0.111)	(0.065)	(0.115)
standard related patents (Total)			0.044	0.092***	0.046
			(0.027)	(0.019)	(0.028)
Constant	3.095***	1.602***	2.925***	-0.109	1.462***
	(0.151)	(0.219)	(0.198)	(0.193)	(0.373)
Time fixed effect	Yes	Yes	Yes	No	Yes
Standard fixed effect	Yes	Yes	Yes	No	Yes
Firm fixed effect	Yes	Yes	Yes	No	Yes
Number of observations	10,434	10,434	10,434	10,438	10,434
R-sq	0.87	0.88	0.87	0.25	0.87

Note: The dependent variable is the number of patents per firm-standard. The method of estimation is the fixed effect model. Standard errors are in parentheses and they allow for serial correlation through clustering by firm-standard. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

Table 14
Effect of IEEE policy change on firm-standard innovation effort - Citation-weighted patents

	OLS Unmatched	OLS Matched	OLS Anticipation Effect
dT	0.569**	1.323***	0.942***
	(0.235)	(0.268)	(0.225)
Post	-0.048	0.027	0.026
	(0.030)	(0.119)	(0.1712)
dT*Post	−0.860***	−1.119***	−1.200***
	(0.108)	(0.138)	(0.147)
R&D expenditure	0.651***	0.331***	0.757***
	(0.018)	(0.0752)	(0.062)
Size (Employees)	0.064***	0.3879***	0.216***
	(0.009)	(0.078)	(0.048)
SEP holders per standard (Total)	0.349***	0.735**	0.185
	(0.083)	(0.276)	(0.217)
Declarations per standard (Total)	−0.282***	−0.711*	-0.115
	(0.082)	(0.274)	(0.205)
standard related patents (Total)	0.042***	0.078*	0.106***
	(0.008)	(0.031)	(0.027)
Constant	1.367***	4.866***	0.941
	(0.231)	(0.905)	(0.704)
Time fixed effect	Yes	Yes	Yes
Standard fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Number of observations	100,882	10,434	9,210
R-sq	0.74	0.87	0.86

Note: The dependent variable is the number of citation weighted patents per firm-standard. The method of estimation is the fixed effect model. Standard errors are in parentheses and they allow for serial correlation through clustering by firm-standard. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

Table 15
Effect of IEEE policy change on outcomes - 2 Years Lag

	OLS Unmatched	OLS Matched	OLS Anticipation effect
Dependent Variable			
standard related patents (baseline specification)	−0.464***	−0.521***	−0.608***
	(0.039)	(0.056)	(0.061)
Citation weighted patents (baseline specification)	−0.958***	−1.121***	−1.170***
	(0.108)	(0.135)	(0.146)
standard related patents (specification excluding R&D)	−0.574***	−0.556***	−0.657***
	(0.037)	(0.054)	(0.059)
Total Patents	−0.286***	−0.286***	−0.348***
	(0.037)	(0.39)	(0.047)

Note: The method of estimation is the fixed effect model. Standard errors are in parentheses and they allow for serial correlation through clustering by firm-standard pair. The covariates of the primary specification are: R&D expenditures, number of employees, number of SEPs holders, total number of patents and number of disclosures per standard, age of the standard, firm, standard and year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

Table 16
Effect of IEEE policy change on firm-standard innovation effort over time

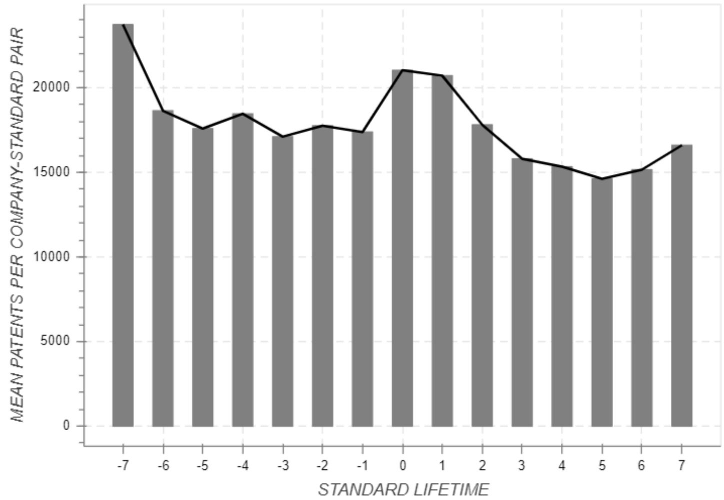
	OLS Unmatched	OLS Matched
dT	0.256**	0.524***
	(0.102)	(0.133)
dT*2012	−0.142*	-0.116
	(0.083)	(0.117)
dT*2013	−0.152*	-0.045
	(0.082)	(0.117)
dT*2014	−0.178*	0.059
	(0.082)	(0.116)
dT*2015	−0.359***	-0.177
	(0.081)	(0.116)
dT*2016	−0.315***	−0.235**
	(0.079)	(0.116)
dT*2017	−0.663***	−0.802***
	(0.079)	(0.117)
dT*2018	−0.811***	−0.855***
	(0.080)	(0.118)
Standard fixed effect	Yes	Yes
Firm fixed effect	Yes	Yes
Number of observations	8,544	7,630
R-sq	0.87	0.87

Note: The dependent variable is the number of patents per firm-standard. The method of estimation is the fixed effect model. The coefficients of interest are the interaction terms between treatment dummy and year dummies. Standard errors are in parentheses and they allow for serial correlation through clustering by firm-standard. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significant levels.

Table 17
Results of the Changes in Changes - Effect of the Treatment on the Treated

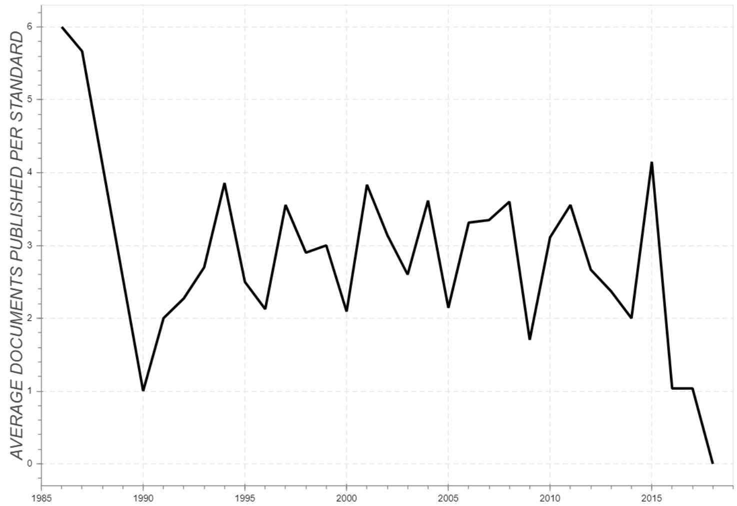
	OLS mean log	OLS 25th	OLS 50th	OLS 75th	OLS 90th
Methodology					
Did-log	-0.549	-0.38	-0.45	- 0.56	-0.74
cic disc	-0.420	-0.63	-0.79	-0.16	1.06
cic disc lower bound	-0.441	-0.63	-0.79	-0.16	1.06
cic disc upper bound	-0.401	-0.63	-0.79	-0.16	1.06

Figure 11
The average number of patents filed in years before and after the standard publication



Data Sources: Searle Center Database, PATSTAT

Figure 12
The average number of standard documents published per standards over years



Data Source: Searle Center Database